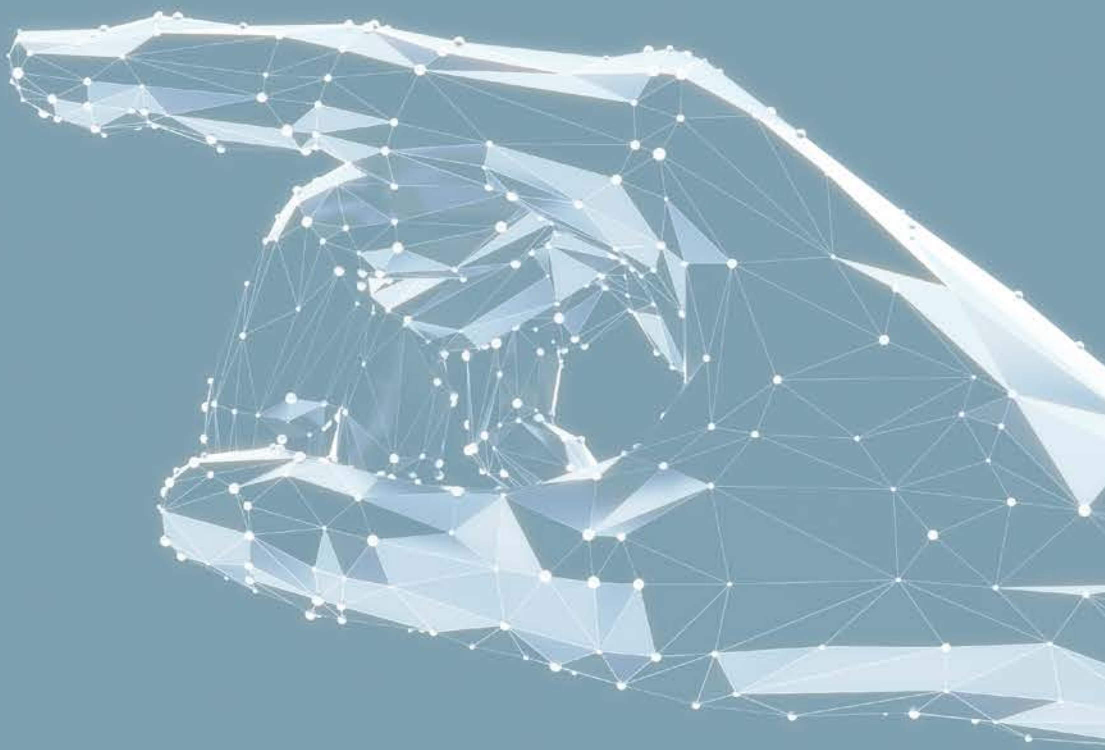
NOT IF, BUT HOW

FIVE

Beyond bonds and equities

Rethinking diversified portfolios to reflect the new investment zeitgeist



FIVE

We believe in numbers.

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Beyond bonds and equities

Rethinking diversified portfolios to reflect the new investment zeitgeist

Traditional balanced portfolios typically combine two classic building blocks: bonds and equities. This asset mix enjoys the reputation of being an all-round investment approach. For a reason, as the risk-adjusted performance of balanced funds has indeed been outstanding in the last decades. The inflows from investors increased accordingly. Balanced portfolios delivered stable returns and relatively good performance in recent stress scenarios when they benefited from decreasing interest rates and comparably high diversification effects.

But can we assume it will continue like this in the future and rely on market dependencies not changing?

In the light of interest rates at record low levels offering probably limited performance potential for bonds, possibly elevated valuation levels in equity markets, a fragile economic growth and emerging trade disputes one might wonder how building diversified portfolios might be improved by adding new sources of return.

Commodities are a frequently mentioned reasonable candidate. But although showing a low correlation to equities and bonds, the prospects of a passive long-only commodity investment to comprise a fundamental risk premium are not that clear. Passive long-only commodities may thus not be an ideal additional source of return. Real Estate and Private Equity are also often added to portfolios, but illiquidity, strong cycles and high(er) transaction costs make those a less favourable choice. Additionally, dynamic risk-management techniques can only be properly carried out in liquid markets.

An increasing number of investors switched to a different approach and started to include investment strategies based on Alternative Risk Premia ("ARP") into their portfolio allocation. ARP-based investment strategies are well-established and -documented approaches following a rules-based trading framework beyond buy-and-hold to extract systematic factor returns from capital markets. These are often originating from structural or behavioural effects. Well-known alternative risk premia include Momentum, Carry or Value. Liquid Alternative Beta ("LAB") investment strategies use long and short positions in the most active financial markets aiming at extracting these alternative risk premia in their purity.

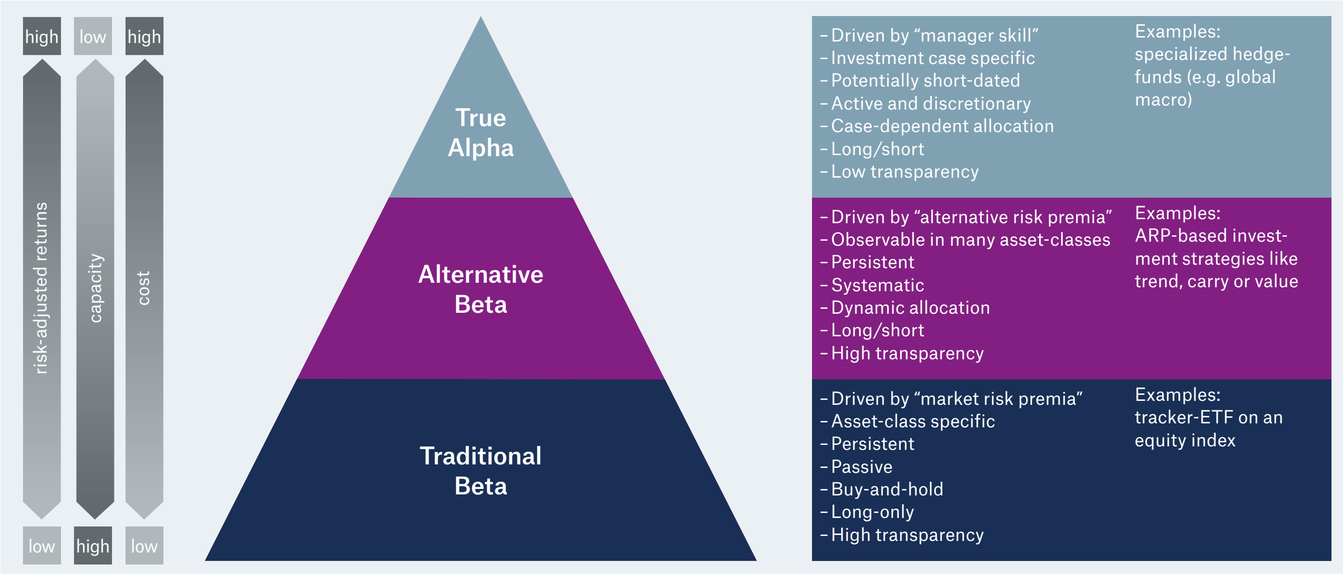


Figure 1: There are different ways of categorising the investment universe. Here we take a perspective based on the nature of the return source. Three dominant groups can be identified: traditional beta, alternative beta and true alpha. In this article, we are focusing on the liquid parts of these (liquid traditional beta like equity markets or liquid alternative beta like trend-following).

