TRADECAP Liquid Alternatives

Machine Learning for Building Hedge Fund Portfolios

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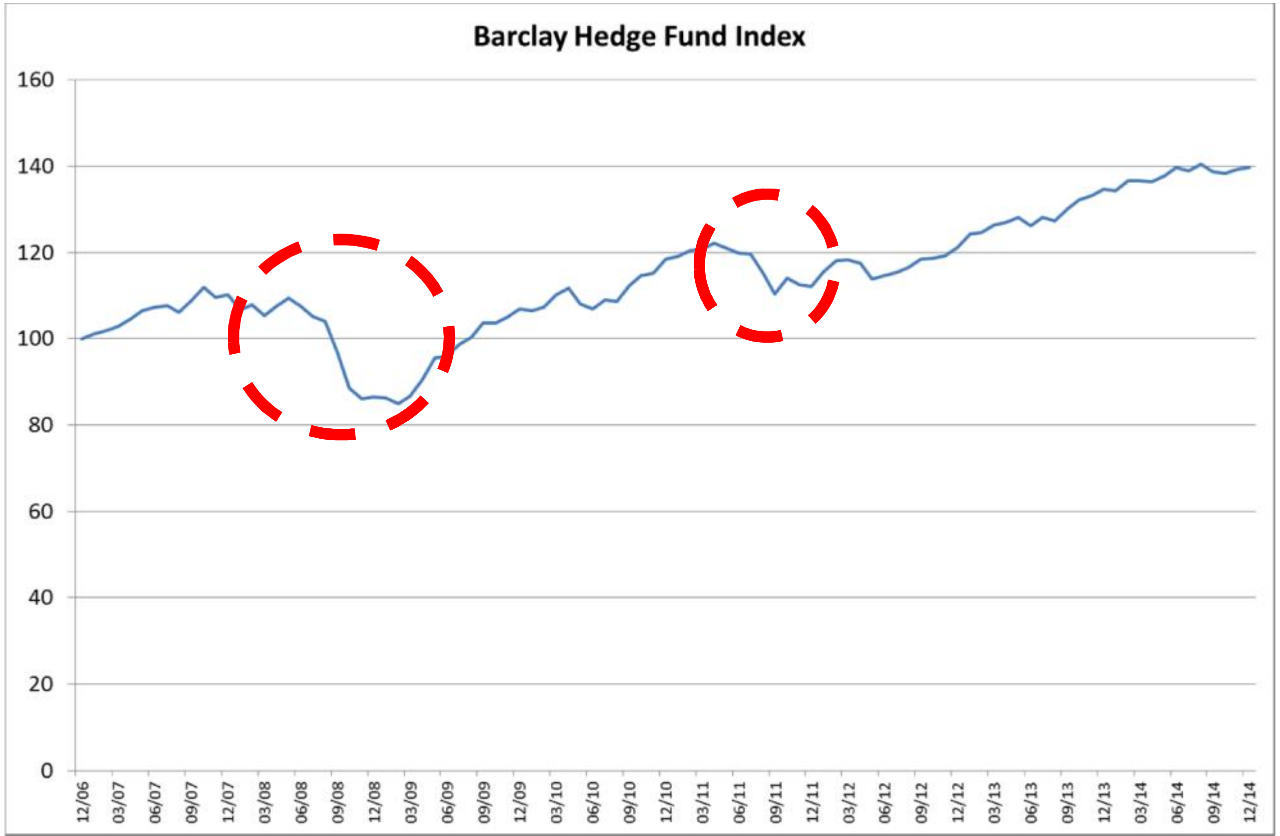
December 2017

TRADECAP
Investment Management

Principles of Hedge Fund Construction

- Achieve stable long-term performance, no trading in and out
- We are interested in building a robust portfolio of different HF managers – generate stable performance, avoid large drawdowns



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Self Organising Maps [SOM] for Identifying Similarities of Hedge Fund Managers

- How can we avoid concentrations in the portfolio?
- A statistical tool for identifying drawdown and style similarities are the Self-Organising Maps [SOM]

