FINTECH RISK MANAGEMENT

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This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 825215. All material presented here reflects only the authors' view. The European Commission is not responsible for any use that may be made of the information it contains.

Artificial Intelligence Use Cases

FIN-TECH HO2020

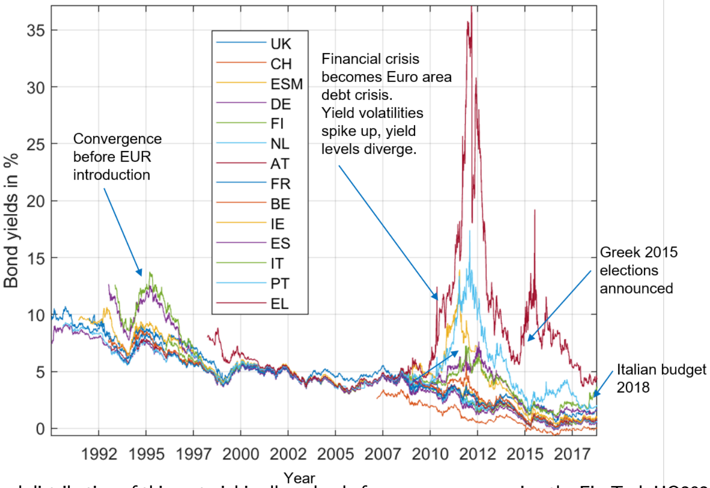
February 10, 2020

Table of contents

Use Case I: Convergence and Divergence in European Bond Correlations (Peter Schwendner, Martin Schüle and Martin Hillebrand, ZHAW and European Stability Mechanism)

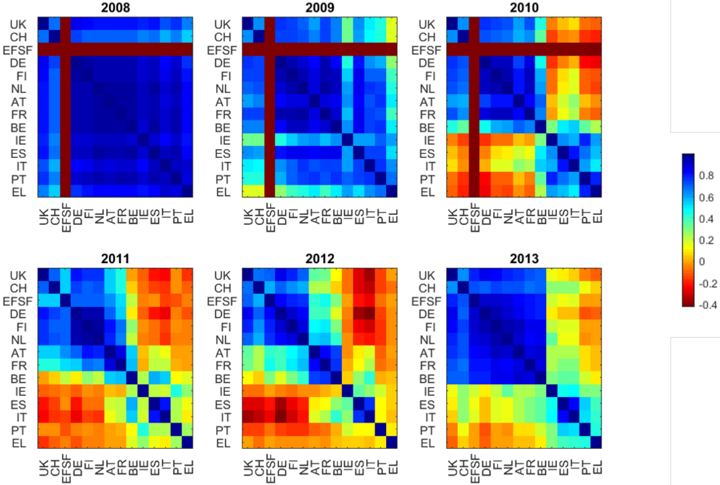
European Bond Yields (daily Bloomberg data)

- Euro convergence for bonds yields during end of 90s.
- Wide spreads during European sovereign debt crisis 2010-2012.
- Since 2015, bond spreads primarily signal political divergence.



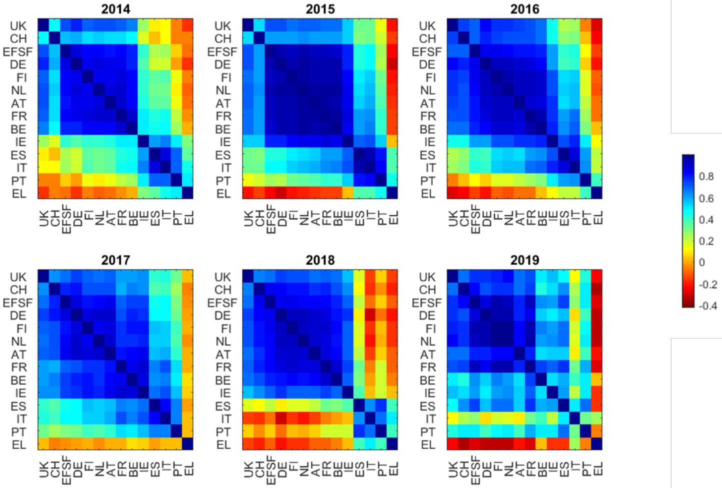
European Bond Return Correlations 2008 - 2013

- Containment of the 2010 sovereign bond crisis



European Bond Return Correlations 2014-2019

- From financial crisis to political divergence



Problems with correlations

- They are unstable in time
- Common factors may lead to spurious correlations
- Too many links: each market is correlated to any other market. Who is driving what?
- Idea: "Correlation influence" shows driving factors of correlations. Bootstrap resampling to simulate statistical noise in return blocks of random length ("wild bootstrap").