One important advantage of mixing traditional market ("Beta") with LAB exposure is that these two sources of return have a minor linkage by construction and thus may add a complementary source of return.

This has the chance to provide a more robust diversification behaviour, especially in market stress scenarios. The improved diversification contributes to avoiding steep drawdowns, which are hard to recover and ultimately diluting a portfolio's future power to profit from compounding effects. The mitigation of drawdowns should be an important aim of asset allocation, as drawdowns can substantially reduce the long-term growth prospects. Moreover, a positive return expectation based on their risk premia rationale for both portfolio components may make the mix appear attractive from a growth perspective.

As this is especially the case for long-term oriented retirement planning, Munich Re launched the FIVE Pension Strategy Index rooted in the above principles; the total return index is contributing to the overall performance of the Munich Re headquarter's company pension scheme.

In this article, we analyse the behaviour of a pure equity beta index ("VEQT-BETA Index[1]"), a LAB index ("VLQDALTS Index[2]") and a combination of both ("VPENSION Index[3]") in different market states. The market states are derived using sophisticated machine learning techniques ("ML"). We show that the LAB strategy provides an attractive source of return, as it improves diversification even in unfavourable market states. Thus, the two return contributions complement each other to improve long-term returns.

[1] ISIN: DE000SLA7PB4, Reuters ticker: .VEQTBETA
[2] ISIN: DE000SLA7PA6, Reuters ticker: .VLQDALTS
[3] ISIN: DE000SLA7N92, Reuters ticker: .VPENSION, Bloomberg ticker: VPENSION <Index>

FIVE Pension Strategy Index

Carry and Momentum are two prominent and established alternative risk factors, available across major asset classes including equity, fixed income, commodity and FX. We have constructed an investable basket consisting of these liquid alternatives which may qualify as an effective enhancement of traditional beta. We combine the corresponding LAB index ("VLQDALTS") with a traditional Beta index ("VEQTBETA") forming the FIVE Pension Strategy Index ("VPENSION").

The traditional Beta index ("VEQTBETA") is a fixed proportion, long-only equity basket composed out of STOXX Europe 600, S&P 500, S&P MidCap 400, Nikkei 225 and S&P/ASX 200 futures covering the lion's share of the global equity market capitalisation. Thus it is a good tracker for the performance of global equities. The LAB index ("VLQDALTS") consists out of four sub-indices: a time-series momentum ("trend-following"), a cross-sectional momentum, a time-series carry and a cross-sectional carry index. These four alternative risk premia strategies take long/short positions in over 40 futures markets in our four asset classes (see section "Asset universe"). The index aims at being a good representative for a diversified momentum/carry ARP-investment strategy.

We scale both the Beta index and the LAB index to a volatility target of 5% (p.a.), each including a leverage cap of 500% in terms of invested market value. Afterwards both indices are combined using a ratio of 60/40, which is a split well known from balanced funds, to form the FIVE Pension Strategy Index ("VPENSION"). We rebalance the 60/40 portfolio each month. The portfolio consisting of Beta and LAB thus follows a risk-based type of allocation in contrast to a notional weight-based allocation. It is again scaled to a volatility target of 5% over time. All indices are calculated on – or in case necessary, transformed to – an excess return basis and include a realistic implementation of transaction costs.

Assessing performance quality: the importance of having an excess return perspective

Excess returns are returns beyond the money market rate. In this context, the term "total return" means the sum of excess returns and money market returns.

To assess the performance of an investment over time or relative to a benchmark strategy, we need to isolate the active performance drivers. As money market returns are assumed to be universally available to every market participant and not unique to an investment strategy, they should not be part of this kind of assessment. Otherwise, the historically higher money market returns would overstate the expected returns that are relevant for the current low-interest rate environment.

Our index construction rule results in the performance and drawdown charts illustrated in figure 2.

Performance:
The liquid alternatives basket (VLQDALTS) shows the best performance, equity markets (VEQTBETA) achieve a lower, but still positive performance. The risk-controlled 60/40 combination of both (VPENSION) results in the middle time-series.

Drawdowns:
The 60/40 combination achieves less pronounced drawdowns and would have lowered equity investors' pain during the presented time period.

Historical performance

Figure 2

Source: Munich Re, Bloomberg L.P. Based on daily data starting on 2 January 2000 and ending on 30 June 2019.

In figure 3, we show the cumulative excess return (i.e. the relative performance) of the VPENSION index compared to VEQTBETA. Our objective is not to claim a potential superiority of LAB over traditional Beta strategies, which cannot and should not be assumed, but to illustrate that LAB can have different and attractive risk and return attributes over time.

Historical spread in performance of VPENSION and VEQTBETA

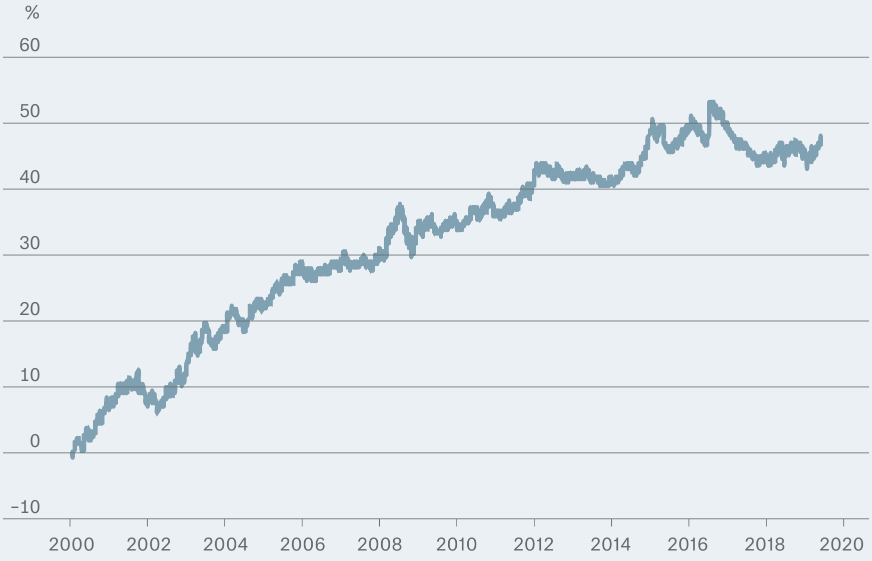


Figure 3

Source: Munich Re, Bloomberg L.P. Based on daily data starting on 2 January 2000 and ending on 30 June 2019.

We present the major performance metrics for the three strategies in table 1. VPENSION achieves a Sharpe ratio[4] of 0.65, whereas the equity-only investment shows 0.25; at the same time, the combination reduces the maximum drawdown from –20.6% to –14.0%.