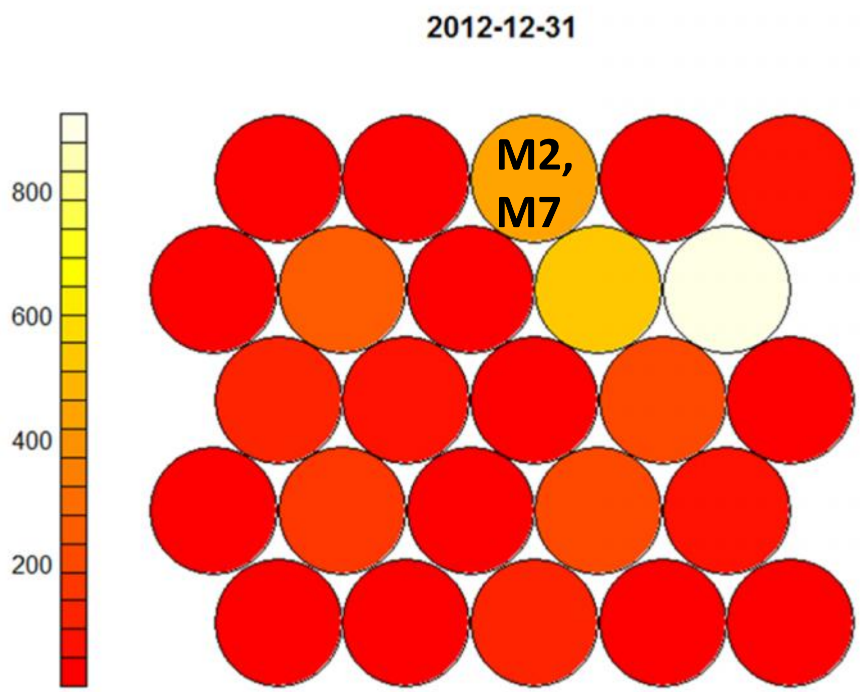
- SOM were developed in the 1980s by Teuvo Kohonen [Kohonen (1982)]
- SOM project objects on a map
- Similar objects are being projected closely together

- Example: SOM with 5 x 5 = 25 units
- Managers with similar return profiles appear on the same unit: Managers M2 and M7 on the same unit

- SOM can be used to identify similarities in risk behaviour: managers with similar risk behaviour appear on near-by units

- Each managers' returns or risk indicators are mapped to one unit

- Examples are:
    - Rating analysis for loans [corporate and retail]
    - Medicine: quick diagnosis of patients based on, for example, blood values



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SOM to identify stable-performing Hedge Funds

1) Remote parts of the SOM

- The most intuitive way to identify managers is to pick hedge funds from remote units of the SOM, e.g., from the 4 units in the bottom left, bottom right, upper left and upper right corners

- In the empirical part this method is called "SOM"

2) Dispersion

- Managers placed on low dispersion (*) unit share many similarities with other managers on the same unit
- Managers placed on 2 distant units are different from each other, but there are other managers on the same unit that share some characteristics
- Managers placed on a high dispersion unit do not share many similarities with other managers
- They can be seen as "leftovers", special or uncorrelated to others, see next slide
- Idea is to pick managers from the 4 units with the highest dispersion among managers

- In the empirical part this method is called "SOM_Disp"

(*) We measure dispersion as Euclidean distances of managers to the winning unit, i.e., the mean Euclidean distance of all managers on the unit they were assigned to in relation to that unit's representative vector [= codebook vector]

