A diversification too far

Strategies that hurt ARP funds in 2018 did better but some cancelled out last year, write Luc Dumontier and Guillaume Garchery

After undershooting risk-free returns by more than 6% on average in 2018, alternative risk premia (ARP) funds made a modest recovery last year. The SG Multi Alternative Risk Premia (MARP) index, which includes returns for the 10 largest multi-asset, multi-alternative risk premia investment funds, posted an excess return over the Federal Funds Rate of +1.7%.

Could they have done better, though? Should they have?

Equity premia, equity index short volatility strategies, cross-asset trend following and emerging currency carry trades were blamed for funds' dismal time the year before. Only equity premia continued to see mixed performance in 2019, though. The other strategies rebounded strongly (see figure 1).

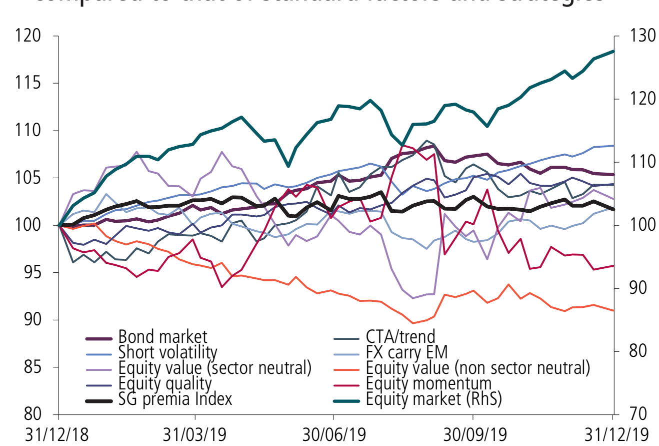
Individual funds, meanwhile – selected as being the most representative of the ARP industry – registered excess returns ranging from -9.5% to +12.3% (see figure 2).

Funds gathered into groups with similar paths of returns that appeared independent of the common trend. The three best-performing funds were up +3.0% while the three worst-performing were down -2.8% in May and June, for example, while the SG MARP index was almost flat.

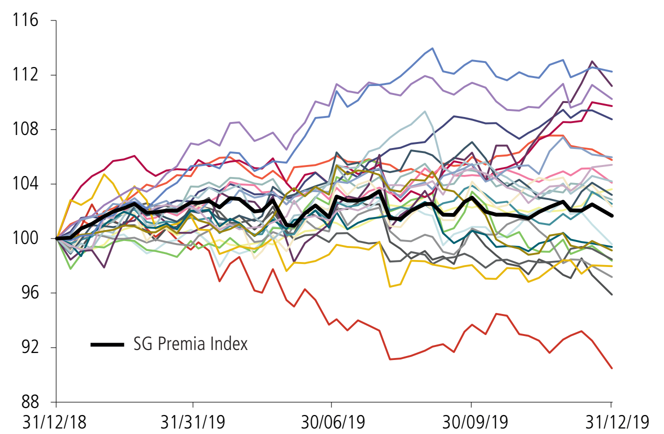
How can these co-movements and the performance of individual funds be explained?

To answer these questions, we applied the same two-step methodology used to explain 2018 performance.[1] First, we performed a principal component analysis (PCA) across individual funds to identify common

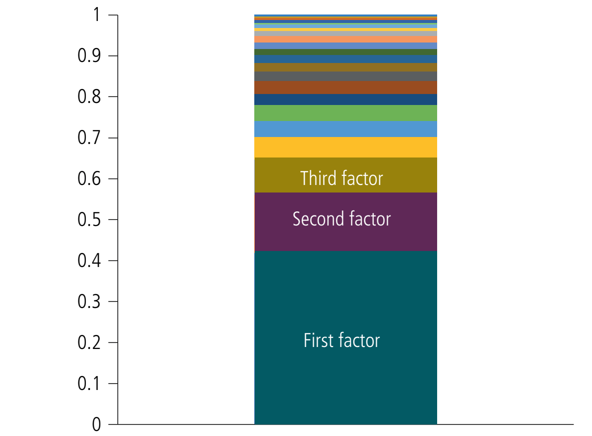
1 The rebound of the ARP industry in 2019 seems modest compared to that of standard factors and strategies



2 Individual funds posted very heterogeneous performance, but groups of funds with similar path of returns do exist



3 Three factors explained two-thirds of the variance of the individual funds



factors. We then regressed those factors on the standard ARP strategies to determine the factors' composition.

