

**Correlation Networks** 

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## **Transaction**: payment, trade, exposure, supply, flow,

...



# **Similarity**: correlation, partial correlation, granger causality, transfer entropy, ...



Stavroglou et al (2016) Causality Networks of Financial Assets

#### **Correlation Networks**

Interconnectivity of markets has increased

We need to be able to understand correlations structures of much larger scale.

Networks help develop intuition, and understand stress tests.



#### Typical view of cross asset correlations

#### Correlation Matrix Over the Last 15 Years (2001-2015)

		Equity			94. B	Fixed Income			Alternative Strategies				Alternative Assets				
		Large Cap	Mid Cap	Small Cap	Int'l	Emerging Mkts	Corp.	High Yield	Treas.	Long/ Short	Mkt Neutral	Event Driven	FI Arbitrage	Mgd Futures	Real Estate	Currency	Comm- odities
Equity	Large Cap	1.00															
	Mid Cap	0.93	1.00														
	Small Cap	0.88	0.96	1.00													
	Int'l	0.88	0.85	0.79	1.00												
	Emer. Mkts	0.78	0.80	0.75	0.87	1.00											
Fixed Income	Corp.	0.17	0.20	0.13	0.30	0.31	1.00										
	High Yield	0.66	0.71	0.66	0.69	0.71	0.52	1.00									
	Treas.	-0.36	-0.35	-0.36	-0.27	-0.25	0.63	-0.19	1.00								
Alt. Strategies	Long/Short	0.75	0.79	0.72	0.84	0.80	0.27	0.61	-0.28	1.00							
	Mkt Neutral	0.27	0.29	0.29	0.26	0.24	-0.09	0.37	-0.29	0.25	1.00						
	Event Driven	0.64	0.70	0.64	0.71	0.70	0.23	0.67	-0.34	0.83	0.32	1.00					
	FI Arbitrage	0.42	0.46	0.37	0.48	0.48	0.42	0.63	-0.10	0.51	0.36	0.55	1.00				
	Mgd Futures	-0.13	-0.10	-0.12	0.00	0.01	0.19	-0.12	0.29	0.19	-0.01	0.09	0.00	1.00			
Alt. Assets	Real Estate	0.08	0.12	0.14	0.08	0.05	-0.03	0.06	-0.08	0.05	0.14	0.04	0.03	0.00	1.00		
	Currency	-0.03	-0.02	0.01	0.02	0.01	0.11	-0.07	0.13	0.13	0.02	0.03	0.00	0.61	0.07	1.00	
	Commodities	0.32	0.38	0.33	0.45	0.47	0.11	0.35	-0.17	0.49	0.28	0.49	0.45	0.18	0.10	-0.08	1.00
		High (0.9-1.0) Moderate High				h (0.7-0.9) Moderate			(0.3-0.7) Low		v (0.0-0.3)		Negative (<0.0)				
Low Diversification High Diversif									ification								

#### Universe of Global Assets (ETFs)

BND	Total Bond Index	FXC	CAD	USO	Oil
DBC	Commodities	FXE	EUR	UUP	USD Index
DIA	DJIA	FXI	China	VGK	Europe
DXJ	Japan Stocks (in JPY)	FXY	JPY	VPL	Asia
EEM	Emerging Markets	GDX	Gold Miners	VXX	VIX ST Futures
EFA	EAFE	GLD	Gold	XIU	TSX 60
EMB	EMBI	IEF	Barclays 1-7Y US	XLB	Materials
EPP	Asia ex Japan	IYR	Real Estate	XLE	Energy
EWG	Germany	JNK	High Yield Bonds	XLF	Financials
EWI	Italy	LQD	Corp Bonds	XLK	Tech
EWJ	Japan	SLV	Silver	XLU	Utilities
EWQ	France	SPY	S&P 500	CSJ	Barclays 1-3Y US
EWU	UK	TIP	TIPS	FXF	CHF
FXB	GBP	TLT	20Y+ Gov't		

#### **Correlation Network of the Assets**

We can view any matrix as a network.

We encode correlations as links between the correlated nodes/assets.

Red link = negative correlation Black link = positive correlation

However, this simple encoding does not give us much.



#### **Transactions & Similarity Based Networks**

Not all correlations are statistically significantly different from 0.

Absence of link marks that asset is not significantly correlated (here at 95% level).

Due to the large number of estimates, we also need for multiple comparisons correction. Eg. Bonferroni or FDR.



#### Network Layout

We can use network layouts to better detect patterns from noise.

E.g. we can try a Force-Directed network layout to identify clusters.



### Filtering

Next, we identify the Minimum Spanning Tree and filter out other correlations (Mantegna, '99).

We need a distance function, here we look at maximum spanning tree with distance function: abs(cor)

This shows us the backbone correlation structure.



We use a radial tree layout algorithm (Bachmeier et al. '05) that places the assets so that:

- Shorter links in the tree indicate higher correlations
- Longer links indicate lower correlations

As a result, we also see how the assets cluster by asset class.



Focus on the links in the Spanning Tree to highlight clustering structure.

Node color indicates last daily return

- Green = positive
- Red = negative

Node size indicates magnitude of return

Bright colors are VaR exceptions



#### Brexit, Friday 24 June 2016



#### Network Analytics : Filtering

Often networks are large and complex and we want to filter out noise. Filtering techniques give solutions.



Soramaki et al (2016). 'A Network-Based Method for Visual Identification of Systemic Risks': Journal of Network Theory in Finance

#### Use Case: Monitoring Housing Markets



Soramaki et al (2016). '<u>A Network-Based</u> <u>Method for Visual Identification of Systemic</u> <u>Risks</u>': Journal of Network Theory in Finance

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