SOM to identify stable-performing Hedge Funds

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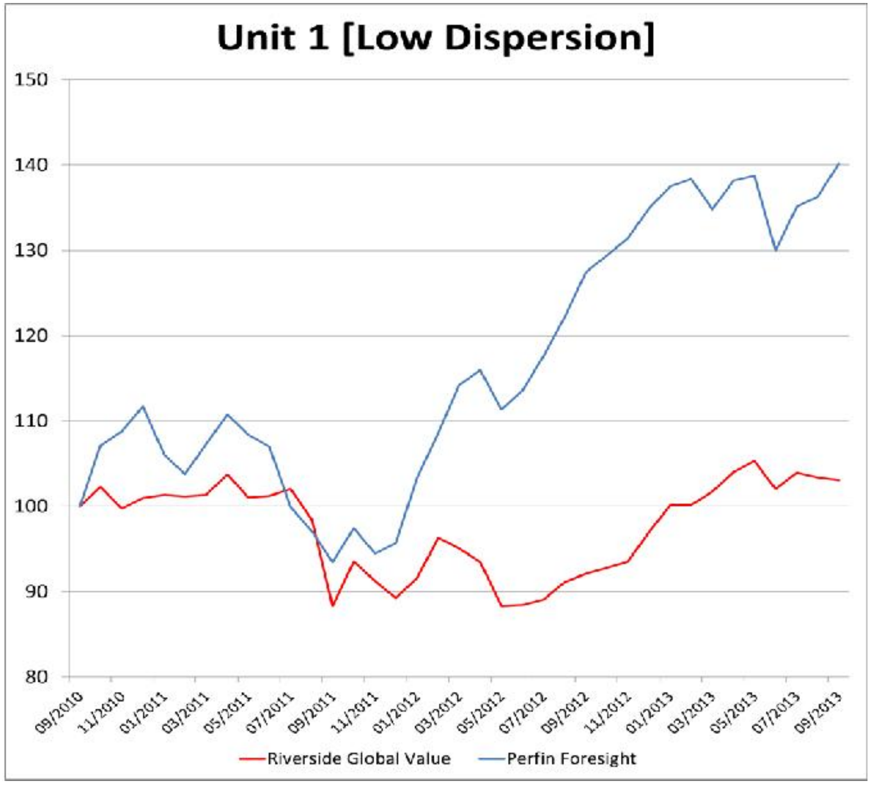
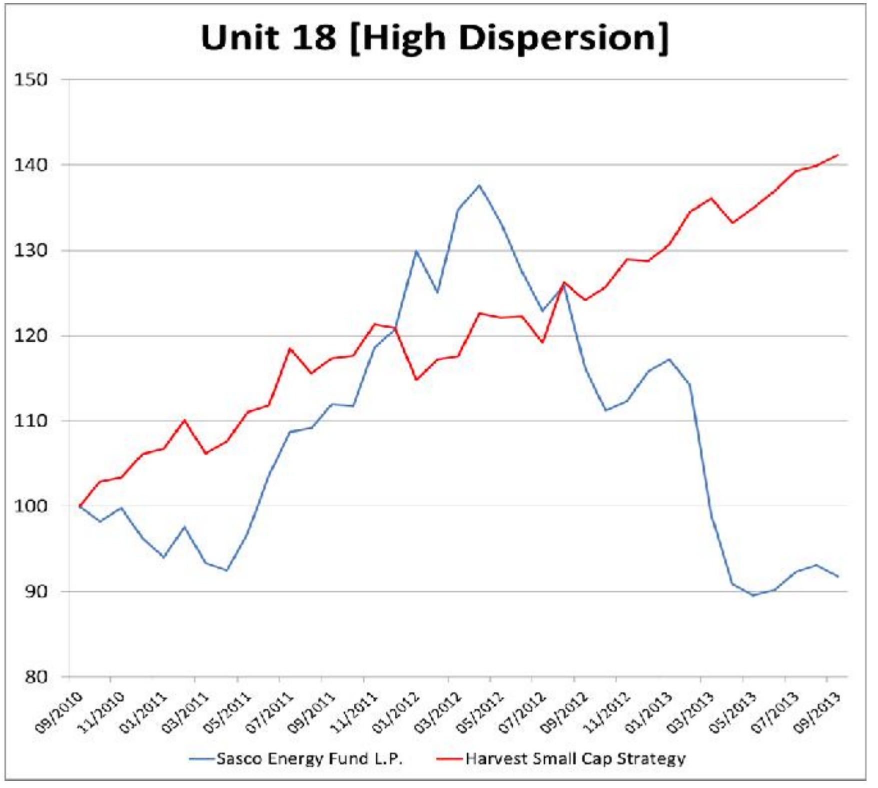
- Examples: 2 managers placed on low dispersion Unit 1 [linear correlation 0.47] vs. 2 managers placed on high dispersion Unit 18 [correlation 0.22], SOM estimated with data from 10/2010 to 9/2014
- The 2 managers on Unit 1 share essentially the same up and down moves, but with different magnitudes
- The 2 managers on Unit 18 share some up and down moves, but also exhibit partly diverging behaviour





- Correlation Matrix:

Unit		1	1	18
		Riverside Global Value	Perfin Foresight	Sasco Energy Fund L.P.
1	Riverside Global Value			
1	Perfin Foresight	0.47		
18	Sasco Energy Fund L.P.	-0.20	-0.05	
18	Harvest Small Cap Strategy	-0.03	-0.26	0.22

SOM in the Investment Process

- How can we integrate a SOM in the investment process and does it create any value added? → Simulation study!
- What are the properties of SOM-based hedge fund portfolios [e.g., correlation to equity markets]?
- Is the risk profile of a SOM-based portfolio enhanced?