Figure 3 shows the percentage of the variance in fund performance explained by the PCA factors.

On average, 42%, 14% and 9% of the risk of the funds is explained by the first, second and third factors, respectively. By comparison, the first factor was even more predominant in 2018, explaining almost 50% of the average variance, while the second and third factors explained only 11% and 7%, respectively.

Figure 4 depicts these factors as baskets of underlying funds. The first factor is a long-only fund portfolio while the others are long/short portfolios. By construction, each basket of funds has no beta versus the others.

Figure 5 shows the exposure of ARP funds to the factors. All funds have a positive beta versus the first factor, from 0.1 to 1.7.

PCA factor secrets

What do these PCA factors comprise?

Let's start with the first factor. We ran five independent regressions, each considering a different set of explanatory variables comprising the main strategies generally accepted as part of ARP funds. Table A shows the results.

To ensure comparable results, annual volatility is scaled to 5% for each explanatory variable. The first column – "Reg 1" – shows results of a regression of the first PCA factor versus the equity market only. The R-squared is low meaning that most of the risk of the first factor is explained by factors other than the equity market.

The second column – "Reg 2" – shows the results of a regression versus the strategies that are generally blamed for poor performance in 2018.

Apart from the carry strategy on emerging currencies, the betas to the other strategies, as well as the R-squared, are almost in line with 2018 results. In other words, the same strategies were the main drivers of risk and return for the ARP industry in 2019 and 2018.

The third column – "Reg 3" – shows that results are almost the same if the carry strategy on emerging currencies, which had a negative beta in the previous regression, is removed from the analysis.

For the fourth regression – "Reg 4" – we considered each equity investment style – value, quality and momentum – independently, rather than equally weighting them within a single factor.

The results here are interesting. They indicate that the ARP industry over-weighted value and momentum, with their similarly high betas of 0.75 and 0.77, respectively, compared with quality, with a much lower beta of 0.28.