Performance measures

	VEQTBETA	VLQDALTS	VPENSION
Annualised Sharpe Ratio (Rf=0%)	0.25	1.04	0.65
Annualised Return	1.2%	4.7%	3.3%
Annualised Standard Deviation[5]	4.9%	4.5%	5.0%
Worst Drawdown	20.6%	8.8%	14.0%

Table 1

Source: Munich Re, Bloomberg L.P. Based on daily data starting on 2 January 2000 and ending on 30 June 2019.

The correlation matrix in figure 4a shows the dependencies of the three time-series to a variety of selected other indices (from 2000 until 2019). VPENSION is highly correlated to equity indices, as well as liquid alternative indices. VEQTBETA is also moving similar to the equity indices, but there is no systematic dependency to VLQDALTS. Instead we observe a high correlation of equity indices to the liquid alternatives proxy index ("QSBASKET"), a popular and existing live index aiming at replicating the performance of the overall hedge fund industry. In this context, VLQDALTS positively stands out from a diversification point of view.

[4] Sharpe ratio is a measure of performance quality. It is calculated by dividing a portfolio's average excess return by its standard deviation; typically, annualised numbers are utilised.

[5] The comparably low realised volatility of the LAB index compared to the 5% target volatility is due to the leverage cap which limits the absolute gross portfolio leverage.

The chart in figure 4b illustrates how the rolling pairwise correlations between the FIVE indices (as well as the additional 4 benchmarks) and the MSCI World equity index ("EQUITIES") evolved in the time period from 2000 to 2019. It becomes visible that the block of less correlated underlyings contains the bond benchmark ("BONDS"), managed futures ("MNGDFTRS") and the FIVE LAB index ("VLQDALTS").

Correlation matrix (monthly data)

	VPENSION	VEQTBETA	VLQDALTS	EQUITIES	BONDS	MNGDFTRS	QSBASKET
VPENSION	100%	86%	55%	68%	-11%	26%	61%
VEQTBETA		100%	9%	79%	-32%	5%	62%
VLQDALTS			100%	-1%	32%	54%	13%
EQUITIES				100%	-28%	-8%	75%
BONDS					100%	36%	-13%
MNGDFTRS						100%	8%
QSBASKET							100%

Figure 4a (Data from January 2000 to June 2019)

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

Rolling correlations (5-year sliding window, monthly data)

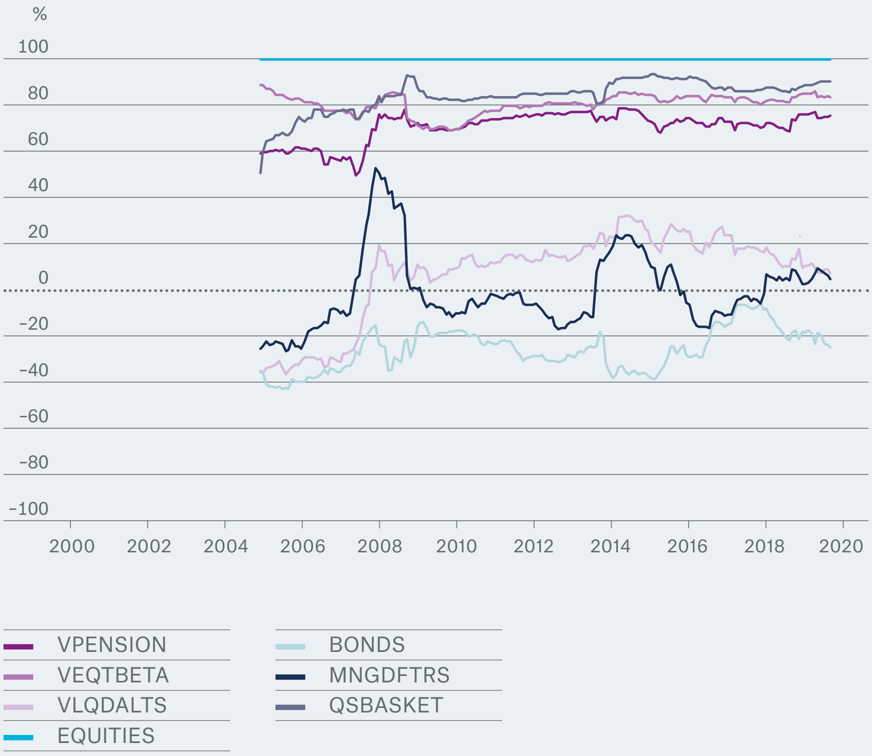


Figure 4b (Data from January 2000 to June 2019)

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

VPENSION	FIVE Pension Strategy	Combines VEQTBETA and VLQDALTS
VEQTBETA	FIVE Pension Strategy Equity Beta	Global equities at a target volatility of 5%
VLQDALTS	FIVE Pension Strategy Liquid Alternative Beta	Combines Momentum and Carry, both cross-asset
EQUITIES	MSCI World (Net TR)	Benchmark for Global equities
BONDS	FTSE World Government Bond Index (WGBI)	Benchmark for investment-grade global sovereign bond markets
MNGDFTRS	Barclay BTOP50	Benchmark for US based managed futures programs (systematic traders)
QSBASKET	Popular live index and benchmark for existing LAB strategy indices	Combines individual quantitative strategy indices – Long/Short, Event Driven, Global Strategies, Merger Arbitrage, Managed Futures

Figure 4c
Source: Munich Re

Return expectations

It is always difficult to conclude a return expectation from past data, and financial market forecasting is in most cases impossible. Because of this conviction, we designed the VPENSION strategy under the proposition that the underlying forces driving the performance ("risk premia") are sound from an economic point of view, tangible and supported by empirical data. The investment strategy aims at capturing the passive equity risk premium using a fixed-proportion global blue chip equity index universe and the targeted alternative risk premia by using straightforward and clear rules, providing robustness over time. This creates confidence in the overall strategy to provide attractive performance in the future.

A risk based approach to allocation has been intentionally chosen in the design of VPENSION in order to maintain a stable balance to different types of risk premia over time. Conversely, the 60/40 allocation has been a discretionary decision, with the following background: overweighting equities is rooted a) in the observation of equity market exposure being a strong market risk premium historically and b) equity exposure being a very popular building block to most investors. In addition, the ratio is conform with classic equity-bond allocations[6].

Reveiling market dynamics using machine learning techniques

One way to get a more elaborated impression on the advantage of an investment concept like VPENSION is to use empirical data and analyse how the index and benchmarks behave in different market states.

This means we need a method for identifying and categorising market phases. For this purpose we use an unsupervised machine learning algorithm, which is able to handle a comparably large set of price data. It identifies three different market states characterised by market performance (in terms of return), risk (in terms of volatility) and diversity (in terms of correlation) for the period January 2000 until June 2019 for 28 markets from three asset classes[7]. In this context, the terms "market" and "market state" refer to the employed asset-universe[8]. The algorithm assigns each month of this period to one of the different states. The details of the derivation of the clusters are summarised in the last section of this article.