Database

- Basis for the simulation exercise is the BarclayHedge database

- No adjustments to performance were made to address the well-known hedge fund data biases [e.g., backfill bias, self-reporting bias, style classification bias]

- Implicitly, our application of the SOM addresses style classification bias, as we utilise SOM to identify risk profiles: data-driven rather than relying on self-declared styles

- Survivorship bias addressed as also graveyard hedge funds included in the analysis

- The database was screened as follows:
  - Min. AuM = USD 50 mln
  - Sharpe Ratio < 10
  - Min. volatility 0%. Max. volatility 200%
  - Minimum of 48 months of data must be available for each hedge fund
  - Each year, ca. 1,000 managers fulfil those criteria

Research Design: Simulation Study

- We simulate 4 ways to construct portfolios:

1) Free: Randomly pick 12 managers from the universe of the corresponding vintage year. 100% of the universe is eligible.

2) Style: Each of the 12 managers needs to come from a different style. The styles are taken from Barclay Hedge [e.g., Equity Long/Short, Macro, Event Driven etc.]. There are 80 styles in the database. All managers are categorised according to one of those self-declared styles.

3) SOM:
    - A SOM with 25 units [5 X 5] is generated.
    - Inputs are vectors with 48 monthly returns.
    - For example, for VY 2008 the database stretches from Oct 2003 until Sep 2007 [48 months].
    - Randomly pick 3 managers each form the 4 most remote units of the SOM, i.e., from the 4 units in the bottom left, bottom right, upper left and upper right corners, together 12 managers

4) SOM_Disp:
    - Like 3), but instead of the remote units the 4 units with the highest dispersion are identified.
    - Again, pick 3 managers from each of those units with high dispersion, together 12 managers

Research Design: Simulation Study

- We assume a 3 month implementation gap [reporting gap, running the model, contacting the managers, due diligence, transferring the money]
  - For VY 2008, we estimate the SOM with data from 10/2003 to 9/2007 [48 months]
  - Invest in Jan 2008 and hold the hedge fund investments until Dec 2008. No rebalancing, just buy & hold → out-of-sample performance
  - Performance is measured for the period Jan 2008 to Dec 2008

- For each of the 4 methods, 10,000 portfolios were randomly created, i.e., 40,000 portfolios overall for each VY

- Move time window 1 year ahead and estimate SOM with data from 10/2004 to 9/2008, run 40,000 simulations and calculate out-of-sample performance for 2009

- Run simulations for out-of-sample performance for VY 2008 to 2014 [7 years]

