



# Alternative Investment Analyst Review

Editor's Letter: Machine Learning and Hedge Fund Classification using Self-Organizing Map Hossein Kazemi and Satyagrota Das, CAIA, CAIA Association Ten Years of Blockchain: Unveiling the Mystery and Moving Beyond the Hype Alessandro Sanos, CAIA, Refinitiv **Alternative Alphas and Asset Allocation** Masao Matsuda, CAIA, Crossgates Investment and Risk Management Infrastructure Debt in a Portfolio Context - A First Exploration David van Bragt, Aegon Asset Management **Managed Futures and the KISS Effect** Urs Schubiger, Egon Ruetsche, and Fabian Dori, Aquila Captial An Introduction to Alternative Risk Premia Guillaume Monarcha, Orion Financial Partners Technology, Innovation, and Disruption Jack Sibley, Nuveen Real Estate, and Filippo Rean, REED MIDEM **Rethinking Real Assets** Peter Hobbs, Guy Hopgood, Anish Butani, and Kathryn Saklatvala, bfinance A Crisis of Beliefs: Investor Psychology and Financial Fragility, An Interview with Andrei Shleifer Barbra J. Mack, Pingry Hill Enterprises, Inc. and Andrei Shleifer, Harvard University The CAIA Endowment Investable Index Hossein Kazemi, The CAIA Association, and Kathryn Wilkens, CAIA, Pearl Quest The List: Alternative Indices The CAIA Association



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### Editor's Letter

#### Machine Learning and Hedge Fund Classification using a Self-Organizing Map

Machine Learning (ML) and Artificial Intelligence (AI) have become ubiquitous in everyday life. Some of the applications of ML and AI affect us directly, while others subtly affect us. They are widely used in technologies associated with applications such as facial recognition, email spam and malware filtering, chatbots, etc., and in advanced applications such as robotic surgery, genomic sequencing, radiation treatment, etc. The field of finance has seen increasing use of ML and AI application, especially in the asset management industry.

Increased use of ML and AI techniques in finance can be attributed both to data from new sources, such as from credit card transactions, mobile phone location information, and from satellite images, and to easier access to highly powerful computational devices. ML and AI techniques in fraud detection and credit approval have been used for a very long time. Asset managers and asset allocators, however, have shown increased interest in the use of ML and AI tools for asset allocation, trading and generating investment ideas more recently. Applications by asset managers include analyzing credit-card data, using textual analysis on company filings, using satellite image analysis for revenue forecasting, etc.

Many of the applications of ML and AI use tools that can broadly be categorized as classification tools. They help categorize a group of data points into a small number of discrete groups containing data points with similar attributes. Whenever we are detecting fraud or making decisions on credit approval, we are essentially grouping all cases into two – good and bad or approve and not approve, and the task can be accomplished by using widely known classification techniques such as logistic regression, neural networks, classification trees and support vector machines.

In this article, we explore an application of a classification technique in finance. In particular, we examine a simple application of the Self-Organizing Map to see if the technique can be used to divide further a group of hedge funds that are already labeled as following the same hedge fund strategy. For example, while a group of hedge funds may be classified as equity long/short managers, there may be several distinct subgroups of managers with some following trend following strategies while others following fundamental strategies. Such an exploratory analysis can be useful for an investor, such as a fund of hedge funds, which is trying to construct portfolios of hedge funds that are highly diversified and do not over allocate to managers that follow the same strategy. Equally, important, the fund of funds manager would want to perform an initial evaluation of many managers to reduce the sample and therefore the due diligence cost. Rather than undertaking a full-fledged analysis of each fund, SOM can help divide the space of all acceptable funds into smaller homogenous groups, which can then be analyzed separately. Portfolios formed by choosing funds from different groups is expected to provide greater diversification benefits.

Our study is similar to the study by Harvey, Rattray, Sinclair and van Hemert (2017), who classify Equity Hedge and Macro Funds into systematic and discretionary funds and analyze their performance. They use textual analysis on each fund's description to bifurcate funds into systematic and discretionary funds and analyze the performance of the two groups, whereas we use monthly returns data to classify funds into many groups and examine the characteristics of the funds in different groups.

Our results indicate that machine learning algorithms can be used effectively to classify funds into homogenous groups. These algorithms are especially good at isolating funds that are very different from the other funds in our sample. Such funds could either be a source of alpha or a problem fund that is most likely not following the stated strategy. At the very least, machine learning tools can be used as a starting point for deeply analyzing a large number of funds.

This article is organized into several sections. We first provide a very brief introduction to the artificial neural network (ANN) and show how a simplified version of it may be used to classify managers. Next, we describe the Self-Organizing Map, which uses ANN to perform classification in a more complex and adaptive way. Then, we discuss the data used in our analysis, and finally, we show some results.

#### Introduction to Artificial Neural Networks (ANN)

Suppose we have historical observations on a set of economic variables such as unemployment, inflation, GDP growth and so on. Given these historical observations, we are interested to see if they can be used to predict the probability that the economy would enter a recession. We represent our historical observations by e\_it, which is our observation of economic variable: at time t. These observations along with our observations of historical recessions can be presented in the following form.

| Time |                  | Output: Recession |                 |                 |   |
|------|------------------|-------------------|-----------------|-----------------|---|
| 1    | e <sub>11</sub>  | e <sub>21</sub>   | e <sub>31</sub> | e <sub>41</sub> | 1 |
| 2    | e <sub>12</sub>  | e <sub>22</sub>   | e <sub>32</sub> | e <sub>42</sub> | 0 |
| 3    | e <sub>13</sub>  | e <sub>23</sub>   | e <sub>33</sub> | e <sub>43</sub> | 0 |
| 4    | e <sub>1</sub> 4 | e <sub>24</sub>   | e <sub>34</sub> | e <sub>44</sub> | 1 |

**Exhibit 1: Economic Variables and Recession** 

As you can see, we have collected four economic variables covering four periods. Also, we can see that recessions followed periods 1 and 4 while recessions did not follow periods 2 and 3.

Our goal is to feed these economic variables (inputs) into a function or functions where the output would be either 0 or 1 depending on whether a recession was observed. Once we have estimated a function that performs well in in-sample, we plan to use future observations of the same economic variables to obtain estimates of the likelihood that a recession could follow. Graphically, the process may look like this:

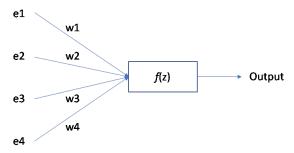


Exhibit 2: A Single Node

Here, the inputs are fed into the neuron containing the function, which produces an output representing the occurrence of no recession (0) or recession (1). Variable z is a function of the economic variables (e.g., average). Since these economic variables may not be equally important in influencing the outcome, it makes sense to take a weighted average of these economic variables. That is, in each date, we estimate the variable  $\theta$  as:

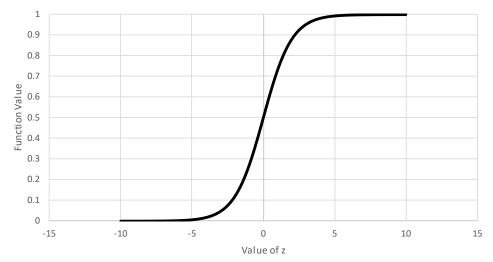
$$z_t = w_1 e_{1t} + w_2 e_{2t} w_3 e_{3t} + w_4 e_{4t} + \theta$$

The parameter  $\theta$  is called the bias. The variable  $\theta$  is then fed into the function:

$$f(z) = \frac{1}{1 + \exp\left(-z\right)}$$

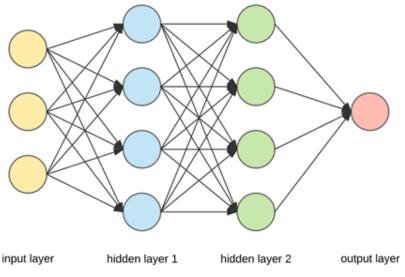
This function has an interesting property that it will be between zero and 1. If z is a very large positive number then the function will approach 1, and if z is a large negative number, then the function will approach 0. The weights are selected such as the value of f(z) is as close as possible to the observed outcome, recession (1) or no recession (0). The following figure displays the behavior of the function:

Behavior of the Function



#### Exhibit 3: Behavior of *f*(*z*)

Exhibit 2 displays a single neuron, where it receives a signal and produces an output. In a neural network, different weighted averages of the economic variables may be fed into many neurons, and the outputs of those neurons could be fed into another set of neurons. Each set of neurons is referred to as a layer. Therefore, if we think of inputs as one layer and the single neuron that produces the output as another layer, then Exhibit 2 has two layers. If there are layers of neurons between the input and the output layers, then they are called the hidden layers. The following figure displays an ANN with four layers.



**Exhibit 4: A Neural Network** 

For each layer, a different weighted average of the outputs of the previous layer is fed into the above function (other functions may be used as well). As data is fed to the ANN, it adapts by adjusting the weights and the bias parameters to improve its performance by reducing its in-sample error until no further improvement can be made. At that point, the researcher can feed new data into the ANN to obtain a new prediction regarding the possibility of a recession in the coming period.

The process described above represents a supervised learning algorithm because we had "labels" for historical outcomes – recession or no recession. That is, we helped the program learn that a particular state of the economy is called a recession and another one is called an expansion.

An example of unsupervised learning would be to feed data about purchasing histories of many customers into an ANN, and then ask the network to determine the number of distinct groups of customers that exist. More commonly we may pre-specify the number of groups and then ask the ANN to create optimal clusters of the customers. The clustering procedure will assign each customer to one of those groups such that members of each group are as similar as possible and that each group is as dissimilar from other groups as possible.

#### Self-Organizing maps

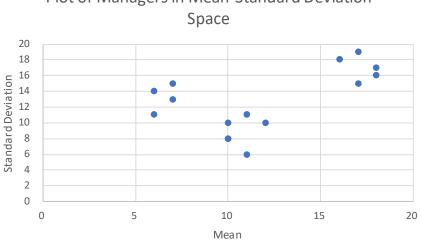
A Self-Organizing Map or SOM, as it is commonly known, is a particular type of neural network that is trained using unsupervised learning to produce a low dimensional representation of a high dimensional input data. For example, suppose we have a large set of companies, and for each company, we have several pieces of information such as size, sales, ROE, leverage, and so on. If we have 50 pieces of information about each firm, there is no way we can visually inspect our sample and decide how many different types of firms are present. A SOM algorithm will reduce this 50-dimensional problem into a two-dimensional problem, which can then be visually inspected. An example can help demonstrate this point.

Suppose we have the following data about 15 money managers.

|     | Mean | Standard<br>Deviation | Correlation with<br>S&P 500 |
|-----|------|-----------------------|-----------------------------|
|     | %    | %                     | %                           |
| M1  | 10   | 10                    | 70                          |
| M2  | 18   | 17                    | 50                          |
| M3  | 11   | 11                    | 20                          |
| M4  | 6    | 11                    | 12                          |
| M5  | 6    | 14                    | 0                           |
| M6  | 7    | 15                    | 60                          |
| M7  | 7    | 13                    | 50                          |
| M8  | 11   | 6                     | 25                          |
| M9  | 16   | 18                    | 40                          |
| M10 | 17   | 19                    | 60                          |
| M11 | 12   | 10                    | 75                          |
| M12 | 18   | 16                    | 65                          |
| M13 | 17   | 15                    | 30                          |
| M14 | 10   | 8                     | 20                          |
| M15 | 10   | 8                     | 10                          |

| Exhibit 5: Manager | s and Their Characteristics |
|--------------------|-----------------------------|
|--------------------|-----------------------------|

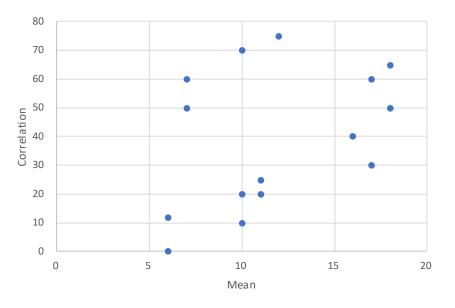
For each manager, we have historical annualized mean and standard deviation as well as correlation with the S&P 500 Index. Suppose we wish to see if these managers form 2-3 distinct groups. Just by looking at the numbers, we may not be able to accomplish this task. However, let us plot these managers in the mean-standard deviation space first.

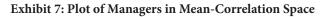






We can see that they form three distinct groups if we were to look at their means and standard deviations. However, if we were to plot these managers in the space of mean-correlation, we would notice that there are perhaps four or five distinct groups.



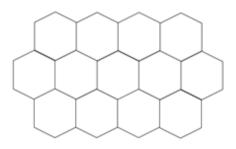


Now, suppose that we have other pieces of information such as skewness, maximum drawdown, Sortino ratio, etc. about these managers. The task of identifying distinct groups of these managers would be impossible unless we use a classification or clustering technique. We could employ the SOM algorithm to look at optimally weighted averages of these characteristics such that the managers can be put in a pre-defined number of distinct groups.

SOM aims to divide a heterogeneous group of data points into smaller homogenous sub-sets. It was introduced by Teuvo Kohonen (1982) and is also known as the Kohonen map. SOM is highly useful for visualization tasks of complex structures that would otherwise be extremely difficult for a human to recognize. An important feature of the Kohonen Map is that it attempts to preserve the relationship in the data while producing a two-dimensional output. It accomplishes this by selecting the weights that are applied to each characteristic (i.e., input) such that they are close to those characteristics. Finally, SOM is a single layer competitive process in the sense that the output nodes compete with each other to best represent the particular input sample. The success of the representation is measured using a discriminant function, where a set of input (i.e., managers) is compared with the weight vector of each output node. The particular node with its connection weights most similar to the input sample is declared the winner of the competition.

A Self-Organizing Map mainly has two distinct components – a node-set data structure representing the actual map with contents and algorithms that apply to that node set. The basic principle of building a SOM is to set certain operational parameters, initialize the node set and apply its algorithms to modify its node set according to the inputs presented. The number of nodes is prespecified by the user in most instances, and the job of the algorithm is to find the position of input data in the grid. Note that SOM can only handle numeric attributes and any categorical data must be converted to a suitable scale before supplying to SOM.

|  | <br> | <br> |
|--|------|------|
|  |      |      |
|  |      | <br> |
|  |      |      |
|  |      |      |
|  |      |      |



b) Hexagonal Grid

a) Rectangular Grid

Exhibit 8: SOM grids

Typically, the grid in the SOM is laid out either in a rectangular or in a hexagonal fashion as shown above with each cell containing a neuron. The hexagonal grid is preferred if greater variance among neighborhood size is desired, although both are equally prevalent in practice. These shapes can cause problems on the edge nodes as the neurons at the edge of the network are less central than the other neurons. To decrease the effects of an edge node, a spherical or geodesic structure can be used.

Some measure of distance, such as Euclidian, correlation, or direction cosine, is used on input data points to map the inputs to the output space. Initially, a set of weights are assigned to each neuron. This can be assigned randomly or by using samples from input data or by using principal components. The objective of the SOM algorithm is to minimize the distance between the input and the neurons. After each iteration, the weights of each neuron can be updated as well as input data points associated with each neuron to minimize the sum of squared distance.

Once the SOM algorithm has run through the input data and found the optimum classification, the output can be plotted as shown in Exhibit 9 for visual inspection. The first part of Exhibit 9 presents the number of input data points in each group while the second part presents the distance among the neurons. Each node can have a different number of data points associated with it as shown in the left part of Exhibit 9. As this is a hexagonal grid, a central node can have six distances with its neighbors. The lighter color cells on the right-hand side of Exhibit 9 indicate shorter distance, while the darker color cells indicate longer distance. It is apparent that although the neighbors can be adjacent, distance from one to the other can vary based on the position of the neighbors. The distance between the neighbors of the top-right corner node is greater than the distances between any other nodes. This indicates data points associated with the top-right node are very different from all other data points and warrants closer inspection.

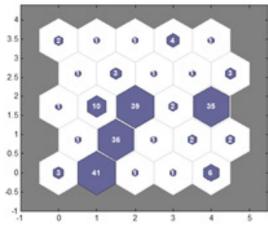
3.5

2.5

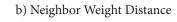
0.5

Ű

-0.5



a) Observations in Each Neuron



**Exhibit 9: Output of SOM** 

#### Data Used:

We used hedge funds that are classified as long-short equity in the Morningstar CISDM Hedge Fund Database for our analysis. Three groups of funds – Global Long/Short Equity, US Long/Short Equity and US Small Cap Long/Short Equity – were used. There are 2,440 funds in these three groups, including the funds that are classified as dead. When we only considered US Dollar denominated funds, the number of funds came down to 1,948. Missing data points can cause SOM algorithms to produce erroneous results. So, we required funds with a monthly return history without any missing monthly returns. After excluding funds that have missing data in any months between January 2012 and December 2017, we ended up with 195 funds. Our goal is to analyze these 195 funds over two different sub-periods – one 4-year long and the other 2-year long. We considered January 2012 to December 2015 as our first study period and January 2016 to December 2017 as our second study period.

#### **Results and Discussions:**

We, first, ran SOM with a 3 by 3 hexagonal grid and returns for the 195 funds from the January 2012 to December 2015. The SOM would put the funds into 9 groups and associate each fund with a label indicating its group. Group numbers provided by SOM are meaningful to a certain extent. If two group numbers are consecutive, their position in the grid is also adjacent, and weights associated with adjacent nodes tend to be similar. Dissimilar nodes are usually placed at the edges.

Exhibit 10 presents summary statistics for the groups produced by the SOM when we ran it with monthly returns from January 2012 to December 2015 as features. Values shown in the table are a cross-sectional average of the respective statistics, i.e., value for each fund is calculated first, and then the average of the values in a group are computed.

| Group<br>Number | Number of<br>Funds | Average Annualized<br>Return (%) | Average Annualized<br>Standard Deviation (%) | Average Maximum<br>Drawdown (%) | Average Correlation<br>with SP500 | Average Pairwise<br>Correlation |
|-----------------|--------------------|----------------------------------|--|---------------------------------|-----------------------------------|---------------------------------|
| 1               | 3                  | 20.82                            | 39.91  | -42.61                          | 0.48                              | 0.78                            |
| 2               | 11                 | -2.38                            | 22.58  | -47.75                          | 0.51                              | 0.46                            |
| 3               | 1                  | 2.32                             | 86.19  | -66.98                          | 0.06                              | -                               |
| 4               | 4                  | -0.97                            | 17.52  | -31.44                          | 0.03                              | 0.99                            |
| 5               | 6                  | 25.93                            | 16.82  | -16.42                          | 0.47                              | 0.59                            |
| 6               | 1                  | 19.00                            | 33.45  | -60.81                          | 0.19                              | -                               |
| 7               | 29                 | 9.33                             | 14.93  | -21.68                          | 0.52                              | 0.46                            |
| 8               | 69                 | 9.79                             | 11.51  | -13.91                          | 0.70                              | 0.55                            |
| 9               | 71                 | 7.93                             | 7.81   | -8.41                           | 0.35                              | 0.16                            |

#### Exhibit 10: Summary Results of Different Groups for the Period 2012 to 2015

Few things to note from Exhibit 10. Some of the groups have few funds, and these funds seem to appear noticeably different from funds in other groups. For example, the lone fund in group 6 has very high return relative to an average fund as well as has high volatility and drawdown, while the single fund in group 3 has a low return, but extremely high volatility and high drawdown. It is also apparent that there are three major groups as the last three groups contain 169 funds out of the 195 funds.

Ideally, we would expect to find that correlation within the groups will be higher than correlation across groups as the goal of the algorithm is to bring together similar funds in the same group. To examine this hypothesis, we found the average correlation among funds from different groups. We, first, found the pairwise correlation for all different combinations of funds between two different groups and then calculated the average of the pairwise correlations. Exhibit 11 shows the correlation matrix among different groups.

Looking at the diagonal of Exhibit 11, we can see that some of the correlations are very high – even close to almost 1. Groups with such high correlation, such as groups 1 and 4 have a small number of funds in them, and these are most likely different share classes of the same fund. The interesting groups are the groups with a large number of funds. If we look at groups 7 and 8, which have 29 and 69 funds, respectively, we see that funds within the group have a high correlation, whereas these funds have low correlation with funds from other groups. This confirms our hypothesis that funds within the group tend to have higher correlation relative to funds across the group.

| Groups          | 1     | 2    | 3     | 4    | 5    | 6    | 7    | 8    | 9    |
|-----------------|-------|------|-------|------|------|------|------|------|------|
| Number of Funds | 3     | 11   | 1     | 4    | 6    | 1    | 29   | 69   | 71   |
| 1               | 0.78  | 0.43 | -0.05 | 0.30 | 0.22 | 0.27 | 0.32 | 0.42 | 0.19 |
| 2               | 0.43  | 0.46 | 0.08  | 0.23 | 0.27 | 0.20 | 0.36 | 0.44 | 0.18 |
| 3               | -0.05 | 0.08 |       | 0.28 | 0.04 | 0.06 | 0.04 | 0.08 | 0.01 |
| 4               | 0.30  | 0.23 | 0.28  | 0.99 | 0.17 | 0.18 | 0.34 | 0.32 | 0.19 |
| 5               | 0.22  | 0.27 | 0.04  | 0.17 | 0.59 | 0.14 | 0.30 | 0.40 | 0.25 |
| 6               | 0.27  | 0.20 | 0.06  | 0.18 | 0.14 |      | 0.09 | 0.16 | 0.10 |
| 7               | 0.32  | 0.36 | 0.04  | 0.34 | 0.30 | 0.09 | 0.46 | 0.42 | 0.22 |
| 8               | 0.42  | 0.44 | 0.08  | 0.32 | 0.40 | 0.16 | 0.42 | 0.55 | 0.27 |
| 9               | 0.19  | 0.18 | 0.01  | 0.19 | 0.25 | 0.10 | 0.22 | 0.27 | 0.16 |

#### Exhibit 11: Average correlation coefficient among funds in different groups - 2012 to 2015

We also ran the funds through SOM using data from January 2016 to January 2017. Exhibit 12 summarizes summary statistics for the groups formed using returns from this period. As with Exhibit 10, funds with extreme values for different statistic are grouped separately from other groups. Groups with a single fund are noticeably different from other funds. These funds are quite distinct from other funds in terms of return, volatility, and drawdown.

| Group<br>Number | Number of<br>Funds | Average Annualized<br>Return (%) | Average Annualized<br>Standard Deviation (%) | Average Maximum<br>Drawdown (%) | Average Correlation<br>with SP500 | Average Pairwise<br>Correlation |
|-----------------|--------------------|----------------------------------|--|---------------------------------|-----------------------------------|---------------------------------|
| 1               | 58                 | 6.27                             | 9.19   | -9.40                           | 0.09                              | 0.04                            |
| 2               | 2                  | 27.24                            | 34.58  | -35.65                          | -0.22                             | 0.99                            |
| 3               | 1                  | 54.58                            | 74.42  | -30.52                          | -0.16                             | -                               |
| 4               | 28                 | 10.07                            | 21.56  | -18.53                          | 0.49                              | 0.53                            |
| 5               | 1                  | 44.80                            | 55.04  | -41.76                          | 0.48                              | -                               |
| 6               | 1                  | -2.06                            | 125.30                                       | -80.70                          | 0.13                              | -                               |
| 7               | 101                | 11.33                            | 10.99  | -8.98                           | 0.63                              | 0.47                            |
| 8               | 1                  | 91.63                            | 51.20  | -27.74                          | 0.50                              | -                               |
| 9               | 2                  | 43.05                            | 47.93  | -31.05                          | 0.41                              | 1.00                            |

#### Exhibit 12: Summary results of different groups for the period 2016 to 2017

One significant observation from comparing Exhibit 10 with Exhibit 11 is that the composition of different groups changes between the two periods. While the first analysis period produced 4 groups with more than 10 funds, the second period resulted in 3 groups with more than 10 funds. Such a change in groups may indicate a change in investment style or a change in investment manager and warrants deeper examination.

To further look at how funds move from one group to the other, we created a transition matrix of the funds between the two periods. This matrix shows how the composition of groups changed between the two periods. Exhibit 13 displays the transition matrix. Rows display funds in different groups using the 2012 to 2015 period, while columns display funds in different groups using the 2016 to 2017 period. Most of the funds in group 9 from the first period moved to group 1 in the next period. This shows funds in this group continued to follow a similar strategy in both periods. Group 8 from the first period also shows a similar pattern by having most of the funds moving to group 7 in the second period. However, funds in group 7 in the first period were divided into 4 groups in the second period.

|  |       | Groups formed using 2016 to 2017 returns |   |   |    |   |   | rns |   |   |       |
|--|-------|--|---|---|----|---|---|-----|---|---|-------|
|  |       | 1  | 2 | 3 | 4  | 5 | 6 | 7   | 8 | 9 | Total |
| SI                                       | 1     |  |   |   |    | 1 |   |     |   | 2 | 3     |
| eturi                                    | 2     | 1  |   | 1 | 5  |   |   | 3   | 1 |   | 11    |
| 015 r                                    | 3     |  |   |   |    |   | 1 |     |   |   | 1     |
| 2 to 2                                   | 4     |  |   |   | 4  |   |   |     |   |   | 4     |
| 2012                                     | 5     |  |   |   | 5  |   |   | 1   |   |   | 6     |
| lsing                                    | 6     | 1  |   |   |    |   |   |     |   |   | 1     |
| ned 1                                    | 7     | 2  | 2 |   | 12 |   |   | 13  |   |   | 29    |
| s for                                    | 8     | 4  |   |   | 1  |   |   | 64  |   |   | 69    |
| Groups formed using 2012 to 2015 returns | 9     | 50                                       |   |   | 1  |   |   | 20  |   |   | 71    |
| 9  | Total | 58                                       | 2 | 1 | 28 | 1 | 1 | 101 | 1 | 2 | 195   |

**Exhibit 13: Transition Matrix of Funds** 

We, next, looked at the characteristics of the funds that were in group 7 when data from 2012 to 2015 were used and were in four different groups when data from 2016 to 2017 were used. Exhibit 14 shows the summary statistics of these funds for the 2016 to 2017 period. Clearly, the funds in the different group look very different, indicating the effectiveness of SOM in classifying funds into different groups when underlying characteristics become different.

| Group Number | Number of<br>Funds | Average Annualized<br>Return (%) | Average Annualized<br>Standard Deviation (%) | Average Maximum<br>Drawdown (%) | Average Correlation<br>with SP500 | Average Pairwise<br>Correlation |
|--------------|--------------------|----------------------------------|--|---------------------------------|-----------------------------------|---------------------------------|
| 1            | 2                  | 1.90                             | 8.88   | -7.02                           | -0.09                             | 1.00                            |
| 2            | 2                  | 27.24                            | 34.58  | -35.65                          | -0.22                             | 0.99                            |
| 4            | 12                 | 12.28                            | 21.05  | -15.83                          | 0.50                              | 0.63                            |
| 7            | 13                 | 14.37                            | 13.35  | -8.90                           | 0.45                              | 0.38                            |

#### Exhibit 14: Summary results of Different Groups for the Period 2016 to 2017

#### **Conclusion:**

We used the Self-Organizing Map on hedge fund returns to classify hedge funds into different groups. We started with all funds categorized as long/short equity with data from January 2012 to December 2017 and found that SOM can effectively group funds into homogenous groups. SOM is especially good at separating input data points that are very different from any other data points. SOM was also able to classify funds that were similar in a particular period but were different in another.

#### **References:**

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Dr. Hossein Kazemi is the Senior Advisor to the CAIA Association's Program. Dr. Kazemi has been involved with the CAIA Association since its inception as a senior advisor and a managing director.

In his current role, he helps with the development of the CAIA program's curriculum and directs the CAIA Association's academic partnership program. In addition, he serves as the editor of Alternative Investment Analyst Review, which is published by the Association. He has worked with universities and industry organizations to introduce them to the CAIA program. Dr. Kazemi is Michael and Cheryl Philipp Distinguished Professor of Finance at the Isenberg School of Management, the University of Massachusetts - Amherst. He is the Director of the Center for International Securities & Derivatives Markets, a nonprofit organization devoted to research in the area of alternative investments, a co-founder of the CAIA Association, and home to CISDM Hedge Fund/CTA Database and the Journal of Alternative Investments, the official research publication of the CAIA Association. He has over 25 years of experience in the financial industry and has served as consultant to major financial institutions. His research has been in the areas of valuations of equity and fixed income securities, asset allocation for traditional and alternative asset classes, and evaluation and replication of active management investment products. He has a Ph.D. in finance from the University of Michigan.



#### **Satyabrota Das,** CAIA, CFA University of Massachusetts Amherst

Satyabrota Das has over ten years of experience working in the financial industry. His main focus has been in the alternative investments areas, particularly in hedge fund replication and commodities. He has developed and traded investable products using liquid exchange-traded

securities in hedge fund replication and commodities. He developed an interactive web-based replication program that allows investors to create customized replication portfolios with different choices of assets. He has also implemented various asset tracking programs for international, emerging markets and US large-cap portfolios. Previously, he supported the Alternative Commodity Benchmark Index, a second generation commodity index, for almost seven years while working for Alternative Investment Analytics. He was involved in designing long-duration commodity strategies and managed futures strategies using ETFs. Satyabrota is currently a doctoral candidate in Finance at UMass-Amherst. He is a CFA charterholder.

## Table of Contents

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Refinitiv

Blockchain, a distributed ledger, emerged as a promising technology more than a decade ago. There are now public and private blockchain types as well as a hyprid consortium type. One blockchain application in the financial world is improving the know your customer compliance process. A common myth is that blockchain is completely immutable, and some potential road blocks to applications include the entry cost of upgrading legacy software and regulatory uncertainty. In this paper the author reviews the types and uses of blockchain today, debunks five common persistent myths about blockchain, and identifies seven major roadblocks that could stall blockchain's expansion such as standardization.

#### 

Masao Matsuda, CAIA

#### Crossgates Investment and Risk Management

Acknowledging and explaining the difficulties inherent in traditional asset allocation, these authors then provide a framework for asset allocation that is based on extended diversification. It provides risk management through diversification to not only control risk but to add value. Specifically, the framework finds sources of return through equity beta, as well as orthogonal factor risk premiums and various sources of alpha. Orthogonal factor risk premiums may be derived from exposure to a range of assets classes. Sources of alpha are derived from skills applied to achieve one or more goals such as to control risk factors or to adjust beta exposure dynamically.

#### 

David van Bragt

Aegon Asset Management

This paper explores the added value of infrastructure debt in a portfolio context for both pension funds and insurance companies. The asset class appears to have an attractive risk-return tradeoff in combination with diversification potential in a fixed income portfolio. Given the limited available benchmark data, care is needed when interpreting the results of the asset and liability management model. The authors therefore also carried out several sensitivity analyses, which in general support the robustness of their findings.

#### 

Urs Schubiger, Egon Ruetsche, and Fabian Dori Aquila Capital

The authors of this paper illustrate that long-short managed futures strategies are well suited as an effective hedge against market turmoil in traditional asset classes. This, and the added value in the strategy's risk/return profile is attributable to several factors, including the possibility to take on profitable short positions when underlying markets decline. Many of us have heard the phrase "keep it simple, stupid," noted by the U.S. Navy in 1960 as a design principle - similar to Ockham's razor. The authors of this paper use the KISS acronym to succinctly and simply describe managed futures as "King In Stress Scenarios."

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## Table of Contents

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Guillaume Monarcha Orion Financial Partners

This paper illustrates the heterogeneity that exists within the same academic alternative risk premia (ARP) strategies due to the many implementation choices available. The author also distinguish between academic ARPs and trading ARPs, examines more than 350 investable ARP indices and reports the frequency of strategies in the sample, statistical characteristics and correlations among the strategies' returns. Results indicate that ARPs tend to deliver absolute returns, but many are sensitive to the market environment. The detailed results highlight the importance of diversification within an ARP strategy across funds to reduce the concentration of model risk, and the use of appropriate risk management tools to address the non-normality of these strategies' returns.

#### 

Jack Sibley, and Filippo Rean Nuveen Real Estate, REED MIDEM

The real estate industry is one that has lagged others in adapting to the recent changes in technology. It has been slow to innovate, yet the industry appears destined to become digitized. This presents several opportunities including better data analytics, digital platforms, and the use of Internet of Things (IoT) for "smart" buildings. It also presents several significant challenges that industry participants must overcome to avoid becoming obsolete. This paper outlines the significant changes expected as the industry experiences a structural shift.

#### 

Peter Hobbs, guy Hopgood, Anish Butani, and Kathryn Saklatvala bfinance

The market for real assets is now mature in the sense that most major asset managers now have an established real asset unit. This paper describes the current state of the real asset market including its many subsectors, and the asset management trend beyond diversification towards real assets: now the trend is also diversification, but within real assets. Implementation can be challenging. Increasingly, real asset diversification includes niche strategies and building direct exposures.

| A Crisis of Beliefs: Investor Psychology and Financial Fragility, An Interview with Andrei Shleifer |
|---|
| The CAIA Endowment Investable Index   |
| The List: Alternative Indices   |



## Ten Years of Blockchain: Unveiling the Mystery and Moving Beyond the Hype

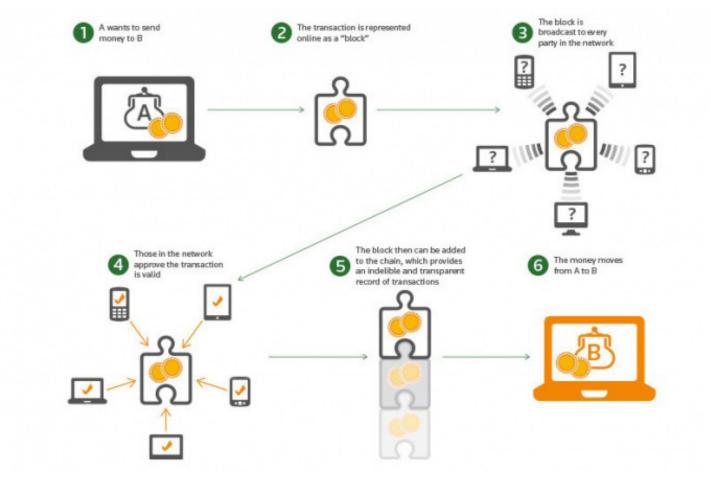
Alessandro Sanos, CAIA Refinitiv The convergence of finance and technology is rapidly reshaping the business landscape as the digital revolution brought by fintech companies is delivering innovation and new technologies at an increased pace.

Ten years since its launch as the technology underpinning bitcoin, blockchain is one of these disruptive technologies but it is still surrounded by a layer of mystery, despite there being a lot of excitement around this technology. To fully understand its true potential and build long-term trust around blockchain, it is therefore important to unveil the layer of mystery, understand what are the roadblocks ahead, and move beyond the current hype.

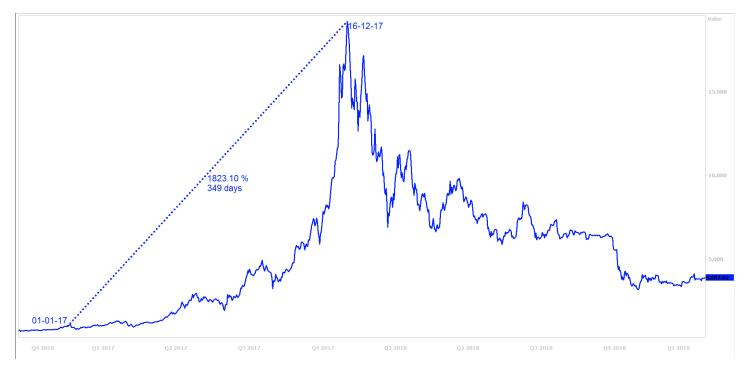
#### How Does Blockchain Work?

Blockchain introduced a "distributed ledger" that provides a distributed way to guarantee and verify transactions by making them publicly available. The technology owes its name to "blocks" of data packages that the distributed ledger stores, transmits, and that are connected to each other in a digital append-only "chain".

By using cryptography and consensus among multiple computers, the system is considered immune to tampering, fraud, or political control as long as no entity controls more than 50% of the computing power of all computers on the network.



**Exhibit 1: A Simple Blockchain Transaction** *Source: Financial Times* 



#### **Exhibit 2: Bitcoin Price on the Bitstamp Exchange** *Source: Eikon*

#### **Types of Blockchain**

Different flavors of blockchains have emerged over the years, with some distributed ledgers being public and others being private. The fundamental distinction between the two is who is allowed to participate in the network, execute the consensus protocol, and maintain the shared ledger.

In a public blockchain, the network is completely open and anyone can join and participate. At the other extreme, a closed private blockchain guarantees privacy by requiring an invitation by the owner or the administrator to join the ledger.

A third hybrid option, known as consortium blockchain, is a partly private ledger that offers many of the same benefits affiliated with private blockchain without consolidating power in a single consortium member.

#### How is Blockchain Being Used?

Blockchain applications are numerous and diverse, and both financial institutions and corporates are exploring the potential of this technology to make their operations faster, more efficient, and more transparent.

The first application of blockchain was bitcoin, the cryptocurrency that went mainstream in 2017 when its price soared by over 1,823% from January to its peak in December. Designed to eliminate the "middleman" from financial transactions, digital currencies enable direct, free, pseudonymous transactions between users.

In the financial world, financial institutions have been investing in blockchain to simplify their record-keeping for payments and transaction reconciliation. Blockchain can also be used in the KYC process where bank clients are identified on a single occasion, and their information is securely shared on a private blockchain network accessed by other banks to mutualize the KYC process and fight financial crime.

In the commodities and energy space, the application of blockchain promises to fundamentally transform a sector that is still analogue and that relies on outdated processes that have not evolved much since the Venetian or Dutch traders from the Renaissance.