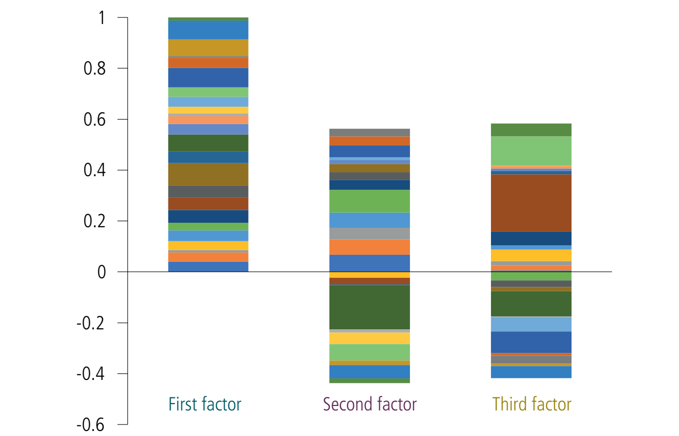
However, when value and momentum are

A. The risk of the first PCA factor is almost fully explained by the same factors/strategies as in 2018

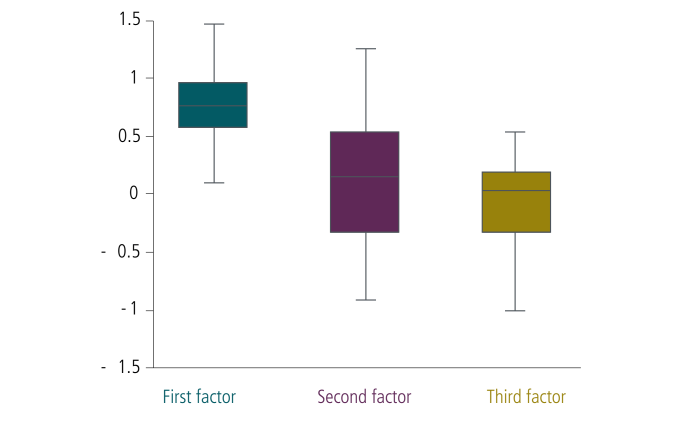
		Reg 1	Reg 2	Reg 3	Reg 4	Reg 5
Alpha (weekly)		-0.06%	-0.11%*	-0.10%*	-0.13%*	-0.12%*
Beta	Equity market	0.35**	0.41**	0.39**	0.36**	0.43**
	CTA/trend	-	0.34**	0.37**	0.36**	0.35**
	Short volatility	-	0.08	0.03	0.08	0.00
	FX carry EM	-	-0.13	-	-	-
	Equity factor	-	0.26**	0.27**	-	-
	Equity value	-	-	-	0.75**	-
	Equity quality	-	-	-	0.28**	0.27**
	Equity momentum	-	-	-	0.74**	-
R-squared		37%	74%	74%	78%	75%
Adjusted R-squared		10%	63%	63%	68%	64%
Correlation v first PCA factor		45%	83%	81%	85%	81%
Excess return		1.4%	1.4%	1.4%	1.4%	1.4%
Standard deviation		1.7%	3.2%	3.2%	3.3%	3.2%
Sharpe ratio		0.8	0.4	0.4	0.4	0.4

Note: ** and * indicates the variables are significant at 99% and 95% level
Source: See end of article

4 Factors made of long-only and long/short baskets of funds



5 Funds varied in their exposure to the PCA factors



removed from the regression, as shown in the fifth column – "Reg 5" – the results are in line with "Reg 3" where the whole equity factor – i.e. equally weighting the three investment styles – is considered rather than quality alone.

This is because value and momentum tended to offset each other in 2019. Figure 6 shows this as of mid-September when the effect was most pronounced. Each stock in the S&P 500 index is represented by a green dot. The x-axis ranks the stocks by momentum, based on performance over the past 12 months excluding the most recent month, and the y-axis shows the ranking in terms of value, by earnings yield.

The correlation between these rankings was -56%. In other words, momentum was almost the exact opposite of value. Combining the two would have delivered a result close to zero – a good example of overdiversification risk.

Investment managers that failed to account for this effect missed out on two opportunities in 2019. Incidentally, correlation levels subsequently fell to -30% at the end of December, indicating that value was once again diversifying versus momentum and vice versa.

The weekly alpha of the regressions ranges from -6 bps to -13 bps, or between approximately -3% and -6% annually. These highly significant figures are in line with those of 2018 and can be attributed to portfolio management choices, including different implementation of the selected strategies; dynamic allocation between strategies or additional returns from the part of the risk that is unaccounted for; or costs including management fees and transactions costs.

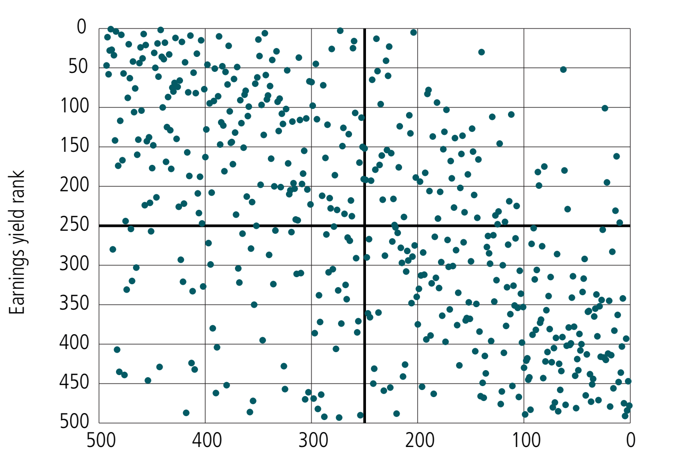
Figure 7 shows the cumulative performance of the first PCA factor versus replication portfolios constructed in line with the betas of the five regressions and considering their respective alphas.