[6] Acknowledging that the popular 60/40 mix refers to notional weights, and not risk weights.
[7] The three asset classes bonds, equities and commodities have been selected, as these are common long-only investment choices in a multi-asset context.
[8] See section "Asset universe" for the individual components.

The identified market states occurring in the considered period can be described as follows:

– State 1: strong negative performance, very high volatility and low correlation
– State 2: mildly positive performance, medium volatility and high correlation
– State 3: positive performance, low volatility and low correlation

Table 2 summarises the key characteristics and average measures for each state.

Key characteristics for each state

State	Occurrence (in %)	Avg. performance (monthly, in %)	Quintile	Avg. volatility (annual, in %)	Quintile	Avg. correlation (in %)	Quintile
1	18.5%	–3.1%	1	26.6%	5	7.5%	2
2	47.2%	0.6%	3	17.0%	3	15.7%	5
3	34.3%	1.8%	4	16.5%	3	7.3%	2

Table 2
Source: Munich Re, Bloomberg L.P. Based on daily data starting on 2 January 2000 and ending on 30 June 2019.

We are now able to analyse the three investment strategies over time. Figure 5 shows the average monthly performance of each index in each state. Please recall that all indices are scaled to a volatility target of 5%, EUR-denominated and uniformly calculated on an excess return basis. Therefore the performance figures are reasonably well comparable.

Average monthly performance per market state

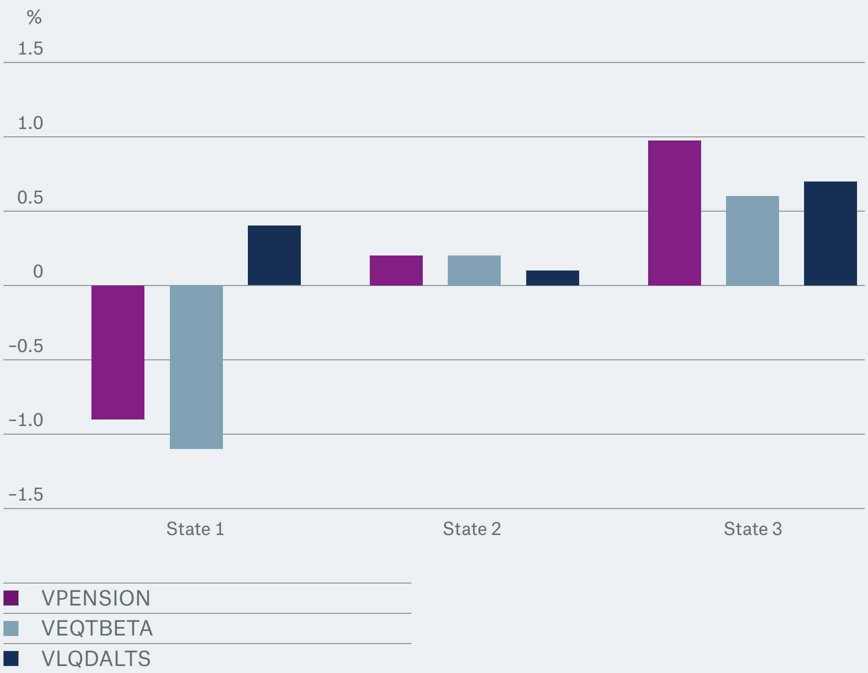


Figure 5
Source: Munich Re, Bloomberg L.P. Based on daily data starting on 2 January 2000 and ending on 30 June 2019.

A positive performance of the FIVE LAB index (VLQDALTS) can be observed in all three states, which indicates the strategy's independence of market direction. Intuitively, this makes sense, as the LAB basket always carries open long and short positions. Furthermore, the alternative risk premia strategy has been delivering well especially in good (state 3) and bad (state 1) times, but had problems in the performance-wise mediocre, high correlation state 2.

The Beta index (VEQTBETA) shows a strong negative performance in state 1, but delivers good results in the more calmer months of states 2 and 3.

The 60/40 combination (VPENSION) improves the negative equity-only result in state 1 and manages to beat the two stand-alone strategies in states 2 and 3. This is emphasised in figure 6, presenting the average correlation between the equities and the liquid alternatives basket in each state. Notably in state 1, which is characterised by negative market performance, the negative correlation helps to mitigate beta drawdowns. LAB has been an effective complement to a traditional global equities investment.

Correlation of BETA (VEQTBETA) and LAB (VLQDALTS)

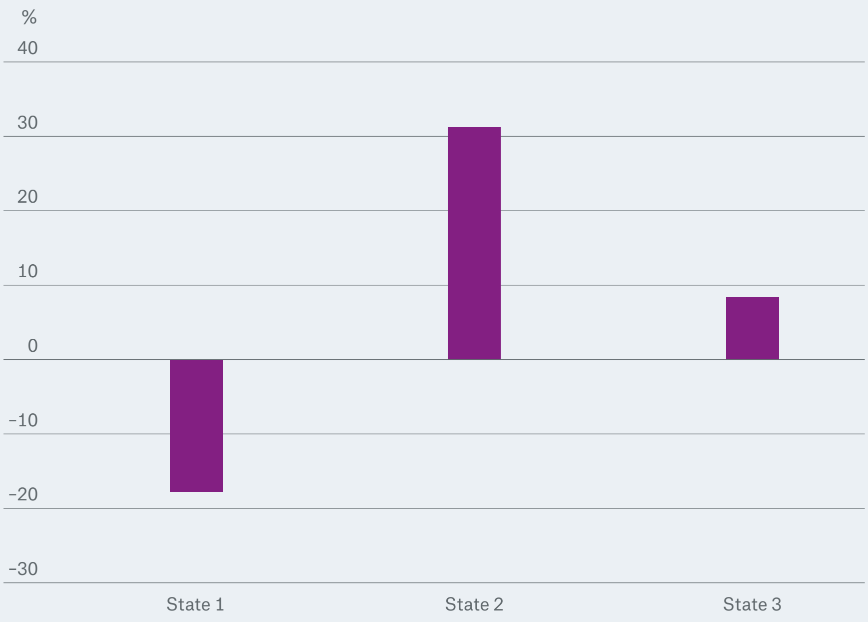


Figure 6

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

Quintessence

In times of low interst rates where classical portfolio allocation approaches like bond-equity are potentially more exposed to higher losses and lower return expectations it becomes important to improve diversification both in the underlying universe itself but also in adding new sources of return. A reliable correlation behavior of these new components is key.

We developed a generic approach to analyse and identify market states utilising modern machine learning algorithms. It can be used to validate the robustness of an investment strategy over time.

Conventional methods (e.g. employing an equity volatility index together with a chosen separating threshold) are often based on indirect sources of information and may employ subjective elements to categorise market data. In contrast, our approach factors in and processes a significantly higher amount of directly available market data. Moreover, this unsupervised machine learning technique is unbiased in the sense that it does not require for example labeling states or setting subjective parameters.

The results show that complementing traditional portfolios with new sources of return like liquid alternative beta adds value. Such combination is profiting from its advantageous and more stable diversification characteristics holding up through various market conditions.