By applying blockchain technology, commodities and energy players can digitalize and standardize their transactions to increase speed and efficiency on one hand, and reduce costs and documentary fraud on the other.

In the global supply chains, the biggest promise of blockchain is probably the adoption of smart contracts. Smart contracts are a set of conditions recorded on the blockchain that can automatically trigger and self-execute a set of activities when these predefined conditions are met. Similar to the "if" formula used in Excel to checks whether certain conditions are met, in a smart contract if something happens then something else will happen in response, as an example the transfer of ownership. To work, smart contracts need data. Oracles such as BlockOne IQ from Refinitiv enable smart contracts to interact with off-chain data such as FX rates, commodity prices, equity prices, corporate actions, etc needed to understand whether the predefined conditions of the smart contract are met, and then trigger the self-execution.

#### Myths and Misconceptions

As with any buzzword, blockchain is characterized by a lot of excitement and several myths surround this technology ten years since its launch.

According to McKinsey, five of these myths account for the most common misconceptions around blockchain's benefits and limitations.

The first myth is that blockchain is bitcoin. As we saw, there is so much more to blockchain than bitcoin, the first application offered by this technology. Blockchain is now being adopted by different industries and its applications cover a variety of use cases.

The second myth is that blockchain is better than traditional databases. In reality, there are different traditional technology alternatives to blockchain, each with its unique properties and trade-offs. It is therefore important not to be tempted by the current hype, and instead deploy the most appropriate technology that can solve the specific business need.

The third myth is that blockchain is immutable, or that it cannot be tampered with. In normal circumstances, blockchain data is "append only" meaning that new blocks can be added on to the ledger and that the previous data cannot be changed. However, blockchain could be tampered with if an entity controls more than 50% of the network computing power, and if all the previous transactions are rewritten. While this scenario would be difficult and largely impractical to achieve, it cannot be excluded a priori. Also, researchers at Cornell University recently showed that there could be creative ways to subvert a blockchain even with less than half the mining power, for instance by gaining an unfair advantage by fooling other nodes into wasting time on already-solved crypto-puzzles.

The fourth myth is that blockchain is 100% secure. In reality, while blockchain uses strong mathematical encryption and cryptography, blockchain does not exist in a vacuum and its security depends on the ecosystem of adjacent software and applications that can, and have been, hacked.

The fifth common myth is that blockchain is a truth machine. While blockchain can verify the transactions and the data that are on the chain itself, it cannot assess the veracity and accuracy of any off-chain data that is written on the blockchain by an Oracle.

#### Sustainability, A Dark Side of Blockchain

From a sustainability angle, there is dark side of blockchain when we look at the energy consumption and carbon footprint of this technology.

Since bitcoin mining can provide a solid stream of revenue in form of bitcoins, bitcoin miners are willing to run specialized software on power-hungry machines to solve the complex computational problems needed to validate transactions before they are added into the chain.

Energy Consumption by Country Chart

### Exhibit 3: Annual Energy Consumption by Bitcoin and Select Countries

Source: Bitcoinenergyconsumption.com

Ten years since its launch, the total energy consumption of the bitcoin network has grown to epic proportions and it now consumes more energy than a number of countries. To put things into perspective, and based on a report published by the International Energy Agency, if bitcoin was a country its energy consumption would rank between Iraq and Singapore.

Also, there is a growing concern around the carbon impact of blockchain. While difficult to estimate, the carbon footprint will ultimately depend on the fossil fuels burned to produce the electricity needed to mine bitcoin.

#### The Main Roadblocks Ahead

As with any innovation, the process of capillary adoption in the global economic and social systems will take some time. According to a recent paper from the Harvard Business Review, blockchain adoption will be gradual and steady, not sudden, as waves of technological and institutional change gain momentum and many barriers will need to fall.

What are the main roadblocks ahead that could stall blockchain's expansion?

- The challenge of industry standards and large-scale adoption. For blockchain to work in any given industry, it is important that defined standards and policy frameworks emerge from the current fragmented landscape. Once a common industry standard has been agreed, it will then be possible to expect a critical mass adoption by the stakeholders of that specific industry.
- In global supply chains for instance, there will be the need to onboard commodity producers, agents, banks, traders, insurers, port authorities, and so on. This is not a trivial task in today's global, complex, and fragmented supply chains.
- The cost of getting started. Financial institutions and corporates rely their daily operations on billions of dollars of existing IT software and infrastructure. To replace the existing systems and justify the transition to blockchain, the business benefits and the ROI will need to be greater than the costs of getting started.

- Sustainability. The current amounts of energy consumed are unsustainable, and sustainability may become a deterrent to many financial institutions and corporations that are now focusing on ESG and sustainability.
- Speed. For use cases such as trading, where low latency is fundamental and measured in milliseconds, the current speed of the blockchain network to clear and settle transactions, approximately 10 minutes for bitcoin, is simply too long.
- Too much transparency. The transparency offered by blockchain could simply be too much for some market players who may not want to give away too much information and could reveal their proprietary strategies or the secret sauce of their success.
- Regulatory uncertainty. The regulatory framework relating to blockchain is still evolving. The current lack of regulatory clarity and consensus from regulators represents a level of uncertainty that some companies may not be willing to face. Understanding which jurisdiction should govern a blockchain contract, or how to align the technology to the General Data Protection Regulation (GDPR), are just two of the legal challenges that companies need to overcome.

#### Conclusion

Ten years since its launch, there is a lot of hype around the potential of blockchain technology, but there are also several myths and misconceptions around it.

How to move forward, and when will it be the pivotal moment for companies to embrace blockchain? For this technology to become ubiquitous, it will all depend when the main roadblocks will be removed from the path of its expansion across industries and society.

Early adopters comfortable with taking the risk, and willing to move beyond proofs of concept, will be the ones that will benefit from blockchain's potential, but will incur the risks of navigating through uncharted waters.

#### Author Bio



**Alessandro Sanos,** CAIA *Refinitiv* 

Alessandro Sanos is heading Refinitiv's Commodities business in Western Europe, the Middle East, and Africa. Most recently, he was heading Thomson Reuters' Risk business in Europe. Prior to joining Reuters, he worked for PwC in Greece covering the shipping and energy market, and for

JPMorgan Chase in the United Kingdom. Alessandro is a regular speaker on market and digital trends at industry events, a guest lecturer on innovation and digital transformation for university Masters degrees, and the Chapter Head of Geneva for the CAIA Association



### **Alternative Alphas and Asset Allocation**

Masao Matsuda, CAIA Crossgates Investment and Risk Management It has been many years since the idea of alternative investments as a mainstream method of investing began to gain a foothold in the investment management community, but applying a traditional framework of asset allocation to alternative investments has revealed some challenges in seamlessly connecting alternative investments to traditional investments. Fundamentally, a traditional framework rests on the assumption that asset classes are its basic building blocks, and that in the long run each asset class has a repeatable pattern of risks and returns, as well as a correlation to other asset classes. However, this assumption contradicts many alternative investment strategies such as those for hedge funds. Moreover, one realizes that within the domain of traditional investments there have been challenges in dealing with extended diversification beyond domestic stocks and bonds.

This paper argues that by focusing on exposure to risk factors that are return drivers, one can intersect the artificial boundary between traditional investments and alternative investments. In addition, by analyzing various investment products and strategies from the perspective of the "complexity of risk management," this paper maintains that each of these diverse products is a part of a continuum connecting market betas, alternative betas and alphas. Finally, this paper proposes an alternative approach to traditional asset allocation, combining three components of return sources: equity systematic risk, orthogonal risk factors, and various types of alphas. Importantly, the alternative approach is better suited to address "outcome oriented investments," the realization of which is the ultimate purpose of determining and implementing an asset allocation.

#### **Extended Diversification**

For the framework of traditional asset allocation to be effective, each asset class should be defined in a systematic manner based on statistical analyses. Specifically, the asset class factor model presents an important basis for classification. When properly implemented, the asset class factor model should entail: (1) mutually exclusive asset classes, (2) exhaustive coverage of securities, and (3) asset classes each having returns that "differ."<sup>1</sup> Insofar as the financial securities are limited to the universe of US stocks and bonds, these requirements may be fulfilled to a reasonable degree.<sup>2</sup> Nonetheless, once the investment universe is extended beyond the two traditional domestic asset classes, these requirements become difficult to fulfill, even for non-exotic asset classes such as international equities.

Take the example of the MSCI EAFE index. EAFE is the index of equity markets in developed countries in Europe, Australasia and the Far East. The index is considered to be a complement to the US equity index, and has been extensively utilized for institutional asset allocation and as a mutual fund benchmark. It may well be preposterous to assume that these geographically diverse markets constitute a coherent group in a way determined by the asset class factor model. For this assertion to be valid, the equity securities within EAFE countries must move together with each other more than they do so with securities outside of EAFE countries. An analysis of actual correlations indicates otherwise.

Exhibit 1 shows various correlation relationships involving: (1) EAFE countries in the Eurozone, (2) non-EAFE countries in the Eurozone, (3) non-Eurozone EAFE countries in Europe and the Middle East, (4) EAFE countries in Asia and Oceania, and (5) the United States. For each of the first four groups, the following are calculated: (A) in-group average correlations, (B) average correlations to other EAFE countries, and (C) average correlations to the US.

It is clear from the table that for each EAFE subgroup, as well as for non-EAFE Eurozone countries, the correlations to the US are higher than those of any other relationships. For instance, one would expect the group 1 countries to have a high in-group

correlation (0.73) as they share a common currency and they are included in the EAFE index as European representatives (along with developed countries in group 3). This appears to be the case as each of the other 3 groups has a correlation which is lower than 0.73. Even so, note that group 1's in-group correlation is lower than its correlation to the U.S. (0.77), signifying the possibility that correlations among equities in group 1 countries are in part due to the secondary effects of each country's having a high correlation to US equities. In addition, the average correlation within the EAFE countries (group 1, group 2 and group 4 combined) is 0.70, whereas the average correlation between the US and EAFE countries is 0.76. Hence, one cannot readily determine if the EAFE countries' equity securities constitute a separate asset class from the one which includes US equities. This situation at minimum violates the first condition for a proper asset class classification: mutually exclusive asset classes.

Importantly, the EAFE index also omits the group 2 countries that are in the Eurozone. These are OECD countries and are regarded as having developed economies. To the degree that EAFE is typically used as a proxy for the equities of non-US developed economies, this represents a significant omission and deviates from the second requirement of the asset class factor model: exhaustive coverage of securities. Whereas for a capitalizationbased allocation such an omission may be justifiable on the grounds that the group 2 countries account for a small portion of the entire capitalization of developed economy equities, it is problematic when one is dealing with an equal-weighted allocation for developed economies as each country contributes equally regardless of its market capitalization (For further discussion of global investing, see Appendix).

Beyond the international equities mentioned above, the definition of asset class becomes even more blurred for non-traditional investment strategies. For example, commodities are often touted for their ability to deliver diversification benefits due to their low correlations to equities. In fact, the correlation between S&P 500 total returns and GSCI total returns for the 30 year period from June 1989 to May 2018 was 0.18.<sup>3</sup> Nevertheless, investment returns in commodity futures<sup>4</sup> are highly varied, partly due to the fact that some commodities are characterized by normal

|   | A. In-Group Correlations | B. Average Correlations to<br>Other EAFE Countries | C. Average Correlation to the US |
|---|--------------------------|--|----------------------------------|
| 1. Eurozone and<br>EAFE Countries                       | 0.73                     | 0.71   | 0.77                             |
| 2. Eurozone and non-<br>EAFE Countries                  | 0.51                     | N/A  | 0.59                             |
| 3. Other EAFE<br>Countries in Europe<br>and Middle East | 0.69                     | 0.70   | 0.77                             |
| 4. EAFE Countries in Asia and Oceania                   | 0.61                     | 0.62   | 0.71                             |
| 5. EAFE Countries                                       | 0.70                     | N/A  | 0.76                             |

#### Exhibit 1: Correlations among EAFE Groups and the US

Source: OECD, author's calculation based on each country's equity price index (monthly data in local currency)

backwardation and other commodities by contango. To make matters more complicated, commodities such as natural gas go back and forth between the states of normal backwardation and contango. Thus, it is difficult to say that the risk-return characteristics of various commodities can be grouped together. Each commodity market tends to have its own unique demandsupply mechanism and the factors that drive commodity prices are as varied as local weather and the global trend on consumer luxury goods. The asset allocation framework that deems commodities to be a single asset class often results in disappointment, as the recent underperformance of commodity indices such as GSCI testifies.<sup>5</sup> In order to derive benefits from commodity investing, one needs to identify a group of commodities whose risk-return characteristics are in concert with one's investment objectives.

To cite another example, hedge funds are a collection of diverse investment strategies that exploit market mispricing and arbitrage opportunities, sometimes adjusting beta exposures dynamically. With a mild sense of bewilderment, it is often pointed out that there are as many hedge fund strategies as there are hedge funds.<sup>6</sup> As is the case with commodities, it is misleading to assume that these funds constitute a single asset class. Due to each fund having its own unique investment universe, a broad-based hedge fund index tends to generate "average" returns that do not apply to any type of strategy. Consequently, the performance of such indices tends to deviate substantially from the true risk-return characteristics of a particular hedge fund. However, in order to determine an allocation to hedge funds as a group, the traditional asset allocation approach often treats these funds as members of a homogeneous asset class for expediency's sake. This is likely to result in a distorted allocation, and bring unintended and often disappointing performance results. To make a successful investment in alternative products including hedge funds, one must pay attention to specific risks involved in an individual fund or strategy, as these risks are often sources of alphas.

#### Asset Class Parameters vs. Factors

In addition to the problem of ill-defined boundary conditions for asset classes, parameter uncertainty is a serious problem associated with optimization for traditional asset allocation. In particular, while the expected return of each asset class is extremely difficult to forecast with some degree of accuracy, this parameter tends to play the most important role in determining allocation weights.<sup>7</sup> Unfortunately, a small change in expected returns can result in a very different asset mix. Moreover, there appears to be a certain cognitive dissonance: in calculating optimal portfolios, a value for the expected return for any asset is rarely made negative. Yet, in real life, negative returns for some asset classes are prevalent and can persist. In this sense, a naïvely applied traditional allocation framework may become unreliable, based unwittingly on "hoped-for" returns rather than truly "expected" returns.

The other parameters, such as correlations, are also known to be non-stationary. To illustrate, as indicated in Exhibit 2, the correlation between US stocks and bonds has reversed its sign several times since 1937. Specifically, the trailing 10 year correlations between the S&P 500 and 10-year Treasury bonds based on annual returns were positive until 1950, after which they turned negative and stayed negative for 21 years. In 1972, the correlations moved back into the positive territory and stayed positive until 2004. During this period, the correlations reached and stayed over 0.7 for several years. However, after 2004, the correlations have become strongly negative and since 2008 they have been near or over -0.8, recording a -0.86 in 2009. In light of the fact that the absolute value of trailing correlations changed by 1.6 out of a maximum 2.0 in just 15 years from a +0.74 in 1994 to a -0.86 in 2009, it is difficult to believe that the correlation between the two key asset classes remains stable for allocation purposes. Needless to say, US equities and fixed income are the core allocations for a typical institutional portfolio, and if a correlation has a positive or negative sign plays a critical role in an optimization process. Thus, even this core allocation is not standing on solid ground, to put it mildly.

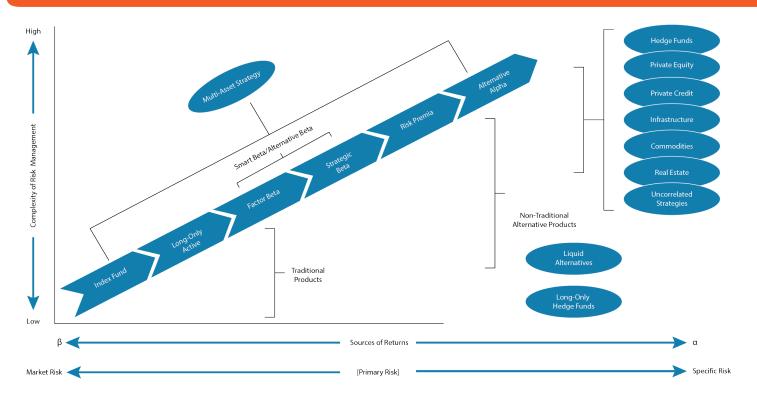


Exhibit 2: Trailing 10 Year Correlations Between Stocks and Bonds

*Source: New York University Stern School of Business, Calculation by Author* 

Another problem with traditional asset allocation lies in its implicit reliance on the single factor model. A traditional asset allocation framework deals with benchmarks with the assumption that most parts of the portfolio returns are determined by beta exposure to systematic risk inherent in each asset class. Alphas, if any, which can be extracted from an asset class are deemed to account for a small portion of return variations. In reality, many asset classes have return drivers beyond systematic risk. In the case of equity, size and value factors, in addition to market risk, constitute the well-known Fama-French factors. Traditional asset allocation has addressed the issue of additional factors by defining different "styles." There is also "credit risk" to be contended with in the case of fixed income securities. Moreover, as the asset classes extend beyond domestic equities and fixed income securities, the correspondence between systematic risk and asset class becomes even more uncertain.

Factor investments are free from artificial demarcation of asset classes based on a tradition or expediency. The drawbacks of traditional asset allocation can be in part remedied by a factorbased allocation where exposures to return generating factors are targeted irrespective of asset class classification. Here, there are at least two important advantages. First, instead of postulating that the non-systematic risks should be diversified away so that each asset class can be effectively represented by a relevant index, a factor-based allocation literally deals with factors directly. In principle, any asset class can be explained by a combination of factors. To illustrate, a commodity can be explained by factors such as roll yield and momentum. Second, while there is a general expectation regarding the size of factor returns, typically no attempt is made to estimate "expected return" of each factor. This eliminates a large and substantive part of uncertainly in



#### **Exhibit 3: Expanding Roles of Alternatives**

determining allocation. Factors should be chosen based on their long-term expectation of positive returns along with their risk characteristics.<sup>8</sup>

#### **Complexity of Risk Management**

Risk management is not merely a means of risk mitigation, but a means of value creation. Perhaps, no other activities demonstrate better the verity of this axiom than those of investment management. The idea of portfolio management is based on the notion that the risk of a portfolio is lower than the sum of the risks of all securities in the portfolio. In addition, the very expression "risk premium" indicates that taking risk generally accompanies returns. Delivering alphas requires pursuing some types of risks while controlling other types of risks. It is no exaggeration to say that investment management firms are primarily in the business of investment risk management.

While a certain set of risk management techniques are welladopted in traditional investment management, alternative investments enjoy an even greater flexibility in undertaking a variety of risk management activities. An important implication of this fact is that in order to make maximum use of the flexibility, managers need to become adept at a whole range of techniques and procedures in risk management. To illustrate, alternative managers can select an investment universe, choose between long and short exposures, and take advantage of derivatives or dynamic strategies to alter risk-return payoff patterns. With the understanding that alternative alphas are generated through various skills and that risk management is an integral part of an investment manager's critical skills, one can see why alternative investment has expanded its role substantially in recent years.

Exhibit 3 illuminates the progression from index funds to alternative products (from beta, through alternative beta, risk premia, and to alternative alpha) in terms of the complexity 20 of risk management. At the same time, the figure also shows alternative investments' expanding sphere. When the sources of returns are static exposure to market betas, the primary risk lies in market risk. On the other hand, when the sources of returns are alternative alphas, the primary risk is found in specific risks. As the sources of returns moves away from straight beta, the complexity of risk management rises. Generally speaking, alpha generating activities accompany very high degrees of complexity in risk management. The concept of "alternative alphas" will be discussed in the next section.

When managing index funds, the complexity of risk management is expected to be low. While formulating and implementing a procedure to replicate an index may require substantial knowledge of risk management, day-to-day management of index funds can be straightforward. The fee levels of straight index funds tend to be lowest among investment products, and these funds and their ETF equivalents have comprised a growing the share of professionally managed investment products.<sup>9</sup>

As the next stage of progression, long-only active mandates attempt to add some alphas, and in the process these mandates need to take some active risk. A performance metric such as an information ratio is used to control added return over a relevant benchmark. Though long-only active management currently enjoys the largest amount of assets under management, its relative share in the investment management industry has been declining steadily.<sup>10</sup> In the process of managing long-only active mandates, many adapted the academic finding that size and value factors also explain the variability of equity returns. A momentum factor was also added. In the institutional investment management community, it had become a common practice to tilt portfolio risk exposure toward these factors. The long-only active mandates require a higher degree of risk management and accordingly charge higher fees than index funds. Index funds and straight long-only mandates, with or without factor tilts, constitute "traditional investment products."

Later, the practice of having exposure to these factors re-emerged with the use of factor betas, and subsequently the set of factors was expanded. These factors have come to be known as smart betas or alternative betas, and they are based on economic factors such as growth or inflation or market factors such as size or value.<sup>11</sup> Factor investing can be viewed as a quantitative equivalent of active investments. While there appears to be no clear consensus on the difference between smart betas and alternative betas, some argue that the former applies to longonly indices and the latter refers to risk factors that are typically employed in hedge fund strategies and pursued through long and short exposures.<sup>12</sup> It is noteworthy that factor betas, as applied to long-only mandates, do not take short positions, and thus have exposure to market risk. By contrast, most alternative betas are constructed so that they are uncorrelated or have low correlations to market risk. In addition, alternative betas include strategic betas whose justification lies in deployment of strategies with potentially resilient performance but without necessarily having well-understood risk premium. The risk parity for equity portfolios13 is an example of strategic beta.14

Exhibit 3 makes a distinction between alternative betas and risk premium investing. This distinction is important since, in risk premium investing, factors are chosen so that they are orthogonal (uncorrelated) to each other. By contrast, in alternative beta investing too many factors may be juxtaposed and some factors are correlated to each other, even if these factors may be uncorrelated to market risk, causing a multi-collinearity problem in modelling. As a result, an issue with factor stability may arise.<sup>15</sup> Exhibit 4 shows an example of orthogonal risk premia latent in different asset types. The set of risk premia can avoid factor instability when properly designed and implemented.

It is interesting that the risk premium "momentum" appears in all of equity, fixed income, currency and commodity strategies. For equity strategies, as is the case for factor beta, both "size" and "value" are important, and "emerging" can be added as an orthogonal source of risk premium.<sup>16</sup> For fixed income strategies, "credit" is the additional source of risk premium, and for currency, "carry" plays an important role. Finally, for commodities, "relative value" and "roll yield" complete the list in this example.<sup>17</sup> These risk premia should be calibrated so that they are minimally correlated to each other and the market risk.

#### **Alternative Alphas**

Alternative investment managers can extract alphas in many different ways. Notable methods by which these managers can add value beyond static exposure to the market and other factors are listed in Exhibit 5. For simplicity, let us label these values as "alternative alphas" as they are based on alternative investment managers' skills in bringing about excess returns by executing various strategies.

First, there are many risk factors that are either explicit or implicit in various active strategies. Some strategies are quantitatively driven whereas other strategies are based on fundamental analyses. Regardless of how investment managers select factors relating to traditional betas and/or alternative betas, these managers attempt to deliver performance in line with a particular investment goal. By exercising effective control over risk factors, investment managers can bring about risk premia from each factor. The controls can be either (1) directly value adding through exposure to the factors that accompany risk premia or (2) pursued indirectly through risk mitigation of factors that detract from value adding.

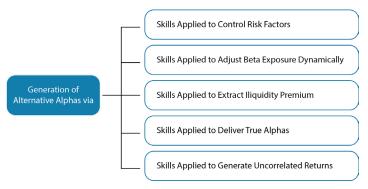
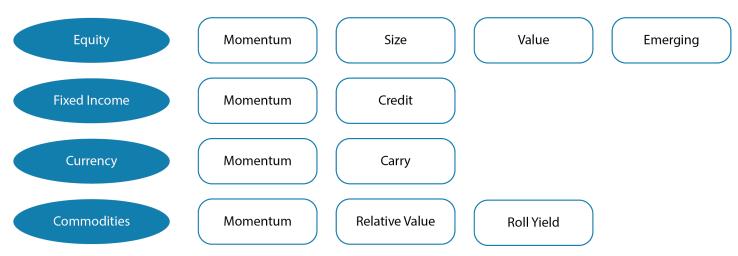


Exhibit 5: Sources of Alternative Alphas (Derived Via the Application of Certain Skills by Investment Managers)



#### Exhibit 4: An Example of Risk Premia\*

Note: \*The same figure appeared in Masao Matusda and Andrew Weisman, "Risk Management Implications of Risk Premium Investing," Risk Intelligence, Global Association of Risk Professionals (August 2017), GARP.org

Some of these strategies may be heuristically or purely empirically derived. For instance, it has been shown that an equal-weighted portfolio often outperforms a capitalization-weighted portfolio. In this case, equal-weighting is a "strategic beta," but, by itself, may not be a driver of risk premium. Actual outperformance may come from a higher than capitalization-based weight being given to a particular group of stocks due to equal weighting. For instance, equal weighting naturally gives a weight higher than their capitalization to small stocks, which have a known size effect. Among different alternative strategies, hedge funds are likely to be best able to exercise control over risk factors, as hedge funds mostly deal with liquid securities.

|                                 | High Volatility<br>Months | Low Volatility<br>Months | Entire<br>Period |  |
|---------------------------------|---------------------------|--------------------------|------------------|--|
| Range of VIX<br>Values          | 23.84-59.89               | 9.51-13.84               | 9.51-59.89       |  |
| Average VIX<br>Value            | 30.90                     | 12.21                    | 19.89            |  |
| Average<br>Annualized<br>Return | 2.3%                      | 5.9%                     | 4.8%             |  |

#### Exhibit 6: Volatility and the Return of Following Month (January 2000 through December 2017)

Soure: CBOE and Dow Jones

Second, from a longitudinal perspective, higher volatility does not translate into higher returns. Exhibit 6 summarizes the relationship between the month-end value of VIX and the return of the S&P 500 for the following month. The high expected volatility months are defined to be those months in which the VIX value was in the top quartile, and the low expected volatility months are those in which the VIX value was in the bottom quartile. The range of VIX value and the average value of VIX, as well as the average annualized return corresponding to each period are shown in the table. During the high volatility months, the average return was 2.3%, whereas during the low volatility months, the average return was 5.9%. It is clear from the table that the market characterized by a high value of VIX at the end of the month tends to lead to the lower than average return (4.8% for the entire period) in the subsequent month.

Investment managers can take advantage of this relationship between expected volatility and subsequent returns. For instance, using the same set of data, if the leverage ratio was adjusted by dividing the current value of VIX by its average value,<sup>18</sup> the cumulative return of the strategy would have been 134.98% during the period while the S&P 500 returned only 81.97%. It is interesting to see that though the average leverage ratio was 1.11, the leverage ranged from 0.32 to 2.04. In this hypothetical strategy, one's ability to dynamically adjust beta exposure clearly contributed to the improvement in risk-return ratios. This type of alpha based on a manager's skill to adjust beta exposure dynamically is sometimes called "allocation alpha."19 This is one area where alternative investments including hedge funds have a clear advantage over traditional benchmark-constrained mandates.

Third, many types of alternative investments lack liquidity, and this illiquidity can be turned into alphas. For instance, private equity funds invest in private companies whose securities are not traded on the stock exchanges and their security prices tend to be discounted. However, by taking these companies public, private equity funds can extract illiquidity premium. Generating alphas requires the investment acumen of general partners (GPs), along with the willingness of limited partners (LPs) to meet capital calls and commit investment for a number of years. In particular, GPs need to conduct a thorough due diligence on potential companies to invest, to negotiate prices and capital structure, to oversee the management of companies, and to implement an exit via public offering or a sale to another entity, in order to extract value from investments. It is a highly active process, and a manager's skills in all of these stages affect outcomes.

Other private investment opportunities, such as infrastructure, real estate, and private credit face similar challenges and rewards. To illustrate, investments in infrastructure come with a variety of types of assets in which a manager can specialize. There are projects in: contract power generation, airports, and telecommunications, to name just a few. While many infrastructure projects share the benefits of limited competition and relatively inelastic demand, investing in each type of asset requires specialized knowledge to manage the risks of infrastructure projects. Investment managers are expected to deliver cash yield while pursuing substantial capital gains. Likewise, investments in private credit require a specialized knowledge of senior debt, subordinated capital, distressed credit or specialty finance, each of which has its own distinct risk-return profile. In addition, for real estate investment, it goes without saying that managing the idiosyncratic risk of each property is the most important element in delivering alphas.

Fourth, some alternative investment managers appear to genuinely possess the capability to select securities that can lead to alpha generation. While rare, value added through this type of capability is called "true alphas." For a number of decades, excess returns over market betas were treated as alphas. These days, however, it has come to be accepted that beta exposures, including alternative betas, account for most excess returns. Along with efforts to control risk factors, to adjust beta exposure dynamically and to extract illiquidity premium, a select group of highly skilled managers can deliver true alphas. With the advent of big data, progress in artificial intelligence and other technological advancements, some managers have been pursuing an edge in identifying investment targets.

Conceptually, true alphas are often associated with the security selection capability of managers, and are considered to apply to long-only mandates as well as to hedge fund strategies. In addition, true alphas can also apply to other alternative investments such as private equity funds. After all, before making investments, a GP needs to select private companies to be included in the fund's portfolio. Managers of other types of private investment strategies may be able to deliver true alphas. It needs to be noted, however, that to the degree that alpha generation involves managing specific or the idiosyncratic risks of portfolio companies or invested assets, it may be difficult to isolate true alphas from other sources of alternative alphas.

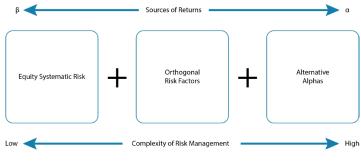
Finally, certain types of specialty finance can deliver truly uncorrelated returns. For instance, litigation finance and life settlement have return sources that are by nature independent from the risk premia that financial securities carry. To wit, in the case of litigation finance, "court decisions and awards are rarely dependent on the performance of financial assets,"<sup>20</sup> and in the case of life settlements, mortality-related risks are affected by many factors such as advances in medicine, but are certainly uncorrelated to financial markets. Importantly, these investments are unlikely to suffer from the tightening of correlations at the time of market crises or a liquidity crunch. For this reason, these investments can generate returns even at times when other types of investments, including some alternatives, fail to deliver diversification benefits.

Both litigation finance and life settlement are considered to be part of private credit opportunities and investors can expect relatively stable and periodic returns. These investments tend to rely on the law of large numbers. In other words, by increasing a number of litigation cases or insurance contracts, each fund can stabilize the relative frequency and magnitude of adverse outcomes occurring as the probability distribution starts resembling a normal curve. For each fund, creating a group that approximates a normal distribution takes skill on the part of managers, and managing periodic cash payouts also requires correctly anticipating future cash flows. Like other private investment opportunities, manager skills are an important source of returns.

#### **Alternative Asset Allocation**

A study conducted by a well-known pension consultant points out that a "60-40" stock and bond portfolio (36% US equity, 24% non-US global equity and 40% US fixed income) has over 90% equity risk concentration.<sup>21</sup> Even when some alternative strategies are added (30% US equity, 20% non-US global equity, 25% US fixed income, 10% hedge funds, 10% real estate, and 5% high yield), there is still 79% equity risk exposure.<sup>22</sup> It is no wonder diversification often fails with traditional asset allocation.<sup>23</sup> This fact unequivocally indicates that an alternative approach to asset allocation is necessary, as an asset-class-based allocation is unlikely to deliver sufficient diversification benefits at a time of turmoil in equity markets.

An alternative approach can take advantage of the factor investing discussed earlier, while addressing some shortcomings of this method of investing.<sup>24</sup> The alternative approach also provides a means to incorporate the traditional assets and alternative investment strategies in a common analytical framework. Unlike the traditional approach, it is not necessary to resort to the



**Exhibit 7: Alternative Asset Allocation Framework** 

expediency of treating various hedge fund strategies as belonging to a single asset class for optimization. The same applies to other alternative strategies. Exhibit 7 highlights the correspondence between the sources of returns and the complexity of risk management, as did Exhibit 3. The figure also demonstrates a potential framework for "Alternative Asset Allocation." The framework has three main components. The first component, exposure to the equity systematic risk, can be easily implemented through investment in an index fund or ETF. Unlike traditional allocation, it is not necessary to decide the weight given to equity risk based on expected returns or forecasted covariance with other asset classes. Instead, the weight is determined relative to the risk premium of other factors.

The second component consists of orthogonal risk factors. These factors should be chosen so that they are uncorrelated to each other, as well as to the market or systematic risk. The advantage of orthogonality lies in the fact that being independent from other factors a given factor can be linearly combined with other factors including the systematic risk of equity. There are an array of factors, but some factors may only have transitory effectiveness and may be dependent on the states of economies or markets. It is advisable to choose factors that have been well-researched and for which the reasons for their ability to bring premia are wellunderstood. Risk premia investing fulfills this requirement well.

The third set of components is alternative alphas. As was described in the previous section, there are five sources of such alphas. These alphas can be pursued through investments in hedge funds, private equity, private credit, infrastructure, commodities, real assets including real estate, as well as specialty financing whose returns are anticipated to be uncorrelated, as shown in Exhibit 3. Some of these investment strategies are liquidity constrained, but managers are capable of turning illiquidity into alphas. Another source of alphas can be extracted through the first component of this framework. More specifically, there is abundant empirical evidence that through allocation alpha one can improve the risk-return profile of such risk based on forecasted volatility.

The ultimate purpose of asset allocation is to deliver the outcomes that investors seek. Being focused on a weight distribution among different asset classes, it is difficult for a traditional asset allocation framework to create direct linkages between asset classes and investment outcomes. The desired outcomes may include any one or more of the following: (1) inflation protection and real return, (2) volatility and risk management, (3) equity risk diversification and market neutrality, (4) alpha opportunities from expanded sources of returns. In addition, in the traditional framework, return parameters are limited to a mean (expected return) and risk (standard deviation), and cash flow timing is not taken into account directly.

By contrast, the alternative framework suggested in this paper can easily adapt to each outcome. To illustrate, some alternative alpha opportunities listed in Exhibit 3, such as those associated with commodity and real estate, can deliver the first outcome ((1) above). The second outcome ((2) above) can be realized through a combination of equity systematic risk and alternative alphas adjusted dynamically to beta exposure. The third outcome ((3) above) can be pursued through orthogonal risk factors used in combination with another source of alternative alphas derived from the generation of uncorrelated returns." Finally, the fourth outcome ((4) above) can be brought about by the exercise of a variety of skills (reference: Exhibit 5) by alternative investment managers in generating alternative alphas.

Before concluding, it is worth mentioning that investing in the third component of alternative asset allocation (Exhibit 7) entails having additional exposure to market risk beyond the exposure taken as part of the first component (Exhibit 7). It is possible to estimate various beta exposures inherent in these alternative strategies including private equity. Once the estimated beta exposures are aggregated, an adjustment can be made to the first component so that the entire portfolio can target the intended level of overall beta exposure. The first component requires periodic adjustment of beta exposure, and thus the estimates of beta for the third components also need to be updated so that the beta exposure of the entire portfolio is at the right level for any given time.

#### Conclusion

In light of the fact that the traditional asset allocation framework tends to result in a lack of effective diversification, particularly when extended asset classes and alternative investments are involved, a different approach to allocation is necessary. This paper has argued that by analyzing various investment opportunities from the perspective of the complexity of risk management, one can develop a framework that can seamlessly integrate alternative investments with traditional investments. It is no longer a question of whether alternatives are becoming a mainstream method of investing. Rather, alternatives should be considered as the main contributor to returns beyond having exposure to equity market risk.

The allocation framework suggested in this paper consists of three components: (1) equity systematic risk, (2) risk factors that are orthogonal to each other; and (3) alternative alphas. Note that while this framework does not directly address nonequity asset classes as traditionally defined, the risk factors in the second component cover the risk premia latent in these asset classes. In addition, five sources of alternative alphas were discussed. Significantly, this framework puts "alphas" back in portfolio management when alphas' boundaries seem to be increasingly narrowing in the investment management industry. The alternative asset allocation framework proposed herein is also better suited to the structuring of an investment portfolio that accords with the specific investment outcome pursued.

#### Appendix

In the field of international equity investing, the issue of whether the integration hypothesis or the segmentation hypothesis explains better the behaviors of the world's equity markets has been discussed for a number of decades. The integration hypothesis argues that the world's equity markets behave essentially as one, and country-specific factors are diversified away. The variability in country returns is due to the differences in each country's beta to the world market risk or a set of global risk factors.<sup>25</sup> On the other hand, the segmentation hypothesis argues that the effects of country specific factors are persistent and explain a substantial portion of variability of each country's equity returns.<sup>26</sup> Depending on the sample period, both hypotheses seem to have proven their validity with supporting empirical evidence. This indicates that the degree of integration may change through time. The observed degree of integration also varies between developed markets and emerging markets. Sometimes the global equity markets essentially act as one, and at other times, the markets exhibit a degree of segmentation. One can argue that as a result of the regime changes, the degree of influence that global factors and local factors exert is time-varying.<sup>27</sup>

The instability of a singular global equity market structure addresses the heart of the problem of a traditional asset allocation framework. If global equity markets were completely integrated, the variability of returns of any equity securities in the world should be measured in terms of beta to the world equity market factor. The one factor model implicit in the framework would be effective, and for ultimate diversification investors should hold a fund that replicates the performance of an integrated and single global equity market. The reality is that global equity markets are always fragmented to some degree and equity securities need to be examined for exposure for both global and local factors.

