Beamer Presentation: Regime Switching

Combining Hierarchical Clustering-Based Asset Allocation and News Sentiment

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Introduction

Early identification of **Regime Switches** of **major importance for Strategic Asset Allocation**.

We propose a **completely model independent** approach for SAA in the context of Regime Switches:

1. **Hierarchical clustering-based asset allocation** → 'all-weather' portfolio
2. Enhance allocation decision with **News Sentiment** → **Bull** or **Bear market cycle**? → Overweight **bonds** or **equities**!

Agenda

1. State of the Art
   - Regime Switching
   - News Sentiment
   - Hierarchical Clustering-Based Asset Allocation
2. Methodology
   - Asset Allocation
   - Investment Procedure
3. Data
   - Assets
   - News Sentiment
4. Results & Discussion
5. Conclusion

State of the Art

Regime Switching

Figure: Sequential data can be represented by using a Markov chain of latent variables, with each observation conditioned on the state of the corresponding latent variable.

Regime Switching

- The Markov chain depends on

$$A = \begin{pmatrix} p & 1-p \\ 1-q & q \end{pmatrix}$$

Regime Switching - Practical Problems

Several problems make Markov models impractical:

- **Optimal number** of states?
- **Initial conditions** for optimization procedure?
- **frequent rebalancing** can eat up the potential excess return

News Sentiment

News Sentiment in finance:

- Tetlock, 2007 is one of the first to show the **predictive power of News Sentiment**
- Further extended to show **persistence for weeks & months**[1]
- **What about long term usage?**

[1] Uhl, Pedersen and Malitius (2015)

News Sentiment - SAA

- Uhl and Rohner (2019) attempt to use **long-term news sentiment** in an SAA framework
- Black-Litterman (BL) framework + mean variance optimization
- **enhanced** the Sharpe Ratios of the benchmark SAAs by almost 20%

News Sentiment - SAA

Problems with BL & mean variance

- **dimensionality curse** of both BL and mean variance
- linear views on the assets which are **assumed to be uncorrelated**
- **hard to quantify** this correlation between views

Hierarchical Clustering-Based Asset Allocation

Problem with Markowitz's approach:

- Conditioning number of a matrix
- **The more correlated the investments**, the higher the conditioning number
- Unstable matrix inversion

Markowitz's curse states that the more correlated the investments, the greater the need for diversification, and yet the more likely we will receive unstable solutions

Hierarchical Clustering-Based Asset Allocation

Prado (2016): "Hierarchical clustering refers to the formation of a recursive clustering, suggested by the data, not defined apriori."

Hierarchical Clustering-Based Asset Allocation

Goal: Construct a binary tree that merges similar clusters.

- Raffinot (2017) analyzes four agglomerative clustering algorithms
- At each of the $N-1$ steps the closest two (least dissimilar) clusters are merged into a single cluster, producing one less cluster at the next higher level

Hierarchical Clustering-Based Asset Allocation

Need of a suitable **distance measure**:

$$D_{i,j} = \sqrt{2(1 - \rho_{i,j})}$$

Need a **measure of dissimilarity** between two clusters C_i, C_j:

1. Single Linkage
2. Complete Linkage
3. Average Linkage
4. Ward's Method

Hierarchical Clustering-Based Asset Allocation - Single

The distance between two clusters is the minimum of the distance between any two points in the clusters.

- $d_{C_i,C_j} = \min_{x,y}\{D(x,y) : x \in C_i, y \in C_j\}$
- the most simple one
- sensitive to outliers
- problem called chaining whereby clusters end up being long and straggly

Hierarchical Clustering-Based Asset Allocation - Complete

The distance between two clusters is the maximum of the distance between any two points in the clusters.

- $d_{C_i,C_j} = \max_{x,y}\{D(x,y) : x \in C_i, y \in C_j\}$
- compact clusters of similar size
- quite sensitive to outliers

Hierarchical Clustering-Based Asset Allocation - Average

The distance between two clusters is the average of the distance between any two points in the clusters.

- $d_{C_i,C_j} = \text{mean}_{x,y}\{D(x,y) : x \in C_i, y \in C_j\}$
- fairly robust

Hierarchical Clustering-Based Asset Allocation - Ward

The distance between two clusters is the increase of the squared error that results when two clusters are merged.

- $d_{C_i,C_j} = \frac{m_i m_j}{m_i+m_j}||c_i - c_j||^2$
- m_i, m_j are the sizes of the two clusters
- c_i, c_j are the centroids for the clusters
- biased towards globular clusters
- less susceptible to noise and outliers

Methodology

Asset Allocation

First step: Focus on the computation of the **HCBAA weights**,

$$f(\mathbf{\Sigma_t^T}, \texttt{method}) = \mathbf{w_t^{HCBAA}}$$

where $\texttt{method} \in \{\texttt{single}, \texttt{complete}, \texttt{average}, \texttt{ward}\}$.

Asset Allocation

Second step: Focus on adjusting the risk of our exposure based on our prediction which relies on news sentiment (-1 to $+1$).