The quantitative results are supported by the fact that alternative investments play an increasingly important role in the investment portfolios of longer-term investors, such as foundations, endowments, or sovereign wealth funds. Lower fees and a higher transparency will pave the way for LAB investments as an integral part of diversified investment portfolios.

A machine learning approach to identify market states

Financial markets are in different states with respect to performance, risk and diversification. To achieve a robust strategy, it is important to perform well in benign scenarios and to be able to preserve capital during market stress.

How can we describe and quantify different market states systematically in order to see how robust investment strategies are over time?

At Munich Re, we have developed a sophisticated Machine Learning ("ML") tool that automatically detects market states and allows for a clear representation in terms of performance, risk and diversification.

To identify different market states, we consider a wide selection of financial markets (cross-asset, see section "Index composition") and group that data into monthly intervals. For each month we calculate three measures using daily returns: performance, risk and diversity. "Performance" is calculated as the average (arithmetic mean) of the returns across all markets in their in domestic currency in the corresponding month. "Risk" is defined as average volatility across these markets. Finally, "Diversity" is calculated as the average pairwise correlation. It should be noted that we do not aim at building a meaningful portfolio at this stage but we are interested in figuring out how the monthly measures vary to form different market states using this information.

In the next step, we apply a subsequence clustering procedure. This algorithm assigns each month to a specific cluster. At the time of this writing, there is little theory on how to find the right number of clusters. Clustering methods like hierarchical clustering or *k*-means give no strict mathematical guidance about how many clusters should be used. Nevertheless there are well-established approaches which are helpful to identify a meaningful number of clusters.

The result of our procedure is a hierarchical clustering with 3 sub-sequences that represent the different market states in the time period under investigation.

This procedure is inspired by the paper "Identifying States of a Financial Market" by Muennix et al. (2011) which has been further developed by Papenbrock and Schwendner (2015).

The result of our clustering algorithm is shown in the three-dimensional scatter plot illustrated in the first part of figure 7, where each dot represents one month of the observed period Jan 2000 until June 2019. The colours present the three market states that were obtained using the machine learning clustering algorithm. It becomes visible that the riskiest state 1 has the fewest observations (18.5%) and a high dispersion. The high correlation state 2, representing almost 50% of all observations, yields a mildly positive average return. The state 3 dots appear to be a relatively homogenous group of low correlation, low risk and relatively high performance.

The average characteristics concerning performance, risk and diversity of each state are visualised in figure 7 using a radar plot (lower chart).

Market state clusters

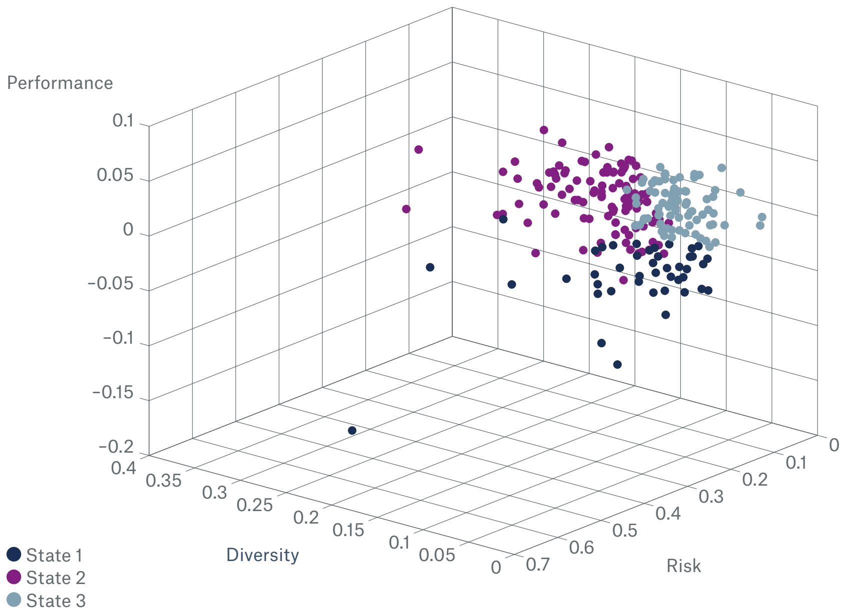
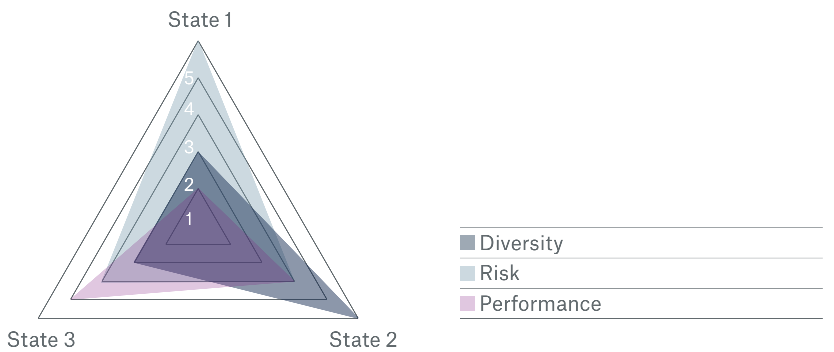


Figure 7a: Each dot shown in the chart represents one month. It's position is defined by the 3 characteristics measured for the reference asset universe.

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

Performance, risk, diversity



- Diversity: low correlation of markets in states 1 and 3, high interdependencies in state 2.
- Risk: highest volatility in state 1, similar and lower values for states 2 and 3.
- Performance: highest return in state 3, mediocre in state 2 and lowest in state 1.

Figure 7b: Radar plot illustrating the characteristics of each state with respect to performance, risk and diversity. The position of each dot is defined by its quintile number (cf. table 2).

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

To chronologically interpret these states, it is helpful to plot them against the performance of a well-known benchmark like the MSCI World Index[9]. This has been carried out in figure 8.

The dotted lines in steel grey indicate the different states. The grey line shows the performance of the MSCI World Index and the light blue vertical line represents the global financial crisis located at the date of default of Lehman Brothers.