#### Endnotes

- 1. Sharpe (1992).
- 2. Some voice concern regarding the use of "the amount of bond outstanding" as a proxy for bond capitalization. When the outstanding amount for each issue is used as a weight, those issuers with higher amounts of debt receive higher allocations. The higher amounts of debt in turn can affect the credit risk of the issuers.
- 3. GSCI was originally known as Goldman Sachs Commodity Index. Now it is referred as "S&P GSCI."
- 4 Typically commodity investments are pursued through commodity futures.
- 5 Commodity indices vary substantially. For instance, S&P GSCI have nearly 60% of the weight given to energy commodities, while Bloomberg Commodity Index limits exposure to the energy sector to around 1/3.
- 6. According to the Hedge Fund Association, there were approximately 10,000 active hedge funds as of August 2017. See https://www.hedgefundassoc.org/about\_hedge\_funds/
- 7. To be sure, there is a method to address this challenge, such as the Black-Litterman model. However, reliance on the accuracy of parameter estimates remains unchanged.
- 8 Under a certain set of assumptions, an asset class-based allocation and a factor-based allocation deliver very similar performances. See Idzorek and Kowara (2013). While this means that neither allocation method may be theoretically superior to the other, it also implies that the latter can be effectively used if it can handle both traditional investments and alternative investments in a theoretically consistent manner.
- 9. Recently, Fidelity Investments has started charging zero management fees for some of its core index products. See https://www.cnbc.com/2018/08/01/fidelity-one-ups-vanguard-first-company-to-offer-no-fee-index-fund.html.

- 10. For instance, in October 2017, actively managed mutual funds accounted for about 18% of the equity market. In 2007 the share was 24%. https://www.marketwatch.com/story/ passive-investments-are-hot-but-remain-a-small-slice-ofthe-stock-market-2017-10-16.
- 11. J.P. Morgan Asset Management, "Factor Risk Management: A Generalized Methodology for Multi-Asset Class Portfolios," 2011.
- 12. J.P. Morgan Asset Management makes this distinction. See, J.P.Morgan Asset Management (2015).
- 13. The idea of risk parity is employed in both asset allocation and equity portfolio construction. For the former, for instance, the risks of investing in equity and the risks of investing in bonds are made equal, typically resulting in much higher allocations to bonds. For equity portfolio construction, risks can be made equal for individual stocks, groups of stocks or risk factors. See, for instance, https://www.etf.com/publications/journalofindexes/joiarticles/21890-risk-parity-strategies-for-equity-portfoliomanagement.html?nopaging=1
- 14. The expression "strategic beta" is often used interchangeably with the expression "smart beta." Morningstar Associates classifies strategic beta into (1) return-oriented, (2) riskoriented, and (3) other.

See, for instance, Schwab Center for Financial Research. In this paper, when the expression "strategic beta" is used, it refers to the risk-oriented types of smart beta.

- 15. J.P. Morgan Asset Management (2011).
- 16. For instance, the "emerging" is extracted as the return differential between emerging and developed markets, and hence is expected to have low correlation to US equity.
- 17. In terms of product offering, some alternative strategies are able to provide frequent liquidity. These products often pursue strategies that take advantage of factor investing in order to generate hedge fund-like returns. There are also products that make use of publicly traded securities to assimilate the returns of private equity strategies. Together, they are known as "liquid alternatives." In addition, hedge fund managers can apply their advanced risk management skills to long-only investments, and these are often referred to as "long-only hedge funds." See, for instance, Institutional Investors (2007). Such hedge fund managers may also take advantage of true alphas if applicable. Both liquid alternatives and long-only hedge funds are generally considered to be "non-traditional alternative products." Finally, there are "multi-asset strategies." Today's multi-asset strategies are generally quantitatively-oriented and often involve factor- or risk-premium-type investments, like those discussed earlier. What is more, the multi-asset strategies can be combined with alternative alphas from a set of private investment opportunities. To the degree that multiasset strategies are operated over multiple asset classes and multiple factors, the right strategy can serve as a de facto asset allocation methodology.

- 18. The long term average VIX and the in-sample average for the period are similar.
- 19. Andrew M. Lo also uses this expression. See Lo (2008).
- 20. The Hedge Fund Journal (2018).
- 21. Callan Institute (2018). This study reports 99.85% equity risk exposure. Other studies also show over 90% equity risk exposure. See, for instance, Karl Merthaler and Helen Zhang, "Public Pension Funds: Asset Allocation Strategies," JP Morgan Investment Analytics and Consulting, June 2010.
- 22. Callan Institute (2018).
- 23. The problem is compounded by the fact that left tail correlations to US equity are very high for many traditional assets. Page and Paneriello demonstrate that developed market stocks, emerging market stocks, corporate bonds, and high yield bonds all have higher than 0.5 correlations to US equity in the left first percentile distribution, as well as the 5th percentile distribution. See Page and Paneiriello (2018).
- 24. Factor-based allocation is not omnipotent and has several obvious shortcomings. First, risk factors are not exhaustive and one may be missing relevant factors. In the same vein, while there are a sufficient number of factors, there is no assurance that the chosen factors are the correct and only factors that matter. Second, some risk factors may not be independent from each other and may compete for the same sources of returns. Many risk factors have exposure to other risk factors. Without a proper theoretical underpinning for each factor, two or more inter-related factors may be included unsuspectingly. As a result, the returns from these factors may converge at an unexpected time, and may also introduce biases and other issues in a statistical modeling process. Third, some factors are based on a heuristic idea. For instance, a minimum volatility strategy or "min vol" can be formed by a simple and ad hoc rule such as volatility rankings. Sometimes heuristic factors indeed may be effective, and may belong to the category of alternative alphas. Finally and critically, unlike traditional asset classes, factors often lack intuitive appeal as they are generally not directly observable.
- 25. For a classic study, see, for instance, Ferson and Harvey (1993).
- 26. For an application of International Capital Asset Pricing Model (ICAPM), see El Hedi (2009).
- 27. For an empirical analysis of the changes in the degree of market integration, see Bekaert and Harvey (1995).

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Masao Matsuda is President and CEO of Crossgates Investment and Risk Management. He has nearly three decades of experience in the global financial services industry. He has acted as CEO of a US broker-dealer and CEO/CIO of a number of investment management firms. In addition

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## Infrastructure Debt in a Portfolio Context: A First Exploration

#### David van Bragt Aegon Asset Management

Infrastructure relates to equipment, facilities and networks providing essential public services. These real assets generate predictable long-term contracted and/or regulated revenues. The rise of infrastructure as an asset class is supported by structural trends like the call by governments on private investors to invest in infrastructure projects. In particular, the EU and national governments have committed themselves to transition to clean and renewable energy, in line with the Paris climate agreement.

This leads to a growing pipeline of renewable energy and clean technology projects, see Exhibit 1. Investing in infrastructure can therefore fundamentally contribute to the energy transition and responsible investment initiatives. Examples are investments in wind and solar energy, environmental projects with a focus on recycling or re-using waste and reducing the carbon footprint with innovative transport projects.

Focusing on infrastructure debt (so excluding infrastructure equity), the total amount of investments in the European Union was €70bn in 2017. Germany, France, Italy, Benelux, Spain and Portugal represent 83% of the euro-denominated market, see Exhibit 2. The United Kingdom is the largest European market.

Infrastructure debt also has a lower capital charge than corporate debt under Solvency II.<sup>1</sup> The European Insurance and Occupational Pensions Authority (EIOPA), the regulator for European insurance companies, has argued that this is reasonable given evidence that infrastructure

Infra deal values (debt and equity) in Europe

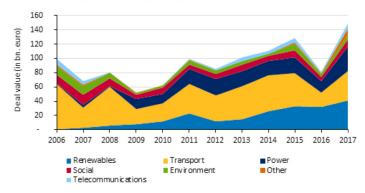
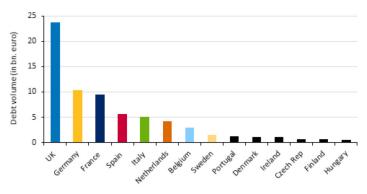


Exhibit 1: Infrastructure Deal Values (Debt and Equity) in Europe (in bn euro).

Source: Inframation, December 31, 2017

Infra debt volumes in Europe



**Exhibit 2: Infrastructure Debt Volumes in Europe (in bn Euro).** Source: Inframation, December 31, 2017

investments exhibit better recovery rates than corporate debt and are less sensitive to broader economic factors. This makes infrastructure debt attractive from a capital point of view for insurance companies.

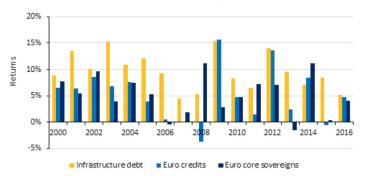
#### Economic Scenario Model

Our economic scenario model is built on the basis of the economic scenarios of Ortec Finance (Steehouwer, 2005). For infrastructure debt, we have developed a tailor-made scenario model. This scenario model is based on benchmark data from the EDHEC Infrastructure Institute.<sup>2</sup> Availability and granularity of benchmark data for infrastructure debt is – by definition – limited. To address this issue, EDHEC has developed an extensive suite of private infrastructure equity and debt indices. We use their benchmark data for project finance debt in continental Europe (Blanc-Brude, 2017).<sup>3</sup> This index includes 89 value weighted live exposures to senior private debt representing approximately €35bn equivalent of market value. The constituents are 8 percent of the identified investable universe by number of investments and 36 percent by outstanding face value.<sup>4</sup>

The historical performance of this benchmark is shown in the Exhibit below. This is an annual total return series between 2000 and 2016. For comparison, we also show the performance in this period of an (investment grade) euro credits benchmark<sup>5</sup> and a euro core sovereign bond benchmark.<sup>6</sup>

Infra project finance debt benchmark returns

in comparison with euro credit and euro core sovereigns



#### Exhibit 3: Infrastructure Project Finance Debt Benchmark Returns in Comparison with Euro Credit and Euro Core Sovereign Bonds

Source: EDHEC Infrastructure Institute, Merrill Lynch, Barclays

Some key characteristics of these series are shown in the exhibit below.

| Characteristics Infrastructure Debt Benchmark (2000-<br>2016) |                        |                 |                         |  |  |  |
|---|------------------------|-----------------|-------------------------|--|--|--|
|   | Infrastructure<br>Debt | Euro<br>Credits | Euro Core<br>Sovereigns |  |  |  |
| Average Return  | 9.6%                   | 5.1%            | 5.2%                    |  |  |  |
| Volatility  | 3.5%                   | 5.2%            | 3.9%                    |  |  |  |
| Autocorrelation   | 1%                     | -22%            | 28%                     |  |  |  |
| Correlation   |                        | 0.69            | -0.11                   |  |  |  |
| Cross Correlation<br>(Lag 1 Year)                             |                        | 0.10            | 0.77                    |  |  |  |

#### Exhibit 4: Characteristics of Infrastructure Debt, Euro Credits and Euro Core Sovereign Bonds (Annual Data from 2000-2016)

Sources: EDHEC, Aegon Asset Management

Infrastructure debt has a relatively high historical return in combination with a low volatility. The correlation with euro credits is relatively high (0.69). Interestingly, the cross correlation with the past year's return on euro sovereign bonds is also quite high (0.77).<sup>7</sup> This is an indication that the impact of interest rate movements may be absorbed by private infrastructure debt with a certain time lag.<sup>8</sup>

Based on the above characteristics, we modelled infrastructure debt as a total return series with an annual volatility of 3.5%, an autocorrelation of zero and the above correlations with euro credits and euro sovereign bonds. The expected return is set using forward-looking assumptions (instead of the high historical value of 9.6% per year). Going forward, we use an expected return which lies 2% above the average euro swap rate.<sup>9</sup> Because the average swap rate is increasing over time in the scenario set, this also implies an increasing expected return for infrastructure debt over time.

An overview of the scenario characteristics is given in the exhibit below. We use 1,000 scenarios with a length of 15 years each. The starting point of the scenarios is December 31, 2017. Notice the attractive return/risk characteristics of infrastructure debt, in comparison with other fixed income categories and equities.

| Economic Scenarios: Average Return and Volatility |                |            |  |  |  |
|---|----------------|------------|--|--|--|
|   | Average Return | Volatility |  |  |  |
| Infrastructure Debt                               | 4.0%           | 3.5%       |  |  |  |
| Euro Core Sovereigns                              | 1.1%           | 4.6%       |  |  |  |
| Dutch Mortgages                                   | 2.2%           | 4.3%       |  |  |  |
| Euro Credits                                      | 2.1%           | 5.7%       |  |  |  |
| World Equities (Hedged)                           | 7.2%           | 17.1%      |  |  |  |

#### Exhibit 5: Return and Risk Characteristics of the Different Assets Classes for the Next 15 Years.

*Sources: Aegon Asset Management, La Banque Postale Asset Management, Ortec Finance* 

An overview of the correlations between the different asset classes is given in Exhibit 6.

Exhibit 6 shows a high correlation with euro credits (0.6), in line with the historical benchmark data. The correlation with the other asset classes is low, meaning that infrastructure debt has diversification potential in a portfolio context.

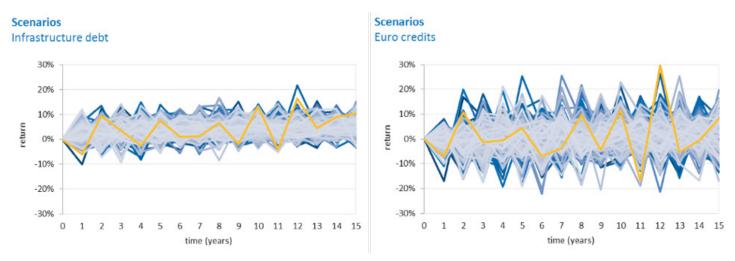
A graphical illustration of the scenarios is given in Exhibit 7. We also show the scenarios for euro credits here. Notice the higher volatility of euro credits compared to infrastructure debt. The yellow line is an example of one specific scenario. This scenario illustrates the high correlation between the scenarios of these two asset classes.

Recall that we observed earlier that infrastructure debt historically has a high cross correlation with the euro sovereign bonds returns of the previous year. We model this effect in our scenario model in an additional sensitivity analysis. We also carry out several other sensitivity analyses in the next section.

| Economic Scenarios: Correlations |                |                         |                 |              |                            |  |
|----------------------------------|----------------|-------------------------|-----------------|--------------|----------------------------|--|
|                                  | Infrastructure | Euro Core<br>Sovereigns | Dutch Mortgages | Euro Credits | World Equities<br>(Hedged) |  |
| Infrastucture Debt               | 1.0            |                         |                 |              |                            |  |
| Euro Core<br>Sovereigns          | -0.1           | 1.0                     |                 |              |                            |  |
| Dutch mortgages                  | 0.1            | 0.5                     | 1.0             |              |                            |  |
| Euro Credits                     | 0.6            | 0.3                     | 0.4             | 1.0          |                            |  |
| World Equities<br>(Hedged)       | 0.3            | 0.0                     | 0.2             | 0.4          | 1.0                        |  |

#### Exhibit 6: Scenarios Correlations Between the Different Asset Classes.

Sources: Aegon Asset Management, Ortec Finance



#### **Exhibit 7: Illustrations of the Scenario Characteristics of Infrastructure Debt and Euro Credits for the Next 15 Years.** Sources: Aegon Asset Management, La Banque Postale Asset Management, Ortec Finance

#### Results

We now investigate the effect of adding infrastructure debt to the asset mix of a typical pension fund. We allocate 5% of the assets to infrastructure debt and study the effect on expected return and risk. We focus on the development of the ratio of assets and liabilities over the next 15 years. The analysis is based on a market valuation of the balance sheet (assets and liabilities). We assume that interest rate risk and currency risk are fully hedged. Exhibit 8 below shows the results.

The base case is a stylized representation of an average pension fund. If we allocate 5% to infrastructure debt, which is funded by selling 5% of euro core sovereigns, the average return on assets/ liabilities increases with 0.3%-point (per year). A slightly smaller effect is visible when funding infrastructure debt with credits or mortgages. A slightly lower average return occurs when we fund infrastructure with equities. We see similar effects for the 5% most positive and negative scenarios, except when we substitute equities with infrastructure. In this case the return in the most positive scenarios decreases (with 0.6%-point). On the other hand, results improve (with 0.5%-point) in the most negative scenarios. We also carried out several sensitivity analyses:

- A higher volatility for infrastructure debt. We set the volatility of infrastructure debt equal to the volatility of euro credits in this case (so, 5.7% instead of 3.5%).
- An increased correlation with euro sovereign bond returns of the previous year (59% instead of 10%).
- A different interest rate hedge percentage (25%, 50% and 75% instead of 100%).
- A lower expected return, starting at 2% above the average euro swap rate but then decreasing to 0.5% above swap in 5 years (instead of 2% above swap in all future years).
- A typical asset mix of a life insurance company (instead of a pension fund).

The first two sensitivity analyses have a small impact on the results. Decreasing the interest rate hedge percentage leads to similar effects as above, but the positive effect of adding infrastructure debt to the portfolio becomes smaller. Decreasing the expected return for infrastructure debt has a significant effect on the results, see Exhibit 9.

| Impact of adding Infrastructure Debt for Pension Funds |                                 |                                |                               |                             |                              |  |  |
|--|---------------------------------|--------------------------------|-------------------------------|-----------------------------|------------------------------|--|--|
|  | Base Case                       | Allocation from:<br>Sovereigns | Allocation from:<br>Mortgages | Allocation from:<br>Credits | Allocation from:<br>Equities |  |  |
| % Infrastructure<br>Debt                               | 0%                              | 5%                             | 5%                            | 5%                          | 5%                           |  |  |
| % Soveregins   | 30%                             | 25%                            | 30%                           | 30%                         | 30%                          |  |  |
| % Mortgages  | 5%                              | 5%                             | 0%                            | 5%                          | 5%                           |  |  |
| % Credits  | 20%                             | 20%                            | 20%                           | 15%                         | 20%                          |  |  |
| % Equities   | 45%                             | 45%                            | 45%                           | 45%                         | 40%                          |  |  |
| Return Assets/Liabil                                   | ities                           | •                              | •                             | •                           |                              |  |  |
| 5% Most Positive<br>Scenarios                          | 9.4%                            | 9.7%                           | 9.6%                          | 9.6%                        | 8.8%                         |  |  |
| Average  | 4.1%                            | 4.4%                           | 4.3%                          | 4.4%                        | 4.0%                         |  |  |
| 5% Most Negative<br>Scenarios                          | -1.0%                           | -0.7%                          | -0.8%                         | -0.8%                       | -0.5%                        |  |  |
| Delta Return Assets/                                   | Delta Return Assets/Liabilities |                                |                               |                             |                              |  |  |
| 5% Most Postive<br>Scenarios                           | 0.0%                            | 0.3%                           | 0.2%                          | 0.2%                        | -0.6%                        |  |  |
| Average  | 0.0%                            | 0.3%                           | 0.2%                          | 0.2%                        | -0.1%                        |  |  |
| 5% Most negative<br>Scenarios                          | 0.0%                            | 0.3%                           | 0.2%                          | 0.2%                        | 0.5%                         |  |  |

**Exhibit 8: Impact on Return Assets/Liabilities When a Typical Pension Fund Allocates Assets to Infrastructure Debt.** Source: Aegon Asset Management

| Impact of Lower Return Expectations for Infrastructure Debt |           |                                |                               |                             |                              |  |  |
|---|-----------|--------------------------------|-------------------------------|-----------------------------|------------------------------|--|--|
|   | Base Case | Allocation from:<br>Sovereigns | Allocation from:<br>Mortgages | Allocation from:<br>Credits | Allocation from:<br>Equities |  |  |
| Delta Return Assets/Liabilites                              |           |                                |                               |                             |                              |  |  |
| 5% Most Positive Scenarios                                  | 0.0%      | 0.2%                           | 0.1%                          | 0.1%                        | -0.7%                        |  |  |
| Average   | 0.0%      | 0.2%                           | 0.1%                          | 0.2%                        | -0.2%                        |  |  |
| 5% Most Negative Scenarios                                  | 0.0%      | 0.2%                           | 0.1%                          | 0.2%                        | 0.4%                         |  |  |

Exhibit 9: Impact on Return Assets/Liabilities when Using Lower Return Expectations for Infrastructure Debt. *Source: Aegon Asset Management* 

This exhibit, however, shows that adding infrastructure debt still has a positive effect on the portfolio level, even with these more moderate return assumptions.

Results for the last sensitivity analysis, where we consider a life insurance company, are shown in Exhibit 10.

Note that the average returns are lower than for a typical pension fund. This is due to the more conservative asset mix (e.g., only 10% instead of 45% equities). However, adding infrastructure debt again has a positive effect on the portfolio level although the effect is smaller than for a typical pension fund.

| Impact of Adding Infrastructure Debt for Life Insurance Companies |              |                                |                               |                             |                              |  |
|---|--------------|--------------------------------|-------------------------------|-----------------------------|------------------------------|--|
|   | Base Case    | Allocation from:<br>Sovereigns | Allocation from:<br>Mortgages | Allocation from:<br>Credits | Allocation from:<br>Equities |  |
| % Infrastructure<br>Debt  | 0%           | 5%                             | 5%                            | 5%                          | 5%                           |  |
| % Sovereigns  | 40%          | 35%                            | 40%                           | 40%                         | 40%                          |  |
| % Mortgages   | 10%          | 10%                            | 5%                            | 10%                         | 10%                          |  |
| % Credits   | 40%          | 40%                            | 40%                           | 35%                         | 40%                          |  |
| % Equities  | 10%          | 10%                            | 10%                           | 10%                         | 5%                           |  |
| Return Assets/Liabi   | lities       |                                | •                             | •                           | •                            |  |
| 5% Most Positive<br>Scenarios                                     | 3.6%         | 3.8%                           | 3.7%                          | 3.7%                        | 3.0%                         |  |
| Average   | 1.7%         | 1.9%                           | 1.8%                          | 1.9%                        | 1.5%                         |  |
| 5% Most Negative<br>Scenarios                                     | 0.1%         | 0.3%                           | 0.2%                          | 0.3%                        | 0.2%                         |  |
| Delta Return Assets   | /Liabilities |                                |                               |                             |                              |  |
| 5% Most Postive<br>Scenarios                                      | 0.0%         | 0.2%                           | 0.1%                          | 0.1%                        | -0.6%                        |  |
| Average   | 0.0%         | 0.2%                           | 0.1%                          | 0.1%                        | -0.2%                        |  |
| 5% Most negative<br>Scenarios                                     | 0.0%         | 0.2%                           | 0.1%                          | 0.2%                        | 0.1%                         |  |

Exhibit 10: Impact on Return Assets/Liabilities when a Typical Insurance Company Allocates Assets to Infrastructure Debt. Source: Aegon Asset Management

#### Conclusion

We have explored the added value of infrastructure debt in a portfolio context. Results are shown for both pension funds and insurance companies. This asset class appears to have an attractive risk-return tradeoff in combination with diversification potential in a fixed income portfolio. Given the limited available benchmark data, care is needed when interpreting the results of the asset and liability management model. We therefore also carried out several sensitivity analyses, which in general support the robustness of our findings.

Disclosure: The views and opinions expressed in this paper are those of the author and do not necessarily reflect the official policy or position of Aegon Asset Management or Aegon N.V.

#### Endnotes

The author would like to thank Oliver Warren, Fernand Schürmann, Jenze Sibma and René Kassis for their useful suggestions when preparing this article.

- 1. When comparing infrastructure and corporate loans with a similar rating and spread duration. See Van Bragt (2018) for more information.
- 2. See http://edhec.infrastructure.institute/ for more information.
- 3. We exclude the UK from our analysis and focus on continental Europe. The specific benchmark that we use is: EDHECinfra Senior Private Debt Continental Europe Project Finance NFX – VW.
- 4. As of 27 September 2018.
- 5. Barclays Euro Aggregate Corporate Index.
- 6. Merrill Lynch Core Eurozone Government Bond Index (customized).
- 7. These two correlations are statistically significant at the 5% level.
- 8. This effect can be observed in all available private infrastructure debt benchmarks of EDHEC.
- 9. This is a gross expected spread, so excluding management fees and expected losses. Source: La Banque Postale Asset Management.
- 10. We model euro core sovereigns.
- 11. We model Dutch residential mortgages.
- 12. We model investment grade euro credits.
- 13. We model world equities (developed markets, euro hedged).
- 14. Based on aggregate data for all Dutch pension funds as collected by the Dutch Central Bank. See www.dnb.nl for more information.

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- 2. Steehouwer H. (2005), Macroeconomic Scenarios and Reality: A Frequency Domain Approach for Analyzing Historical Time Series and Generating Scenarios for the Future", PhD Thesis, Free University of Amsterdam. Available at http://dare.ubvu.vu.nl/handle/1871/9058.
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#### **Author Bio**



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David van Bragt is a member of the Investment Solutions team at Aegon Asset Management. David holds a M.Sc. and Ph.D. in applied physics and a M.A. in philosophy. From 1998-2002, he worked at the Dutch research institute for mathematics and computer science (CWI). From 2004-

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### **Managed Futures and the KISS Effect**

**Urs Schubiger** Aquila Capital

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**Fabian Dori** Aquila Capital Recent developments have not only driven numerous financial markets to record highs, but also significantly increased the correlations between various asset classes. Following one of the longest bull markets in history, current price levels and the co-movement behaviors of traditional asset classes suggest reduced expected returns and diversification benefits in the future. The question, therefore, is whether investment strategies exist that still provide an attractive risk/return profile and consistent diversification benefits.

The hypothesis and aim of this paper is to demonstrate that the unambiguous answer is yes! The risk premia of correlations between asset classes are time varying, and strategies that dynamically adjust to changing attractiveness and co-movements can harvest positive returns in various market environments. However, these strategies inherently need to be highly liquid to allow for dynamic exposure management. One type of alternative strategy that combines liquidity with adaptiveness is a managed futures strategy. This paper elaborates on the differences in the risk/return profiles of traditional balanced mandates and a long-short risk-balanced CTA strategy. It shows that the latter is not only well suited to withstand adverse bond or equity market conditions, but it may even find attractive return opportunities in turbulent times. We call this the King In Stress Scenarios (KISS) effect of long-short managed futures strategies. This robust and diversifying risk/return profile is mainly attributable to its broad and adaptively weighted investment portfolio, as well as the possibility of taking on short positions.

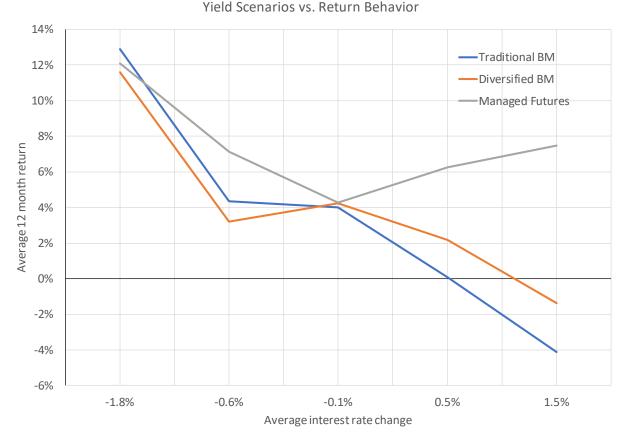
#### Data and Methodology

Using a broad set of different asset classes and a long data history<sup>1</sup>, we analyzed the risk/return profile of a CTA strategy alongside two classical, statically balanced portfolios. We simulated a managed futures strategy (MF) that combines momentum and carry with a risk budgeting engine and allows for both long and short positions. The strategy measured the current attractiveness of the risk premia of the various asset classes based on momentum and carry. The more attractive an asset class, the bigger its share in the portfolio. In case of negative momentum and carry signals, the strategy took on short positions. To spread market risk evenly, a risk budgeting engine adjusts the positions by examining both the volatility of and co-movements between the individual assets. The more risk a specific asset exhibits, the smaller its share in the final allocation. In order to dynamically adapt exposure to changing market conditions, leveraged positions were allowed. Rebalancing took place daily, factoring in transaction costs.

The benchmark consisted of a classic, capital-weighted portfolio that always was fully invested 60% in bonds and 40% in equities. This portfolio is called the traditional benchmark (TB). While it still represents the point of reference for many institutional investors, its focus on only two asset classes forgoes significant diversification benefits. Therefore, we additionally simulate a portfolio invested 50% in bonds, 40% in equities and 10% commodities and call it the diversified benchmark (DB). Both benchmarks are rebalanced monthly. To factor in various scenarios, we first compared the change in yield level with the average return delivered by the different strategies over a fixed twelve-month time window. In order to attain stably underpinned scenarios in the analysis, we divided the evolution of yield into quintiles. The same concept is then applied to changes in equity markets.

#### Interest Rate Scenarios vs. Empirical Risk/Return Characteristics

What basic findings did this empirical analysis bring to light? Let us first focus on the interest rate scenarios. The top section of Exhibit 1 compares the interest rate change over twelve months with the average return from the individual asset classes under the different yield scenarios. The returns from bonds are significantly inversely correlated with changes in interest rates. Equities also benefit from falling yields but, on average, maintain gains even during periods of strong interest rate increases. We attribute this to the fact that interest rates are usually positively correlated with the business cycle and therefore corporate profitability. Commodities and gold live up to their reputations as inflation hedges, if one takes interest rate levels as a proxy for inflationary pressures. They gain the most during periods of rising yields and associated inflation. Finally, FX shows a remarkably uncorrelated return pattern, with gains when interest rates stay relatively constant, and losses when they move disproportionally in either direction.



**Exhibit 1: Interest Rate Scenarios vs. Return Behavior** *Source: Aquila Capital Concepts GmbH, Bloomberg* 

|                                     | 1st Qntl | 2nd Qntl | 3rd Qntl | 4th Qntl | 5th Qntl |
|-------------------------------------|----------|----------|----------|----------|----------|
| Market environment and asset prices |          |          |          |          |          |
| Change in interest rates            | -1.8%    | -0.6%    | -0.1%    | 0.5%     | 1.5%     |
| Return on bonds                     | 14.3%    | 5.0%     | 0.7%     | -3.7%    | -10.8%   |
| Return on equities                  | 10.9%    | 3.3%     | 9.1%     | 5.9%     | 6.9%     |
| Return on commodities               | 1.7%     | -6.0%    | 2.8%     | 18.7%    | 18.0%    |
| Return on gold                      | 4.5%     | 2.3%     | 3.9%     | 3.7%     | 11.0%    |
| Return on FX                        | -2.3%    | 2.4%     | 0.3%     | -2.3%    | -0.2%    |
| Total return and return attribution |          |          |          |          |          |
| Traditional benchmark (TB)          | 12.9%    | 4.4%     | 4.0%     | 0.1%     | -4.1%    |
| Diversified benchmark (DB)          | 11.6%    | 3.2%     | 4.2%     | 2.2%     | -1.4%    |
| Managed futures (MF) <sup>2</sup>   | 12.1%    | 7.1%     | 4.3%     | 6.3%     | 7.5%     |
| TB bonds                            | 8.3%     | 3.0%     | 0.4%     | -2.2%    | -6.6%    |
| DB bonds                            | 6.9%     | 2.5%     | 0.4%     | -1.8%    | -5.6%    |
| MF bonds                            | 5.3%     | 2.0%     | -0.5%    | -0.3%    | 0.7%     |
| TB equities                         | 0.4%     | 0.2%     | 0.3%     | 0.2%     | 0.0%     |
| DB equities                         | 0.4%     | 0.2%     | 0.3%     | 0.2%     | 0.0%     |
| MF equities                         | 2.6%     | 1.0%     | 0.6%     | 0.5%     | 1.0%     |
| TB commodities                      | 0.0%     | 0.0%     | 0.0%     | 0.0%     | 0.0%     |
| DB commodities                      | 0.0%     | 0.0%     | 0.0%     | 0.1%     | 0.2%     |
| MF commodities                      | 0.6%     | 1.1%     | 0.9%     | 2.5%     | 1.6%     |
| MF gold                             | 0.3%     | 0.3%     | 0.4%     | 0.6%     | 1.0%     |
| MF FX                               | 3.1%     | 2.6%     | 2.9%     | 3.0%     | 3.1%     |
| Net exposure data                   |          |          |          |          |          |
| Total exposure                      | 1.50     | 1.23     | 1.06     | 0.40     | -0.02    |
| Bond exposure                       | 0.84     | 0.70     | 0.46     | 0.03     | -0.23    |
| Equities exposure                   | 0.21     | 0.16     | 0.23     | 0.19     | 0.21     |
| Commodities exposure                | 0.08     | 0.05     | 0.07     | 0.09     | 0.09     |
| Gold exposure                       | 0.04     | 0.02     | 0.04     | 0.04     | 0.03     |
| FX exposure                         | 0.00     | 0.06     | 0.03     | 0.02     | -0.06    |

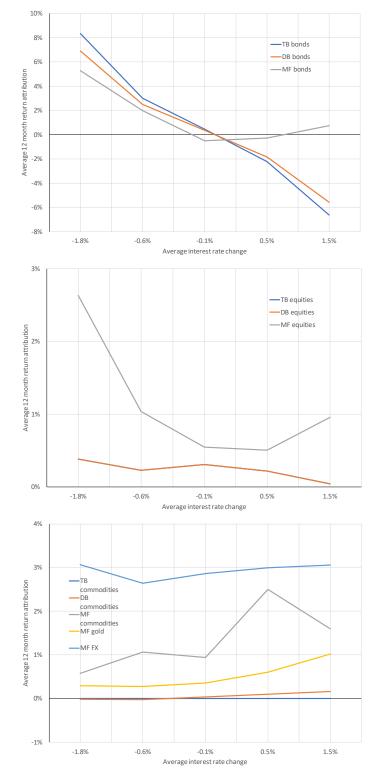
#### **Exhibit 2: Interest Rate Scenarios**

Source: Aquila Capital Concepts GmbH, Bloomberg

How well did the various asset allocation strategies exploit the diverse characteristics of the different asset classes to generate a stable performance? To glean an answer, the middle section of Exhibit 2 and Exhibit 1 (above) show the average twelve-month returns of the strategies. The two benchmark strategies obviously prefer falling rather than rising interest rates. For that matter, the traditional benchmark correlates most negatively with interest rates due to its significant bond exposure. The diversified benchmark tempers that dependency somewhat, benefiting from gains from commodities as yields rise. What's striking is the long interest rate volatility nature of the CTA strategy, which performs positively irrespective of the interest rate scenario, but is strongest the more pronounced the yield moves are.

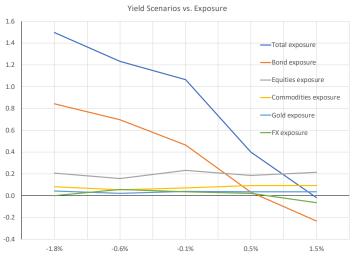
What influences these different risk/return characteristics? The middle section of Exhibit2 and Exhibit 3 provide initial answers; for each strategy they compare the returns from the individual asset classes under different interest rate scenarios. Regarding the return attribution for bonds, the findings indicate that the traditional benchmark exhibits the highest interest rate sensitivity in the extreme scenarios of the strongest 20% yield movements both to the up and down-side. The diversified benchmark manages to slightly decrease its bond dependency through a broader asset mix, yet still suffers significantly when rates increase. The CTA strategy, on the other hand, demonstrates a distinct convex return attribution from bonds. As with the capital-weighted benchmarks, bonds contribute positively to the managed futures strategy when yields decrease. However, they also provide a positive return when rates jump. Bond returns for the CTA strategy are only flat to slightly negative in steady interest rate scenarios where bonds show a non-trending behavior. But the CTA strategy not only copes best with falling bond prices, it also enjoys the broadest diversification benefits from other asset classes. When it comes to the return attribution for equities, it is remarkable that the managed futures program substantially gains from equities when yields jump, while the two benchmarks only benefit negligibly from equities in times of interest rate stress. The same holds true with respect to the commodity return attribution. The managed futures strategy profits the most from commodities markets, which are a hedge against inflation and yield shocks. Furthermore, the dynamically adjusted gold and FX exposures additionally stabilize the strategy when interest rates jump. It therefore provides a much stronger diversification by exploiting the inverse correlation between bonds and the other asset classes than the two benchmarks.

To confirm this supposition, the bottom section of Exhibit 2 and Exhibit 4 show the average net exposure of the CTA strategy under different interest rate scenarios. The overall net exposure is the highest when interest rates plummet the most. It decreases when yields rise and becomes virtually zero in the scenario of the 20% strongest rate increases. This effect is mainly driven by a significant decrease in bond and FX exposure, which both turn negative when yields spike. While, especially, the inverse relationship between bond exposure and interest rate level makes intuitive sense, the exposure patterns of the other asset classes are more interesting. Even though equities perform best in the negative interest rate change quintiles, their net exposure is kept relatively constant across the different scenarios. This is partly due to the elevated market volatility that often accompanies significantly falling yields during a flight to less-risky asset



**Exhibit 3: Interest Scenarios vs. Return Attribution** *Source: Aquila Capital concepts GmbH, Bloomberg* 

classes. Another explanation is the negative correlation between bonds and equities, and its impact on the risk contribution to total portfolio volatility. When yields fall, both bonds and equities perform on average positively, resulting in a positive co-movement. Accordingly, the risk contributions of both asset classes increase on a ceteris paribus basis. On the other hand, bonds experience losses when yields jump, while equities uphold their on-average positive return contribution. Accordingly, the co-movement between these two asset classes becomes negative in higher interest rate change quintiles, reducing their risk contribution to total portfolio volatility – ceteris paribus.