- Overall, 7 * 40,000 = 280,000 portfolios were simulated

Empirical Results: Overview

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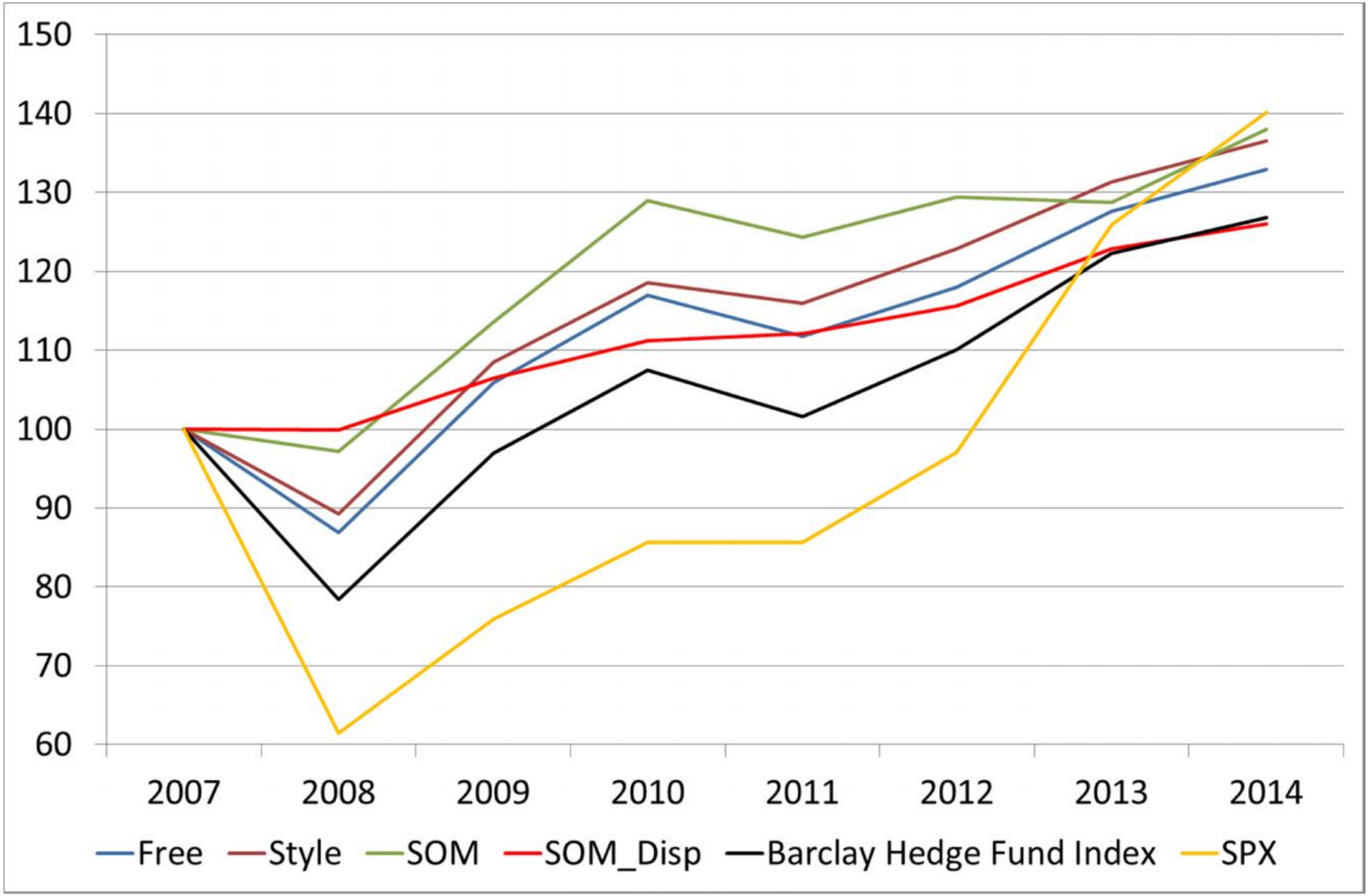
- Equity lines out-of-sample for rolling simulations



Empirical Results: Overview

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- Best performer only based on equity line is SPX with an index level of 140 in Dec 2014, followed by SOM [138] and Style [137]
- SPX exhibits the largest drawdown on 2008 of -38%, followed by Barclay Hedge Fund Index [-22%]
- Simulated Hedge Fund portfolios show less severe drawdowns in 2008: the worst is from Free [-13%], followed by Style [-11%], SOM [-3%] and SOM_Disp [0%]
- SOM methods reduce 2008 and 2011 drawdowns of HF massively
- Most stable performer is SOM_Disp: low drawdowns, low vol, but lagging in years of recovery → highest Ratio Mean/Vol = 1.33, also lowest correlation to SPX
- SOM achieves the highest mean together with Style, but at reduced vol and reduced drawdowns

- As yet only random selection deployed
- We could spice up our selection by incorporating more intelligent selection criteria [e.g., Sharpe Ratio, Appraisal Ratio, Risk Factor Neutrality, …]

2008-2014	Free	Style	SOM	SOM_Disp	Barclay HF	SPX
Mean	4.7%	5.0%	5.0%	3.4%	4.4%	7.3%
Vol	11.1%	10.0%	8.0%	2.5%	14.4%	16.8%
Mean/Vol	0.42	0.50	0.62	1.33	0.30	0.43
SPX_Worst	-2.2%	-2.0%	-1.3%	-0.2%	-3.1%	-7.8%
Corr.SPX	0.67	0.68	0.54	0.23	0.86	1.00

- SPX_Worst is average P/L when SPX suffers its worst monthly loss in each vintage year