[9] ISIN: XC0009692739, Reuters ticker: .MIWO00000PUS, Bloomberg ticker: MXWO <Index>

Market states over time

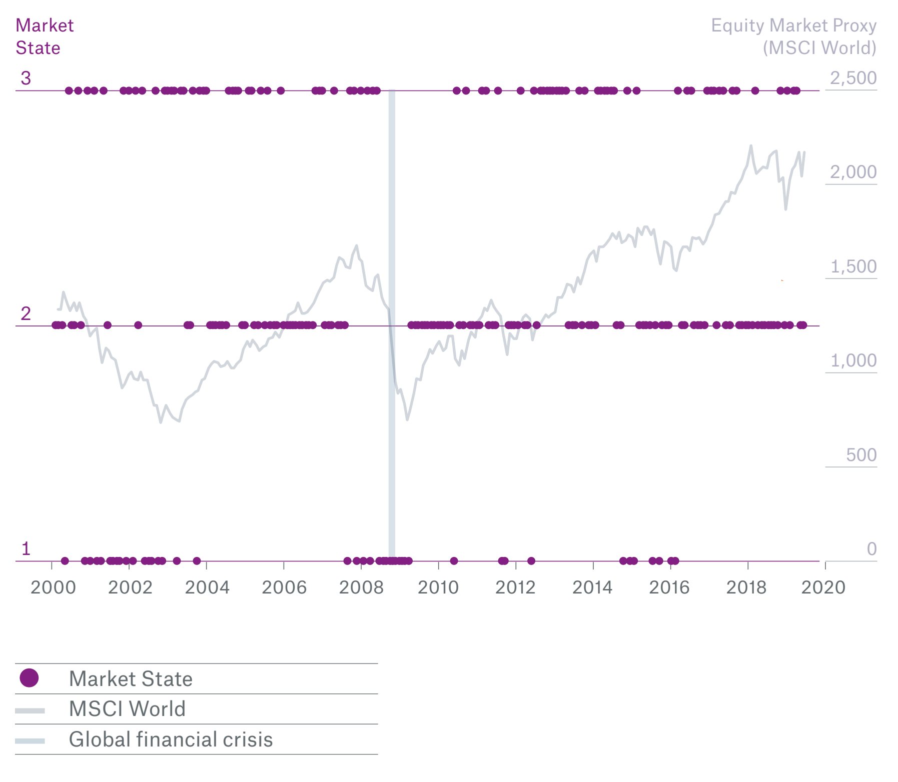


Figure 8

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

Focusing on the most distinct states regarding the three measures we observe that state 1 (worst performance, highest volatility) unsurprisingly appears mostly[10] during equity market downturns. This pattern becomes more pronounced as market stress is increasing. During the end of the Dot-Com Bubble lasting from September 2000 to September 2002, 48% of all months have been assigned to state 1. In the Global Financial Crisis from November 2007 to February 2009, 75% of all month are assigned to state 1.

State 2 and 3 are more pronounced in longer upward trending markets (e.g. 2003–2007 and 2009–2018). Even though not clearly visible in the chart, state 2 (high correlation) is dominat prior to and during short sell-off phases.

An example for a longer-lasting repetition of "state 2 months" is the time from October 2017 to October 2018[11]. This time period contains slowly and gradually climbing equity markets, but also two fast sell-offs, one in February 2018 (negative US labour market news, new fears of inflation) and one in October 2018 (international trade tensions, Italian government confronting EU).

The transition matrix (table 3) highlights that states 1 are often accompanied by state 3 and vice versa. State 2 months are very rarely followed by state 1 months.

[10] Almost 40% of state 1 occurrences can be observed during stress periods.
[11] With the exception of March 2018, which is a state 3 month.

Transition matrix

	State 1	State 2	State 3
State 1	44.2%	9.1%	17.5%
State 2	9.3%	67.3%	40.0%
State 3	46.5%	23.6%	42.5%

Table 3

Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

The transition matrix shows the transition probability for moving from one state to another.

Method for defining the market states based on subsequence clustering

We apply a two-step procedure that first determines the optimal number of clusters and then executes a subsequence clustering.

In the first step, we use a hierarchical clustering algorithm using Ward's method (see Ward, J. H., Jr. (1963), "Hierarchical Grouping to Optimise an Objective Function", Journal of the American Statistical Association, 58, 236–244). This algorithm assigns each month to a specific cluster. The advantage using Ward's method compared to other hierarchical clustering algorithms is that this method yields more uniform states whereas other methods tend to build sparse clusters containing often only one single entry. Ward's method tends to be more robust and builds homogeneous clusters.

The Ward method minimises the total within-cluster variance. At each step the pair of clusters with minimum cluster distance are merged. To implement this method, at each step find the pair of clusters that leads to minimum increase in total within-cluster variance after merging.

An important step is to define the optimal number of clusters. We test the number of cluster k from at least 3 clusters up to 10 clusters. For each k we use 26 different indices that reflect the cluster quality:

1. "kl" (Krzanowski and Lai 1988)
2. "ch" (Calinski and Harabasz 1974)
3. "hartigan" (Hartigan 1975)
4. "ccc" (Sarle 1983)
5. "scott" (Scott and Symons 1971)
6. "marriot" (Marriot 1971)
7. "trcovw" (Milligan and Cooper 1985)
8. "tracew" (Milligan and Cooper 1985)
9. "friedman" (Friedman and Rubin 1967)
10. "rubin" (Friedman and Rubin 1967)
11. "cindex" (Hubert and Levin 1976)
12. "db" (Davies and Bouldin 1979)
13. "silhouette" (Rousseeuw 1987)
14. "duda" (Duda and Hart 1973)
15. "pseudot2" (Duda and Hart 1973)
16. "beale" (Beale 1969)
17. "ratkowsky" (Ratkowsky and Lance 1978)
18. "ball" (Ball and Hall 1965)
19. "ptbiserial" (Milligan 1980, 1981)
20. "frey" (Frey and Van Groenewoud 1972)
21. "mcclain" (McClain and Rao 1975)
22. "dunn" (Dunn 1974)
23. "hubert" (Hubert and Arabie 1985)
24. "sdindex" (Halkidi et al. 2000)
25. "dindex" (Lebart et al. 2000)
26. "sdbw" (Halkidi and Vazirgiannis 2001)

According to the majority rule we pick that k with highest cluster quality criteria which is k=3.

Appendix 1: Asset universe

The following table contains all financial markets which comprise the VPENSION index. The last column specifies which markets have been used in the Machine Learning tool to identify the different market states. For this purpose, we excluded the FX futures markets (as it is not a long-only investment asset-class) and all markets starting later than January 2000.