**Exhibit 4: Interest Rates vs Exposure** Source: Aquila Capital Concepts GmbH, Bloomberg

Empirical evidence therefore confirms a negative correlation between the change in the overall interest rate level and returns from the benchmark strategies. While the CTA strategy also prefers falling rates, it manages to perform positively even when rates rise, by taking short positions in bonds and benefiting from compensating gains from the other asset classes. The traditional benchmark exhibits the highest interest rate sensitivity, due to its significant bond exposure and lack of diversification into other asset classes. Consequently, its returns match the gains of the managed futures strategy when yields plummet, but it suffers the most when they increase. The diversified benchmark enjoys diversification effects from its commodity exposure when interest rates advance. However, given its limitation to long-only positions and a restricted investment universe, the losses from bonds cannot be fully compensated.

#### Equity Scenarios vs. Empirical Risk/Return Characteristics

The question of how each asset allocation strategy has historically performed under different yield scenarios is only one side of the coin. Against the backdrop of record high equity valuations, a similarly pressing question relates to how the strategies have performed in explicit relation to the equity environment.

The top section of Exhibit 3 compares changes in equities over twelve months with the average returns from the individual asset classes under different equity scenarios. Interest rates and, consequently, the returns from bonds do not exhibit an unambiguous correlation structure with equity markets. They



#### **Exhibit 5: Equity Scenarios vs Return Behavior** *Source: Aquila Capital Concepts GmbH, Bloomberg*

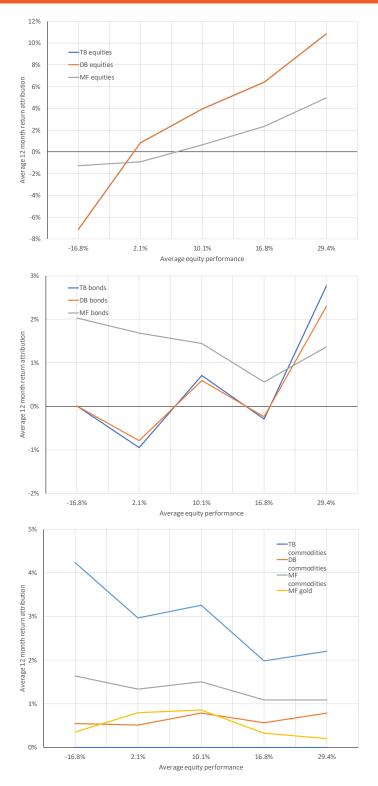
perform on average positively when equity markets perform ordinarily, lose somewhat when equities return slightly more or less than average, and gain the most when stocks rally. The strong performance of bonds in the scenario of the strongest 20% of equity markets is, however, mainly attributable to the 1980s, when both bonds and equities rose. Commodities are not strongly linked to the development of stocks but tend to perform better when equities rise. Gold on the other hand proves a hedging characteristic by performing better when equity markets are weaker. Like bonds, FX performs best in an average equity market scenario, but loses in both extreme scenarios.

How does this translate into the risk/return profile of the different strategies? The middle section of Exhibit 3 and Exhibit 5 show that all three strategies significantly benefit from rising equity markets. The capital-weighted benchmarks perform the better the stronger equity markets are. However, they suffer significant losses when equities tumble. Only the managed futures strategy is, on average, able to avoid losses when equity markets slump. Noteworthy is the managed futures strategy's ability to perform positively almost detached from the different equity scenarios.

What lies behind these different risk/return characteristics? The middle section of Exhibit 6 and Exhibit 7 show that, irrespective of the scenario, the balanced portfolios consistently allocate more capital to equities than the managed futures strategy. Therefore, they benefit more when equity markets rise, but suffer significantly more when they fall. The CTA strategy struggles somewhat in trendless equity markets, but almost manages to avoid losses even in the quintile of the most severe equity losses. Interesting to see is the bond contribution, which looks similar in the various scenarios for the two benchmarks, with a positive spike when equities jump. The managed futures strategy, on the other hand, benefits from its bond exposure irrespective of the equity market scenario. The positive return contribution is higher the weaker equity markets are. Accordingly, the managed futures strategy exploits a more pronounced diversification effect from bonds than its two capital-weighted peers. The bottom chart of Exhibit 7 indicates that both commodities and gold provide considerable diversification benefits when equity markets are falling. However, it is particularly the FX exposure that helps to compensate for equity drawdowns. By accessing two further,

|                                     | Falling equity marke | ts       | Rising equity markets |          |          |  |  |  |  |  |
|-------------------------------------|----------------------|----------|-----------------------|----------|----------|--|--|--|--|--|
|                                     | 1st Qntl             | 2nd Qntl | 3rd Qntl              | 4th Qntl | 5th Qntl |  |  |  |  |  |
| Market environment and asset prices |                      |          |                       |          |          |  |  |  |  |  |
| Change in interest rates            | 0.0%                 | 0.2%     | -0.2%                 | 0.1%     | -0.6%    |  |  |  |  |  |
| Return on bonds                     | 0.0%                 | -1.6%    | 1.2%                  | -0.5%    | 4.7%     |  |  |  |  |  |
| Return on equities                  | -16.8%               | 2.1%     | 10.1%                 | 16.8%    | 29.4%    |  |  |  |  |  |
| Return on commodities               | 5.7%                 | 5.3%     | 8.2%                  | 5.9%     | 8.1%     |  |  |  |  |  |
| Return on gold                      | 4.2%                 | 10.0%    | 9.5%                  | 1.7%     | 0.8%     |  |  |  |  |  |
| Return on FX                        | -1.0%                | -0.6     | 0.4%                  | 0.7%     | -1.7%    |  |  |  |  |  |
| Total return and return attribution |                      |          |                       |          |          |  |  |  |  |  |
| Traditional benchmark (TB)          | -7.1%                | -0.1%    | 4.7%                  | 6.1%     | 13.9%    |  |  |  |  |  |
| Diversified benchmark (DB)          | -6.6%                | 0.6%     | 5.4%                  | 6.8%     | 14.3%    |  |  |  |  |  |
| Managed futures (MF) <sup>2</sup>   | 7.0%                 | 5.9%     | 7.9%                  | 6.3%     | 10.0%    |  |  |  |  |  |
| TB bonds                            | 0.0%                 | -0.9%    | 0.7%                  | -0.3%    | 2.8%     |  |  |  |  |  |
| DB bonds                            | 0.0%                 | -0.8%    | 0.6%                  | -0.2%    | 2.3%     |  |  |  |  |  |
| MF bonds                            | 2.0%                 | 1.7%     | 1.4%                  | 0.6%     | 1.4%     |  |  |  |  |  |
| TB equities                         | -7.1%                | 0.8%     | 3.9%                  | 6.4%     | 10.9%    |  |  |  |  |  |
| DB equities                         | -7.1%                | 0.8%     | 3.9%                  | 6.4%     | 10.9%    |  |  |  |  |  |
| MF equities                         | -1.3%                | -0.9%    | 0.6%                  | 2.3%     | 5.0%     |  |  |  |  |  |
| TB commodities                      | 0.0%                 | 0.0%     | 0.0%                  | 0.0%     | 0.0%     |  |  |  |  |  |
| DB commodities                      | 0.6%                 | 0.5%     | 0.8%                  | 0.6%     | 0.8%     |  |  |  |  |  |
| MF commodities                      | 1.6%                 | 1.3%     | 1.5%                  | 1.1%     | 1.1%     |  |  |  |  |  |
| MF gold                             | 0.4%                 | 0.8%     | 0.9%                  | 0.3%     | 0.2%     |  |  |  |  |  |
| MF FX                               | 4.2%                 | 3.0%     | 3.3%                  | 2.0%     | 2.2%     |  |  |  |  |  |
| Net exposure data                   |                      |          |                       |          |          |  |  |  |  |  |
| Total exposure                      | 0.10                 | 0.47     | 0.97                  | 0.95     | 1.52     |  |  |  |  |  |
| Bond exposure                       | 0.13                 | 0.17     | 0.44                  | 0.32     | 0.43     |  |  |  |  |  |
| Equities exposure                   | -0.01                | 0.18     | 0.26                  | 0.28     | 0.30     |  |  |  |  |  |
| Commodities exposure                | 0.07                 | 0.05     | 0.09                  | 0.09     | 0.09     |  |  |  |  |  |
| Gold exposure                       | 0.04                 | 0.05     | 0.04                  | 0.02     | 0.02     |  |  |  |  |  |
| FX exposure                         | -0.11                | -0.02    | -0.04                 | 0.04     | 0.22     |  |  |  |  |  |

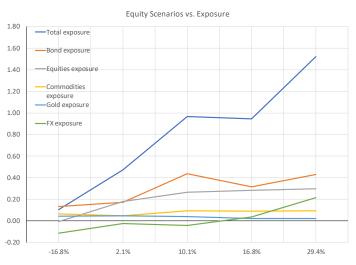
**Exhibit 6: Equity Scenarios** Source: Aquila Capital Concepts GmbH, Bloomberg



**Exhibit 7: Equity Scenarios vs. Return Attribution** *Source: Aquila Capital Concepts GmbH, Bloomberg* 

uncorrelated return sources such as gold and FX, the CTA strategy therefore achieves the most robust risk/return profile when equities plummet.

The bottom section of Exhibit 6 and Exhibit 8 show the average net exposure of the CTA futures strategy under different equity scenarios. If the net exposure is higher, the equity markets perform better. It decreases when equities fall and becomes almost zero for the strongest market correction. This effect is mainly driven by a significant correlation between total net exposure and the exposures to bonds, equities and FX, which all move relatively in sync with average equity market returns. This is not surprising given the result of the top section of Exhibit 6, which shows that bonds exhibit an astonishingly unstructured return pattern across the different equity scenarios, but with a tendency to rally when stocks perform the strongest. The commodity exposure remains relatively constant irrespective of equity market returns, given its stable risk/return profile across the various scenarios. The gold exposure, on the other hand, is negatively correlated with equity market performance, allowing the managed futures strategy to fully exploit the diversification potential of this asset class.



**Exhibit 8: Equity Scenarios vs. Exposure** *Source: Aquila Capital Concepts GmbH, Bloomberg* 

To summarize, empirical evidence highlights that equity performance considerably impacts the two benchmark strategies, while the CTA strategy seems to be quite immune to equity market movements. The significant sensitivity of the benchmark strategies to equity markets is caused by their distinct equity exposures and lack of diversification into other asset classes. Even though the diversified benchmark benefits in all scenarios from its commodities exposure, it is not able to fully exploit the diversification benefits, given that it holds its asset allocation steady across all scenarios. The CTA strategy, on the other hand, adapts its allocation swiftly on two dimensions. First, it dynamically reduces its exposure to losing asset classes to minimize losses or even gain slightly on short positions. Second, it shifts its allocation into diversifying asset classes that provide a more attractive risk/return profile, under a given market scenario.

#### Conclusion

By means of an empirical analysis that takes the US as a point of reference, we have demonstrated that a long-short managed futures strategy that focuses on balancing the risk contributions within a portfolio and accounts for both momentum and carry effects is well suited to not only withstand adverse market conditions, but even benefits from market turmoil, whether that turmoil is impacting bonds or equities. By these means, it not only stands up well from an absolute perspective, but also against traditional capital-weighted portfolios over a period that dates back as far as the 1970s. This added value in the risk/return profile is attributable to three main factors:

- The long-short managed futures strategy invests in the broadest investment universe.
- The high dynamism of the strategy better exploits the diversified characteristics of the different asset classes.
- The possibility of taking on short positions allows the strategy to perform positively even when underlying markets fall.

These favorable findings predestine the strategy to be an effective hedge against market turmoil in traditional asset classes. It is therefore well suited to diversifying portfolios against the current backdrop of historically high equity valuations and record low interest rates. Nevertheless, it should be kept in mind that there exists a wide variety of different managed futures strategies. The question of which trend is your friend should, therefore, always be answered by a holistic portfolio setup.

Disclosure: Please note that all information has been collected and examined carefully and to the best of our knowledge; however, the information is provided without any guarantee. All information is believed to be reliable, but we are not able to warrant its completeness or accuracy.

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Urs Schubiger has comprehensive experience in the research, development and implementation of quantitative investment strategies as well as leading business development initiatives. Prior to founding prime Capital and Achievement AM's Swiss subsidiary, he held senior

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Fabian Dori has more than ten years' experience in fund management and was previously Chief Investment Officer and member of the Management Board of La Roche Private Bank. Prior to this, he was Head of Portfolio Management and a member of the Management Board at 1741

Asset Management, as well as a portfolio manager at Wegelin & Co. Private Bankers. Fabian Dori holds a master's degree in Quantitative Economics and Finance from the University of St. Gallen and is Certified Risk Manager and Chartered Financial Analyst.



## An Introduction to Alternative Risk Premia

**Guillaume Monarcha** Orion Financial Partners

Investors can apprehend the ARP universe from two angles. The first one is the academic literature on risk factors, from which they have been developed. The second one is the information communicated by ARP providers, which are essentially operational research documents, commercial presentations, and two-pagers describing the individual ARP strategies they offer. If the academic literature has the drawback of being purely theoretical, the documentation provided by asset managers and investment banks is heterogeneous and often specific. It is therefore difficult for investors to have a global vision of the industry. What are the ARP strategies offered by investment banks? How are they constructed? What are their specific statistical properties? What issues should be addressed in a sound selection / investment / risk management process?

In the first part, we retrace the link between academic factors and ARPs. Through the analysis of their operational implementation process, we show that – contrary to what we would expect – ARPs aiming to replicate similar factors can show significant heterogeneity. We then discuss the frontier between academic ARPs and trading ARPs, as well as their positioning in the factor investing industry and in the alternative investment universe.

In the second part, we analyze the features of the current ARP offering from a proprietary database, that combines the current offering of 9 investment banks (more than 400 ARP). It turns out that only one half of the investable ARPs are academic premia, the other half of the offering being composed of trading risk premia, which aim to capture market anomalies or to replicate hedge fund strategies.

Finally, we analyze the statistical properties of 293 ARPs over the period 01/05/2007 – 09/07/2018. Our results put forward an attractive risk-return profile in different market configurations, with the counterpart of increased extreme risks (non-Gaussian returns), especially for trading ARPs. Second, the analysis of their correlation structure shows significant diversification properties, between ARPs and other asset classes, between the various ARPs strategies, and more surprisingly between ARPs based on the same risk factors.

To conclude, we highlight the issues that arise from their specific features, both qualitative and quantitative, and that must be addressed by investors.

## From Academic Risk Premia to the Current ARP Offering

ARPs are systematic, rule-based investment strategies, aiming to harvest risk premia delivered by exposures to systematic risk factors, that have been extensively documented in the academic literature (value, quality, momentum...). Investment banks put forward this connection with the academic universe, as the main argument in their marketing approach. However, the analysis of investable ARPs shows that they can significantly differ from the risk factors identified in the academic literature, for two reasons. First, as the implementation process of risk premia has not been addressed by academics, investment banks follow their own one, that can diverge from each other. Second, they incorporate trading (i.e. non-academic) risk premia in their ARP offering, which objective is to exploit market anomalies, rather than risk factors exposure.

#### Academic Risk Factors and Academic Risk Premia

Since the seminal work of Fama and French (1992), the theme of risk factors has developed strongly within the academic community, with the objective to explain the cross-sectional returns of the various asset classes. Roughly, these factors are designed as market neutral or dollar neutral<sup>1</sup> portfolios to capture the orthogonal<sup>2</sup> performances and risks generated by the exposures to specific features (or economic factors) of the underlying securities, such as their quality or valuation level. They are formed of a long and a short portfolio, respectively formed of securities that exhibit the highest and lowest exposure level to the underlying economic factor (e.g., long high-quality stocks vs. short low-quality stocks in the quality factor).

From then, many academics focused the research on factors showing an ability to generate robust long-term performance, (i.e. a risk premium) around the theme of factor investing. Risk premia are then considered as systematic quantitative investment strategies, relegating the original objective of risk factors<sup>3</sup> to the background. Exhibit 1 provides a non-exhaustive list of the main risk premia documented in the academic literature.

| Risk premia                              | Economic intuition  | Implementation  | Asset classes                                | References  |
|--|---|---|--|---|
| Value                                    | Benefit from the price convergence between<br>undervalued and overvalued assets. The<br>relative value of a security is evaluated by an<br>economic measure (price to book ratio for<br>the shares, PPP for the currencies)   | Buy undervalued<br>securities, sell over-<br>valued securities.   | Equities, rates, credit,<br>FX, commodities. | Fama et French (1992, 1993); Asness,<br>Frazzini (2013); Asness, Moskowitz,<br>Pedersen (2013).   |
| Momentum                                 | The momentum premium is based on a be-<br>havioral bias: demand for securities with the<br>best recent performance tends to be larger<br>than demand for securities with weaker<br>recent performance.  | Long positions in<br>the best- perform-<br>ing stocks, short<br>positions in the<br>least performing<br>stocks. | Equities, rates, credit,<br>FX, commodities. | Jagadeesh et Titman (1993); Carhart<br>(1997); Rouwenhorst<br>(1998); Moskowitz and<br>Grinblatt (1999); Asness,<br>Moskowitz, Pedersen (2013). |
| Low risk,<br>low beta, low<br>volatility | According to the CAPM theory, investors who<br>cannot use leverage are forced to allocate<br>their assets in a non-optimal manner, over-<br>allocating to riskier stocks. This generates a<br>market anomaly that, overall, is beneficial to<br>the least risky securities (less susceptible to<br>market corrections). | Long positions<br>on the least risky<br>stocks, short<br>positions on the<br>riskiest stocks.                   | Equities, rates, credit,<br>FX, commodities. | Ang, Hodrick, Xing, Zhang (2006); Ang,<br>Hodrick, Xing, Zhang (2009); Frazzini<br>and Pedersen (2014).   |
| Carry                                    | Benefit from the yield differential (rates, cou-<br>pons, dividends, etc.) between similar assets.  | Long positions in<br>high yield securi-<br>ties, short on low<br>yielding ones.                                 | Equities, rates, credit,<br>FX, commodities. | Koijen, Moskowitz, Pedersen, Vrugt<br>(2016); Gorton, Hayashi, Rouwenhorst<br>(2012); Brooks,<br>Moskowitz (2017).                              |
| Quality                                  | Benefit from the outperformance of com-<br>panies that show superior quality, in terms<br>of profitability, dividend distribution, credit<br>quality, governance  | Long high qual-<br>ity compagnies,<br>short low quality<br>compagnies.  | Equities.                                    | Greenblatt (2006); Asness,<br>Frazzini, Pedersen (2013);<br>Novy-Marx (2014).   |

#### Exhibit 1: Main Risk Premia Identified in the Academic Literature

Source: Orion Financial Partners

## The Implementation of ARPs: from Theory to Practice

Academic risk factors are purely theoretical, in the sense that they are not directly investable. Indeed, many operational parameters – such as the liquidity of the underlying securities, the possibility of selling them short, transaction costs – are not considered in their construction. This is where alternative risk premiums take over: they are investable versions of academic risk premia.

Although the economic factors involved in the construction of academic premia are well documented in the literature, the absence of clear guidelines leaves a significant margin in their operational implementation. It appears that ARPs aiming to replicate the same academic premium can show significant divergences between each other (i.e., a relatively low correlation), but also with the academic factor they aim to replicate. These divergences find their source at different levels in the ARP construction process, which can be summarized around the steps detailed below.

**Step 1: The definition of the investment universe** consists in identifying all the securities – most often within a given market benchmark – to which the strategy will be applied. The universe will be jointly determined by common criteria (liquidity, market capitalization...) and more discretionary criteria, specific to certain providers. In that case, their investment universe may exclude securities that have recently had "excessive" volatility, securities that are subject to specific market situations (takeover bids, etc.) or securities belonging to a specific sector (notably banking).

**Step 2: The definition of economic factors and their measures.** The construction of certain academic factors leaves little room for interpretation. For example, this is the case of the size factor whose only measure is the market capitalization of companies. But in other cases, there is no real consensus in the literature about the criteria that should be used to define the factors. This is particularly true for the quality factor, which is based on the identification of profitable, operationally efficient, and low-risk companies, whose governance is sound and stable. This wide definition leaves room for interpretation, and results in heterogenous measures this factor. For example, Novy-Marx (2013) measures the quality of a company by its gross profit / gross asset ratio as the main measure of quality, whereas Piotroski (2000) or Asness, Frazzini and Pedersen (2013) combine different measures and criteria to define this factor.<sup>4</sup>

**Step 3: Scoring** consists in measuring the exposure level of the securities to the risk factors. The scores generally take the form of an aggregation of the various measures of the underlying factor into a z-score.

**Step 4: The classification and selection step** consists in identifying the securities that will enter the composition of the long and short portfolios. The construction of academic factors is generally based on the classification of the investment universe into three groups, according to their respective scores. The group composed of the securities with the highest (worst) scores will compose the long (short) leg of the portfolio. The group composed of the securities with intermediate scores is excluded from the construction of the factor. If there is no consensus on the size of the groups, the top and worst groups must be of equivalent size (long top 10% vs. short worst 10%, long top 25% vs. short worst 25% ...). Tighter groups naturally imply less diversification and a significant increase the impact of both specific selection criteria and model risk.<sup>5</sup>

Step 5: The construction of long and short portfolios is a key step in the construction of ARPs. In the academic literature, there is no consensus on the weighting method to use. For example, int the size and value factors of Fama and French (1992) or in the quality factor of Asness, Frazzini and Pedersen (2013), the security's weights are determined by their market cap. In Frazzini and Pedersen (2014), the weight the securities in the BAB (betting against beta) factor is defined by their exposure to market risk (beta). In the ARP offering of investment banks, we have identified many simple<sup>6</sup> or optimized<sup>7</sup> allocation methods. It is important to point out that in practice, the short leg of the factor's portfolios is often replaced by a short exposure in the benchmark future contract. This point marks a real divergence between ARPs and academic factors. This substitution of the short portfolio by a future position can be justified by the research of cost efficiency, or by the potential liquidity management issues that may arise from short sales.

**Step 6: The long/short allocation methodology** defines the orthogonality, i.e. the market neutrality, of ARPs. In the literature, academic risk factors can alternatively be defined as portfolios that are equally allocated between the long and the short leg (sum of the weights equals zero, dollar neutral portfolios), or as market neutral portfolios constructed to neutralize exposure to market risks (beta neutral). In practice, equity, rate, and credit ARPs tend to be structured as market neutral strategies (with null beta for equities, null duration for rates and credit), whereas the long and short legs of commodity and FX ARPs tend to be dollar neutral.

**Step 7: The level of leverage** employed in the investment strategy can substantially vary, depending on the risk management policy of the ARP (target volatility level vs. fixed ad hoc risk constraints).

Almost all the steps listed above leave significant freedom in the implementation process of ARPs. Consequently, ARPs proposed by different providers with the aim of capturing the same risk premium, can show significant differences in their portfolio composition and, ultimately, show relatively low levels of correlation. This may be especially the case when the investment universes are similar, but not identical. For example, two European equity momentum ARPs, whose universes are respectively the Eurostoxx 50 and the Stoxx 600, will probably have only a marginal number of common stocks in their allocations.<sup>8</sup> Furthermore, differences in factor definitions, classification thresholds, or weighting and allocation methodologies will have an impact on both the constituents and the allocation of the long and short leg of ARP portfolios.

To summarize, as the operational implementation of theoretical risk premia have not been addressed by academics, ARPs which display apparently similar strategies can indeed display very specific features and deliver significantly heterogeneous performances. Some providers could see in this freedom of implementation the opportunity to fine tune the parametrization

of their ARPs, in order to differentiate from external offering, or to enhance the risk/return characteristics<sup>9</sup> of the backtested strategies.

#### The Frontier Between Academic Risk Premia and Trading Risk Premia

We distinguish two types of ARPs in bank's offering. Academic ARPs are directly aimed to replicate the risk premia presented in Exhibit 1. They are based on factors that have been well documented in the academic literature, and that essentially involve the trading of listed and liquid products. Backed by academic research, academic ARPs are expected to be resilient in various market configurations and in the different phases of the economic cycle.

On their side, trading ARPs (listed in Exhibit 2) encompass a set of systematic and rule-based quantitative investment strategies, that alternately aim to replicate hedge fund strategies (trend following, M&A...) or to exploit market anomalies, whose economic rationale may be hard to apprehend. Unlike academic ARPs, trading ARPs are mostly backed by applied research, academic research being limited by data availability (especially in the case they rely on the trading of OTC derivatives) or by the lack of theoretical foundations. They also differ from academic ARPs in their construction process. They are not necessarily market neutral,<sup>10</sup> and may be based on a more discretionary stock selection process.<sup>11</sup> They also generally incorporate more parameterization, which can potentially increase model risk and imply a disconnection between the behavior of the strategy between the backtest and the live period.<sup>12</sup>

Overall, these differences do not prejudge the potential of over- or underperformance of trading ARPs vs. academic ARPs. But they must be considered in the selection, in the investment, and in the risk management processes.

#### ARP, Factor Investing and Hedge Funds

The purpose of factor investing is to tilt the allocation of investment portfolios towards specific factors, in order to add a layer of performance and diversification from systematic risk premia. The universe drawn by this definition is quite broad. It encompasses many heterogeneous investment strategies, which can be traditional (long only) or alternative (long/short, market neutral), active or passive. systematic (often) or discretionary<sup>13</sup> (more rarely).

During the last decade, smart beta strategies have been the main development vector for the factor investing industry. Roughly, these are traditional investment strategies,<sup>14</sup> whose allocation process aims to overweight securities with specific features (factor exposure) with the objective to enhance their risk-return profile by capturing particular risk premia. But the contribution of risk premia in their overall performance remains limited (if not marginal) as their regulatory environment (mutual funds, ETFs) imposes strong investment constraints (long only, no leverage, no short sales...), and therefore limit factor exposures.

ARPs can be viewed as the "alternative" evolution of smart beta strategies, with the objective of delivering pure (instead of marginal) factor exposure. Their alternative nature comes from the joint use of short positions, leverage, and derivatives (future contracts in most cases). Consequently, the border between ARPs and hedge funds (especially quantitative hedge funds) may seem blurred, as they require similar investment techniques and instruments. There are, however, fundamental differences between these two universes. First, ARPs aim to capture the risk premia from risk factors, whereas hedge funds aim to generate alpha in a

| Risk premia                              | Economic intuition  | Implementation  | Asset classes   | Academic references  |
|--|---|---|---|--|
| Short volatility                         | The structural demand for protection<br>implies a structural difference between<br>the levels of implied (higher) volatility<br>and realized volatility.                          | Short straddle, delta hedged by<br>a long position in the underlying<br>market.   | Equities, rates,<br>credit, FX, com-<br>modities.             | Coval, Shumway (2001); Ang,<br>Israelov, Sullivan, Tummala<br>(2018) |
| Volatility carry                         | Profit from the teem structure of the volatility curve.   | Short volatility future (delta<br>hedged) when the curve is in<br>contango. Reverse position when<br>the curve is in backwardation.                 | Volatility  |  |
| Mean reversion                           | Exploit short-term market<br>overreaction, generally measured by<br>the difference between short (daily)<br>realized volatility and longer-term<br>volatility (one or two weeks). | Long or short position in the<br>underlying index in order to<br>replicate the market sensitivity<br>(delta) induced by a variance<br>swap.         | Equities, rates,<br>credit, FX, com-<br>modities, volatility. | Poterba, Summers (1988)  |
| Trend following<br>/ absolute momentum   | Exploit trends in asset prices,<br>similar CTA strategies.  | Long positioning on securities<br>with positive trend and/or short<br>ones with negative trend.<br>Directional strategy (long or<br>short bias).    | Equities, rates,<br>credit, FX, com-<br>modities, volatility. | Moskowitz, Ooi, and Peder-<br>sen (2012);<br>Fung, Hsieh (2001)      |
| Directional versions<br>of academic ARPs | Cf. Table 1.  | Long and/or short positions on<br>the securities from the investment<br>universe, defined by their exposure<br>level to the underlying risk factor. | Equities, rates, credit,<br>FX, commodities.                  | Cf. references in <b>Table 1</b> .                                   |

**Exhibit 2: Main Trading Risk Premia Identified in the Offering of Investment Banks** Source: Orion Financieal Partners

broader sense, via factor exposures, but also (and mainly) to more specific risk premia. In that sense, hedge funds are not part of the factor investing universe. Second, the strategies implemented in ARPs are systematic and based on strict investment rules, whereas those of hedge funds are more discretionary and managed in a more flexible framework. Finally, ARPs offer significantly higher levels of transparency and liquidity than hedge funds, for a lower cost structure.

### Typology of the ARP Offering

We present the features of the current market offering, from a proprietary database of more than 350 investable ARP indices provided by 9 investment banks.<sup>15</sup>

#### **Classification and Distribution of Strategies**

As far as we know, there is no standard classification of ARPs. The different providers generally differentiate them according to three dimensions: the underlying asset class, the underlying risk factor, and the geographical focus. However, academic ARPs and trading ARPs are generally not dissociated and are merged in their

offering. We propose a classification based on four dimensions: the previous three dimensions to which we add the nature of ARPs (academic or trading). The typology of the investment universe referenced in our database is detailed in Exhibit 3. It appears that:

- Less than one half of the ARPs offered by investment banks are academic ARPs.
- 46% of ARPs are focused on equity markets, 18% on currencies, 15% on interest rates, 15% on commodity markets, and a little 5% on credit.
- The offering of academic ARPs is significantly concentrated on equity markets (60%), and to a lesser extent on the FX markets (20%). It remains marginal for other asset classes. Conversely, the supply of trading ARPs is more heterogeneous among the various asset classes.
- Almost 90% of academic ARPs are focused on academic factors (carry, value, momentum, quality, and low risk), whereas trading ARPs are more concentrated on short volatility (29%), trend (24%), and carry (17%) strategies.

| Nature        | Factor             | Equities | FX    | Underlying asset class<br>Credit | Rates | Commos | Total  |
|---------------|--------------------|----------|-------|----------------------------------|-------|--------|--------|
|               | Carry              | 1.7%     | 7.7%  | 1.7%                             | 2.6%  | 2.0%   | 15.6%  |
|               | Growth             | 0.3%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 0.3%   |
|               | Liquidity          | 0.3%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 0.3%   |
|               | Low risk           | 5.7%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 5.7%   |
| ARPs          | Mean reversion     | 0.6%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 0.6%   |
| Academic ARPs | Momentum           | 5.7%     | 0.6%  | 0.0%                             | 0.3%  | 0.6%   | 7.1%   |
| cade          | Profitability      | 1.4%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 1.4%   |
| 4             | Quality            | 4.5%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 4.5%   |
|               | Size               | 2.8%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 2.8%   |
|               | Value              | 6.5%     | 2.0%  | 0.0%                             | 0.9%  | 0.6%   | 9.9%   |
|               | Total              | 29.5%    | 10.2% | 1.7%                             | 3.7%  | 3.1%   | 48.3%  |
|               | Carry              | 1.7%     | 0.0%  | 1.1%                             | 3.1%  | 3.1%   | 9.1%   |
|               | Liquidity          | 0.0%     | 0.3%  | 0.0%                             | 0.0%  | 2.3%   | 2.6%   |
|               | M&A                | 1.1%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 1.1%   |
|               | Mean reversion     | 1.4%     | 1.1%  | 0.0%                             | 0.0%  | 0.0%   | 2.6%   |
| <b>RPs</b>    | Momentum           | 0.0%     | 0.3%  | 0.0%                             | 0.3%  | 0.6%   | 1.1%   |
| Trading ARPs  | Trend              | 1.4%     | 3.1%  | 2.3%                             | 3.7%  | 1.7%   | 12.2%  |
| Trac          | Value              | 0.0%     | 0.3%  | 0.0%                             | 0.0%  | 0.3%   | 0.6%   |
|               | Long volatility    | 0.6%     | 0.0%  | 0.0%                             | 1.1%  | 0.0%   | 1.7%   |
|               | Short volatility   | 5.7%     | 2.8%  | 0.3%                             | 2.6%  | 3.7%   | 15.1%  |
|               | Volatility carry   | 1.4%     | 0.0%  | 0.0%                             | 0.9%  | 0.0%   | 2.3%   |
|               | Volatility trading | 3.4%     | 0.0%  | 0.0%                             | 0.0%  | 0.0%   | 3.4%   |
|               | Total              | 16.8%    | 8.0%  | 3.7%                             | 11.6% | 11.6%  | 51.7%  |
|               | Total              | 46.3%    | 18.2% | 5.4%                             | 15.3% | 14.8%  | 100.0% |

#### **Exhibit 3: Distribution of the ARP Offering of 9 Investment Banks** Source: Orion Financial Partners

|        | Equities | FX   | Credit | Rates | Commos. | % aca. | % trading | % od global offering |
|--------|----------|------|--------|-------|---------|--------|-----------|----------------------|
| Bank 1 | 6.8%     | 2.0% | 1.1%   | 1.4%  | 1.4%    | 35.6%  | 64.4%     | 12.8%                |
| Bank 2 | 8.5%     | 2.0% | 1.1%   | 3.1%  | 5.1%    | 44.3%  | 55.7%     | 19.9%                |
| Bank 3 | 7.7%     | 0.9% | 0.0%   | 1.4%  | 0.6%    | 43.2%  | 56.8%     | 10.5%                |
| Bank 4 | 4.3%     | 2.3% | 2.0%   | 3.4%  | 4.8%    | 47.5%  | 52.5%     | 16.8%                |
| Bank 5 | 1.4%     | 6.0% | 0.0%   | 1.7%  | 0.0%    | 59.4%  | 40.6%     | 9.1%                 |
| Bank 6 | 0.9%     | 2.0% | 0.6%   | 1.1%  | 1.1%    | 40.0%  | 60.0%     | 5.7%                 |
| Bank 7 | 1.4%     | 0.0% | 0.0%   | 0.0%  | 0.0%    | 100.0% | 0.0%      | 1.4%                 |
| Bank 8 | 12.2%    | 2.3% | 0.6%   | 2.6%  | 1.7%    | 50.0%  | 50.0%     | 19.3%                |
| Bank 9 | 3.1%     | 0.9% | 0.0%   | 0.6%  | 0.0%    | 81.3%  | 18.8%     | 4.5%                 |

**Exhibit 4: Distribution of ARPs Between the Various Providers** Source: Orion Financial Partners

#### Distribution of the Offering by Provider

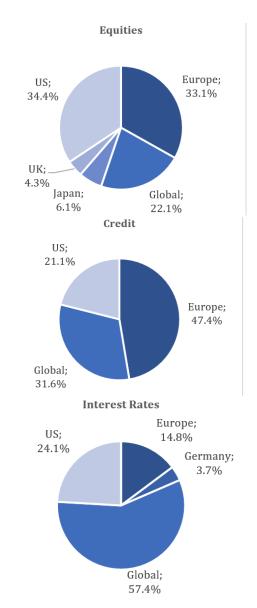
Exhibit 4 summarizes the distribution of the ARP offering among the providers. It appears that (i) the first 3 investment banks<sup>16</sup> deliver 56% of the ARP offering; (ii) the offering of certain banks is concentrated on specific risk premia, (for instance, bank 9 that offers 81% of academic ARPs, whereas bank 1 offers 65% of trading ARPs); (iii) certain banks are specialized on specific asset classes, like bank 5 which offers 65% of FX premia. This specialization is not surprising, as investment banks will tend to develop ARPs that fall in their expertise field, to benefit from comparative advantage and bring greater added value.

#### **Geographical Distribution**

Except for FX and commodity ARPs that have a global focus by nature, ARPs can focus on specific regions or be global. In detail (Exhibit 5), 80% of equity ARPs exhibit a geographical bias (balanced between USA and Europe), whereas more than 50% of interest rate premia have a global focus. Credit ARPs, on the other hand, are more concentrated in Europe (47% of the offer, vs. 21% in the US).

## Risk, Return, and Diversification Properties of ARPs

In this section, we present the risk, return, and diversification properties of ARPs, through the analysis of their univariate and multivariate statistical properties. The results reported here are based on the analysis of 273 mono-factor and mono-asset class ARPs (73% of our database), over the period 01/05/2007 – 09/07/2018.