These beta-weighted baskets resemble the performance of the overall ARP industry, further indicating that the industry remained highly exposed to the same factors as in 2018. All the replication portfolios are strongly correlated to their underlying factor and all have a Sharpe ratio around 0.4.

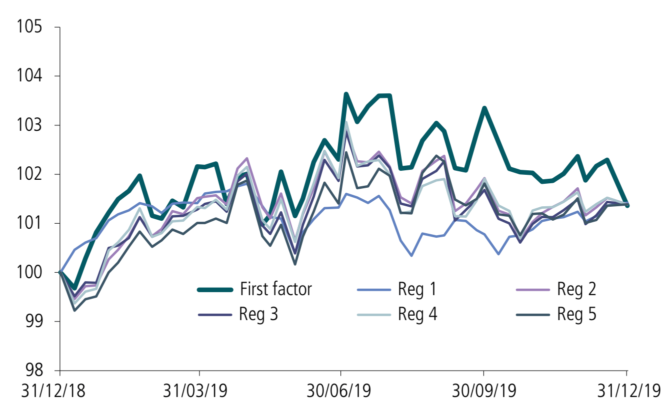
Let us now turn our attention to the second PCA factor which, as a reminder, explained on average 14% of the variance among funds in 2019.

We performed the same regression exercise, but this time with the government bond market as an additional variable (see table B). "Reg 1" considers the full set of explanatory variables. As with the regression of the first PCA factor, we excluded the offsetting equity value and momentum factors in the second regression "Reg 2". Finally, as the betas of the short

6 Correlation between value and momentum ranks for S&P 500 stocks reached -57% in September 2019



7 Replication portfolios of the first PCA factor look like the performance of the overall ARP industry



B. The second PCA factor is strongly exposed to bonds

		Reg 1	Reg 2	Reg 3
Alpha (weekly)		0.01%	0.01%	0.01%
Beta	Equity market	-0.10	-0.14*	-0.15*
	Bond market	0.30**	0.27**	0.28**
	CTA/trend	0.10	0.12*	0.13*
	Short volatility	0.00	0.04	-
	FX carry EM	0.06	0.05	-
	Equity value	-0.44*	-	-
	Equity quality	0.04	0.04	-
	Equity momentum	-0.45*	-	-
R-squared		73%	70%	75%
Adjusted R-squared		61%	57%	64%
Correlation v second PCA factor		83%	80%	80%
Excess return		1.9%	1.9%	1.9%
Standard deviation		2.1%	2.0%	2.0%
Sharpe ratio		0.9	1.0	1.0

Note: ** and * indicates the variables are significant at 99% and 95% level
Source: see end of article

C. The third PCA factor is strongly exposed to both equity and government bond markets

		Reg 1	Reg 2
Alpha (weekly)		-0.01%	-0.02%
Beta	Equity market	0.31**	0.31**
	Bond market	0.28**	0.26**
	CTA/trend	-0.17*	-0.20**
	Short volatility	-0.03	-
	FX carry EM	0.05	-
	Equity value	-0.26	-
	Equity quality	-0.10	-
	Equity momentum	-0.23	-
R-squared		58%	51%
Adjusted R-squared		41%	30%
Correlation v third PCA factor		70%	65%
Excess return		4.1%	4.1%
Standard deviation		1.5%	1.4%
Sharpe ratio		2.7	2.9

Note: ** and * indicates the variables are significant at 99% and 95% level.
Source: see end of article

> "ARP funds that were positively exposed to this factor benefitted a lot from the strong performance of government bonds – either explicitly, or implicitly"

volatility, foreign exchange carry and equity quality strategies were not significant, we also eliminated them in the last regression "Reg 3".

Here we find another interesting result: the second PCA factor resembles a long/short factor comprising equities with a negative beta on one hand and bonds and trend-following strategies with positive betas on the other.