#	Name	Ticker	Asset Class	Currency	Clustering
1	WTI Crude Oil	CLA Comdty	Commodities	USD	true
2	Brent Crude Oil	COA Comdty	Commodities	USD	true
3	Gold	GCA Comdty	Commodities	USD	true
4	Copper	HGA Comdty	Commodities	USD	true
5	Diesel (ULS NY Harbor)	HOA Comdty	Commodities	USD	true
6	Natural Gas	NGA Comdty	Commodities	USD	true
7	Platinum	PLA Comdty	Commodities	USD	true
8	Gasoil	QSA Comdty	Commodities	USD	true
9	Silver	SIA Comdty	Commodities	USD	true
11	RBOB Gasoline	XBA Comdty	Commodities	USD	false
13	CAC 40	CFA Index	Equities	EUR	true
15	DJIA	DMA Index	Equities	USD	false
16	S&P 500	ESA Index	Equities	USD	true
17	S&P MidCap 400	FAA Index	Equities	USD	false
18	DAX	GXA Index	Equities	EUR	true
20	Hang Seng	HIA Index	Equities	HKD	true
21	Nikkei 225	NKA Index	Equities	JPY	true
22	NASDAQ-100	NQA Index	Equities	USD	true
23	Russell 2000	RTYA Index	Equities	USD	false
25	SMI	SMA Index	Equities	CHF	true
26	EURO STOXX 600	SXOA Index	Equities	EUR	true
27	Topix	TPA Index	Equities	JPY	true
28	EURO STOXX 50	VGA Index	Equities	EUR	true
30	SPI 200	XPA Index	Equities	AUD	false
33	FTSE 100	Z A Index	Equities	GBP	true
34	Canada 10Y Govt Bonds	CNA Comdty	Fixed Income	CAD	true
36	Switzerland 10Y Govt Bonds	FBA Comdty	Fixed Income	CHF	true
37	UK 10Y Govt Bonds	G A Comdty	Fixed Income	GBP	true
10	Italy 10Y Govt Bonds	IKA Comdty	Fixed Income	EUR	false
12	Japan 10Y Govt Bonds	JBA Comdty	Fixed Income	JPY	true
14	Spain 10Y Govt Bonds	KOAA Comdty	Fixed Income	EUR	false
19	France 10Y Govt Bonds	OATA Comdty	Fixed Income	EUR	false
24	Germany 10Y Govt Bonds	RXA Comdty	Fixed Income	EUR	true
29	USA 10Y Govt Bonds	TYA Comdty	Fixed Income	USD	true
31	Germany 30Y Govt Bonds	UBA Comdty	Fixed Income	EUR	false
32	USA 30Y Govt Bonds	USA Comdty	Fixed Income	USD	true
35	Australia 10Y Govt Bonds	XMA Comdty	Fixed Income	AUD	true
38	AUD/USD	ADA Curncy	FX	USD	false
39	GBP/USD	BPA Curncy	FX	USD	false
40	CAD/USD	CDA Curncy	FX	USD	false
41	EUR/USD	ECA Curncy	FX	USD	false
42	JPY/USD	JYA Curncy	FX	USD	false
43	NOK/USD	NOA Curncy	FX	USD	false
44	NZD/USD	NVA Curncy	FX	USD	false
45	SEK/USD	SEA Curncy	FX	USD	false
46	CHF/USD	SFA Curncy	FX	USD	false

Appendix 2: Correlation heatmaps

It is also valuable to have a look at the correlation heatmaps for each of the three market states. The asset-class blocks are clearly visible in all three states, where "state 3 intra-asset-class correlations" are least pronounced.

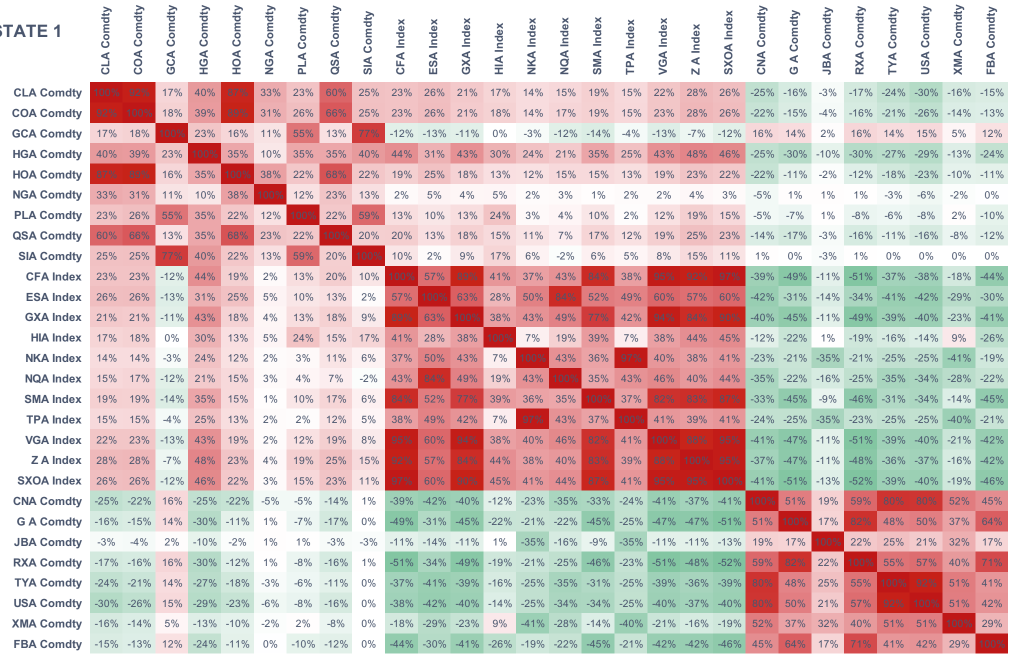
From this correlation perspective, states 1 and 3 appear quite similar. An exception are equities-commodities dependencies, which are notably stronger in state 1. Only the state 2 matrix differs already on first sight, as bond-equity correlation is negative on average, but elevated compared to state 1 and 3.

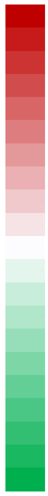
A low dependency between bonds and equities in state 2 months during the considererd period of time becomes visible in the second heatmap, which has been a primary source of diversification benefits in the past arising from bond-equity portfolios.

Figure 8: Correlation heatmaps

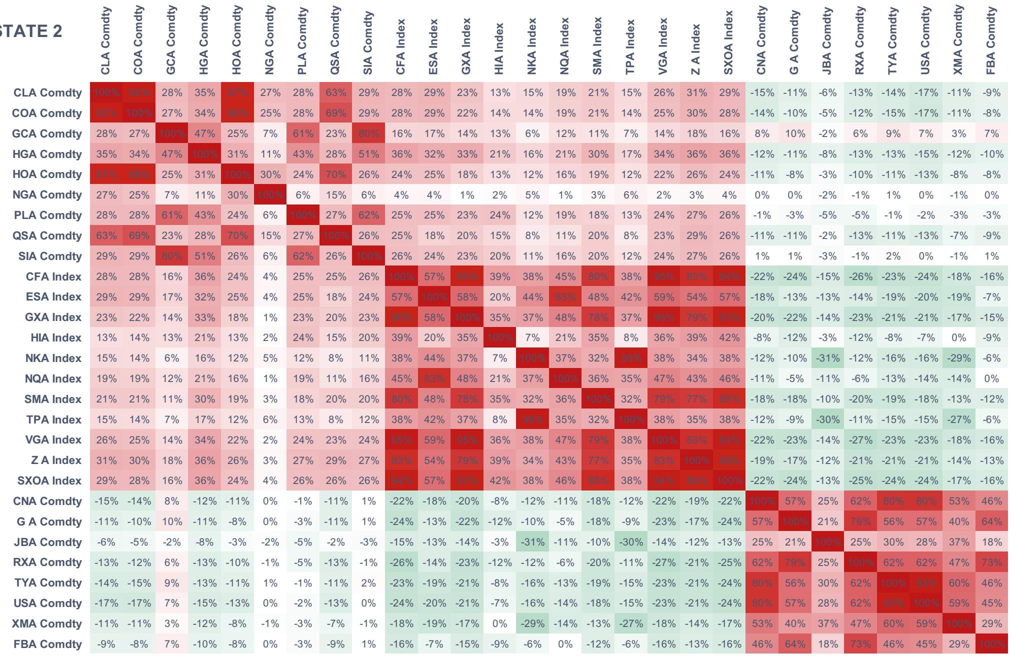
Source: Munich Re, Bloomberg L.P. Based on monthly data starting on 2 January 2000 and ending on 30 June 2019.