**Exhibit 5: Geographic Repartition of Equity, Credit, and Interest Rate ARPs** *Source: Orion Financial Partners* 

|   |      |      |       | ARPs and ot | her assets cl | asses |      |       |       |       |  |  |  |  |
|---|------|------|-------|-------------|---------------|-------|------|-------|-------|-------|--|--|--|--|
|   | N    | μ    | σ     | IR          | μ+            | σ+    | IR+  | μ-    | σ-    | IR-   |  |  |  |  |
| ARP   | 293  | 3.1% | 6.6%  | 0.51        | 3.3%          | 5.6%  | 0.58 | 2.4%  | 8.4%  | 0.47  |  |  |  |  |
| Equities (1)                                  | -    | 6.8% | 17.8% | 0.38        | 25.1%         | 12.9% | 1.95 | -42%  | 25.9% | -1.63 |  |  |  |  |
| Bonds (2)                                     | -    | 3.3% | 5.5%  | 0.61        | 3.8%          | 5.2%  | 0.74 | 2.1%  | 6.4%  | 0.32  |  |  |  |  |
| Hedge funds (3)                               | -    | 0.0% | 4.78% | 0.00        | 6.1%          | 3.9%  | 1.56 | -16%  | 6.0%  | -2.70 |  |  |  |  |
| Academic ARPs                                 |      |      |       |             |               |       |      |       |       |       |  |  |  |  |
| Underlying asset N μ σ IR μ+ σ+ IR+ μ- σ- IR- |      |      |       |             |               |       |      |       |       |       |  |  |  |  |
| Equities                                      | 102  | 2.3% | 6.1%  | 0.39        | 2.1%          | 5.4%  | 0.36 | 3.1%  | 7.6%  | 0.50  |  |  |  |  |
| FX  | 36   | 1.4% | 8.1%  | 0.19        | 4.5%          | 7.1%  | 0.62 | -7.1% | 10.1% | -0.65 |  |  |  |  |
| Credit  | 6    | 2.4% | 3.5%  | 0.68        | 3.8%          | 3.0%  | 1.33 | -1.4% | 4.7%  | -0.32 |  |  |  |  |
| Rates   | 13   | 1.6% | 3.8%  | 0.42        | 1.4%          | 3.2%  | 0.45 | 2.1%  | 4.9%  | 0.45  |  |  |  |  |
| Commodities                                   | 9    | 6.0% | 9.0%  | 0.72        | 3.4%          | 8.4%  | 0.46 | 12.9% | 10.2% | 1.31  |  |  |  |  |
| Total   | 166  | 2.3% | 6.4%  | 0.38        | 2.7%          | 5.7%  | 0.47 | 1.2%  | 8.0%  | 0.26  |  |  |  |  |
|   |      |      |       | Trad        | ling ARPs     |       |      |       |       |       |  |  |  |  |
| Underlying asset                              | Ν    | μ    | σ     | IR          | μ+            | σ+    | IR+  | μ-    | σ-    | IR-   |  |  |  |  |
| Equities                                      | 29   | 5.2% | 9.5%  | 0.54        | 7.4%          | 7.4%  | 0.96 | -0.5% | 13.3% | 0.08  |  |  |  |  |
| FX  | 22   | 3.0% | 6.7%  | 0.44        | 2.1%          | 5.6%  | 0.39 | 5.5%  | 8.8%  | 0.56  |  |  |  |  |
| Credit  | 8    | 4.4% | 6.4%  | 0.66        | 6.2%          | 5.5%  | 1.18 | -0.5% | 8.4%  | -0.14 |  |  |  |  |
| Rates   | 36   | 3.1% | 4.4%  | 0.74        | 2.3%          | 3.7%  | 0.59 | 5.2%  | 5.9%  | 1.14  |  |  |  |  |
| Commodities                                   | 32   | 5.0% | 6.9%  | 0.89        | 4.1%          | 5.9%  | 0.77 | 7.4%  | 8.7%  | 1.19  |  |  |  |  |
| Total   | 0.68 | 4.1% | 5.5%  | 0.72        | 4.1%          | 8.9%  | 0.73 |       |       |       |  |  |  |  |

#### Exhibit 6: Risk-Return Profile of ARPs

Source: Bloomberg, Orion Financial Partners

Notes.  $\mu$ : average annualized return,  $\sigma$ : volatility, IR: information ratio ( $\mu/\sigma$ ). Suffixes + and – denote bullish and down periods of the MSCI world index, as defined in Appendix A. Reported statistics are computed over the period 01/05/2007 – 09/07/2018, from weekly data. They are the averages of statistics computed for individual ARPs. (1) MSCI World index (bloomberg: NDDUWI). (2) Bloomberg-Barclays Global Bond Aggregate (bloomberg: LEGATRUU). (3) HFRX Global Hedge Fund index (Bloomberg: HFRXGL).

|                 |                    |              | ARPs and oth           | ner asset classes                               |   |   |                             |
|-----------------|--------------------|--------------|------------------------|---|---|---|-----------------------------|
|                 | Ν                  | Skewness (1) | Excess kurtosis<br>(2) | % non-Gaussian<br>Distribution, JB-<br>stat (3) | % non-Gaussian<br>Distribution,<br>BSL-stat (4) | Worst negative choc<br>(standard deviation<br>multiple) | % VaR (99%)<br>crossing (5) |
| ARP             | 293                | -0.15        | 7.81                   | 98%   | 90%   | 5.47  | 1.6%                        |
| Equities (6)    | -                  | -1.04        | 9.28                   | Prob<1%   | Prob<1%   | 8.14  | 2.0%                        |
| Bonds (7)       | -                  | -0.01        | 1.23                   | Prob<1%   | Prob<1%   | 3.58  | 1.1%                        |
| Hedge Funds (8) | -                  | -2.07        | 11.91                  | Prob<1%   | Prob<1%   | 8.61  | 2.8%                        |
|                 |                    |              | Acader                 | nic ARPs  |   |   |                             |
|                 | Ν                  | Skewness (1) | Excess kurtosis<br>(2) | % non-Gaussian<br>Distribution, JB-<br>stat (3) | % non-Gaussian<br>Distribution,<br>BSL-stat (4) | Worst negative choc<br>(standard deviation<br>multiple) | % VaR (99%)<br>crossing (5) |
| Equities        | 102                | -0.06        | 3.87                   | 97%   | 86%   | 4.89  | 1.5%                        |
| FX              | 36                 | -0.45        | 6.42                   | 100%  | 94%   | 5.76  | 1.8%                        |
| Credit          | 6                  | -0.50        | 5.78                   | 100%  | 100%  | 5.68  | 2.4%                        |
| Rates           | 13                 | -0.24        | 7.77                   | 100%  | 69%   | 5.53  | 1.5%                        |
| Commodities     | 9                  | 0.04         | 1.51                   | 100%  | 44%   | 4.00  | 1.4%                        |
| Total           | 166                | -0.17        | 4.67                   | 98%   | 85%   | 5.11  | 1.6%                        |
|                 |                    |              | Tradir                 | ng APRs   |   |   |                             |
|                 | Ν                  | Skewness (1) | Excess kurtosis<br>(2) | % non-Gaussian<br>Distribution, JB-<br>stat (3) | % non-Gaussian<br>Distribution,<br>BSL-stat (4) | Worst negative choc<br>(standard deviation<br>multiple) | % VaR (99%)<br>crossing (5) |
| Equities        | 29                 | -0.86        | 25.80                  | 100%  | 100%  | 7.94  | 1.9%                        |
| FX              | 22 0.04 12.39      |              | 12.39 100%             |   | 100% 95%  |   | 1.5%                        |
| Credit          | Credit 8 0.14 5.65 |              | 5.65                   | 100% 100%                                       |   | 5.12  | 1.8%                        |
| Rates           | 36                 | -0.07        | 7.36                   | 100%  | 100%  | 5.47  | 1.7%                        |
| Commodities     | 32                 | 0.32         | 5.72                   | 94%   | 88%   | 4.71  | 1.6%                        |
| Total           | 127                | -0.12        | 11.92                  | 98%   | 96%   | 5.94  | 1.7%                        |

#### Exhibit 7: Highter Moments, Normality tests and extreme Risks

Source: Bloomberg, Orion Financial Partners

Notes. Reported results are the averages of the statistics computed for individual ARPs, over the period 01/05/2007 – 09/07/2018, from weekly data. (1) Asymmetry coefficient. When negative, occurrence probability of extreme losses is higher than for extreme gains. (2) When excess kurtosis is significantly positive, the probability of extreme events is higher than, in the gaussian case. (3) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Jarque-Bera test. For other asset classes, in Table 4.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (4) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Kolmogorov-Smirnov test. For other asset classes, in Table 4.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (5) % of weekly returns that are inferior to the gaussian VaR (weekly, 99%). (6) MSCI World index (bloomberg: NDDUWI). (7) Bloomberg-Barclays Global Bond Aggregate (bloomberg: LEGATRUU). (8) HFRX Global Hedge Fund index (Bloomberg: HFRXGL).

#### **Mean-Variance Properties**

#### ARP universe vs. other asset classes

The average annualized returns, volatilities, and information ratios in different market environments<sup>17</sup> are reported in Exhibit 6. It appears that:

- On average, individual ARPs display similar volatility and annualized returns than bonds. Their average risk-return ratio is higher than those of equities and investable hedge funds<sup>18</sup> (0.51 vs. 0.38 and 0.00 respectively).
- While the risk-return profile of equities deteriorates logically between bullish and bearish periods, that of ARPs remains particularly stable, which is in line with their objective of absolute performance. This is not the case for hedge funds, whose performance deteriorates significantly with market conditions.<sup>19</sup>

#### For individual ARPs

A more detailed analysis confirms some of the previous results, and also highlights the heterogeneity of the risk-returns profiles within the ARP industry (detailed results in Annex B).

- On average, the return to risk ratio of trading ARPs appears to be more attractive than that of academic ARPs (0.68 vs. 0.38). This difference is mainly due to a higher level of profitability, computed volatility levels being similar.
- Some ARPs show significant sensitivity to a deterioration in market conditions. This is the case for short volatility strategies, which are negatively affected by sudden increases in volatility levels, as illustrated by drop in the average performance of equity short volatility premia from +13.9% in bull markets vs. -12.9 % in down markets. Conversely, momentum, long volatility, and trend strategies show particularly attractive performance levels in bear markets.
- On average, commodity ARPs exhibit the highest information ratios (0.89 on average), followed by interest rate premia (0.74). This outperformance relies on their defensive nature: the highest information ratios are observed for bear market environments, while remaining significant in bull period. Conversely, credit and equity ARPs display the most attractive properties in bull markets (risk-return ratios of 1.18 and 0.96, respectively), but deteriorates significantly during market downturns.
- The review of the risk-return profiles of similar ARPs reveals unexpected level of heterogeneity. For instance, over the same sample period, the equity quality premia display information ratios ranging from 0.06 to 1.34. This perfectly illustrates the impact of the divergences in the implementation processes.

In summary, these results illustrate the ability of ARPs to deliver absolute performance. However, the performance and risk level of certain ARPs appears to be sensitive to the market environment, depending on their nature (academic vs. trading), on the type of premium, or on the underlying asset traded. We also pointed out a significant heterogeneity among the industry, both between and within the various ARP strategies. Selecting and managing ARP allocations thus appears to be less straightforward than expected.

## Non-normality of Return Distributions and Extreme Risks

The analysis of higher moments – skewness<sup>20</sup> and kurtosis<sup>21</sup> – is reported in Exhibit 7. It appears that:

- The normality assumption for the return distribution is rejected for 98% of the individual ARPs, mainly because of significant excess kurtosis (7.81 on average), which however remains below the levels measured for equities or hedge funds over the same period (9.2 and 11.9 respectively). This result is not surprising as our analysis period encompasses the 2007-2008 crisis, a period that accounts for the most extreme movements recorded for many asset classes. In Appendix C, we present the results from a partial sample, i.e. with years 2007 and 2008 removed. While we observe a drastic reduction of the excess kurtosis for equities and hedge funds (around 2.2), that of ARPs remains significant (4.52), which underlines that the non-Gaussian nature of their return distributions is more structural.
- As a consequence, extreme losses are more frequent than in the gaussian framework (on average, the 99% VaR was crossed between 1.4 and 2.4 times out of 100 on average, against theoretically 1 time out of 100) and their magnitude is up to 7.9 standard deviations (in the case of equity trading ARPs), corresponding to a theoretical (gaussian) probability of occurrence of 1/10.<sup>15</sup>
- The average kurtosis level of trading ARPs is significantly higher than that of academic ARPs (11.9 vs. 4.6), especially for equity and FX risk premia (25.8 and 12.3 respectively). Intuitively, these figures reflect the binary nature of the risks conveyed by certain strategies, that combine optional derivatives and leverage.
- A more detailed analysis (Appendix D) shows that, for academic ARPs, momentum and value currency premia, as well as rate carry premia, are the most exposed to extreme risks. In terms of trading ARPs, the distributions of the short volatility and mean reversion premiums show particularly heavy distribution tails, accompanied by particularly negative skewness levels for the former.

As in the case of hedge funds and more generally alternative investment strategies, the Gaussian hypothesis is clearly not suited to the analysis of the performances and risks of ARPs (overestimation of performance, underestimation of risks). As previously shown from the mean-variance analysis, our results highlight a strong heterogeneity between academic and trading ARPs on the one hand, and between similar risk premia on the other.

#### **Correlation Analysis**

The low level of correlation between the various risk premia strategies, as well as between risk premia and traditional asset classes, is a central argument for ARP investing. They emphasize both the all-weather feature of diversified ARP allocations and the diversification they can bring into a global asset allocation. This strong diversification property comes from the academic foundation of risk premia. Indeed, they are based on the replication of academic factors that have been designed to be (quasi-) orthogonal to market risks, and therefore to carry specific risks. It implicitly follows that the risk premia they generate should be (i) poorly correlated with each other and (ii) exhibit little correlation with market risks (i.e., with the return of the main asset classes). One should therefore expect extremely low correlation levels between ARPs and their underlying market on the one hand, and between the different types of ARPs on the other hand. In contrast, ARPs from different providers aiming to replicate similar risk premia should be significantly correlated, as they are based on the same risk factors.

#### Correlations between ARPs and other asset classes

The average correlation levels between ARPs, equities, bonds and, hedge funds are reported in Exhibit 8.

- The average correlation levels between ARPs and other asset classes remains generally low, thus justifying their diversification potential in a global portfolio context. This is especially the case for the various academic ARPs (Appendix E1).
- Whatever the underlying asset class, we note the exception of carry premia, that exhibit significant correlations to equities and hedge funds (for FX and credit ARPs), or bonds (rate ARPs). This result is in line with the increased sensitivity of carry strategies to sharp increases in risk aversion, (i.e., during market reversal).
- The correlation levels of trading ARPs with other asset classes also remain contained, except for trading equity premia (average correlation of 0.30 with hedge funds), short volatility and mean reversion premia (significant correlation levels with both equity markets and hedge funds).

| All ARPs    |     |          |             |             |  |  |  |  |  |  |  |  |  |
|-------------|-----|----------|-------------|-------------|--|--|--|--|--|--|--|--|--|
|             |     |          | Asset class |             |  |  |  |  |  |  |  |  |  |
| Underlying  | N   | Equities | Bonds       | Hedge Funds |  |  |  |  |  |  |  |  |  |
| Equities    | 131 | 0.06     | 0.02        | 0.10        |  |  |  |  |  |  |  |  |  |
| FX          | 58  | 0.24     | -0.04       | 0.24        |  |  |  |  |  |  |  |  |  |
| Credit      | 14  | 0.17     | -0.03       | 0.19        |  |  |  |  |  |  |  |  |  |
| Rates       | 49  | -0.06    | 0.21        | -0.02       |  |  |  |  |  |  |  |  |  |
| Commodities | 41  | -0.05    | 0.02        | 0.00        |  |  |  |  |  |  |  |  |  |
| Total       | 293 | 0.06     | 0.04        | 0.10        |  |  |  |  |  |  |  |  |  |
|             |     | Academi  | c ARPs      |             |  |  |  |  |  |  |  |  |  |
| Asset class |     |          |             |             |  |  |  |  |  |  |  |  |  |
| Underlying  | N   | Equities | Bonds       | Hedge Funds |  |  |  |  |  |  |  |  |  |
| Equities    | 102 | 0.00     | 0.04        | 0.04        |  |  |  |  |  |  |  |  |  |
| FX          | 36  | 0.35     | -0.06       | 0.31        |  |  |  |  |  |  |  |  |  |
| Credit      | 6   | 0.29     | -0.05       | 0.28        |  |  |  |  |  |  |  |  |  |
| Rates       | 13  | 0.01     | 0.24        | 0.03        |  |  |  |  |  |  |  |  |  |
| Commodities | 9   | -0.06    | 0.03        | 0.02        |  |  |  |  |  |  |  |  |  |
| Total       | 166 | 0.08     | 0.03        | 0.11        |  |  |  |  |  |  |  |  |  |
|             |     | Trading  | ARPs        |             |  |  |  |  |  |  |  |  |  |
|             |     |          | Asset class |             |  |  |  |  |  |  |  |  |  |
| Underlying  | N   | Equities | Bonds       | Hedge Funds |  |  |  |  |  |  |  |  |  |
| Equities    | 29  | 0.28     | -0.04       | 0.30        |  |  |  |  |  |  |  |  |  |
| FX          | 22  | 0.05     | 0.01        | 0.13        |  |  |  |  |  |  |  |  |  |
| Credit      | 8   | 0.09     | -0.01       | 0.12        |  |  |  |  |  |  |  |  |  |
| Rates       | 36  | -0.09    | 0.20        | -0.04       |  |  |  |  |  |  |  |  |  |
| Commodities | 32  | -0.05    | 0.02        | -0.01       |  |  |  |  |  |  |  |  |  |
| Total       | 127 | 0.04     | 0.05        | 0.08        |  |  |  |  |  |  |  |  |  |

**Exhibit 8: Average Correlation Levels Between ARPs and Various Asset Classes** *Source: Bloomberg, Orion Financial Partners* 

#### Correlations Within the ARP Universe

As mentioned earlier, one can expect that the correlation levels between similar ARPs should be significant, and conversely that correlation levels between different ARPs (different factor type or underlying asset class) should be marginal. We reported the average correlation levels between ARPs in Exhibits 9 to 11. It spreads out that:

- As expected, the most significant correlation levels are recorded between similar ARPs (diagonal elements of Exhibits 10 and 11). However, one could have expected more significant levels: they range between -0.05 and 0.80 depending on the ARP strategy, with an average level of 0.40. These relatively low correlation levels can be explained by the differences in the implementation processes of the various providers (factor definition and measurement, selection, allocation, and hedging methodology...), as mentioned previously. Within correlation levels are significantly higher for trading ARPs (0.47 on average vs. 0.30 for academic ARPs).
- The second expectation is also met: the correlation levels between ARPs exploiting different premia and different asset-classes are particularly low (between 0.06 and 0.14), the lowest correlation levels being estimated between academic and trading ARPs (Exhibit 9), whatever the asset class or the premia considered. Correlation levels get reinforced when the nature (trading or academic) and the underlying asset class are the same,<sup>22</sup> diagonal areas in (Exhibits 10 and 9).

It spreads out that the diversification potential in ARP allocations is more important than expected: whereas the argument of cross-premia diversification has been mentioned in the academic literature (and largely taken up by practitioners), the diversification potential between similar ARPs also appears to be significant.

|              |             |  |       |             |              |       |      |      |      | Acade | mic ARF | Ps   |       |       |       |       |       |         |
|--------------|-------------|--|-------|-------------|--------------|-------|------|------|------|-------|---------|------|-------|-------|-------|-------|-------|---------|
|              |             |  |       |             |              | Equit | ies  |      |      |       |         | FX   |       | Cred. | Ra    | tes   | Comm  | odities |
|              |             |  | Carry | Low<br>risk | Mean<br>rev. | Mom   | Prof | Qual | Size | Value | Carry   | Mom  | Value | Carry | Carry | Value | Carry | Mom     |
|              |             |  | 2%    | 4%          | 1%           | 6%    | 1%   | 2%   | 5%   | 6%    | 12%     | -10% | 1%    | 4%    | 3%    | 3%    | 4%    | -2%     |
|              |             | M&A Mean reversion                           | -5%   | 14%         | 12%          | 3%    | -9%  | 2%   | -7%  | -2%   | 21%     | -9%  | 1%    | 6%    | 5%    | 0%    | 0%    | -6%     |
|              | Equities    | Trend Short volatility<br>Volatility trading | 2%    | -3%         | -12%         | 6%    | 3%   | 2%   | 0%   | -5%   | 4%      | 25%  | -1%   | 4%    | -13%  | -5%   | 7%    | 15%     |
|              |             | volatility trauling                          | -3%   | 8%          | 8%           | 2%    | -5%  | 1%   | -2%  | 3%    | 31%     | -13% | -5%   | 18%   | 3%    | -1%   | 4%    | -7%     |
|              |             |  | -1%   | 4%          | 3%           | 0%    | -2%  | 1%   | -1%  | 0%    | 11%     | 0%   | 0%    | 2%    | -4%   | -1%   | 1%    | 2%      |
|              |             | Mean reversion Tren                          | -4%   | 11%         | 16%          | 5%    | 2%   | 7%   | -2%  | 0%    | 18%     | -19% | 5%    | 3%    | 7%    | 5%    | 5%    | -7%     |
|              | FX          | Short volatility                             | -1%   | 0%          | -9%          | 7%    | 1%   | 3%   | -1%  | -5%   | -3%     | 25%  | -2%   | 1%    | -5%   | -1%   | 3%    | 11%     |
|              |             |  | -2%   | 12%         | 4%           | 4%    | -3%  | 3%   | -2%  | 0%    | 20%     | -11% | -4%   | 9%    | 7%    | 2%    | 3%    | 3%      |
| <b>RPs</b>   | Credit      | Carry<br>Trend                               | 4%    | -2%         | 1%           | -2%   | -1%  | -3%  | 6%   | 5%    | 17%     | -8%  | -4%   | 19%   | 0%    | -1%   | 4%    | 3%      |
| Trading ARPs |             |  | 1%    | -5%         | -15%         | -4%   | -2%  | -4%  | -1%  | 1%    | 7%      | 9%   | 1%    | 17%   | -9%   | -6%   | -1%   | 4%      |
| Trad         |             |  | 0%    | 7%          | 3%           | 4%    | 5%   | 5%   | 0%   | -3%   | -3%     | 2%   | -3%   | -6%   | 18%   | 8%    | 1%    | 3%      |
|              | Rates       | Carry Trend<br>Long volatility               | 0%    | 12%         | 0%           | 5%    | 4%   | 7%   | -2%  | -5%   | -9%     | 6%   | -2%   | -10%  | 23%   | 10%   | 3%    | 9%      |
|              | Tattos      | Short volatility                             | -1%   | -6%         | -7%          | 2%    | 7%   | 2%   | 0%   | -5%   | -16%    | 12%  | -1%   | -7%   | -8%   | 3%    | 0%    | 10%     |
|              |             |  | -4%   | 10%         | 7%           | 2%    | -3%  | 3%   | -3%  | 1%    | 19%     | -10% | -2%   | 11%   | 12%   | 3%    | 2%    | -5%     |
|              |             | Carry  | 0%    | -1%         | 2%           | 3%    | 5%   | 2%   | 1%   | 0%    | -2%     | 9%   | -1%   | -3%   | 1%    | -1%   | 29%   | 20%     |
|              | Commodities | Liquidity                                    | 1%    | -4%         | 3%           | -3%   | 3%   | -1%  | 3%   | 4%    | -2%     | 3%   | 0%    | -1%   | 1%    | -1%   | 9%    | 4%      |
|              |             | Momentum                                     | -1%   | -3%         | 4%           | 0%    | 3%   | 0%   | 0%   | 2%    | -1%     | 7%   | 1%    | -2%   | -1%   | 0%    | 24%   | 13%     |
|              |             | Trend  | -6%   | 4%          | -8%          | 10%   | 0%   | 4%   | -5%  | -8%   | -10%    | 22%  | 0%    | -2%   | -1%   | -3%   | 18%   | 44%     |
|              | Sho         | Short volatility                             | 0%    | 2%          | 1%           | 3%    | 2%   | 2%   | 2%   | 1%    | 14%     | -2%  | -4%   | 7%    | -1%   | 1%    | 2%    | 2%      |

#### Exhibit 9: Average Correlation Levels Between Academic ARPs and Trading ARPs

Source: Orion Financial Partners

|               |                |                                     |       |             |              |       |      |      |      | Acad  | lemic AR | Ps  |       |        |       |       |             |     |
|---------------|----------------|-------------------------------------|-------|-------------|--------------|-------|------|------|------|-------|----------|-----|-------|--------|-------|-------|-------------|-----|
|               |                |                                     |       |             |              | Equit | ies  |      |      |       |          | FX  |       | Credit | Ra    | ites  | Commodities |     |
|               |                |                                     | Carry | Low<br>risk | Mean<br>rev. | Mom   | Prof | Qual | Size | Value | Carry    | Mom | Value | Carry  | Carry | Value | Carry       | Mom |
|               |                |                                     | 23%   | -3%         | 2%           | -4%   | 13%  | -1%  | 28%  | 20%   | 8%       | 1%  | 0%    | 5%     | -1%   | -3%   | 0%          | -1% |
|               |                |                                     | -3%   | 43%         | 3%           | 9%    | 5%   | 21%  | -9%  | -9%   | -4%      | 0%  | 2%    | -3%    | 10%   | 3%    | 1%          | 6%  |
|               |                | Carry                               | 2%    | 3%          | 2%           | -1%   | 0%   | 1%   | 4%   | 2%    | 5%       | -6% | -1%   | -4%    | 5%    | 5%    | 2%          | -5% |
|               | Equities       | Low risk<br>Mean reversion          | -4%   | 9%          | -1%          | 30%   | 16%  | 16%  | 3%   | -10%  | -1%      | 10% | -3%   | -2%    | 6%    | 1%    | 6%          | 7%  |
|               | Equities       | Momentum Profit-<br>ability Quality | 13%   | 5%          | 0%           | 16%   | 38%  | 24%  | 20%  | 0%    | -1%      | 5%  | -2%   | -2%    | -1%   | -1%   | 8%          | 7%  |
|               |                | Size Value                          | -1%   | 21%         | 1%           | 16%   | 24%  | 21%  | 1%   | -8%   | -3%      | 4%  | 0%    | -3%    | 3%    | 2%    | 5%          | 6%  |
| RPs           |                |                                     | 28%   | -9%         | 4%           | 3%    | 20%  | 1%   | 33%  | 21%   | 5%       | -1% | 1%    | 6%     | -1%   | 0%    | 0%          | -3% |
| Academic ARPs |                |                                     | 20%   | -9%         | 2%           | -10%  | 0%   | -8%  | 21%  | 22%   | 6%       | -6% | 2%    | 4%     | -1%   | -1%   | 0%          | -5% |
| cade          |                |                                     | 8%    | -4%         | 5%           | -1%   | -1%  | -3%  | 5%   | 6%    | 59%      | -9% | -4%   | 20%    | 2%    | -2%   | 2%          | -5% |
| A             | FX             | Carry Momentum<br>Value             | 1%    | 0%          | -6%          | 10%   | 5%   | 4%   | -1%  | -6%   | -9%      | 36% | -5%   | -7%    | -1%   | -5%   | 8%          | 14% |
|               |                |                                     | 0%    | 2%          | -1%          | -3%   | -2%  | 0%   | 1%   | 2%    | -4%      | -5% | 17%   | -3%    | -5%   | 2%    | 0%          | -1% |
|               | Credit         | Carry                               | 5%    | -3%         | -4%          | -2%   | -2%  | -3%  | 6%   | 4%    | 20%      | -7% | -3%   | 45%    | 0%    | -2%   | -3%         | -8% |
|               | Rates          | Carry Value                         | -1%   | 10%         | 5%           | 6%    | -1%  | 3%   | -1%  | -1%   | 2%       | -1% | -5%   | 0%     | 39%   | 7%    | 2%          | 2%  |
|               | Kates          | Carry value                         | -3%   | 3%          | 5%           | 1%    | -1%  | 2%   | 0%   | -1%   | -2%      | -5% | 2%    | -2%    | 7%    | -5%   | -1%         | 1%  |
|               | Commodition    | Carry Momentum                      | 0%    | 1%          | 2%           | 6%    | 8%   | 5%   | 0%   | 0%    | 2%       | 8%  | 0%    | -3%    | 2%    | -1%   | 43%         | 33% |
|               | Commodities Ca | Carry Momentum                      | -1%   | 6%          | -5%          | 7%    | 7%   | 6%   | -3%  | -5%   | -5%      | 14% | -1%   | -8%    | 2%    | 1%    | 33%         | 35% |

## Exhibit 10: Average Correlation Levels Between Academic ARPs Source: Orion Financial Partners

|              |             |  |       |             |         |              |             |             |       |              | Trac  | ding AR | Ps    |       |             |              |             |      |     |       |              |  |  |
|--------------|-------------|--|-------|-------------|---------|--------------|-------------|-------------|-------|--------------|-------|---------|-------|-------|-------------|--------------|-------------|------|-----|-------|--------------|--|--|
|              |             |  |       |             | Equitie | s            |             |             | FX    |              | Cre   | dit     |       | Rat   | es          |              | Commodities |      |     |       |              |  |  |
|              |             |  | M&A   | Mean<br>rev | Trend   | Short<br>vol | Vol<br>trad | Mean<br>rev | Trend | Short<br>vol | Carry | Trend   | Carry | Trend | Long<br>vol | Short<br>vol | Carry       | Liqu | Mom | Trend | Short<br>vol |  |  |
|              |             |  | 56%   | 21%         | -5%     | 19%          | 8%          | 27%         | -2%   | 18%          | 9%    | -7%     | -1%   | -4%   | - 16%       | 16%          | 1%          | 0%   | 4%  | -4%   | 6%           |  |  |
|              |             | M&A<br>Mean reversion                  | 21%   | 50%         | 5%      | 41%          | 26%         | 30%         | -2%   | 17%          | 7%    | 2%      | -3%   | -5%   | - 19%       | 17%          | -3%         | -3%  | 0%  | -1%   | 7%           |  |  |
|              | Equities    | Trend                                  | -5%   | 5%          | 80%     | 1%           | 18%         | -23%        | 30%   | -1%          | -3%   | 41%     | 0%    | 1%    | 9%          | -6%          | 5%          | 0%   | 2%  | 32%   | 2%           |  |  |
|              |             | Short volatility<br>Volatility trading | 19%   | 41%         | 1%      | 61%          | 23%         | 24%         | -5%   | 29%          | 20%   | 0%      | -7%   | -9%   | - 29%       | 28%          | -5%         | -4%  | -3% | -10%  | 18%          |  |  |
|              |             |  | 8%    | 26%         | 18%     | 23%          | 22%         | 7%          | 3%    | 9%           | 5%    | 11%     | -2%   | -4%   | -5%         | 6%           | 1%          | 0%   | -1% | 7%    | 4%           |  |  |
|              |             | N                                      | 27%   | 30%         | -23%    | 24%          | 7%          | 69%         | -21%  | 21%          | 11%   | -16%    | 3%    | -2%   | - 17%       | 21%          | 0%          | 1%   | 6%  | -16%  | 8%           |  |  |
|              | FX          | Mean reversion<br>Trend                | -2%   | -2%         | 30%     | -5%          | 3%          | -21%        | 47%   | -2%          | -1%   | 16%     | 0%    | 6%    | 10%         | -6%          | 4%          | 0%   | 0%  | 32%   | 0%           |  |  |
|              |             | Short volatility                       | 18%   | 17%         | -1%     | 29%          | 9%          | 21%         | -2%   | 61%          | 12%   | -1%     | 0%    | -1%   | - 10%       | 27%          | 1%          | 1%   | 1%  | 2%    | 16%          |  |  |
| Trading ARPs | Credit      | Carry<br>Trend                         | 9%    | 7%          | -3%     | 20%          | 5%          | 11%         | -1%   | 12%          | 38%   | 1%      | -4%   | -7%   | - 12%       | 13%          | -1%         | -1%  | 1%  | -3%   | 9%           |  |  |
| ıding.       | Credit      |  | -7%   | 2%          | 41%     | 0%           | 11%         | -16%        | 16%   | -1%          | 1%    | 66%     | -2%   | -3%   | 12%         | -8%          | 2%          | 2%   | -1% | 21%   | 1%           |  |  |
| Tra          |             |  | -1%   | -3%         | 0%      | -7%          | -2%         | 3%          | 0%    | 0%           | -4%   | -2%     | 21%   | 24%   | 5%          | 6%           | 2%          | -1%  | -2% | 3%    | 0%           |  |  |
|              | Rates       | Carry<br>Trend                         | -4%   | -5%         | 1%      | -9%          | -4%         | -2%         | 6%    | -1%          | -7%   | -3%     | 24%   | 42%   | 8%          | -1%          | 5%          | 1%   | 2%  | 9%    | -5%          |  |  |
|              | Kates       | Long volatility<br>Short volatility    | - 16% | -19%        | 9%      | -29%         | -5%         | -17%        | 10%   | -10%         | -12%  | 12%     | 5%    | 8%    | 61%         | -25%         | 3%          | 1%   | 2%  | 16%   | -8%          |  |  |
|              |             | ·                                      | 16%   | 17%         | -6%     | 28%          | 6%          | 21%         | -6%   | 27%          | 13%   | -8%     | 6%    | -1%   | - 25%       | 49%          | -3%         | -4%  | -2% | -13%  | 14%          |  |  |
|              |             |  | 1%    | -3%         | 5%      | -5%          | 1%          | 0%          | 4%    | 1%           | -1%   | 2%      | 2%    | 5%    | 3%          | -3%          | 25%         | 17%  | 31% | 18%   | 1%           |  |  |
|              | Commodities | Carry Liquidity                        | 0%    | -3%         | 0%      | -4%          | 0%          | 1%          | 0%    | 1%           | -1%   | 2%      | -1%   | 1%    | 1%          | -4%          | 17%         | 26%  | 30% | 1%    | -3%          |  |  |
|              |             | Momentum<br>Trend                      | 4%    | 0%          | 2%      | -3%          | -1%         | 6%          | 0%    | 1%           | 1%    | -1%     | -2%   | 2%    | 2%          | -2%          | 31%         | 30%  | 25% | 10%   | -2%          |  |  |
|              |             | Short volatility                       | -4%   | -1%         | 32%     | -10%         | 7%          | -16%        | 32%   | 2%           | -3%   | 21%     | 3%    | 9%    | 16%         | -13%         | 18%         | 1%   | 10% | 77%   | 2%           |  |  |
|              |             |  | 6%    | 7%          | 2%      | 18%          | 4%          | 8%          | 0%    | 16%          | 9%    | 1%      | 0%    | -5%   | -8%         | 14%          | 1%          | -3%  | -2% | 2%    | 24%          |  |  |

**Exhibit 11: Average Correlation Levels Between Trading ARPs** Source: Orion Financial Partners

#### Conclusion

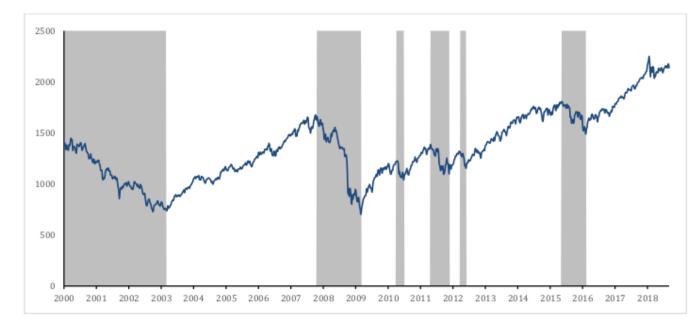
The ARP market can be accessed in three different ways. The first one is to buy ARP indexed products directly from investment banks. The investor then has the complete freedom in the selection process and in the management of his allocation. In return, he must have the necessary skills for selection, portfolio construction, and risk management, both quantitative and qualitative (due diligences). He must also directly manage the swap lines with the various providers.<sup>23</sup> This last point can be blocking for investors whose regulatory constraints or internal investment policy imply a limited use of OTC derivatives, even more when the underlying is not plain vanilla. The second approach consists in investing in ARP funds. In this case, the investor delegates to the manager the selection of the premiums among the investment banks' offering, the construction of the allocation and the risk management. In addition, investing in a fund rather than in swap lines greatly facilitates the operational management of the investment and allows investors subject to a strict regulatory framework to access the ARP market. On the other hand, this delegation generates an additional cost layer at the fund level. The third way is to invest in funds of asset managers that implement their own risk premiums. All investment decisions, from the construction of the premiums themselves to the construction of the allocation and to the risk management are then totally delegated to the manager. If the cost structure is theoretically deflated from the costs inherent to the management of indices and swap lines, investors will generally be charged potentially higher fees at the fund level (management fees and potential performance fees). Furthermore, the diversification

level can be severely limited in that case: investing only in the risk premia implemented by the manager induces a high concentration of model risk.

Whatever the investment support considered, investors should keep in mind that ARPs are alternative investment strategies. The implications are particularly important in terms of risk management. Statistical distributions of ARP returns are not Gaussian. They are characterized by negative skewness and a significant kurtosis which, in financial terms, results in a potentially significant exposure to extreme risks. It is therefore appropriate, as in the case of hedge funds, to use appropriate risk management tools.