As the average correlation between stocks and bonds was strongly negative in 2019, -36% on average and -46% at the lowest, this factor can be interpreted as a long bond exposure.

Figure 8 shows the cumulative performance of the second PCA factor versus its replication portfolios, allocated in line with the betas of the three regressions and considering their respective alphas. The replication portfolios are strongly correlated to the relevant underlying factor and all having a Sharpe ratio of around 1.

ARP funds that were positively exposed to this factor benefitted a lot from the strong performance of government bonds – either explicitly, or implicitly through the implementation of relative value strategies that were not market neutral – reinforced by the strong performance of trend following.

Indeed, commodity trading adviser (CTA) funds – as represented by the HFRX Macro Systematic Diversified CTA index – gradually increased their exposure to government bonds, positioning that paid off until August 2019. Figure 9 illustrates how closely CTA funds tracked inverted US rates over 2019.

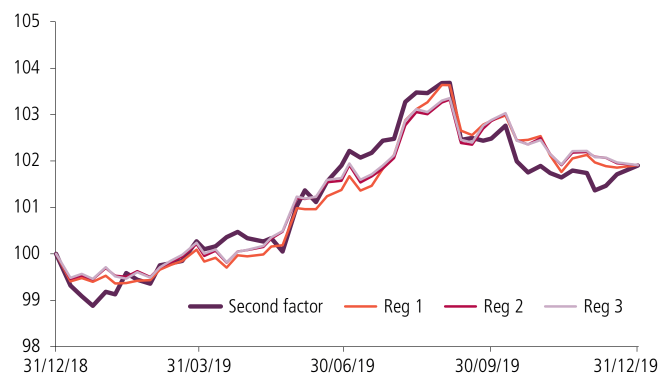
Finally, let us turn our attention to the third PCA factor, which explained 9% on average of the variance among funds in 2019.

We performed the same regression exercise again (see table C). "Reg 1" considers the full set of explanatory variables. Again, we excluded offsetting equity value and momentum factors, as well as low beta, short volatility, forex carry and equity quality strategies in the second regression "Reg 2".

The third factor resembles a long/short factor with positive beta to equities and bonds and negative beta to trend following. As the positive beta to bonds and equities is higher than the negative beta to trend following, the third factor looks rather like a long exposure to an equity/bond risk parity strategy.

The replication portfolios are strongly correlated to their underlying factor (see figure 10), even if the absolute level is lower than for the first two PCA factors. The Sharpe ratio is above 2.5. ARP funds that were

8 Replication portfolios of the second PCA factor look like government bonds



> "The ARP industry benefitted – explicitly or implicitly – from the positive performance of risky asset classes in 2019"

explicitly or implicitly exposed to this factor therefore benefitted significantly from its strong performance. The equity/bond risk parity strategy gained especially from increased negative correlation between equity and government bond markets, levels of which reached -45%.

What have we learned, then? The ARP industry benefitted – explicitly or implicitly – from the positive performance of risky asset classes in 2019. But the rebound would have been greater if the implementation of the strategies had been more efficient.

Additionally, the wide dispersion in fund performance is mainly due to different levels of exposure, via the first three factors, to equities and government bonds.

Lastly, figure 11 shows the distribution of correlation levels between individual funds and the asset classes and factors. This illustrates overdiversification risk of investing in multiple ARP funds. An investor in an equally weighted basket of all individual ARP funds, represented by the large dots, would have been correlated at almost 50% to the equity market and almost 85% to the replication portfolio of the first factor.

The ARP industry's 2019 results show – as in 2018 – that the industry is highly heterogeneous, but investors in multiple funds could end up with naïve and costly exposure to the first factor.