- **High risk assets** which include equities
- **Low risk assets** which include bonds
- Non-risk-categorized assets such as infrastructure indices

Asset Allocation

Computation of risk adjusted weights $w_t^{RA'}$

$$\mathbf{w_t^{RA'}} = \mathbf{w_t^{HCBAA}} * \mathbf{o_j} = \begin{pmatrix} w_{t,1} \\ \vdots \\ w_{t,N} \end{pmatrix} * \begin{pmatrix} \lambda \\ \vdots \\ 1 \end{pmatrix}$$

where $j \in \{\texttt{high risk}, \texttt{low risk}\}$.

Re-normalize $\mathbf{w_t^{RA'}} \rightarrow \mathbf{w_t^{RA}}$ such that we have **100% exposure** again.

Investment Procedure

We follow following **investment procedure**:

- Weight finding procedure is repeated at **every rebalancing key date**
- **Rebalance** every 12 month (SAA)
- **Same exposure** during the whole holding period
- **Lookback window** length T of 12 months
- λ **parameter** as risk-tolerance proxy $\rightarrow$ To have clearly distinguishable results, we set this factor to 2

Data

Assets

Asset	Low Risk	High Risk	Beta	Standard Deviation
Bonds CHF	X		0.008	0.867
Bonds Global Government (CHF hedged)	X		-0.002	1.105
Bonds Global (CHF hedged)	X		0.043	1.185
Gold	X		0.173	5.246
Equities Switzerland		X	0.692	4.641
Equities Global Developed		X	1.000	4.840
Equities Emerging Markets		X	1.100	6.447
Equities Global Small Cap		X	1.021	5.196
Private Equity		X	1.070	5.936
Bonds Emerging Markets hard currency (CHF hedged)			0.310	3.063
Bonds Emerging Markets local			0.647	3.881
Insurance-Linked Securities (desmoothed)			0.379	3.230
Infrastructure			0.766	3.959

Table: List of available assets and their **categorization into the three different sub-asset classes**. Betas and standard deviations computed from 31.01.1972 to 31.08.2019 using the MSCI Global as benchmark.

Assets

We want to be able to invest in all available assets.

Therefore the data set ...

- **starts** on the 2003-01-31 &
- **ends** on the 2019-08-31.

News Sentiment

Same data set used by Uhl, Pedersen and Malitius (2015) and is provided by **Thomson Reuters**.

Investing **globally** (in the context of **SAA & RS**) → Focus on the **macro-economical news sentiment** with following indicators[2]:

- Monetary Policy/ Central Bank Actions
- Economic Indicators
- Credit/ Government Debt Ratings
- Politics/ War/ Environment

[2] (Uhl, Pedersen and Malitius, 2015, p. 103)

News Sentiment

Using these indicators each news document is analyzed for its **positive**, **neutral**, and **negative sentiment**.

- **Each document** is assigned a news sentiment $\in [-1, +1]$
- Daily observations $\rightarrow$ very **noisy**
- 10 day rolling **exponential weighted mean**
- Shift data back by one day to remove any **forward looking bias**
- Aggregate data to **monthly** by summing up
- **Normalize** time series such that values $\in [-1, +1]$

Results & Discussion

Performance - Without News Sentiment Enhancement

Figure: Performance of strategies excluding transaction costs.

Performance with TC - Without NS Enhancement

Figure: Performance of strategies including transaction costs.

Summary Statistics - Without NS Enhancement

	Single	Complete	Average	Ward	BM Ivp	BM Eq
Geometric Average Excess Return	0.39	0.45	0.39	0.5	0.25	0.4
Geometric Average Total Return	0.45	0.49	0.43	0.54	0.3	0.45
Arithmetic Average Total Return	0.46	0.49	0.44	0.54	0.29	0.46
Arithmetic Average Excess Return	0.42	0.47	0.41	0.52	0.25	0.44
Standard Deviation Excess Returns	2.27	2.01	2.0	2.0	0.85	2.45
Sharpe Ratio Arithmetic	0.63	0.8	0.7	0.9	1.04	0.61
Sharpe Ratio Geometric	**0.6**	**0.77**	**0.67**	**0.86**	**1.02**	**0.57**
Minimum Excess Return	-8.13	-8.74	-7.59	-8.03	-3.2	-13.0
Maximum Excess Return	7.87	7.73	7.92	7.15	3.13	8.23
Skewness Excess Return	-0.24	-0.56	-0.4	-0.46	-0.35	-1.23
Kurtosis Excess Return	2.17	2.84	2.31	2.16	1.35	5.0

Table: Summary statistics of the four different portfolios (Single, Complete, Average and Ward) together with the two benchmarks for no News Sentiment enhancement. Data is monthly with the Sharpe Ratios annualized.

Performance - With News Sentiment Enhancement

Figure: Performance of strategies excluding transaction costs.

Performance with TC - With NS Enhancement

Figure: Performance of strategies including transaction costs.

Conclusion

Comparison WARD - With and without NS Enhancement

Figure: Comparison ward clustering approach with and without News Sentiment starting in May 2004.

Comparison WARD - With and without NS Enhancement

Figure: Comparison `ward` clustering approach with and without News Sentiment starting in July 2004.

Comparison WARD - With and without NS Enhancement

Figure: Comparison `ward` clustering approach with and without News Sentiment starting in January 2005.

Q&A

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