Beyond these quantitative issues, it is also important to understand the economic origin of these specific risks, especially in the case of trading ARPs. For example, short volatility strategies - whose objective is to capture the structural difference between realized and implied volatility - are particularly exposed to sudden increases in the level of volatility. In the case of currency or credit carry strategies, investors are implicitly exposed to rare but potentially violent risk aversion or liquidity shocks. From an in-depth qualitative analysis, one can anticipate a potential correlation jump between short volatility and carry risk premia during extreme markets events, even if they exploit different premia and focus on different asset classes! Therefore, we see the interest of completing quantitative analysis by qualitative analysis through due diligences in a sound risk management process. Qualitative analysis is even more important as the available historical data provided by investment banks are partly derived from backtests, and therefore convey potentially significant bias.<sup>24</sup>

#### Appendix



#### Appendix A: Definition of bull and bear periods

Source: Bloomberg, Orion Financial Partners

We have defined as bear market conditions periods for which the MSCI World Index (bloomberg: NDDUWI) recorded drawdowns of at least 10% (shaded in grey on the chart below). This are the periods January 2000 – February 2002; October 2007 – March 2009; April 2010 – July 2010; April 2011 – November 2011; March 2012 – June 2012; May 2015 – February 2016. Remaining periods are considered as bull periods.

|                  |                |        |              | B1– Aca       | idemic ARI   | Ps            |               |               |                |                |              |
|------------------|----------------|--------|--------------|---------------|--------------|---------------|---------------|---------------|----------------|----------------|--------------|
| Underlying asset | Risk premia    | N      | μ            | σ             | IR           | μ+            | σ+            | IR+           | μ-             | σ-             | IR-          |
|                  | Carry          | 6      | 1.4%         | 6.6%          | 0.26         | 2.6%          | 5.4%          | 0.49          | -1.8%          | 8.8%           | -0.14        |
|                  | Growth         | 1      | 2.1%         | 5.4%          | 0.39         | -1.9%         | 4.7%          | -0.39         | 12.7%          | 6.6%           | 1.93         |
|                  | Liquidity      | 1      | 1.8%         | 4.6%          | 0.39         | 1.9%          | 4.0%          | 0.48          | 1.4%           | 5.9%           | 0.24         |
|                  | Low risk       | 20     | 3.1%         | 5.9%          | 0.53         | 1.7%          | 5.2%          | 0.30          | 6.8%           | 7.2%           | 1.03         |
|                  | Mean reversion | 2      | 2.4%         | 3.7%          | 0.67         | 2.0%          | 3.3%          | 0.66          | 3.7%           | 4.5%           | 0.80         |
| Equities         | Momentum       | 20     | 2.4%         | 7.3%          | 0.31         | 1.7%          | 6.5%          | 0.23          | 4.3%           | 8.9%           | 0.50         |
|                  | Profitability  | 5      | 3.6%         | 5.2%          | 0.66         | 2.4%          | 4.4%          | 0.51          | 6.9%           | 6.9%           | 0.97         |
|                  | Quality        | 16     | 3.4%         | 5.0%          | 0.66         | 2.1%          | 4.5%          | 0.39          | 6.9%           | 5.8%           | 1.23         |
|                  | Size           | 9      | 1.8%         | 6.9%          | 0.29         | 2.9%          | 5.9%          | 0.50          | -1.0%          | 9.0%           | 0.00         |
|                  | Value          | 22     | 1.0%         | 6.2%          | 0.16         | 2.3%          | 5.4%          | 0.41          | -2.5%          | 7.7%           | -0.30        |
|                  | Total          | 102    | 2.3%         | 6.1%          | 0.39         | 2.1%          | 5.4%          | 0.36          | 3.1%           | 7.6%           | 0.50         |
|                  | Carry          | 27     | 0.8%         | 8.4%          | 0.10         | 5.4%          | 7.3%          | 0.73          | -11.5%         | 10.5%          | -1.10        |
| FX               | Momentum       | 2      | 3.9%         | 10.5%         | 0.38         | 1.9%          | 8.6%          | 0.17          | 9.2%           | 14.2%          | 0.67         |
|                  | Value          | 7      | 2.7%         | 6.3%          | 0.44         | 1.8%          | 5.7%          | 0.32          | 5.2%           | 7.5%           | 0.68         |
|                  | Total          | 36     | 1.4%         | 8.1%          | 0.19         | 4.5%          | 7.1%          | 0.62          | -7.1%          | 10.1%          | -0.65        |
| Credit           | Carry          | 6      | 2.4%         | 3.5%          | 0.68         | 3.8%          | 3.0%          | 1.33          | -1.4%          | 4.7%           | -0.32        |
| Credit           | Total          | 6      | 2.4%         | 3.5%          | 0.68         | 3.8%          | 3.0%          | 1.33          | -1.4%          | 4.7%           | -0.32        |
|                  | Carry          | 9      | 1.6%         | 3.7%          | 0.42         | 1.4%          | 3.1%          | 0.49          | 2.0%           | 4.9%           | 0.42         |
| Rates            | Momentum Value | 1<br>3 | 2.4%<br>1.2% | 4.7%<br>3.6%  | 0.51<br>0.38 | 1.5%<br>1.1%  | 4.1%<br>3.1%  | 0.35<br>0.35  | 5.0%<br>1.5%   | 5.9%<br>4.5%   | 0.84<br>0.42 |
|                  | Total          | 13     | 1.6%         | 3.8%          | 0.42         | 1.4%          | 3.2%          | 0.45          | 2.1%           | 4.9%           | 0.45         |
|                  | Carry          | 6      | 6.3%         | 7.8%          | 0.83         | 4.3%          | 7.5%          | 0.61          | 11.8%          | 8.5%           | 1.39         |
| Commo.           | Momentum Value | 2<br>1 | 3.4%<br>9.1% | 12.1%<br>9.9% | 0.29<br>0.93 | -0.1%<br>5.4% | 10.8%<br>9.3% | -0.05<br>0.58 | 12.9%<br>19.2% | 14.8%<br>11.1% | 0.87<br>1.72 |
|                  | Total          | 9      | 6.0%         | 9.0%          | 0.72         | 3.4%          | 8.4%          | 0.46          | 12.9%          | 10.2%          | 1.31         |
| Acaden           | nic ARPs       | 166    | 2.3%         | 6.4%          | 0.38         | 2.7%          | 5.7%          | 0.47          | 1.2%           | 8.0%           | 0.26         |

#### Appendix B: Risk-return profile of ARPs: detailed results

Source: Bloomberg, Orion Financial Partners

Average annualized return,  $\sigma$ : volatility, IR: information ratio ( $\mu/\sigma$ ). Suffixes + and – denote bullish and down periods of the MSCI world index, as defined in Appendix A. Reported statistics are computed over the period 01/05/2007 – 09/07/2018, from weekly data. They are the averages of statistics computed for individual ARPs.

|                  |                    |         |              |              | 1            |              |              |              |               |              |               |
|------------------|--------------------|---------|--------------|--------------|--------------|--------------|--------------|--------------|---------------|--------------|---------------|
|                  |                    |         |              | B2– Tra      | ading ARP    | S            |              |              | [             |              |               |
| Underlying asset | Risk premia        | N       | μ            | σ            | IR           | μ+           | σ+           | IR+          | μ-            | σ-           | IR-           |
|                  | M&A                | 4       | 2.7%         | 5.1%         | 0.54         | 3.3%         | 4.0%         | 0.85         | 1.2%          | 7.2%         | 0.22          |
| Equities         | Mean reversion     | 5       | 6.0%         | 9.2%         | 0.62         | 6.4%         | 5.8%         | 1.19         | 5.1%          | 14.7%        | 0.30          |
|                  | Trend              | 5       | 0.8%         | 7.3%         | 0.13         | 0.9%         | 6.8%         | 0.18         | 0.3%          | 8.6%         | 0.03          |
|                  | Short volatility   | 7       | 6.6%         | 12.3%        | 0.52         | 13.9%        | 8.7%         | 1.48         | -12.9%        | 18.3%        | -0.54         |
|                  | Volatility trading | 8       | 7.5%         | 10.9%        | 0.76         | 8.4%         | 9.3%         | 0.91         | 5.4%          | 14.1%        | 0.46          |
|                  | Total              | 29      | 5.2%         | 9.5%         | 0.54         | 7.4%         | 7.4%         | 0.96         | -0.5%         | 13.3%        | 0.08          |
|                  | Liquidity          | 1       | 9.2%         | 7.7%         | 1.19         | 7.5%         | 6.9%         | 1.09         | 13.6%         | 9.5%         | 1.43          |
|                  | Mean reversion     | 4       | 5.1%         | 9.9%         | 0.45         | 2.6%         | 7.0%         | 0.38         | 12.0%         | 15.2%        | 0.65          |
| FX               | Trend Value        | 11<br>1 | 2.7%<br>3.1% | 7.3%<br>5.1% | 0.46<br>0.61 | 2.1%<br>2.1% | 6.7%<br>4.3% | 0.41<br>0.49 | 4.2%<br>5.8%  | 8.8%<br>6.8% | 0.56<br>0.86  |
|                  | Short volatility   | 5       | 0.7%         | 2.8%         | 0.20         | 0.5%         | 2.3%         | 0.18         | 1.2%          | 3.9%         | 0.26          |
|                  | Total              | 22      | 3.0%         | 6.7%         | 0.44         | 2.1%         | 5.6%         | 0.39         | 5.5%          | 8.8%         | 0.56          |
| Credit           | Carry Trend        | 2<br>6  | 2.8%<br>4.9% | 4.5%<br>7.1% | 0.62<br>0.68 | 5.9%<br>6.3% | 3.5%<br>6.2% | 1.70<br>1.01 | -5.5%<br>1.1% | 6.4%<br>9.0% | -0.86<br>0.10 |
| Credit           | Total              | 8       | 4.4%         | 6.4%         | 0.66         | 6.2%         | 5.5%         | 1.18         | -0.5%         | 8.4%         | -0.14         |
|                  | Carry              | 11      | 1.5%         | 2.2%         | 0.71         | 0.9%         | 2.0%         | 0.54         | 2.9%          | 2.6%         | 1.09          |
|                  | Momentum           | 1       | 1.2%         | 2.0%         | 0.61         | -0.2%        | 1.6%         | -0.10        | 4.9%          | 2.7%         | 1.84          |
|                  | Trend              | 13      | 3.1%         | 4.5%         | 0.83         | 1.0%         | 4.1%         | 0.40         | 8.7%          | 5.3%         | 1.80          |
| Rates            | Long volatility    | 4       | 3.7%         | 5.8%         | 0.63         | 0.9%         | 4.4%         | 0.20         | 11.2%         | 8.5%         | 1.32          |
|                  | Short volatility   | 6       | 6.4%         | 8.4%         | 0.72         | 9.3%         | 6.1%         | 1.43         | -1.3%         | 12.5%        | -0.19         |
|                  | Volatility carry   | 1       | 0.5%         | 1.3%         | 0.41         | 0.9%         | 1.0%         | 0.90         | -0.5%         | 1.8%         | -0.31         |
|                  | Total              | 36      | 3.1%         | 4.4%         | 0.74         | 2.3%         | 3.7%         | 0.59         | 5.2%          | 5.9%         | 1.14          |
|                  | Carry              | 10      | 5.1%         | 6.4%         | 0.93         | 3.6%         | 5.8%         | 0.69         | 9.0%          | 7.6%         | 1.43          |
|                  | Liquidity          | 8       | 2.9%         | 3.0%         | 1.18         | 1.8%         | 2.9%         | 0.92         | 5.7%          | 3.3%         | 1.80          |
|                  | Momentum           | 2       | 5.0%         | 4.5%         | 1.26         | 3.6%         | 4.2%         | 1.09         | 8.7%          | 5.3%         | 1.66          |
| Commo.           | Trend              | 6       | 6.0%         | 10.5%        | 0.53         | 2.1%         | 7.7%         | 0.24         | 16.4%         | 15.6%        | 1.00          |
|                  | Value              | 1       | 3.5%         | 4.3%         | 0.82         | 2.7%         | 4.2%         | 0.64         | 5.8%          | 4.6%         | 1.25          |
|                  | Short volatility   | 5       | 7.6%         | 11.1%        | 0.68         | 11.8%        | 9.9%         | 1.22         | -3.7%         | 13.4%        | -0.22         |
|                  | Total              | 32      | 5.0%         | 6.9%         | 0.89         | 4.1%         | 5.9%         | 0.77         | 7.4%          | 8.7%         | 1.19          |
| ARP de           | e trading          | 127     | 4.1%         | 6.7%         | 0.68         | 4.1%         | 5.5%         | 0.72         | 4.1%          | 8.9%         | 0.73          |

#### Appendix B: Risk-return profile of ARPs: detailed results

Source: Bloomberg, Orion Financial Partners

Average annualized return,  $\sigma$ : volatility, IR: information ratio ( $\mu/\sigma$ ). Suffixes + and – denote bullish and down periods of the MSCI world index, as defined in Appendix A. Reported statistics are computed over the period 01/05/2007 – 09/07/2018, from weekly data. They are the averages of statistics computed for individual ARPs.

|                  |     |              | C.1 – ARP a         | nd other asset classes                               |         |      |                               |
|------------------|-----|--------------|---------------------|--|---------|------|-------------------------------|
| Underlying       | N   | Skewness (1) | Excess kurtosis (2) | % of non- gaussian<br>distributions JB-stat<br>) (3) | 0       | U    | % of VaR(99%)<br>crossing (5) |
| ARP              | 293 | -0.18        | 4.52                | 97%  | 81%     | 4.81 | 1.7%                          |
| Equities (6)     | -   | -0.36        | 2.27                | Prob<1%  | Prob<1% | 4.09 | 2.2%                          |
| Bonds (7)        | -   | -0.12        | 1.03                | Prob<1%  | Prob>5% | 3.70 | 1.6%                          |
| Hedge Funds (8)  | _   | -0.88        | 2.22                | Prob<1%  | Prob<1% | 4.92 | 2.8%                          |
|                  |     |              |                     | Academic ARPs  |         |      |                               |
| Underlying asset | N   | Skewness (1) | Excess kurtosis (2  | % of non- gaussian<br>) distributions JB-stat<br>(3) |         |      | % of VaR(99%)<br>crossing (5) |
| Equities         | 102 | -0.01        | 2.06                | 94%  | 71%     | 4.18 | 1.5%                          |
| FX               | 36  | -0.40        | 4.38                | 97%  | 89%     | 5.12 | 1.7%                          |
| Credit           | 6   | -0.23        | 3.42                | 100%   | 100%    | 4.74 | 2.1%                          |
| Rates            | 13  | -0.03        | 2.99                | 100%   | 69%     | 4.37 | 1.5%                          |
| Commodities      | 9   | -0.09        | 1.45                | 89%  | 22%     | 4.10 | 1.5%                          |
| Total            | 166 | -0.11        | 2.65                | 95%  | 73%     | 4.42 | 1.6%                          |
|                  |     |              | C.3 -               | Trading ARPs   |         |      |                               |
| Underlying asset | N   | Skewness (1) | Excess kurtosis (2) | % of non- gaussian<br>) distributions JB-stat<br>(3) |         |      | % of VaR(99%)<br>crossing (5) |
| Equities         | 29  | -0.96        | 11.99               | 100%   | 100%    | 6.34 | 2.1%                          |
| FX               | 22  | -0.13        | 7.58                | 100%   | 82%     | 5.37 | 1.7%                          |
| Credit           | 8   | -0.15        | 4.44                | 100%   | 100%    | 5.31 | 1.7%                          |
| Rates            | 36  | -0.17        | 4.11                | 100%   | 94%     | 4.89 | 1.8%                          |
| Commodities      | 32  | 0.09         | 5.84                | 97%  | 81%     | 4.90 | 1.8%                          |
| Total            | 127 | -0.28        | 6.97                | 99%  | 91%     | 5.33 | 1.8%                          |

#### Appendix C: Higher moments, normality tests and extreme risks (2009-2018)

Source: Bloomberg, Orion Financial Partners

Reported results are the averages of the statistics computed for individual ARPs, over the period 01/01/2009 – 09/07/2018, from weekly data. (1) Asymmetry coefficient. When negative, occurrence probability of extreme losses is higher than for extreme gains. (2) When excess kurtosis is significantly positive, the probability of extreme events is higher than, in the gaussian case. (3) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Jarque-Bera test. For other asset classes, in Table C.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (4) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Kolmogorov-Smirnov test. For other asset classes, in Table C.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (4) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Kolmogorov-Smirnov test. For other asset classes, in Table C.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (5) % of weekly returns that are inferior to the gaussian VaR (weekly, 99%). (6) MSCI World index (Bloomberg: NDDUWI). (7) Bloomberg-Barclays Global Bond Aggregate (Bloomberg: LEGATRUU). (8) HFRX Global Hedge Fund index (Bloomberg: HFRXGL).

|                     |                |         |                | D1 – Academi             | c ARP        |  |  |                               |
|---------------------|----------------|---------|----------------|--------------------------|--------------|--|--|-------------------------------|
| Underlying<br>asset | Risk premia    | N       | Skewness (1)   | Excess kurto-<br>sis (2) |              | % of non- gauss-<br>ian distributio ns<br>KSL-stat (4) | Worst negative<br>choc (in standard<br>deviations) | % of VaR(99%)<br>crossing (5) |
|                     | Carry          | 6       | 0.32           | 4.51                     | 67%          | 67%  | 4.31   | 1.4%                          |
|                     | Growth         | 1       | -0.18          | 1.46                     | 100%         | 100%   | 3.50   | 1.8%                          |
|                     | Liquidity      | 1       | 0.08           | 1.01                     | 100%         | 0%   | 3.84   | 1.0%                          |
|                     | Low risk       | 20      | -0.54          | 6.08                     | 100%         | 100%   | 6.19   | 1.6%                          |
|                     | Mean reversion | 2       | 0.72           | 7.45                     | 100%         | 100%   | 4.48   | 1.6%                          |
| Equities            | Momentum       | 20      | -0.39          | 2.29                     | 100%         | 80%  | 4.74   | 1.8%                          |
|                     | Profitability  | 5       | 0.05           | 3.93                     | 100%         | 60%  | 5.11   | 1.2%                          |
|                     | Quality        | 16      | -0.07          | 2.09                     | 94%          | 75%  | 4.33   | 1.5%                          |
|                     | Size           | 9       | 0.29           | 4.90                     | 100%         | 100%   | 4.95   | 1.5%                          |
|                     | Value          | 22      | 0.33           | 3.88                     | 100%         | 95%  | 4.49   | 1.3%                          |
|                     | Total          | 10<br>2 | -0.06          | 3.87                     | 97%          | 86%  | 4.89   | 1.5%                          |
|                     | Carry          | 27      | -0.63          | 4.32                     | 100%         | 100%   | 5.64   | 2.0%                          |
| FX                  | Momentum Value | 2<br>7  | 1.32<br>-0.26  | 13.44<br>12.51           | 100%<br>100% | 100%<br>71%  | 4.26<br>6.63                                       | 1.2%<br>1.0%                  |
|                     | Total          | 36      | -0.45          | 6.42                     | 100%         | 94%  | 5.76   | 1.8%                          |
|                     | Carry          | 6       | -0.50          | 5.78                     | 100%         | 100%   | 5.68   | 2.4%                          |
| Credit              | Total          | 6       | -0.50          | 5.78                     | 100%         | 100%   | 5.68   | 2.4%                          |
|                     | Carry          | 9       | -0.30          | 10.08                    | 100%         | 67%  | 6.08   | 1.4%                          |
| Rates               | Momentum Value | 1<br>3  | -0.37<br>-0.01 | 3.12<br>2.37             | 100%<br>100% | 100%<br>67%  | 5.19<br>4.00                                       | 1.3%<br>1.6%                  |
|                     | Total          | 13      | -0.24          | 7.77                     | 100%         | 69%  | 5.53   | 1.5%                          |
|                     | Carry          | 6       | 0.03           | 0.96                     | 100%         | 33%  | 3.71   | 1.4%                          |
| Commo.              | Momentum Value | 2<br>1  | 0.11<br>-0.06  | 3.32<br>1.25             | 100%<br>100% | 100%<br>0%   | 4.67<br>4.37                                       | 1.5%<br>1.1%                  |
|                     | Total          | 9       | 0.04           | 1.51                     | 100%         | 44%  | 4.00   | 1.4%                          |
| ARF                 | académiques    | 16<br>6 | -0.17          | 4.67                     | 98%          | 85%  | 5.11   | 1.6%                          |

#### Appendix D: Higher moments, normality tests and extreme risks: detailed results

Source: Bloomberg, Orion Financial Partners

Reported results are the averages of the statistics computed for individual ARPs, over the period 01/05/2007 – 09/07/2018, from weekly data. (1) Asymmetry coefficient. When negative, occurrence probability of extreme losses is higher than for extreme gains. (2) When excess kurtosis is significantly positive, the probability of extreme events is higher than, in the gaussian case. (3) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Jarque-Bera test. For other asset classes, in Table D.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (4) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Kolmogorov-Smirnov test. For other asset classes, in Table D.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (4) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Kolmogorov-Smirnov test. For other asset classes, in Table D.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (5) % of weekly returns that are inferior to the gaussian VaR (weekly, 99%). (6) MSCI World index (Bloomberg: NDDUWI). (7) Bloomberg-Barclays Global Bond Aggregate (Bloomberg: LEGATRUU). (8) HFRX Global Hedge Fund index (Bloomberg: HFRXGL).

|                     |                           |         |               | D2 – Trading             | ARPs  |   |  |                               |
|---------------------|---------------------------|---------|---------------|--------------------------|---|---|--|-------------------------------|
| Underlying<br>asset | Risk premia               | N       | Skewness (1)  | Excess kurto-<br>sis (2) | % of non- gauss-<br>ian distributio ns<br>JB-stat (3) | % of non- gaussian<br>distributio ns KSL-<br>stat (4) | Worst negative<br>choc (in standard<br>deviations) | % of VaR(99%)<br>crossing (5) |
|                     | M&A                       | 4       | -0.01         | 17.33                    | 100%  | 100%  | 6.99   | 1.4%                          |
|                     | Mean reversion            | 5       | 0.10          | 32.65                    | 100%  | 100%  | 8.61   | 1.7%                          |
| Equities            | Trend<br>Short volatility | 5<br>7  | 0.65<br>-4.08 | 14.71<br>41.29           | 100%<br>100%  | 100%<br>100%  | 5.29<br>11.21                                      | 1.8%<br>2.2%                  |
|                     | Volatility trading        | 8       | -0.01         | 19.13                    | 100%  | 100%  | 6.80   | 2.1%                          |
|                     | Total                     | 29      | -0.86         | 25.80                    | 100%  | 100%  | 7.94   | 1.9%                          |
|                     | Liquidity                 | 1       | 2.74          | 20.91                    | 100%  | 100%  | 5.45   | 1.0%                          |
|                     | Mean reversion            | 4       | 0.36          | 31.45                    | 100%  | 100%  | 8.26   | 1.0%                          |
| FX                  | Trend Value               | 11<br>1 | 0.26<br>1.26  | 4.43<br>15.72            | 100%<br>100%  | 91%<br>100%   | 4.74<br>5.39                                       | 1.3%<br>1.6%                  |
|                     | Short volatility          | 5       | -1.47         | 12.29                    | 100%  | 100%  | 7.88   | 2.4%                          |
|                     | Total                     | 22      | 0.04          | 12.39                    | 100%  | 95%   | 6.15   | 1.5%                          |
|                     | Carry                     | 2       | -0.79         | 6.68                     | 100%  | 100%  | 5.78   | 3.0%                          |
| Credit              | Trend                     | 6       | 0.45          | 5.30                     | 100%  | 100%  | 4.90   | 1.4%                          |
|                     | Total                     | 8       | 0.14          | 5.65                     | 100%  | 100%  | 5.12   | 1.8%                          |
|                     | Carry                     | 11      | -0.17         | 4.43                     | 100%  | 100%  | 5.39   | 1.7%                          |
|                     | Momentum                  | 1       | 0.65          | 5.21                     | 100%  | 100%  | 4.53   | 1.1%                          |
|                     | Trend                     | 13      | -0.07         | 2.76                     | 100%  | 100%  | 4.66   | 1.7%                          |
| Rates               | Long volatility           | 4       | 1.37          | 14.97                    | 100%  | 100%  | 4.95   | 1.0%                          |
|                     | Short volatility          | 6       | -0.89         | 18.09                    | 100%  | 100%  | 7.84   | 2.1%                          |
|                     | Volatility carry          | 1       | -0.77         | 6.79                     | 100%  | 100%  | 5.60   | 2.6%                          |
|                     | Total                     | 36      | -0.07         | 7.36                     | 100%  | 100%  | 5.47   | 1.7%                          |
|                     | Carry                     | 10      | 0.18          | 2.75                     | 90%   | 80%   | 4.44   | 1.4%                          |
|                     | Liquidity                 | 8       | 1.16          | 8.47                     | 88%   | 75%   | 4.29   | 1.3%                          |
|                     | Momentum                  | 2       | 0.50          | 2.54                     | 100%  | 100%  | 3.64   | 1.6%                          |
| Commo.              | Trend                     | 6       | 0.50          | 9.26                     | 100%  | 100%  | 5.57   | 1.7%                          |
|                     | Value                     | 1       | -0.17         | 0.92                     | 100%  | 100%  | 4.07   | 1.8%                          |
|                     | Short volatility          | 5       | -0.95         | 5.25                     | 100%  | 100%  | 5.47   | 2.5%                          |
|                     | Total                     | 32      | 0.32          | 5.72                     | 94%   | 88%   | 4.71   | 1.6%                          |
| AR                  | RP de trading             | 12<br>7 | -0.12         | 11.92                    | 98%   | 96%   | 5.94   | 1.7%                          |

#### Appendix D: Higher moments, normality tests and extreme risks: detailed results

Source: Bloomberg, Orion Financial Partners

Reported results are the averages of the statistics computed for individual ARPs, over the period 01/05/2007 – 09/07/2018, from weekly data. (1) Asymmetry coefficient. When negative, occurrence probability of extreme losses is higher than for extreme gains. (2) When excess kurtosis is significantly positive, the probability of extreme events is higher than, in the gaussian case. (3) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Jarque-Bera test. For other asset classes, in Table D.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (4) % of ARPs for which the gaussian assumption is rejected at the 5% level, using the Kolmogorov-Smirnov test. For other asset classes, in Table D.1, we reported the probability associated with the test statistic. If inferior to 5%, normality is rejected. (5) % of weekly returns that are inferior to the gaussian VaR (weekly, 99%). (6) MSCI World index (Bloomberg: NDDUWI). (7) Bloomberg-Barclays Global Bond Aggregate (Bloomberg: LEGATRUU). (8) HFRX Global Hedge Fund index (Bloomberg: HFRXGL).

|                      | E.1 -          | Academi | : ARPs         |               |                |
|----------------------|----------------|---------|----------------|---------------|----------------|
| Underlying<br>assets | Risk premia    | N       | Equities       | Bonds         | Hedge<br>Funds |
|                      | Carry          | 6       | 0.08           | 0.10          | 0.04           |
|                      | Growth         | 1       | -0.61          | 0.10          | -0.36          |
|                      | Liquidity      | 1       | 0.05           | 0.09          | 0.13           |
|                      | Low risk       | 20      | -0.06          | 0.06          | -0.02          |
|                      | Mean reversion | 2       | 0.12           | 0.09          | -0.01          |
| Equities             | Momentum       | 20      | -0.04          | 0.04          | 0.11           |
|                      | Profitability  | 5       | -0.07          | 0.05          | -0.02          |
|                      | Quality        | 16      | -0.08          | 0.00          | -0.01          |
|                      | Size           | 9       | 0.08           | 0.06          | 0.09           |
|                      | Value          | 22      | 0.12           | 0.02          | 0.08           |
|                      | Total          | 102     | 0.00           | 0.04          | 0.04           |
|                      | Carry          | 27      | 0.50           | -0.03         | 0.44           |
| FX                   | Momentum Value | 2<br>7  | -0.19<br>-0.08 | 0.04<br>-0.22 | -0.05<br>-0.09 |
|                      | Total          | 36      | 0.35           | -0.06         | 0.31           |
| Custit               | Carry          | 6       | 0.29           | -0.05         | 0.28           |
| Credit               | Total          | 6       | 0.29           | -0.05         | 0.28           |
|                      | Carry          | 9       | 0.02           | 0.30          | 0.04           |
| Rates                | Momentum Value | 1<br>3  | -0.05<br>-0.01 | 0.26<br>0.05  | 0.06<br>0.01   |
|                      | Total          | 13      | 0.01           | 0.24          | 0.03           |
|                      | Carry          | 6       | -0.01          | 0.03          | 0.04           |
| Commo.               | Momentum Value | 2<br>1  | -0.16<br>-0.09 | 0.03<br>0.10  | -0.06<br>0.00  |
|                      | Total          | 9       | -0.06          | 0.03          | 0.02           |
| Acad                 | emic ARPs      | 166     | 0.08           | 0.03          | 0.11           |

| Appendix E: Correlation between ARPs and other asset classes: |
|---|
| detailed results  |

Source: Bloomberg, Orion Financial Partners

|                     | E                         | .2 – Trac | ling ARPs      |                |               |
|---------------------|---------------------------|-----------|----------------|----------------|---------------|
| Underlying<br>asset | Risk premia               | N         | Equities       | Bonds          | Hedge Funds   |
|                     | M&A                       | 4         | 0.23           | -0.06          | 0.30          |
|                     | Mean<br>reversion         | 5         | 0.41           | -0.04          | 0.32          |
| Equities            | Trend Short<br>volatility | 5<br>7    | -0.04<br>0.56  | -0.10<br>0.02  | 0.17<br>0.54  |
|                     | Volatility<br>trading     | 8         | 0.18           | -0.05          | 0.15          |
|                     | Total                     | 29        | 0.28           | -0.04          | 0.30          |
|                     | Liquidity                 | 1         | 0.00           | 0.06           | -0.07         |
|                     | Mean<br>reversion         | 4         | 0.31           | 0.01           | 0.22          |
| FX                  | Trend<br>Value            | 11<br>1   | -0.12<br>-0.03 | -0.01<br>-0.01 | 0.06<br>-0.07 |
|                     | Short<br>volatility       | 5         | 0.23           | 0.03           | 0.28          |
|                     | Total                     | 22        | 0.05           | 0.01           | 0.13          |
|                     | Carry                     | 2         | 0.27           | 0.04           | 0.28          |
| Credit              | Trend                     | 6         | 0.03           | -0.03          | 0.06          |
|                     | Total                     | 8         | 0.09           | -0.01          | 0.12          |
|                     | Carry                     | 11        | -0.09          | 0.23           | -0.07         |
|                     | Momentum                  | 1         | -0.30          | 0.16           | -0.16         |
|                     | Trend                     | 13        | -0.20          | 0.30           | -0.10         |
| Rates               | Long<br>volatility        | 4         | -0.31          | 0.02           | -0.26         |
|                     | Short<br>volatility       | 6         | 0.27           | 0.06           | 0.29          |
|                     | Volatility<br>carry       | 1         | 0.26           | 0.02           | 0.17          |
|                     | Total                     | 36        | -0.09          | 0.20           | -0.04         |
|                     | Carry                     | 10        | -0.09          | 0.01           | -0.05         |
|                     | Liquidity                 | 8         | -0.02          | 0.01           | -0.05         |
|                     | Momentum                  | 2         | -0.05          | -0.04          | -0.04         |
| Commo.              | Trend                     | 6         | -0.23          | 0.03           | -0.03         |
|                     | Value                     | 1         | -0.03          | 0.04           | -0.09         |
|                     | Short<br>volatility       | 5         | 0.18           | 0.05           | 0.21          |
|                     | Total                     | 32        | -0.05          | 0.02           | -0.01         |
|                     |                           |           |                |                |               |

## Appendix E: Correlation between ARPs and other asset classes: detailed results

Source: Bloomberg, Orion Financial Partners

|              |          |  |             |      |       |       |      |      | 1    | Academi | c ARP |       |       |       |       |       |         |      |
|--------------|----------|--|-------------|------|-------|-------|------|------|------|---------|-------|-------|-------|-------|-------|-------|---------|------|
|              |          |  |             |      |       | Equi  | ties |      |      |         | FX    |       | Cred. | Ra    | ites  | Comm  | odities |      |
|              |          |  | ' KISK Kev. |      |       |       |      |      |      |         | Carry | Mom   | Value | Carry | Carry | Value | Carry   | Mom  |
|              |          |  | 23%         | -3%  | 2%    | -4%   | 13 % | -1%  | 28 % | 20%     | 8%    | 1%    | 0%    | 5%    | -1%   | -3%   | 0%      | -1%  |
|              |          |  | -3%         | 43%  | 3%    | 9 %   | 5%   | 21%  | -9%  | -9%     | -4 %  | 0%    | 2%    | -3%   | 10 %  | 3%    | 1%      | 6%   |
|              |          | Carry<br>Low risk  | 2%          | 3%   | 2%    | -1%   | 0%   | 1%   | 4%   | 2%      | 5%    | -6 %  | -1%   | -4%   | 5%    | 5%    | 2%      | -5%  |
|              | Equities | Mean reversion   | -4%         | 9%   | -1%   | 30%   | 16%  | 16%  | 3%   | -10 %   | -1%   | 10 %  | -3%   | -2%   | 6%    | 1%    | 6%      | 7%   |
|              | 1        | Momentum<br>Profitability Quality  | 13 %        | 5%   | 0%    | 16%   | 38%  | 24%  | 20%  | 0%      | -1%   | 5%    | -2%   | -2%   | -1%   | -1%   | 8%      | 7%   |
|              |          | Size Value   | -1%         | 21%  | 1%    | 16%   | 24%  | 21%  | 1%   | -8 %    | -3%   | 4%    | 0%    | -3%   | 3%    | 2     | 5%      | 6%   |
| đ            |          |  | 28%         | -9%  | 4%    | 3%    | 20%  | 1%   | 33%  | 21%     | 5%    | -1%   | 1%    | 6%    | -1%   | 0     | 0%      | -3%  |
| ic AF        |          |  | 20%         | -9%  | 2%    | -10 % | 0%   | -8 % | 21%  | 22%     | 6%    | -6 %  | 2%    | 4%    | -1%   | -1%   | 0%      | -5%  |
| Academic ARP |          |  | 8%          | -4 % | 5%    | -1%   | -1%  | -3 % | 5%   | 6%      | 59 %  | -9 %  | -4%   | 20%   | 2%    | -2%   | 2%      | -5%  |
| Aca          | FX M     | Carry<br>Momentum Value  | 1%          | 0%   | -6 %  | 10 %  | 5%   | 4%   | -1%  | -6 %    | -9 %  | 36%   | -5%   | -7%   | -1%   | -5%   | 8%      | 14~% |
|              |          |  | 0%          | 2%   | -1%   | -3%   | -2%  | 0%   | 1%   | 2%      | -4%   | -5%   | 17%   | -3 %  | -5%   | 2%    | 0%      | -1%  |
|              | Crzdit   | Carry  | 5%          | -3%  | -4%   | -2%   | -2%  | -3 % | 6%   | 4%      | 20%   | -7%   | -3 %  | 45%   | 0%    | -2%   | -3 %    | -8 % |
|              |          |  | -1%         | 10 % | 5%    | 6%    | -1%  | 3%   | -1%  | -1%     | 2%    | -1%   | -5%   | 0%    | 39%   | 7%    | 2%      | 2%   |
|              | Rates    | Carry Value  | -3%         | 3%   | 5%    | 1%    | -1%  | 2%   | 0%   | -1%     | -2%   | -5%   | 2%    | -2%   | 7%    | -5%   | -1%     | 1%   |
|              |          | Carry  | 0%          | 1%   | 2%    | 6%    | 8%   | 5%   | 0%   | 0%      | 2%    | 8%    | 0%    | -3 %  | 2%    | -1%   | 43%     | 33%  |
|              | Commo.   | Momentum   | -1%         | 6%   | -5%   | 7%    | 7%   | 6%   | -3%  | -5%     | -5%   | 14 %  | -1%   | -8 %  | 2%    | 1%    | 33%     | 35%  |
|              |          | M&A<br>Mean reversion<br>Trend<br>Short volatility<br>Volatility trading | 2%          | 4%   | 1%    | 6%    | 1%   | 2%   | 5%   | 6%      | 12 %  | -10%  | 1%    | 4%    | 3%    | 3%    | 4%      | -2%  |
|              |          |  | -5%         | 14%  | 12%   | 3%    | -9 % | 2%   | -7%  | -2%     | 21%   | -9%   | 1%    | 6%    | 5%    | 0%    | 0%      | -6 % |
|              | Equities |  | 2%          | -3%  | -12 % | 6%    | 3%   | 2%   | 0%   | -5%     | 4%    | 25%   | -1%   | 4%    | -13 % | -5%   | 7%      | 15%  |
|              |          |  | -3%         | 8%   | 8%    | 2%    | -5%  | 1%   | -2%  | 3%      | 31%   | -13 % | -5%   | 18 %  | 3%    | -1%   | 4%      | -7%  |
|              |          | , 0  | -1%         | 4%   | 3%    | 0%    | -2 % | 1%   | -1%  | 0%      | 11%   | 0%    | 0%    | 2%    | -4 %  | -1%   | 1%      | 2%   |
|              |          | Mean reversion   | -4 %        | 11%  | 16 %  | 5%    | 2%   | 7%   | -2%  | 0%      | 18 %  | -19 % | 5%    | 3%    | 7%    | 5%    | 5%      | -7%  |
|              | FX       | Trend  | -1%         | 0%   | -9 %  | 7%    | 1%   | 3%   | -1%  | -5%     | -3 %  | 25%   | -2 %  | 1%    | -5%   | -1%   | 3%      | 11%  |
|              |          | Short volatility   | -2 %        | 12 % | 4%    | 4%    | -3%  | 3%   | -2%  | 0%      | 20%   | -11%  | -4 %  | 9%    | 7%    | 2%    | 3%      | 3%   |
| ARP          | Credit   |  | 4%          | -2%  | 1%    | -2%   | -1%  | -3 % | 6%   | 5%      | 17%   | -8 %  | -4 %  | 19%   | 0%    | -1%   | 4%      | 3%   |
| Trading ARP  | Credit   | Carry Trend  | 1%          | -5%  | -15%  | -4%   | -2%  | -4%  | -1%  | 1%      | 7%    | 9%    | 1%    | 17%   | -9%   | -6%   | -1%     | 4%   |
| Trac         |          |  | 0%          | 7%   | 3%    | 4%    | 5%   | 5%   | 0%   | -3%     | -3 %  | 2%    | -3 %  | -6 %  | 18 %  | 8%    | 1%      | 3%   |
|              | D.       | Carry Trend  | 0%          | 12 % | 0%    | 5%    | 4%   | 7%   | -2%  | -5%     | -9 %  | 6%    | -2%   | -10%  | 23%   | 10%   | 3%      | 9%   |
|              | Rates    | Long volatility<br>Short volatility                                      | -1%         | -6%  | -7%   | 2%    | 7%   | 2%   | 0%   | -5%     | -16 % | 12 %  | -1%   | -7%   | -8 %  | 3%    | 0%      | 10%  |
|              |          |  | -4%         | 10%  | 7%    | 2%    | -3 % | 3%   | -3%  | 1%      | 19 %  | -10 % | -2%   | 11%   | 12 %  | 3%    | 2%      | -5%  |
|              |          |  | 0%          | -1%  | 2%    | 3%    | 5%   | 2%   | 1%   | 0%      | -2%   | 9%    | -1%   | -3%   | 1%    | -1%   | 29%     | 20%  |
|              |          | Carry Liquidity  | 1%          | -4%  | 3%    | -3%   | 3%   | -1%  | 3%   | 4%      | -2%   | 3%    | 0%    | -1%   | 1%    | -1%   | 9%      | 4%   |
|              | Commo.   | Momentum Trend   | -1%         | -3%  | 4%    | 0%    | 3%   | 0%   | 0%   | 2%      | -1%   | 7%    | 1%    | -2%   | -1%   | 0%    | 24%     | 13 % |
|              |          | Short volatility   | -6 %        | 4%   | -8 %  | 10 %  | 0%   | 4%   | -5%  | -8%     | -10 % | 22%   | 0%    | -2%   | -1%   | -3%   | 18 %    | 44%  |
|              |          |  | 0%          | 2%   | 1%    | 3%    | 2%   | 2%   | 2%   | 1%      | 14 %  | -2 %  | -4%   | 7%    | -1%   | 1%    | 2%      | 2%   |