STATE 1

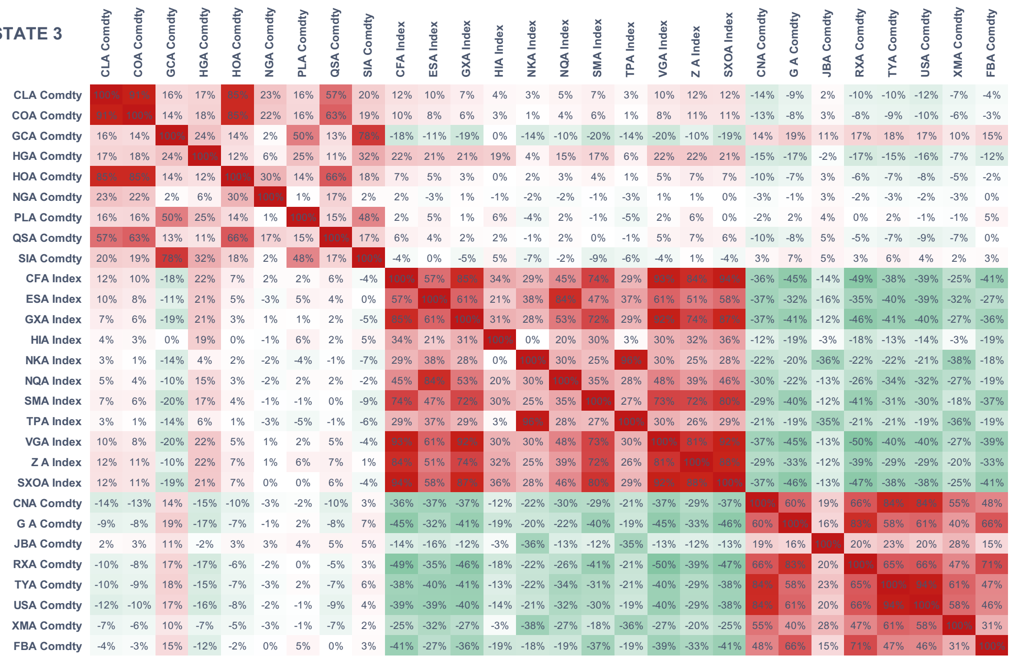




STATE 2



STATE 3



Appendix 3: Return triangles

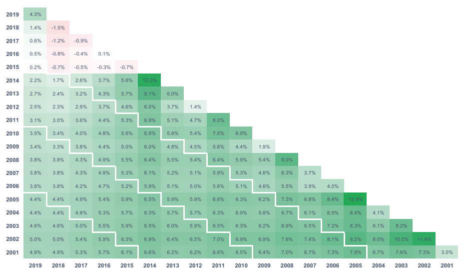
VPENSION

Investment

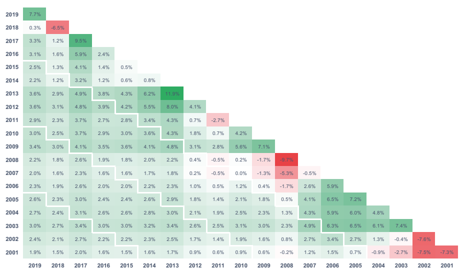
	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
2019	7.9%																		
2018	1.8%	-4.0%																	
2017	6.3%	5.6%	16.0%																
2016	5.3%	4.4%	8.9%	2.1%															
2015	3.7%	2.7%	5.0%	-0.1%	-2.2%														
2014	3.0%	2.0%	3.6%	-0.3%	-1.5%	-0.7%													
2013	3.6%	2.9%	4.4%	1.6%	1.5%	3.4%	7.7%												
2012	3.6%	3.0%	4.2%	2.0%	2.0%	3.4%	5.6%	3.5%											
2011	2.9%	2.2%	3.2%	1.2%	1.0%	1.8%	2.6%	0.2%	-3.0%										
2010	2.9%	2.3%	3.1%	1.4%	1.3%	2.0%	2.7%	1.1%	-0.1%	2.9%									
2009	3.2%	2.8%	3.6%	2.1%	2.1%	2.8%	3.6%	2.6%	2.3%	5.0%	7.1%								
2008	2.0%	1.5%	2.1%	0.7%	0.5%	0.9%	1.1%	-0.1%	-1.0%	-0.3%	-1.9%	-10.1%							
2007	2.0%	1.6%	2.1%	0.8%	0.6%	1.0%	1.2%	0.2%	-0.4%	0.2%	-0.7%	-4.3%	1.8%						
2006	2.6%	2.2%	2.7%	1.6%	1.5%	2.0%	2.3%	1.5%	1.2%	2.1%	1.9%	0.2%	5.8%	10.0%					
2005	2.7%	2.3%	2.8%	1.8%	1.8%	2.2%	2.5%	1.9%	1.6%	2.4%	2.4%	1.2%	5.3%	7.1%	4.2%				
2004	2.9%	2.6%	3.1%	2.1%	2.1%	2.5%	2.9%	2.3%	2.2%	3.0%	3.0%	2.2%	5.5%	6.8%	5.2%	6.2%			
2003	3.3%	3.1%	3.6%	2.7%	2.8%	3.2%	3.6%	3.1%	3.1%	3.9%	4.0%	3.5%	6.5%	7.7%	7.0%	8.4%	10.6%		
2002	2.8%	2.5%	2.9%	2.1%	2.1%	2.4%	2.7%	2.2%	2.1%	2.7%	2.7%	2.1%	4.3%	4.8%	3.5%	3.2%	1.8%	-6.3%	
2001	2.2%	1.9%	2.3%	1.5%	1.4%	1.7%	1.9%	1.4%	1.2%	1.6%	1.5%	0.8%	2.5%	2.6%	1.2%	0.5%	-1.4%	-6.9%	-7.5%

Divestment

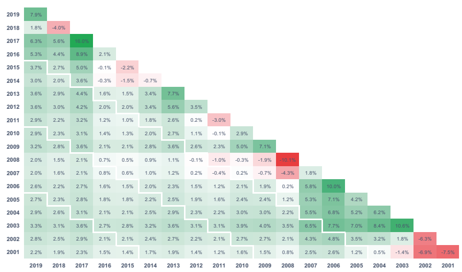
VLQDALTS



VEQTBETA



MSCI World



A return triangle visualises the performance of an investment over a variety of holding periods. Holding periods are divided into calendar years, and it is assumed that the investor buys at the beginning of a calendar year (y-axis) and sells at the end of a later year (x-axis). Example: in the VPENSION return triangle, we chose to buy in 2003 (row "2003") and sell at the end of 2015 (column "2015"), which leaves us with an annual return of 5.0% during our holding period.

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