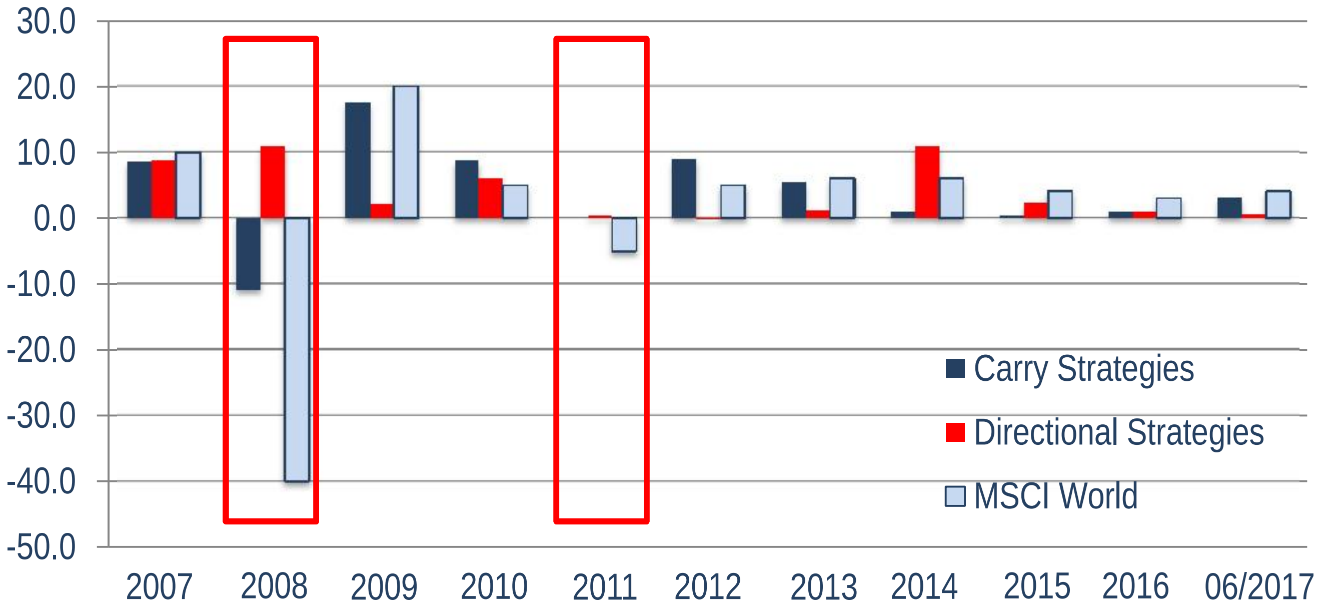
TRADECAP INVESTMENT MANAGEMENT

Commercial Implementation

- Tradecap INNOHedge
- Seed commitment received of USD 100 mln by Swiss institutional investor in Sep 2017
- Manager selection based on SOM as discussed in the simulation approach, but with “more intelligence” in the selection process
- Innovative multi-asset and multi–strategy approach with effective tail-risk management
- Portfolio comprises Carry and Tail Risk part
- Target return: 4 – 6%, Target volatility: 4 – 6 %
- TER at around 200 basis points [vs. 400-600 for traditional funds of hedge funds]
- Weekly liquidity (UCITS format)
- Position-level transparency

INNOHedge: Backtest Performance

Annual performance in %, asset weighted (illustrative backtest)*



	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	06/2017
Fund performance (in %):	17.1	0.1	19.6	14.7	0.3	8.8	6.6	11.9	2.8	2.1	3.5
Fund volatility (in %, 12 mt):	16.2	7.8	6.4	5.4	5.2	5.2	6.6	4.6	6.5	4.1	4.4

* Sample portfolio with 6 managers, subject to change; some strategies proxied based on their tradional peers‘ return data; annual rebalancing

Source: Tradecap Analysis

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INVESTMENT MANAGEMENT

Summary & Outlook

- SOM can project complex relationships in data on to a 2-dimensional map → visualisation capabilities of SOM allow users to quickly grasp the main features of the data
- SOM add value in areas where there is lots of data, also partly missing data
- SOM can add value to the investment process of [hedge fund] manager selection
- Portfolios based on SOM generate returns more independently from equity markets and more stable than, for example, style allocation
- For real life applications, the process of manager selection can be enhanced by more sophisticated selection processes, e.g., i) identify “special” managers in a first step and ii) pick managers according to appraisal ratio, risk factor exposure or similar
- TraceCap INNOHedge, our commercial implementation of the SOM investment process, has attracted significant interest from institutional players and received USD 100 mln seed commitment

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