Appendix F: Average correlation levels between ARPs Source: Orion Financial Partners

|      |             |        |               |            |             |       |              | Tra   | ding A       | RP    |       |          |              |       |             |      |       |              |  |  |
|------|-------------|--------|---------------|------------|-------------|-------|--------------|-------|--------------|-------|-------|----------|--------------|-------|-------------|------|-------|--------------|--|--|
|      |             | Equiti | es            |            |             | FX    |              | Cre   | Credit Rates |       |       |          |              |       | Commodities |      |       |              |  |  |
| M&A  | Mean<br>Rev | Trend  | Short<br>Vol. | Vol. Trade | Mean<br>Rev | Trend | Short<br>Vol | Carry | Trend        | Carry | Trend | Long Vol | Short<br>Vol | Carry | Liqu        | Mom  | Trend | Short<br>Vol |  |  |
| 2%   | -5%         | 2%     | -3%           | -1%        | -4%         | -1%   | -2%          | 4%    | 1%           | 0%    | 0%    | -1%      | -4%          | 0%    | 1%          | -1%  | -6 %  | 0%           |  |  |
| 4%   | 14%         | -3 %   | 8%            | 4%         | 11%         | 0%    | 12 %         | -2%   | -5%          | 7%    | 12 %  | -6%      | 10%          | -1%   | -4%         | -3%  | 4%    | 2%           |  |  |
| 1%   | 12%         | -12 %  | 8%            | 3%         | 16 %        | -9 %  | 4%           | 1%    | -15%         | 3%    | 0%    | -7%      | 7%           | 2%    | 3%          | 4%   | -8 %  | 1%           |  |  |
| 6%   | 3%          | 6%     | 2%            | 0%         | 5%          | 7%    | 4%           | -2%   | -4%          | 4%    | 5%    | 2%       | 2%           | 3%    | -3%         | 0%   | 10 %  | 3%           |  |  |
| 1%   | -9 %        | 3%     | -5%           | -2 %       | 2%          | 1%    | -3%          | -1%   | -2%          | 5%    | 4%    | 7%       | -3%          | 5%    | 3%          | 3%   | 0%    | 2%           |  |  |
| 2%   | 2%          | 2%     | 1%            | 1%         | 7%          | 3%    | 3%           | -3 %  | -4%          | 5%    | 7%    | 2%       | 3%           | 2%    | -1%         | 0%   | 4%    | 2%           |  |  |
| 5%   | -7%         | 0%     | -2%           | -1%        | -2%         | -1%   | -2%          | 6%    | -1%          | 0%    | -2%   | 0%       | -3%          | 1%    | 3%          | 0%   | -5%   | 2%           |  |  |
| 6%   | -2%         | -5%    | 3%            | 0%         | 0%          | -5%   | 0%           | 5%    | 1%           | -3%   | -5%   | -5%      | 1%           | 0%    | 4%          | 2%   | -8%   | 1%           |  |  |
| 12 % | 21%         | 4%     | 31%           | 11%        | 18 %        | -3 %  | 20%          | 17%   | 7%           | -3 %  | -9 %  | -16 %    | 19 %         | -2%   | -2%         | -1%  | -10 % | 14 %         |  |  |
| -10% | -9%         | 25%    | -13 %         | 0%         | -19 %       | 25%   | -11%         | -8 %  | 9%           | 2%    | 6%    | 12 %     | -10 %        | 9%    | 3%          | 7%   | 22%   | -2%          |  |  |
| 1%   | 1%          | -1%    | -5%           | 0%         | 5%          | -2%   | -4%          | -4 %  | 1%           | -3%   | -2%   | -1%      | -2%          | -1%   | 0%          | 1%   | 0%    | -4%          |  |  |
| 4%   | 6%          | 4%     | 18 %          | 2%         | 3%          | 1%    | 9%           | 19%   | 17%          | -6%   | -10%  | -7%      | 11%          | -3%   | -1%         | -2%  | -2%   | 7%           |  |  |
| 3%   | 5%          | -13 %  | 3%            | -4 %       | 7%          | -5%   | 7%           | 0%    | -9%          | 18%   | 23%   | -8%      | 12 %         | 1%    | 1%          | -1%  | -1%   | -1%          |  |  |
| 3%   | 0%          | -5%    | -1%           | -1%        | 5%          | -1%   | 2%           | -1%   | -6%          | 8%    | 10%   | 3%       | 3%           | -1%   | -1%         | 0%   | -3%   | 1%           |  |  |
| 4%   | 0%          | 7%     | 4%            | 1%         | 5%          | 3%    | 3%           | 4%    | -1%          | 1%    | 3%    | 0%       | 2%           | 29%   | 9%          | 24%  | 18 %  | 2%           |  |  |
| -2%  | -6 %        | 15%    | -7%           | 2%         | -7%         | 11%   | 3%           | 3%    | 4%           | 3%    | 9%    | 10%      | -5%          | 20%   | 4%          | 13 % | 44%   | 2%           |  |  |
| 56 % | 21%         | -5%    | 19 %          | 8%         | 27%         | -2%   | 18%          | 9%    | -7%          | -1%   | -4%   | -16%     | 16%          | 1%    | 0%          | 4%   | -4%   | 6%           |  |  |
| 21%  | 50 %        | 5%     | 41%           | 26%        | 30%         | -2%   | 17%          | 7%    | 2%           | -3%   | -5%   | -19%     | 17%          | -3%   | -3%         | 0%   | -1%   | 7%           |  |  |
| -5%  | 5%          | 80%    | 1%            | 18 %       | -23 %       | 30%   | -1%          | -3 %  | 41%          | 0%    | 1%    | 9%       | -6 %         | 5%    | 0%          | 2%   | 32%   | 2%           |  |  |
| 19 % | 41%         | 1%     | 61%           | 23%        | 24%         | -5%   | 29%          | 20%   | 0%           | -7%   | -9%   | -29 %    | 28%          | -5%   | -4%         | -3%  | -10 % | 18 %         |  |  |
| 8%   | 26%         | 18 %   | 23%           | 22%        | 7%          | 3%    | 9%           | 5%    | 11%          | -2%   | -4%   | -5%      | 6%           | 1%    | 0%          | -1%  | 7%    | 4%           |  |  |
| 27%  | 30%         | -23 %  | 24%           | 7%         | 69%         | -21%  | 21%          | 11%   | -16 %        | 3%    | -2%   | -17%     | 21%          | 0%    | 1%          | 6 %  | -16 % | 8%           |  |  |
| -2%  | -2%         | 30%    | -5%           | 3%         | -21%        | 47%   | -2 %         | -1%   | 16 %         | 0%    | 6%    | 10 %     | -6 %         | 4%    | 0%          | 0%   | 32%   | 0%           |  |  |
| 18%  | 17%         | -1%    | 29%           | 9%         | 21%         | -2 %  | 61%          | 12 %  | -1%          | 0%    | -1%   | -10 %    | 27%          | 1%    | 1%          | 1%   | 2%    | 16 %         |  |  |
| 9%   | 7%          | -3 %   | 20%           | 5%         | 11%         | -1%   | 12 %         | 38%   | 1%           | -4%   | -7%   | -12 %    | 13 %         | -1%   | -1%         | 1%   | -3%   | 9%           |  |  |
| -7%  | 2 %         | 41%    | 0%            | 11%        | -16 %       | 16 %  | -1%          | 1%    | 66%          | -2%   | -3%   | 12 %     | -8 %         | 2%    | 2%          | -1%  | 21%   | 1%           |  |  |
| -1%  | -3%         | 0%     | -7%           | -2 %       | 3%          | 0%    | 0%           | -4%   | -2%          | 21%   | 24%   | 5%       | 6%           | 2%    | -1%         | -2%  | 3%    | 0%           |  |  |
| -4%  | -5%         | 1%     | -9%           | -4 %       | -2 %        | 6%    | -1%          | -7%   | -3 %         | 24%   | 42%   | 8%       | -1%          | 5%    | 1%          | 2%   | 9%    | -5%          |  |  |
| -16% | -19%        | 9%     | -29 %         | -5%        | -17%        | 10 %  | -10 %        | -12 % | 12 %         | 5%    | 8%    | 61%      | -25%         | 3%    | 1%          | 2%   | 16 %  | -8%          |  |  |
| 16%  | 17%         | -6 %   | 28%           | 6%         | 21%         | -6 %  | 27%          | 13 %  | -8 %         | 6%    | -1%   | -25%     | 49%          | -3%   | -4%         | -2%  | -13 % | 14 %         |  |  |
| 1%   | -3%         | 5%     | -5%           | 1%         | 0%          | 4%    | 1%           | -1%   | 2%           | 2%    | 5%    | 3%       | -3%          | 25%   | 17%         | 31%  | 18 %  | 1%           |  |  |
| 0%   | -3%         | 0%     | -4%           | 0%         | 1%          | 0%    | 1%           | -1%   | 2%           | -1%   | 1%    | 1%       | -4%          | 17%   | 26%         | 30%  | 1%    | -3%          |  |  |
| 4%   | 0%          | 2%     | -3%           | -1%        | 6%          | 0%    | 1%           | 1%    | -1%          | -2%   | 2%    | 2%       | -2%          | 31%   | 30%         | 25%  | 10 %  | -2%          |  |  |
| -4%  | -1%         | 32%    | -10 %         | 7%         | -16 %       | 32%   | 2%           | -3 %  | 21%          | 3%    | 9%    | 16%      | -13 %        | 18 %  | 1%          | 10 % | 77%   | 2%           |  |  |
| 6%   | 7%          | 2%     | 18 %          | 4%         | 8%          | 0%    | 16 %         | 9%    | 1%           | 0%    | -5%   | -8%      | 14 %         | 1%    | -3%         | -2%  | 2%    | 24%          |  |  |

Appendix F: Average correlation levels between ARPs Source: Orion Financial Partners

#### Endnotes

- 1. In market neutral portfolios, the allocations of the long and the short legs are determined from their respective exposure to market risk (i.e. their beta), whereas dollar neutral portfolios are of equivalent dollar value.
- 2. i.e. decorrelated from market risk.
- 3. As being pricing elements on the right-hand side of factor models derived from the CAPM.
- 4. Asness, Frazzini et Pedersen (2013) measure the quality of a company by four criteria: its profitability, its growth, its safety and the stability of its earning distributions. Each of these criteria is evaluated from different measures (e.g. profitability is measured by the gross margin,ROE, ROA).
- 5. That is the risk of misclassifying the securities.
- 6. Equally-weighted, risk parity, score weighting, capitalization weighting.
- 7. Sector or geographic neutrality, orthogonalization to given factors, Sharpe ratio maximization...
- 8. Assuming that (i) these two investment universes are each divided in two groups (long and short leg), that (ii) long and short portfolios are equally-weighted, and that (iii) the remaining parameters are similar, these two ARPs will only have, at most, 8.3% of their allocation in common (50/600).
- 9. The historical performances of ARPs offered by investment band encompass significant part of backtested performances, and therefore incorporate potential biases (Naya and Tuchschmid, 2018).
- 10. For instance, the market exposure of trend following strategies varies through time, being alternatively net long or net short.
- 11. In the M&A premium for example.
- 12. See Naya and Tuchschmid (2018).
- 13. Not in factor construction, but rather in the allocation between the various risk premia.
- 14. Long-only and mainly applied to equity markets, marginally to credit or rates.
- 15. Our database contains 400 ARPs We however excluded multi asset class asset and multi-factor indices.
- 16. In number of ARPs, not in volume. As ARPs are generally packaged under total return swaps, the amounts managed by the various entities are not available.
- 17. We consider 3 market environments: for the entire sample, for bullmarket periods and for down market periods (defined in Appendix A).
- 18. Over the same period, HFRI index (investable and noninvestable hedge funds) exhibits a risk/return profile that is in line with that of ARPs.

- 19. This statement is reinforced using the HFRX index (investable). The same analysis on the HFRI index over the same period confirms the sensitivity of hedge fund returns to crisis periods (+10.1% of annualized performance in bull markets vs. -10.7 in bear markets).
- 20. The skewness of a statistical distribution measures its symmetry. A positive (negative) skewness implies an asymmetric distribution on the right (left), with extreme events more frequent on the right (left) of the distribution, the skewness of gaussian distributions being equal to 0.
- 21. The kurtosis of a distribution measures the thickness of its tails. A kurtosis greater than 3 (or a positive excess kurtosis) implies that the tails of the distribution are thicker than those of a Gaussian distribution, which results in a probability greater occurrence for extreme events (both positive and negative).
- 22. The type of premia remaining different, e.g. between equity momentum vs. equity quality.
- 23. The lines swapped are the principle vehicles used to access the ARP dveloped by the banks, under th eindices form.
- 24. Naya and Tuchschmid (2018).

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Guillaume Monarcha holds a PhD in Economics. He is partner and head of research at Orion Financial Partners, teaches at the Paris Dauphine University, and speaks at academic and professional conferences. His research activity focuses on the fields of quantitative asset allocation,

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# Technology, Innovation and Disruption

Jack Sibley Nuveen Real Estate

Filippo Rean REED MIDEM To an external observer, the commercial real estate industry might appear slow-moving and conservative. Many industries have experienced technological disruption since the millennium, however software and technology have not started 'eating the world' of real estate until relatively recently. So why has it taken until the last couple of years for the word 'innovation' to become a buzzword in real estate?

This report is a collaboration between Nuveen Real Estate and MIPIM. It includes our thoughts on the rise of digital disruption and innovation in the commercial real estate industry, and discusses whether real estate is ready to embrace innovation as the industry evolves. We also highlight our favorite 'MIPIM talk' topics from this year's conference. The 'Mapping World Urbanity' theme placed great emphasis on technology and innovation, sparking a number of insightful conversations, demonstrating that technology is front of mind for those in the industry. We hope this report gives you further insight, and will inspire you to turn ideas into actions. We welcome any feedback you may have and hope to see you at MIPIM 2019.

#### **Ready for Change?**

The structural characteristics of real estate as an asset class may not be naturally suited to certain models of innovation and disruption, which emphasize accelerated product iteration, scalability and a 'disruptive' mentality. The low velocity of turnover in assets and leases, the heterogeneous nature of properties, and the relatively high cost of experimentation, all present obstacles to successful, persistent innovation. However, obstacles can be overcome. Larger barriers for innovation have resulted from the industry's culture, which is more malleable. Obstructive

elements of this culture include being risk-averse, a lack of alignment between real estate stakeholders, and overall expectations in the industry that the future will be rigidly linear. Fundamentally, real estate is a relatively opaque industry, where connections matter and relationships involve building trust incrementally over time. There is a clear link between the characteristics of real estate as an asset class and the industry's culture, and to a degree this symmetry will undoubtedly prevail. However, some aspects are being challenged. Over the past few years, we have seen increasing expectations for industry players to engage with start-ups, disruptors and the emerging PropTech ecosystem.

#### **Reasons for Change**

#### **Disruption in Adjacent Industries**

The commercial real estate industry is being forced to acknowledge that disruption can happen to anyone. The retail sector has been shouting about e-commerce displacing traditional retailing models. Tesla and Uber are revolutionizing transport, leading the pack in producing electric, driverless and on-demand mobility. Elsewhere, over 80% of financial institutions believe their business is at risk of being overtaken by innovators, from FinTech start-ups to Bitcoin.

#### Emergence of PropTech Start-ups & Big Tech

The ecosystem of PropTech start-ups has been maturing fast and 'Big Tech' is creeping into the industry. Venture capital investment in PropTech has increased dramatically in recent years, and larger, later fundraising rounds are increasingly common. Real estate unicorns are starting to impact the industry and its fundamentals, for example, WeWork became the largest occupier in the Central London office market last year. Google has started to make moves through Sidewalk Labs by redeveloping an area of Toronto in Canada, Amazon has launched bricks-and-mortar stores, and Alibaba is investing heavily in offline retail, recently spending \$2.9bn for a stake in one of China's leading hypermarket operators.

#### **Optimizing UX**

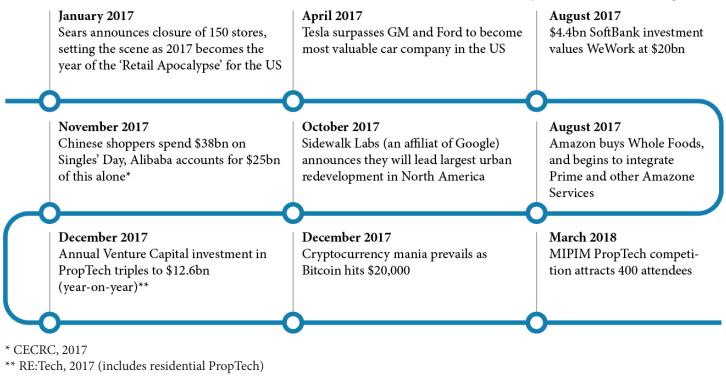
Businesses have dedicated their time to improving the online user experience (UX), however consumers are now expecting them to raise the stakes offline. Furthermore, traditional real estate sectors are being challenged as the nature of demand for space changes: retail is embracing leisure and offices are focusing more on hospitality. We can see a slow moving supply side reaction to these trends, which will only accelerate.

#### On the Cusp of Technological Distruption?

Real estate is not yet on the cusp of technological disruption, but the seeds of innovation are now firmly planted and are starting to germinate. The relevant question is not if, but when and how will the industry reap the rewards. There is no single answer, however the potential consequences of technology, innovation and disruption is an ongoing, industry-wide conversation that spans from inward-looking digital transformation strategies, to outward-looking re-examination of investment theses, key value propositions and core business objectives. Many other industries have faced technological disruption and have successfully transitioned to become more dynamic, flexible and responsive. Now is the start of this transition for commercial real estate.

#### **Challenges for the Industry**

In reacting to technology, innovation and disruption, there are two main challenges that real estate must overcome. The first is navigating the short-term, technology-driven shift in the purpose of real estate, the second is adapting to a heightened pace of obsolescence. These challenges shaped the debate at MIPIM and were reflected across many conversations. Embracing these



#### Exhibit 1

challenges means embarking on the transition to becoming a future-proof industry that is equipped to disrupt itself before it is disrupted, and an endogenous driver of technology and innovation. None of this is easy, as it means changing the mindset and culture of the industry and, ultimately, will likely alter the structural characteristics of real estate as we know it.

#### Navigating the Technology-Driven Shift

A major challenge will be understanding what people want from real estate, particularly in the two largest sectors: retail and office. The digital world has become a cornerstone in people's lives – the average adult in the UK spends more time online than sleeping – and this will increase. The reality is that people can work and shop remotely if they choose to. Real estate must differentiate itself by providing an experience, or align with the same trends driving its success by prioritizing efficiency. In the case of the former, this means navigating the transition of real estate from passive to active, from delivering a product to intermediaries towards providing an experience to end-users.

In retail, gone are the days when 'being a place to buy things' was a good enough reason for an asset to attract consumers. Some retail assets will increasingly align with e-commerce through initiatives like click-and-collect, a focus on efficiency and convenience, and a weighting towards more 'defensive' areas of retail, such as groceries. This model is driven by the same forces as logistics, and, if executed successfully, will retain a distinct purpose in Tomorrow's World. Conversely, other retail assets will move towards 'experiential' retail. In practice, this will likely be driven by successful 'activation' of the asset, an unrelenting focus on UX, and hosting 'service providers', be it food and beverage, leisure (e.g. cinemas), or retailers who understand that their customers are more than 'shoppers', and to an extent embrace showrooming.

Offices are not yet facing the same scale of potential disruption, but we have reason to believe that difficult questions will also be asked in this sector in the foreseeable future. Constant connectivity has led to the death of the traditional 'worklife' balance. Work is now considered a key part of people's lifestyle, rather than a '9-to-5' duty. Add to this the overall rise of the knowledge economy, and the result is that the quality and experience of the office is increasingly important, from attracting and retaining talent, influencing productivity, boosting collaboration, and acting as the bedrock of a company's culture. Faced with this almost meteoric rise in expectations, offices are quickly shifting towards hospitality, with many of the same attributes seen in retail's move towards leisure, such as an increase in animation, intensive asset management, and more focus on the end-user.

#### Adapting to a Heightened Pace of Obsolescence

Keeping up with, and responding to a heightened pace of obsolescence, driven by technology and new business models, is a major challenge to real estate that threatens assets, business processes and the industry itself. With high transaction costs and private market illiquidity, real estate has one of the longest typical hold periods of any asset class, often around 8-10 years. If an asset is bought today, the disposal can sometimes be expected as late as 2030 and beyond. If sold earlier, the buyer will still be

underwriting the asset on a similar hold period. It makes sense to consider the structural trends that will impact real estate over medium- and long-term horizons - historically these have been large infrastructure projects and demographic changes, which evolve at a 5-10-15 year pace. When it comes to technology, 2030 feels like a long time away for a lot of change to happen. Accordingly, there are several large-scale technological changes that are expected to impact real estate within this timeframe. One of these will be autonomous vehicles, which will spearhead a transportation revolution as the sector moves towards new forms of personal and shared mobility. Another is 5G, which will herald a connectivity revolution. Although the impact of trends like these on real estate is sometimes difficult to conceive, to ignore them when making investment and asset management decisions is to implicitly assume they will have no impact, or worse, will mean that we miss opportunities. The industry will have to get better at dealing with technological trends whose knock-on impact on real estate is high probability but low predictability.

In addition to these exogenous technological impacts, the rapid changes in the nature of consumer demand should not be considered a one-off shift, rather they will continue to evolve at an accelerated pace. E-commerce is still in its infancy even over a medium-time horizon, and its influence on consumer behaviour will continue to evolve. Moreover, the preferences of millennials – currently described as self-centered, requiring instant gratification and addicted to the internet – are still in the process of being deciphered. In five years' time, the young talent coming into businesses will be from Generation Z, not Y. Although many of this new generation's traits are likely to be accentuations of the previous generation's, it is very possible they will be considered as different from Y, in the way that Y are from X.

Finally, we can no longer predict all of what will come to influence the nature of real estate in the next decade. We should acknowledge that unknown disruptive business models, new technological breakthroughs or consumer-led shifts, will likely materialize and require a reaction.

Technological disruption is not just an isolated event to which defensive action has to be taken, but a realignment of the industry to a new plateau, where real estate will have to adapt to a faster pace of obsolescence, with innovation, change and disruption as constant threats. One worry is that the cost of keeping assets ahead of this wave of obsolescence will require an increased level of capital expenditure, which may dilute returns.

However, evidence from other industries, such as computing, advertising, and media, suggests that as the pace of obsolescence accelerates, the reward for innovation increases proportionately, with those that can keep up being generously compensated for doing so.

The impact on returns may seem an obvious threat. However, the failure to react to this structural realignment may prove costly, given the industry is often considered slow-moving, backward-looking and resistant to change. Successful adaption will require a significant change in mentality, culture and even skill-sets across the board. The ability to react at speed, scale and with conviction will also become important. The real estate industry has a lot of work to do.

#### How do We Keep Up?

As an industry, we can do more to encourage and reward creativity, forward-thinking and innovation. Having a designated 'innovation lead' within real estate firms is increasingly common. Larger organizations may benefit from a dedicated resource – a Chief Innovation or Chief Technology Officer – which helps the business to keep up and drive the top-down strategy.

Thinking more strategically and applying research around both the nature of demand for real estate and the potential impact of key technological trends over five and ten year horizons is needed to help identify, understand and react to potential sources of disruption.

To comprehensively address this structural shift, the industry will need to proactively embrace and leverage the latest technology to their advantage. In other words, the real estate industry will have to digitize. This is a broad area and the major themes of digitization today will be explored next.

#### **Digitizing the Industry**

If we are going to digitise the industry, we must change the way we do things across the entire lifecycle of property investment, from research and transaction, to management and development. There are many areas of interest here, however three themes represent the most immediate opportunities: data, smart buildings and digital platforms.

#### **Opportunity: Data**

The value of data has long been neglected by the real estate industry. Some argue that the industry has thrived because of its lack of transparency, which has maintained the illiquidity premium of the asset class. Aggregated data initiatives have existed at scale to provide performance benchmarks, however collecting and sharing granular data on real estate and the built environment has not been a priority. Valuable information is often hoarded, usually in the brains of market participants rather than in formal databases. Despite this, data (both big and small) is slowly but surely making its way to real estate's center stage.

Seeking to improve 'hard' real estate market data (rents, yields, and vacancies), several initiatives have launched to improve the sharing and democratisation of market data. So far they have failed to gain the critical mass and momentum needed to change the industry. It is possible that blockchain could be part of shifting this tide, but it will likely be more of an enabler rather than a driver of change – historically the main obstacle has been culture and incentives to sharing data, rather than the technology infrastructure. However, within the real estate industry, larger organizations have got serious about managing their own data, having realized they are sitting on commodity which, if correctly leveraged, could be highly valuable.

The potentially bigger story, however, is 'soft' data becoming 'better' in every sense – volume, velocity, variety and veracity. The public sector is a leading driver of improving the quality of soft data, as cities, local authorities and land registries adopt open data initiatives and allow third parties to gain access to publicallycollected data that was previously not leveraged to create value. Data points including taxi trips, air quality, local population characteristics and more, can now be freely accessed across cities globally, as well as detailed property-specific information about ownership and even leases in many countries.

With mobile phones now ubiquitous, it is also possible to gauge a better understanding of city dynamics through online activity and location trackers, be it the number of Instagram photos posted across different locations, Yelp restaurant ratings in the local area, Airbnb pricing trends, or anonymized geolocation data from mobile GPS. These create a digital tapestry through which to view the evolution of a city and its spaces. In Europe, the development of GDPR has positively encouraged innovation in these areas by providing certainty around the regulatory environment.

This soft data is usually complementary to conventional approaches and can help build a more three-dimensional picture of an investment by providing greater context and more comprehensively describing the built environment. Although hard real estate market data will always form the backbone of real estate research and underwriting, those that have the bandwidth and ability are taking the opportunity to broaden their view, to absorb a wider range of data points, and better inform investment and asset management decisions.

#### **Opportunity: Smart Buildings**

Smart buildings have been around in many different forms over the years. Historically, it has sometimes been a descriptive term that has somewhat overpromised and under-delivered. However, especially as the value of data has become recognized in real estate and data analysis tools have evolved, this area is maturing fast. Two major areas of development have been the 'Internet of Things' (IoT), where the falling costs of sensors is leading to more useful data being generated, and energy efficiency, where both software and hardware are making significant progress.

The rise of IoT has been largely driven by the long-heralded miniaturization and cost-effectiveness of sensors. After some minor false starts, small and cheap sensors have now arrived in commercial real estate, with some sensors shrinking to the size of postage stamps and prices falling across the board. Although it is now possible to generate millions of data points per second from any building, at relatively low cost, it is crucial to link back these initiatives directly to enhancing user experience.

An obvious example of this is the increasingly common deployment of sensors that measure environmental factors such as temperature, humidity, light and air quality. These show how the decisions taken at the business management system (BMS) level are cascading through the space itself and affecting end-users. The data from these sensors then provide the basis upon which to make dynamic adjustments to optimize the environment – enhancing the overall user experience of the space. In practice, this means improving the health and wellbeing of users, including reducing exposure to pollutants, maximizing natural light and reducing stress. It also means realizing that productivity is directly linked to the experience of the space itself, and recognizing that if productivity can be boosted by just a few percent, the cost of these improvements is more than validated.

Space utilization is another example of an IoT application. Using combinations of sensors and cameras, it is now possible to understand in granular detail how a space is being used. Leveraging its advantages of scale, WeWork has been leading the wider movement in applying Artificial Intelligence (AI) to these data sets to understand how space is used, and see how it can be made more architecturally efficient. In practice, this means providing data-backed answers to questions like how many meeting rooms of what size are needed, what impact the layout and design of a shop or shopping centre has on dwell times in certain areas, and so forth. Again, the focus is on enhancing UX.

Improving energy efficiency has increasingly become a point of focus for landlords and tenants alike, especially since the Paris Agreement. In the last 12-18 months, smart building software has made significant strides in solving the problem that the BMS running buildings are designed to control the systems themselves, not provide visibility on how the building is performing. There are now options to resolve this pain point, as software can plug into the building (often through the BMS itself), extract the relevant data and turn it into actionable recommendations sometimes adding in relevant external data (e.g. weather) into the analysis. These tools lean on sophisticated data analysis including AI and, although most of the last step is still manual (hence 'recommendations') it is also possible to instruct the BMS directly. In essence, this could be one of the first instances of almost complete automation of an entire function, from data collection to interpretation, to action

Smart building hardware targeted at energy efficiency is also evolving fast. The price of solar panels continues to fall and in certain cases can now be accretive to property-level performance. Smart glass that can generate electricity is also becoming a more attractive option, especially if installed from construction. Aside from generating energy, new buildings seeking to minimize their environmental footprint can leverage new materials, modular construction, and more sophisticated insulation and cooling systems, all of which have seen significant progress in recent years. Although the most cutting-edge technology is easiest to apply to new builds, solutions adapted specifically for retrofitting are also gaining traction and are becoming easier to integrate.

Previously, the adoption of these solutions would sometimes be driven by broader sustainability concerns. It is increasingly easy to make the case for energy efficiency solutions (both hardware and software) purely on the basis of the financial return-oninvestment (ROI). This means that the pay-back period for implementing these initiatives, based on energy costs saved, is getting progressively shorter, if not immediate in some cases.

#### **Opportunity: Data**

Digital platforms are a diverse category, with different applications targeting a variety of end-users, asset managers and real estate investors.

Starting with end-users, a key theme that has been topical recently is how to provide the best blend of online and offline experience. In practice, this encompasses efforts to improve the online presence of retail locations (often through simple strategies like revamping websites), improving the shopping experience through downloadable apps (e.g. introducing elements of artificial reality into the experience), or providing tenants with access to a digital platform that aims to create a sense of community and digital place. Following a flurry of development, there is now what might feel like an abundance of apps and digital platforms that seem to 68 Some of these solutions go a step further than enhancing enduser experience. When asset-specific data becomes collated onto one digital platform – rather than simply serving several individual use cases – there is the potential to create a 'digital twin' of a physical building. This requires collating a broad range of data on a building, ranging from BMS data to ownership and tenant information, and real-time data on temperature, to space utilisation. Although the standard for what a digital twin looks like has not yet been established, many buildings now have enough data points and information to build one. As more data is generated from buildings, these digital twins will become more comprehensive, insightful and useful for all stakeholders in real estate, including owners, asset managers, tenants and end-users alike, who can each gain access to the information they need, when they need it.

There are also more comprehensive and value-adding platforms being built for commercial real estate asset managers and investors. Many of these reflect the current default of the real estate industry to work primarily on Outlook and Excel as the day-to-day dashboard, something which many other industries have long since left behind. Many of these platforms are effectively cloud-based, workflow management tools that aggregate the relevant sources of data into one place and allow all relevant parties to input as and when required. Although sometimes described as a prettier way to look at the same data you would in Excel, when applied at scale these can yield tangible efficiency benefits and will continue to build out their functionality and value-add.

Finally, several platforms have launched which aim to create digital marketplaces, and simultaneously engage both buyers and sellers onto one platform. Some of these have integrated payment functionality (sometimes using Blockchain to do so), others do not and concentrate simply on matching buyers and sellers. A large part of their current value proposition offers access to fractional direct real estate investment for retail and high net-worth segments, although as platforms mature they will move towards encompassing smaller institutions. Those that are currently making the most progress usually focus on those areas of real estate which tend to be more homogenous and commoditized, namely commercial real estate debt. Promisingly, several emerging players in this area have found the necessary backing and momentum to become genuine forces within the market, while others are clearly at much earlier stages.

#### Conclusion

The industry faces many challenges, both internal and external, some of which go to the very heart of what real estate is today. However, the industry will not suffer from deep disruption overnight – we do have time to process, react, and reposition ourselves. This means shedding some elements of real estate and improving others. Those that can align themselves with this structural shift will succeed in Tomorrow's World, and those that can't or choose not to, will struggle. A warning – if you don't like change, you'll like irrelevance even less!

#### Less of the Same

- 1. Silos: Real estate has been guilty of not evolving in parallel with mass instant communication. Valuable information has been known to not travel beyond silos within businesses, and there's a resistance to trying new ways of collaboration with a sense of 'if it isn't broken don't fix it'. Those that continue to adhere to convention for the sake of convention are increasingly likely to be left out in the cold.
- 2. Treating real estate like a bond: A traditional real estate investment strategy might be described as being contractually secured, and having inflation-linked income, with a focus on mitigating downside risks and any upside generated through the evolution of market rents and yields. Although this will not change overnight, these characteristics are becoming more closely linked to the operation of the asset and the end-user's experience, and less dependent on the surrounding market fundamentals.
- 3. Excel: Although Excel will continue to be a cornerstone software for real estate investors and other stakeholders, the industry's reliance on it is likely to wane as more sophisticated tools for storing, viewing and analyzing information develop.
- 4. Exclusivity: Real estate can be quite an insular industry, based on relationships built up over time, suspicious of outsiders and resistant to promises of positive change. Although the culture of real estate is entrenched, the most successful models will find ways to keep the best of the old while embracing new opportunities for innovation and technology. Encouraging diversity of thought will be key.
- 5. Focus on cycles: Although property and business cycles will always remain close to the top of the agenda, their relative importance will diminish as investors grapple with something more fundamental, as the ultimate purpose of real estate itself evolves and the pace of obsolescence accelerates.

#### More of the New

- 1. Focus on UX: An unrelenting focus on the end-user and how UX is crucial to maintaining relevance in Tomorrow's World.
- 2. Data: Now referred to as 'the oil of the 21st century', the importance and value of data (both market and proprietary) has been historically overlooked in the industry. As a result, real estate's sophistication around data management is currently far behind other industries. This is changing, fast.
- 3. Asset management expertise: As real estate undergoes a structural shift, expertise at all scales asset, portfolio and strategic will be needed across the risk spectrum, with each asset needing more specialist attention and continuous evaluation.

- 4. Collaboration: In order to keep up with the pace of change, more proactive collaboration is needed between all stakeholders across the industry, including incumbents and start-ups, investors and operators, occupiers and property managers, and more; as well as more conversations with adjacent industries like transport and finance which are a few years ahead of real estate in adapting to technological disruption.
- 5. Strategic thinking: At a time when the next 15 years look to be more transformative for real estate than perhaps the last 50, maintaining a long-term, strategic perspective, and concentrating on the fundamental drivers of real estate demand is even more important for successful investment strategies.

#### Authors' Bio



#### Jack Sibley

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Jack leads Nuveen Real Estate's initiative to embrace technological innovation, change and disruption within its tomorrow's world philosophy. His focus includes analysis and solutions for how technology is changing what end-users want from real estate, proactive engagement with PropTech start-

ups and disruptors, and efforts seeking to leverage emerging technologies such as Big Data and AI. These efforts are integrated into Nuveen Real Estate's investment process, driving asset selection, asset management and portfolio resilience.

Prior to his current role, Jack worked in the business' R&D team, which he joined in 2016. Jack graduated with a B.A., honors, in Land Economy from the University of Cambridge and is a member of the Cambridge University Land Society.



#### **Filippo Rean** *REED MIDEM*

Filippo Rean joined Reed MIDEM in October 2010 as Director of MIPIM and MIPIM Asia, the leading international real estate tradeshows and conferences. Since September 2014, he has become Director of Reed MIDEM's Real Estate Division, hence is in charge of supervising all MIPIM & MAPIC markets.

He started his career in the marketing department of Procter & Gamble in Italy and then joined Bain & Company where he focused his activity on the financial sector and real estate. He joined the European headquarters of GE Capital Real Estate in Paris in 2005 and held various roles in strategic marketing and product development.

Filippo Rean has an engineering degree from the Politecnico di Torino, holds an MBA in Business Administration from Harvard and is fluent in Italian – his mother tongue – English and French.



## **Rethinking Real Assets**

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#### Why read on?

As investors have moved towards "real asset" portfolios rather than segregated sector-specific buckets, three significant trends have emerged.

The heart of this often-discussed shift is a mindset that is less focused on labels and prioritizes core characteristics or risk factors, such as inflation sensitivity, diversification from equity and yield. Yet, as is becoming increasingly clear late in the cycle, these characteristics are not hard-wired to real assets in the way that the equity risk factor is hard-wired into equities. In addition, different subsectors possess these traits to varying degrees.

The first trend: while unlisted real estate and infrastructure often sit at the heart of real asset portfolios, investors are becoming increasingly sophisticated and granular in their approaches to these two asset classes, and more cognizant of drifts in managers' risk exposures and characteristics.

Trend two: holistic approaches have facilitated diversification into niche sectors that may not sit within the old buckets, such as agriculture. High valuations in mainstream real assets have helped to encourage both of these trends, although pricing pressure has spilled into the niches and 'uncharted territory' is ever-more elusive.