Luc Dumontier is head of factor investing and Guillaume Garchery is head of quantitative research at quantitative investment manager LFIS. This article reflects the authors' opinions and not necessarily those of their staff

Notes:

[1] The common drivers behind alt risk premia's difficult year, *Risk.net, February 5, 2019 (www.risk.net/asset-management/6363596/the-common-drivers-behind-alt-risk-premias-difficult-year)*

Graph and table sources:

Sources: LFIS, Bloomberg, JP Morgan.
SG Premia Index = SG Multi Alternative Risk Premia Index.
Bond market = JP Morgan Broad Index hedged in US dollar.
Equity market = S&P 500 Net Total Return.
CTA/trend = HFRX Macro Systematic Diversified CTA Index.
Short volatility = SGI Vol Premium US.
FX carry EM = DB Emerging Currencies Basket Index.
Equity value (sector neutral), quality and low risk = GDM style factors from JP Morgan.
Equity value (non-sector neutral) = MSCI World (Value - Growth) Net TR index.
The panel of 24 individual funds was created by the authors as being the most representative of the alternative risk premia (ARP) industry.
For funds with only share classes in euros, calculations account for spread between Fed funds and Eonia.
Returns are all considered in excess of Fed funds from December 31, 2018 to December 31, 2019.
Statistical analyses such as PCA, regressions and correlations are performed by LFIS using weekly data from December 31, 2018 to December 31, 2019.
Regressions are performed vs standard factors with annual volatilities scaled to 5%, so the betas are comparable.

Additional information for figure 6:

Each stock in the S&P 500 Index is represented by a green dot. The x-axis ranks the stocks by momentum (based on performance over the last 12 months excluding the most recent month) and the y-axis shows the ranking in terms of value (by earnings yield). Data is as of September 16, 2019.

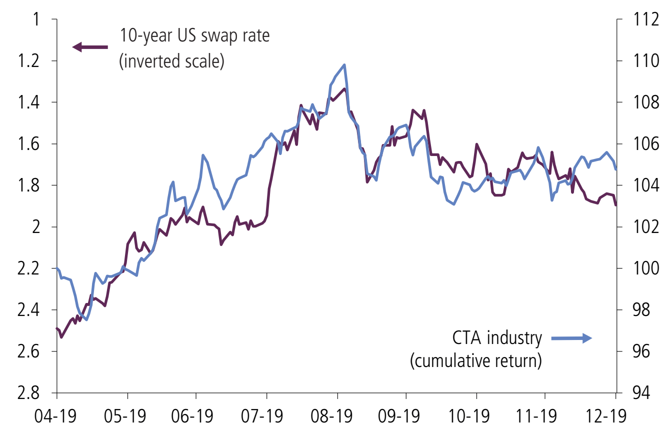
Additional information for figure 11:

First factor replication = "Reg 5" replication portfolio of the first PCA factor.
Second factor replication = "Reg 3" replication portfolio of the second PCA factor.
Third factor replication = "Reg 2" replication portfolio of the third PCA factor.
Equally weighted = Arithmetic average of the returns of the 24 individual funds.

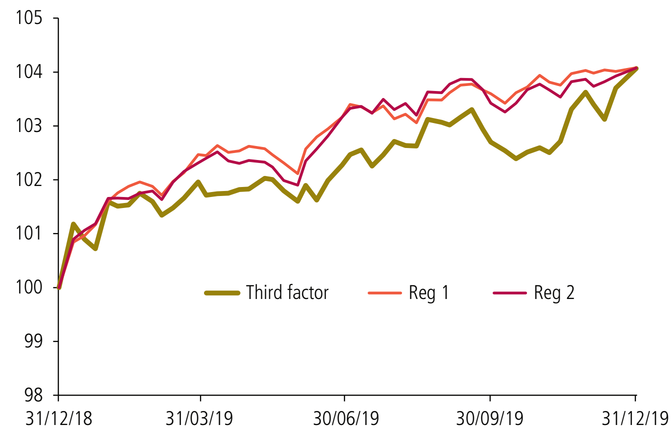
>> Further reading on www.risk.net

- Mirror-image factors are wiping out quant alpha *www.risk.net/7050761*

9 The CTA/trend-following industry delivered returns strongly linked to that of government bonds



10 Replication portfolios of the third PCA factor look like equity/bond risk parity strategies



11 Individual funds displayed significantly different correlations versus the assets classes and PCA factors