The third and newest development is the rise of multi-real-asset investment strategies. Asset managers are launching strategies or structuring wrappers that offer breadth across multiple sectors. They can include conventional or more esoteric investments, while structures range from "funds of in-house funds" to true diversified pooled funds. There are powerful reasons why a

number of bfinance clients have sought broader mandates in 2017-18. Investors should be aware that those principles don't necessarily translate into real-life practices.

In some ways this latest step was a logical extension to major shifts in the asset management industry. Many firms have built or branded "real asset" divisions and the pattern continues into 2018. Some have bought boutiques in sub-sectors where they are historically weak, such as CBRE's acquisition of Canadian infrastructure manager Caledon or Hamilton Lane's purchase of RAPM. Many have built new teams to flesh out their real asset suite. Others have consolidated existing teams under a new unit.

The managers and consultants arguing that diversified real asset portfolios outperform real estate or infrastructure during weaker periods in the cycle may be correct in theory. Indeed, today's investment climate may have strengthened the case for a broader approach. Yet implementation, as is so often the case in private markets, represents the critical challenge.

### The Rise of the Real Asset Portfolio

The concept of the "real asset," "tangible asset," or "inflationsensitive" portfolio, firmly established in certain asset owner circles, has gained ground in recent years.

Among U.S. endowments, a portfolio comprising real estate, natural resources and TIPS has long been popular. Canadian and Australian institutional investors, leaders in infrastructure, were also early to institute real asset units. The trend reached its zenith in 2016, when CalPERS instituted a Real Assets division and CPPIB appointed a Head of Real Assets.

For European asset owners, this approach has been slower to gain traction. To some extent this is a side effect of portfolio composition. Real assets other than real estate seldom featured until the post-global financial crisis wave of infrastructure investment. Timberland, a U.S. staple, has only recently become popular. Master Limited Partnerships (MLPs), used in the U.S. for some traditional energy-related investing, do not have an international equivalent.

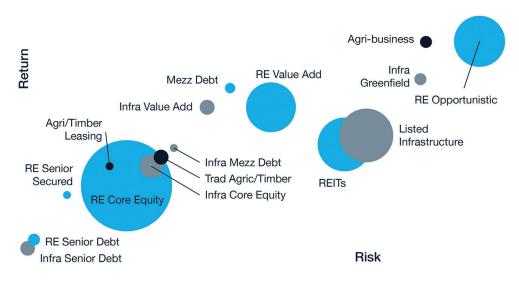
Yet the rise of infrastructure investment has been a catalyst for change. Infrastructure can be grouped with real estate due to its similarities, creating a bedrock for a real asset portfolio founded on core characteristics rather than labels.

While the post-GFC phase was marked by diversification towards real assets, later years have seen greater emphasis on diversification within real assets.

A summary of real asset segments, arranged by risk/return profile and market size, is provided in Exhibit 1. Their common theme: values based on contractual claims on physical assets. Exhibit 2 shows how attractive traits are available to varying degrees in the different sub-sectors, making a combination potentially beneficial.

At bfinance, demand for the more "niche" sectors increased substantially during the past three years. This has been encouraged by a compression in returns for core/core-plus real estate and infrastructure. Likewise, within real estate and infrastructure what was niche is now mainstream. Infrastructure funds are tapping into sectors that would not have previously been included, such as energy storage or data centres. UK pension fund real estate portfolios often now include Private Rented, Long Leased and Emergent sectors.

Investors can think of real assets in terms of the 'four quadrants' traditionally applied to real estate: unlisted/listed; debt/ equity. Some vehemently argue against the inclusion of listed infrastructure and REITS (#fakeinfra), but we urge a focus on contents rather than labels. Although they are correlated with stocks, correlation is also evident in some unlisted sectors. There is a similar divergence over the inclusion of 'debt' strategies, which can offer yield and downside protection at a time of aggressive pricing.



#### **Exhibit 1: Risk Return Spectrum for a Selection of Real Asset Classes** *Source: bfinance, MSCI, Preqin, Rare*

Note: Placement based on long term historic return and risk measures. Size based on estimates of investor capital (Real Estate \$5.5tn; Infrastructure \$2.2tn; Agric/Timber \$400bn).

|                              | Asset Class (core/<br>core+ profile unless<br>otherwise stated) | Definition  |        | relations with fixed | Hedge<br>during high<br>inflation /<br>inflationary | level,<br>and level<br>relative to | Atipinological<br>Overall<br>liquidity for<br>investors<br>accessing<br>the asset | to ESG-<br>relevant | standard<br>costs of<br>exposure<br>through<br>funds / |
|------------------------------|---|---|--------|----------------------|---|------------------------------------|---|---------------------|--|
| Private Equity /<br>Unlisted | Real Estate -<br>Traditional                                    | Main commercial sectors inc. office, retail,<br>industrial and [Germany, Netherlands,<br>U.S.] multifamily              | equity | income               | shocks  | total return                       | class   | sectors             | SMAs   |
|                              | Real Estate -<br>Resilient                                      | Resilient to real estate cycle eg. long<br>lease, inflation linked, demographically<br>oriented                         |        |                      |   |                                    |   |                     |  |
|                              | Infrastructure -<br>Economic                                    | GDP linked infrastructure with strong contractual underpinning  |        |                      |   |                                    |   |                     |  |
|                              | Infrastructure -<br>Social/Environmental                        | Supported by availability payments or subsidy. Not geared to economic cycles  |        |                      |   |                                    |   |                     |  |
|                              | Transportation  | Transportation and energy operations inc.<br>aviation or maritime leasing rather than<br>physical assets                |        |                      |   |                                    |   |                     |  |
|                              | Real Assets<br>Private Equity                                   | Value Added or Opportunitistic real<br>estate/infrastructure etc; turn-around,<br>development, high asset-specific risk |        |                      |   |                                    |   |                     |  |
|                              | Agriculture/Timber  | Traditional strategies to generate cashflow<br>as well as improvements in NOI and value<br>through better productivity  |        |                      |   |                                    |   |                     |  |
| Public Equities              | REITS   | Publicly listed real estate operating<br>companies and REITs  |        |                      |   |                                    |   |                     |  |
|                              | Listed Infrastructure   | Publicly listed Infrastructure companies  |        |                      |   |                                    |   |                     |  |
| Debt                         | Real Estate Debt  | Loans secured against real estate assets, generally senior, unitranche or mezz  |        |                      |   |                                    |   |                     |  |
|                              | Infrastructure Debt   | Loans secured against infrastructure assets, generally senior, unitranche or mezz                                       |        |                      |   |                                    |   |                     |  |

**Exhibit 2: Characteristics of Real Asset Sub-Sectors (Excludes Overall Risk and Return Shown in Exhibit 1)** Source: bfinance, Deutsch Bank, JPM Hamilton Lane, Partners Group, Preqin, Bloomberg

# Does Diversification Among Real Assets Really Add Value?

Today's investment climate has, in theory, strengthened the case for a more diversified real asset portfolio. The late stage of the cycle has compressed returns in traditional sectors. It has also increased the tensions between certain key traits, such as "returns" and "diversification vs. stocks." With investors creeping towards "value-add" end of the spectrum in infrastructure and real estate, for example, they may also increase sensitivity to cyclical risks.

Readers should remember that Exhibit 2 involves considerable oversimplification. In agriculture and timber, for example, available strategies span a broad range of risk/return profiles, as illustrated in a snapshot from a recent manager selection exercise (Exhibit 3).

Over the past year, we have observed multiple managers and consultants advocating a 'diversified real assets' approach. This argument takes many forms: advocacy for listed infrastructure or real estate, marketing of multi-real-asset strategies, marketing of niche sub-sectors and more. A recent paper from Cohen and Steers, for instance, indicated that diversified real asset portfolios outperformed standalone infrastructure, real estate or agriculture portfolios in periods when market returns were lower than usual (The Benefits of Real Assets Diversification in Defined Contribution Plans). Such arguments should be handled with care.

Firstly, it is critical to remember the main objective: the end investor's priority is not (except in cases of poor institutional governance!) to have a resilient real asset bucket; the priority is to have a resilient total portfolio. Intra-asset class diversification is not valuable if its results can be mirrored by adding stocks or bonds to the mix: that's where inter-asset class diversification should come into play. Secondly, these arguments tend to overlook the most significant challenge: implementation.

## A Changing Industry Landscape

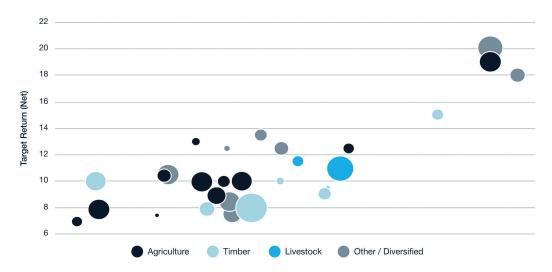
Build it, buy it or brand it, many asset managers have now established Real Assets units in a bid to take advantage of industry trends.

Ten years ago, it would have been hard to name a Head of Real Assets at a major asset management firm. Today, the role is a common one as divisions bearing this label have sprung up at most global asset managers. This nominal change has frequently been accompanied by the establishment of new asset classes and products: although many firms had historic expertise in at least one sub-sector, additional teams have been developed or acquired to flesh out the wider suite.

Meanwhile, specialist real estate or infrastructure managers have spread into each other's territory and/or other real asset sectors, again through growth, M&A, or a combination of the two. Exhibit 4 illustrates these two variants of real asset managers, alongside two other distinct types: fund of funds and investor-owned houses.



Exhibit 4: The Rise of "Real Assets" Managers



**Exhibit 3: Agriculture/Timber Managers Long-Listed for a Search in November 2017** *Source: Sector in Brief: Agriculture and Timberland, bfinance, November 2017* 

No type is inherently superior but, given the recent organizational overhauls involved, investors should pay close attention to how the real assets function at a prospective manager has evolved. Where the group's constituents have been brought together, they can face significant challenges in overcoming previous silos, developing a strong single leadership and working together on integrated products (including the real asset strategies with allocations to multiple sleeves that are explored next). In the case of mergers, staff turnover can be a significant problem. With acquisitions come risks around integration and the potential loss of key personnel.

### New in Town: Multi-Real-Asset Strategies

A growing number of asset managers are developing a multi real asset capability: delivering several real asset types under one mandate.

With investors creating more holistic real asset portfolios and asset managers developing broader divisions, it is perhaps logical that diversified real asset mandates would be the next step. These can be implemented in a range of different ways.

During 2017-18, bfinance has supported a number of investors with searches for "diversified real assets" managers. These have varied significantly in terms of preferred sub-sectors and implementation approach. A small minority of investors appear to be interested in integrating real estate and infrastructure in this manner. More popular is the single mandate for a range of niche real assets. Such mandates have necessitated fresh approaches to the market, with few "off the peg" solutions.

Structures fall into three primary categories: pooled funds, 'fund of in-house funds' and 'fund of external funds' (classic fundof-funds). Pooled funds blending real estate and infrastructure are relatively rare (Exhibit 5), but there is a substantial group of managers offering wrappers around in-house products to achieve this effect. Meanwhile, pooled funds for multiple niche real assets are somewhat more mainstream. Some of these niches were very esoteric indeed: the likes of pharmaceutical intellectual property and music catalogue royalties stretched 'real asset' definitions to the limit. The allocation approach for 'fund of in-house funds' varies considerably. In some cases, an internal team allocates clients' assets to the funds. In other cases, managers offer a passive allocation (e.g. 50/50 between two funds).

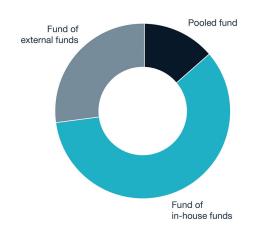
What are the pros and cons of different 'multi-real-asset' structures? Each of the three structures shown in Exhibits 5 and 6 have strengths and pitfalls. 'Funds of external funds' tend to be the most expensive, due to the double layer of fees, but the increasing use of secondary and co-investment strategies can help to cut the fee load. When a manager structures a wrapper around its own funds there is generally no additional layer of fees versus a pooled fund (Exhibit 7). Meanwhile, pooled fund charges are on a par with single-sector versions of the strategies.

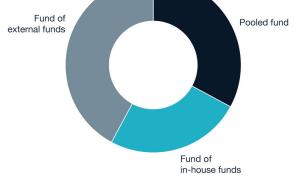
Analysis of track records and teams can be tricky for 'fund of inhouse funds,' since track records are composites of products and thus not highly representative, while pooled funds tend to have short live track records.

Alignment of interest should be watched with care: where an allocation capability exists, it is not always clear that clients' assets are being invested in the sub-funds in a manner that best suits their interests as opposed to the manager's fundraising timeline. In comparison, it is more straightforward to assess alignment of interest for pooled funds.

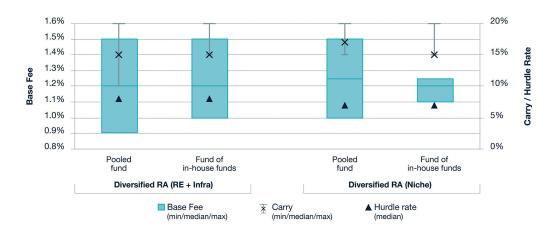
Customization is critical to real assets; this is a label that means very different things to different investors. Here, fund of in-house funds may have a customization edge. Their ability to piece together chunks of sub-funds can match well with the varying nature of investors' demands. The potential downside, however, is the narrower opportunity set.

It is worth noting that very few multi real asset strategies exploit one potential advantage of breadth: taking a more tactical view on current market dynamics and pricing. In our analysis, the allocation teams for wrapper products are not generally engaging in this type of decision-making.





**Exhibit 5: Available Structures, £50m Diversified Assets Mandate (Real Estate and Infrastructure)** *Source: bfinance manager analysis, 2018*  **Exhibit 6: Available Structures, Diversified Real Assets Mandate (Niche Real Assets)** *Source: bfinance manager analysis, 2018* 



**Exhibit 7: Quoted (Pre-Negotiation) Fees for Real Assets Strategies Shown in Exhibits 5-6** *Source: bfinance* 

As always in this sector, investors should beware of the labels. For example, one real estate manager pitched a strategy incorporating 'social infrastructure,' – a term traditionally associated with availability-based payments from the public sector but, in this case, applied to nursery site freeholds and urban car parks with long-term corporate leases.

# Client Demand and the Importance of Customization

Over the past year we have worked with a variety of pension funds, foundations and other clients on implementing real asset investments, either broadly or within particular sectors. They range from institutions with extensive experience across many of the sectors detailed in Exhibit 2 to others that are far less familiar.

In general, where clients are relatively new to the asset class, we do encourage them to start with more traditional property and infrastructure, but with an eye to building potential exposure to other sectors over the long term.

For institutions that are highly advanced in their approaches due to a long experience with different genres of real asset investment, including some Australian and Canadian clients, we could also draw a general conclusion: the main priority has been building complementary niche exposures around the traditional strategies, such as water titles and royalties.

Yet generalizations should always be treated with caution. Investors' needs from real asset investments vary widely, even for institutions of the same type and size in the same country with an equivalent level of experience. For example, we have recently assisted very similar UK institutional clients with nominally similar projects targeting Diversified Real Assets (as in Exhibits 5 and 6). These institutions have been seeking real assets as part of their equity diversification strategy and looking for decent returns, with ESG as an important consideration. Yet the resulting implementation has been very different depending on the investor.

In that example, it was particularly helpful to research a large universe of managers that offered a wide range of strategy types and flavors, ranging from more traditional and well-established sectors to niches such as agriculture, timberland, transportation assets and even leisure parks. As well as ensuring breadth of choice, we worked closely with each client to understand their preferences and answer the key questions: "how is this going to fit with my existing portfolio?"; "how will this achieve our objectives?"

The project reinforced what is perhaps the most important lesson in this sector: 'real assets' is only a label; what's inside the tin is what matters.

### Conclusion

- The concept of the "real asset," "tangible asset" or "inflation-sensitive" portfolio, firmly established in certain asset owner circles, has gained ground in recent years. While the post-GFC phase was marked by diversification toward real assets, later years have seen greater emphasis on diversification within real assets.
- The new mindset prioritizes characteristics or risk factors rather than labels. Yet, as is becoming increasingly clear late in the cycle, these characteristics are not hard-wired to real assets. Current conditions have produced greater tensions between particular traits, such as 'yield' and 'low correlation to equities.'
- Diversification within real assets can be useful in theory. Yet implementation is the critical challenge. Many investors are building out diversified real asset exposures directly. Managers are changing the way they deliver these strategies, including taking advantage of their new organizational breadth across this space.

#### **Author Bio**



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Peter Hobbs is Managing Director of Private Markets and a member of the Senior Management Team. His division covers Real Estate, Infrastructure, Private Equity and Private Debt, providing a range of services including portfolio design, manager selection and due diligence. Peter has over

25 years of both principal investing and research experience. He joined bfinance from MSCI where he was Managing Director for Real Estate Research and Key Global Accounts, responsible for portfolio analysis, benchmarking and risk services. Prior to this, he held roles with IPD, RREEF (the alternatives asset management division of Deutsche Bank) and Property & Portfolio Research. In 2015 he was shortlisted for Outstanding Industry Contribution at the IPE Real Estate Global Awards. Peter has a PhD and is a member of the Royal Institution of Chartered Surveyors (MRICS).



## **Guy Hopgood** *bfinance*

Guy is a Senior Associate within the Private Markets team, having joined bfinance as an Associate in June 2016. He joined from JLT Investment Consulting, where he was an Investment Consultant and Head of Alternatives Manager Research, advising clients on portfolio construction

and manager selection across alternative asset classes. Guy is responsible for manager research, evaluating investment proposals and analysing track records and other financial information provided by fund managers. He primarily focuses on infrastructure, real estate and other real asset strategies such as agriculture and timber. Guy graduated with an Economics degree from Rollins College in the US having also spent part of his course studying in Shanghai, China.

#### A b A 2 c I I I I I

#### Anish Butani, bfinance

Anish Butani joined bfinance in April 2017 to provide specialist coverage to clients seeking to deploy capital to the Infrastructure sector and support initiatives in Real Estate and Private Equity Markets. Anish has over 10 years of experience in total, which included 8 years with KPMG

Corporate Finance based in London, where he was a senior member of the infrastructure corporate finance team. Anish has significant experience acting as an M&A and valuations advisor to global infrastructure fund managers across all sub-sectors in the asset class, including renewable energy, regulated utilities, transport and social infrastructure.

Prior to joining bfinance, Anish was at John Laing Group plc, the international investor in infrastructure, where he was responsible for leading and shaping divestment processes of their infrastructure project portfolio. Anish has a degree in Economics, Politics and International Studies from Warwick University.



# Kathryn Saklatvala, bfinance

Kathryn joined bfinance in 2016 and oversees the firm's publications, thought leadership and investment content. An experienced writer, editor and researcher focused on investment management and institutional investors, Kathryn was previously a Managing Editor at

Euromoney Institutional Investor. She holds a BA (Hons) and an MA from the University of Cambridge. Other previous roles include Editor of the Institutional Investor Networks, Director of the Sovereign Investor Institute and Associate Director of the European Institute. She has spoken and moderated at various industry conferences (OECD, World Bank Group, AVCA, IRN, Institutional Investor), been quoted occasionally in the press (Financial Times, Responsible Investor, Citywire) and been interviewed by the BBC on sovereign wealth fund trends.

# A Crisis of Beliefs: Investor Psychology and Financial Fragility, An Interview with Andrei Shleifer

Barbara J. Mack Pingry Hill Enterprises, Inc.

Over t

### Andrei Shleifer

Harvard University

#### Overview

Over the past ten years, many books about the financial crisis have been published, including first-person accounts from Henry Paulson and Tim Geithner, post mortems by bankers and other industry participants, and analyses by a full spectrum of economists and academics. Rounding out the collection are government documents, including the 662-page *Financial Crisis Inquiry Report*.

As deep and broad as the coverage has been, one of the latest additions to the growing literature on the subject offers a new and profound perspective. In *A Crisis of Beliefs*, Andrei Shleifer, professor of economics at Harvard University, and Nicola Gennaioli, professor of finance at Bocconi University in Italy, cover themes that lie at the intersection of finance, economics, and public policy. Their work blends both philosophical observations and behavioral economics to evaluate the events and attitudes leading up to the GFC.

The book has been very well-received, with strong positive reviews in a number of major news outlets noting the unique nature of the work. In *The New York Times*, for example, Robert J. Shiller commented, "Focusing on the stock market, Professor Gennaioli and Professor Shleifer demonstrate how changeable expectations for the future really are. People tend to believe that recent changes will continue, whatever they may be, and then, when things shift, they change their expectations again."<sup>1</sup> This type of mental adjustment influences behavior, from individual and household decision-making to macroeconomic perspectives and public policy formulation.

Among other accolades, the *Financial Times* recently featured *A Crisis of Beliefs* on its lists for the "Best Books of the Year 2018: Economics" and the "Readers' Choice Best Books of the Year."

We had a chance to discuss the key lessons from the book with Professor Shleifer recently.

#### Interview

BJM: We know that there are many views on the events and aftermath of the GFC. What were some of your reasons for writing the book?

AS: The book has two principle motivations. First, we wanted to gain a better understanding of what happened in 2007 and 2008. Why was this crisis so severe and why did it lead to the Great Recession?

Second, we wanted to show that all of these ideas about credit cycles, exuberance, and neglect of risk, which are somewhat ephemeral and lie in the domain of economic historians, can also be discussed and analyzed with standard economic models.

BJM: What were some of the main misunderstandings about the crisis, in retrospect?

AS: We find two that were of central importance. One common misperception in the public's mind (and widely disseminated in the media) has been that the crisis could be attributed almost completely to moral hazard and the "too big to fail" scenario. This was based on the idea that the banks had somehow conspired to trick everybody with defective mortgages because they knew that in the end there was going to be a government bailout. That is simply not accurate.

There were many actors in the housing bubble and subsequent crisis and they were all involved at the same time: the consumers who used credit cards and the households that bought homes, the banks that lent money to those people, the financial industry that created mortgage-backed securities (MBS), and the investors that purchased them. And perhaps most importantly, the policy-makers who, as the bubble was growing, were all betting on the notion that the housing markets would continue to do well. Then, when the bubble started to deflate, they were all betting on the notion that the system was robust enough to survive. This is not to say that there wasn't bad behavior going on as well, but the situation was far more complex than that.

The second, more profound misconception is the view that the financial crisis came out of the blue, unforeseen. The book documents how the '07-'08 crisis was actually developing for a long time: it began when the housing bubble start to deflate, leading to losses on the MBS and reductions in the value of mortgages held by banks. These were leading indicators of the financial collapse to come. Given the effects rippling through the system in those early days, the full scope of the financial crisis could not have been anticipated with certainty, but it was clear early in 2008 that there was serious trouble ahead. Yet we see a serious lack of appreciation for how fragile the system really was and then there was a panic after Lehman.

BJM: This is reminiscent of the dot-com bubble, at some point the question was not if it would burst, but when.

AS: Yes, exactly. But the difference between the dot-com bubble and the financial crisis was the scope of the damage – for the dot-com bubble naturally it affected the tech sector, investors, and some companies that went out of business. However, no major financial institutions were threatened during that period. There was a mild recession in 2001 and then we emerged. In the financial crisis, those institutions were highly exposed to the consequences of the housing bubble, the subsequent panic, and the great recession. The events were not just hitting a single sector of the economy; they were tackling the entire system all at once.

BJM: What are some of your key takeaways for economists, policy makers, and investors?

AS: For economists, we advise: "Yes, you can." Which is to say that you can think about the problems of financial stability while using the tools of standard macroeconomics.

For policymakers, we show that it is best to act as early and as aggressively as possible. The idea that you should not do anything until a Lehman-type event happens is incorrect. As we see, they could have started preparing in early 2007 – by telling the banks not to pay dividends, compelling them to raise equity and shore up their balance sheets, for example. All of the policies would have been effective and so the issue becomes one of planning and action before a crisis, not during and afterwards.

For investors, we would say that if it looks like a bubble and feels like a bubble, it probably is a bubble. Deflation can come slowly, but if valuations seem to be unrelated to fundamentals, then it is probably a good idea to start getting out.

**BJM:** One of the common themes for investors comes back to diversification and these days there are more vehicles – from traditional alternatives to newer forms accessible through '40 Act funds and UCITS. What would you say to CAIA members who are evaluating the options for their clients?

AS: As we now know, during a crisis many of these assets become more highly correlated than they are under normal circumstances. So, the elements that might typically be diversifying – European debt, emerging market debt, private equity – may not be that helpful after all. However, this does not mean that one should sell everything in a panic. Some of the most sophisticated investors, including university endowments, chose to liquidate after Lehman in late 2008 and early 2009. That turned out to be a very costly decision for those institutions. So, we would say, "Observe carefully and act in advance, but not in a hurry."

BJM: Very good – thank you for your time.

This book covers a range of errors in beliefs in a compelling technical and analytical framework, so there is plenty of food for thought on these and many other issues related to the GFC. As economic historian and UCal-Berkeley professor, J. Bradford de Long noted on his blog, "For a decade now, people have been looking for a silver lining to the disasters of 2008-2018, hoping that this period will bring about a more productive integration of finance, behavioral economics, and macroeconomic orthodoxy. So far, they have been searching in vain. But with the publication of *A Crisis of Beliefs*, there is hope yet."<sup>2</sup> We would agree – there is always hope!

A Crisis of Beliefs: Investor Psychology and Financial Fragility, by Nicola Gennaioli and Andrei Shleifer on Princeton University Press https://press.princeton.edu/titles/14150.html and on Amazon https://www.amazon.com/Crisis-Beliefs-Psychology-Financial-Fragility/dp/0691182507.

#### Endnote

- "Why Our Beliefs Don't Predict Much About the Economy," by Robert J. Shiller, *The New York Times*, Economic View, October 12, 2018. https://www.nytimes. com/2018/10/12/business/why-our-beliefs-dont-predictmuch-about-the-economy.html.
- 2. "Self-Fulfilling Financial Crises," by J. Bradford DeLong, via *Project Syndicate*, October 15, 2018. https://www. project-syndicate.org/commentary/crisis-of-beliefs-andthe-2008-crash-by-j--bradford-delong-2018-10.

### **Author Bios**



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Andrei Shleifer is John L. Loeb Professor of Economics at Harvard University. He holds an undergraduate degree from Harvard and a Ph.D. from MIT. Before coming to Harvard in 1991, he has taught at Princeton and the Chicago Business School. Professor Shleifer has worked in the areas

of comparative corporate governance, law and finance, behavioral finance, as well as institutional economics. He has published seven books, including *The Grabbing Hand: Government Pathologies and Their Cures* (with Robert Vishny), *Inefficient Markets: An Introduction to Behavioral Finance*, and *A Crisis of Beliefs: Investor Psychology and Financial Fragility* (with Nicola Gennaioli), as well as over a hundred articles.

Professor Shleifer is an Editor of the *Quarterly Journal of Economics*, and a fellow of the Econometric Society, the American Academy of Arts and Sciences, and the American Finance Association. In 1999, he won the John Bates Clark medal of the American Economic Association. According to RePEc, he is the most cited economist in the world.



#### **Barbara J. Mack** *Pingry Hill Enterprises, Inc.*

Barbara J. Mack is founder and president of the consulting firm Pingry Hill Enterprises, Inc. For over fifteen years, she has worked as a consultant, editor, writer, and researcher on projects involving alternative investments, international economics, and technological innovation. Her previous

work experience includes appointments as a case writer at Harvard Business School and a research affiliate at the Computer Science and Artificial Intelligence Lab (CSAIL) at MIT.

Barbara has a Masters degree from Harvard University's Kennedy School of Government, with a focus on law and policy in the European Union. She also has a Bachelor of Arts from Tufts University, where she focused on English Literature, Anthropology, and Fine Art.



# The CAIA Endowment Investable Index

## Hossein Kazemi

**Kathryn Wilkens**, CAIA Pearl Quest

#### We present the historical weights, allocation as of month-end December 2018, and historical performance to the replication portfolio that was introduced in our AIAR publication Volume 6 Issue 1.

The graph on the following page shows the exposures of the Multi-Asset ETF portfolio through time. It is important to note that the volatility displayed by these exposures does not imply that endowments alter their asset allocations as frequently as the Multi-Asset ETF portfolio. While an endowment may hold a fixed allocation to various asset classes, the underlying assets/manager may display time-varying exposures to different sources of risk. For instance, a hedge fund manager may decide to increase her fund's exposure to energy stocks while reducing the fund's exposure to healthcare stocks. Though the endowment's allocation to that manager has remained unchanged, its exposures to energy and healthcare sectors have changed. Also, if returns on two asset classes are highly correlated, then the algorithm will pick the one that is less volatile. For instance, if returns on venture capital and small cap stocks are highly correlated, then the program will pick the small cap index if it turns out to be less volatile.



**Hossein Kazemi,** *Ph.D., CFA CAIA Association Isenberg School of Managment, University of Massachusetts Amherst* 

Dr. Hossein Kazemi is the Senior Advisor to the CAIA Association's Program. Dr. Kazemi has been involved with the CAIA Association since its inception as a senior advisor

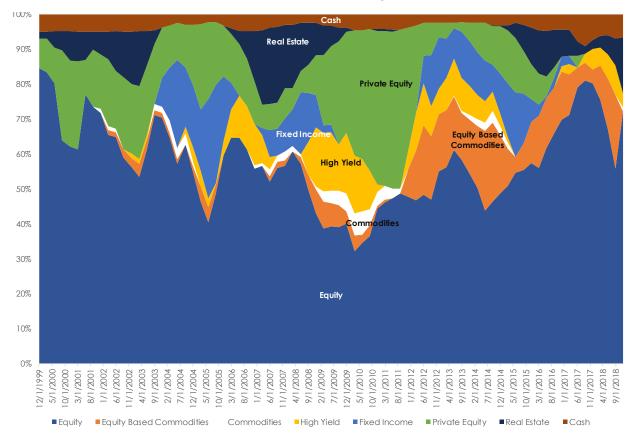
and a managing director. In his current role, he helps with the development of the CAIA program's curriculum and directs the CAIA Association's academic partnership program. In addition, he serves as the editor of *Alternative* Investment Analyst Review, which is published by the Association. He has worked with universities and industry organizations to introduce them to the CAIA program. Dr. Kazemi is Michael and Cheryl Philipp Distinguished Professor of Finance at the Isenberg School of Management, the University of Massachusetts - Amherst. He is the Director of the Center for International Securities & Derivatives Markets, a nonprofit organization devoted to research in the area of alternative investments, a co-founder of the CAIA Association, and home to CISDM Hedge Fund/ CTA Database and the Journal of Alternative Investments, the official research publication of the CAIA Association. He has over 25 years of experience in the financial industry and has served as consultant to major financial institutions. His research has been in the areas of valuations of equity and fixed income securities, asset allocation for traditional and alternative asset classes, and evaluation and replication of active management investment products. He has a Ph.D. in finance from the University of Michigan.



#### **Kathryn Wilkens,** *Ph.D., CAIA Pearl Quest LLC*

Kathryn Wilkens is the president and founder of Pearl Quest LLC, a consulting company currently focused on tracking and replication products, and educational services in the alternative investments space. She is also an RIA with S Capital Wealth Advisors and assistant editor for the *Journal of Alternative Investments*.

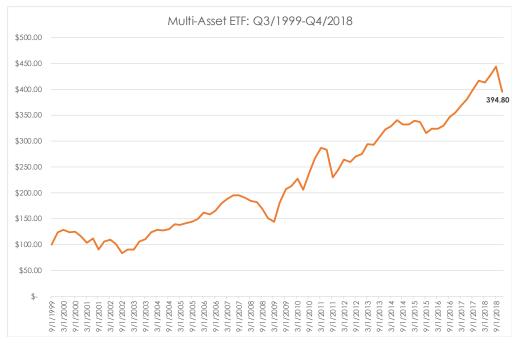
#### **Endowment Index Weights**



#### Allocation Suggested by Algorithm

|              |            |            | Materials | Energy    | Health Care | BBgBarc US    | SPDR® Dow   |            |
|--------------|------------|------------|-----------|-----------|-------------|---------------|-------------|------------|
|              | Power      |            | Select    | Select    | Select      | Corporate     | Jones       | Cash &     |
| Russell 2000 | Shares QQQ | MSCI World | Sector    | Sector    | Sector      | High Yield TR | Global Real | Short-Term |
| ETF          | ETF        | Free ETF   | SPDR® ETF | SPDR® ETF | SPDR® ETF   | USD           | Estate ETF  | Treasuries |
| 24.3%        | 8.2%       | 33.9%      | 2.4%      | 3.4%      | 1.2%        | 4.0%          | 16.0%       | 6.6%       |

#### **Historical Performance**





# The List: Alternative Indices

The performance table, on the following page, is a collection of both traditional and alternative indices for the 1, 5, and 10-year period annualized through December 2018. Both the annualized volatility and draw-down figures are calculated using a 10 year quarterly return series.

Alternative investments have been growing markedly over the past few years, creating a multitude of opportunities for owners and allocators alike. As the number and type of alternative asset classes continue to proliferate, we believe they are playing a more unique role in assisting investors achieve their desired investment outcomes. As we expect this trend to continue, we found it necessary to structure a pure alternative assets portfolio to have visibility in this exciting marketplace.

We set out to strike a balance between available assets in proportion to their market value, and to reflect the average "alternative investor". We defined the investment opportunity to simply be the following three assets classes: Real Asset, Private Equity/Venture Capital, and Hedge Funds. Real assets are comprised of real estate, commodities, timberland, farmland, infrastructure, bank loans, and cat bonds; within real asset the weights were structured to reflect the market portfolio<sup>1</sup> within that universe. To arrive at our weight's, we researched various endowments and foundations, as well as surveys conducted by Willis Towers Watson and Russell Investments. Based on our research, alternative historical allocations have not had material deviation and therefore we decided to implement a market weight of 1/3 across each of those asset classes. A few of the constituents are not investable, and some may be reported gross or net of fee.

#### Ending March 2018

|                                     | <u>1 Yr</u>   | <u>5 Yr</u> | <u>10 Yr</u>  | <u>Ann. Vol</u> | <u>10 Yr Max</u><br>Drawdown |
|-------------------------------------|---------------|-------------|---------------|-----------------|------------------------------|
| MSCI World Free                     | -7.44%        | 5.52%       | 11.07%        | 15.39%          | -16.52%                      |
| Barclays Global Agg                 | -1.15%        | 1.22%       | 2.61%         | 5.60%           | -7.17%                       |
| MSCI Emerging Markets               | -15.10%       | 2.61%       | 9.67%         | 19.97%          | -23.90%                      |
| Barclays Global High Yeild          | -4.04%        | 3.44%       | 11.14%        | 10.65%          | -8.27%                       |
| HFRI Fund Weighted Composite        | -4.68%        | 2.19%       | 5.00%         | 6.09%           | -7.63%                       |
| CISDM EW Hedge Fund                 | -4.71%        | 2.93%       | 6.02%         | 6.80%           | -7.84%                       |
| CISDM CTA EW                        | -5.66%        | 3.75%       | 2.92%         | 6.35%           | -7.94%                       |
| CISDM Distressed Securities         | -0.86%        | 2.69%       | 7.00%         | 5.94%           | -7.08%                       |
| CISDM Equity Long/Short             | -6.27%        | 2.88%       | 5.68%         | 6.89%           | -8.79%                       |
| CA US Private Equity**              | 17.29%        | 13.06%      | 11.94%        | 8.08%           | -4.19%                       |
| CA US Venture Capital**             | 18.24%        | 14.54%      | 10.99%        | 8.09%           | -3.41%                       |
| LPX Mezzanine Listed Private Equity | -1.99%        | 5.34%       | 14.42%        | 27.90%          | -37.79%                      |
| FTSE NAREIT All Equity REITs        | -3.36%        | 8.70%       | 14.18%        | 21.11%          | -31.87%                      |
| NCREIF Property                     | 6.98%         | 9.26%       | 6.43%         | 5.71%           | -23.75%                      |
| S&P Global Property                 | -11.06%       | 1.69%       | 8.09%         | 18.81%          | -20.92%                      |
| S&P Global Infrastructure           | -13.71%       | 0.64%       | 4.27%         | 14.72%          | -18.18%                      |
| Bloomberg Commodities               | -11.43%       | -8.13%      | -2.75%        | 14.91%          | -53.55%                      |
| NCREIF Timberland                   | 3.94%         | 5.91%       | 4.01%         | 3.61%           | -5.69%                       |
| NCREIF Farmland                     | 6.67%         | 9.63%       | 11.27%        | 4.85%           | 0.00%                        |
| Alternative Assets Portfolio ***    | <b>2.69</b> % | 5.88%       | 7.08%         | <b>3.2</b> 1%   | <b>-2.40</b> %               |
| Global 60/40                        | -4.92%        | 3.80%       | <b>7.69</b> % | 1 <b>0.23</b> % | <b>-9.52</b> %               |
| 60% Alternative / 40% Global 60/40  | -0.35%        | 5.05%       | 7.32%         | <b>6.02</b> %   | <b>-4.18</b> %               |

NOTE: All returns are calculated using arithmetic mean

\*\* Lagging by One Quarter

\*\*\* As of Quarter Ended 12/31/2018

Source: CAIA, CISDM, HFRI, Cambridge Associates and Bloomberg

1. Global Invested Capital Market by Hewitt EnnisKnupp, an Aon Company



Founded in 2002, the Chartered Alternative Investment Analyst (CAIA) Association is the global authority in alternative investment education. The CAIA Association is best known for the CAIA Charter®, an internationally recognized finance credential and the gateway to a network of more than 10,000 alternative investment leaders in more than 95 countries.

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