Original return matrix

UK	CH	...	PT	EL
1	1	1	1	1
2	2	2	2	2
3	3	3	3	3
4	4	4	4	4
5	5	5	5	5
6	6	6	6	6
7	7	7	7	7

One of 10.000 bootstrap resamples

UK	CH	...	PT	EL
3	3	3	3	3
5	5	5	5	5
2	2	2	2	2
3	3	3	3	3
6	6	6	6	6
1	1	1	1	1
2	2	2	2	2

Correlation influence Network

- The partial correlation measure is defined as

$$\rho_{ij:k} = \frac{C_{ij} - C_{ik} C_{kj}}{\sqrt{1 - C_{ik}^2}\sqrt{1 - C_{kj}^2}}. \tag{1}$$

- Correlation influence is defined as

$$d_{i,j:k} = C_{ij} - \rho_{ij:k}. \tag{2}$$

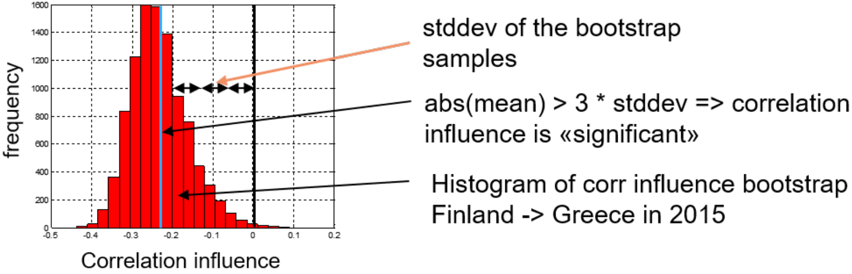
- The average correlation influence is defined as

$$d_{i:k} = mean(d_{i,j:k_{j \neq i,k}}). \tag{3}$$

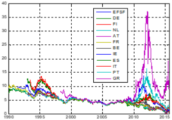
This is a directed arrow from market k pointing to market i.

Bootstrap filter

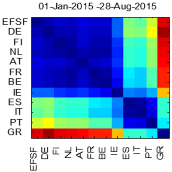
- For each resample, we compute the average correlation influence matrix.
- The standard deviation across all resamples is a measure for the noise in the correlation influence.
- We filter out correlation influences with a threshold of three standard deviations.



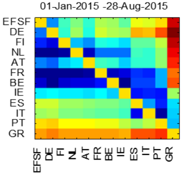
Overview: Generate Filtered Correlation Influence Network



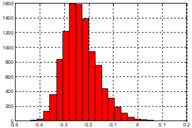
Bond yield time series



Correlation matrix of yield changes



Correlation influence



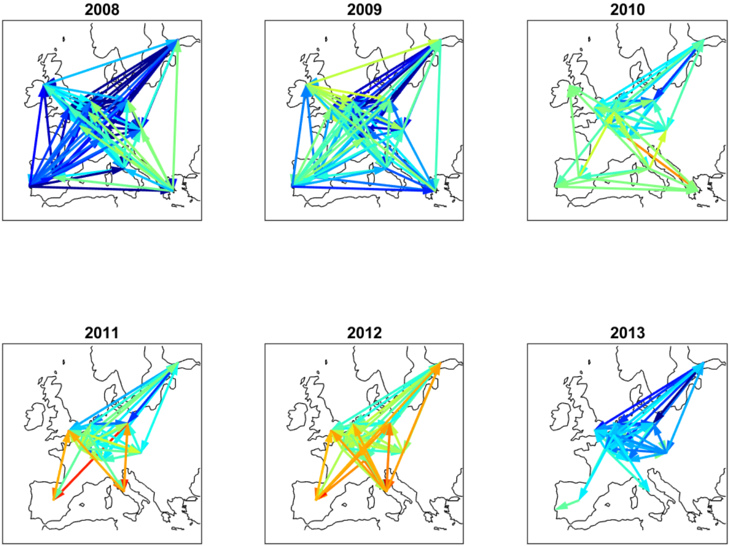
Bootstrap filter

Filtered influence network

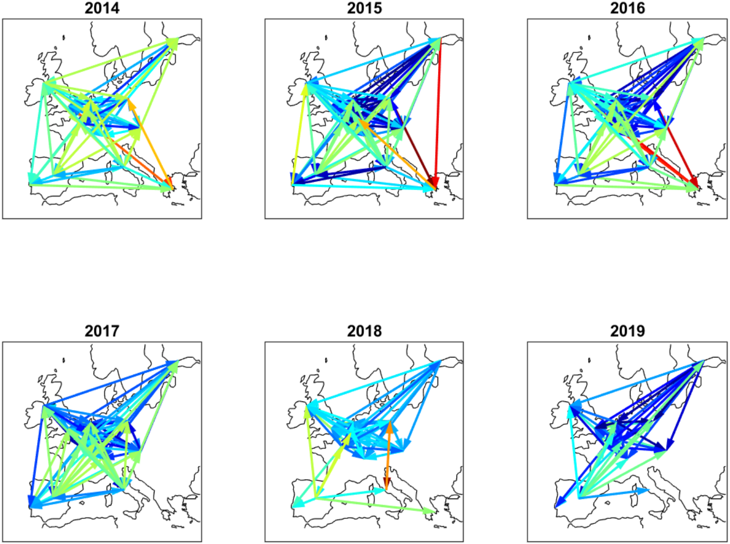
Positive correlation influences: blue arrows

Negative correlation influences: red arrows

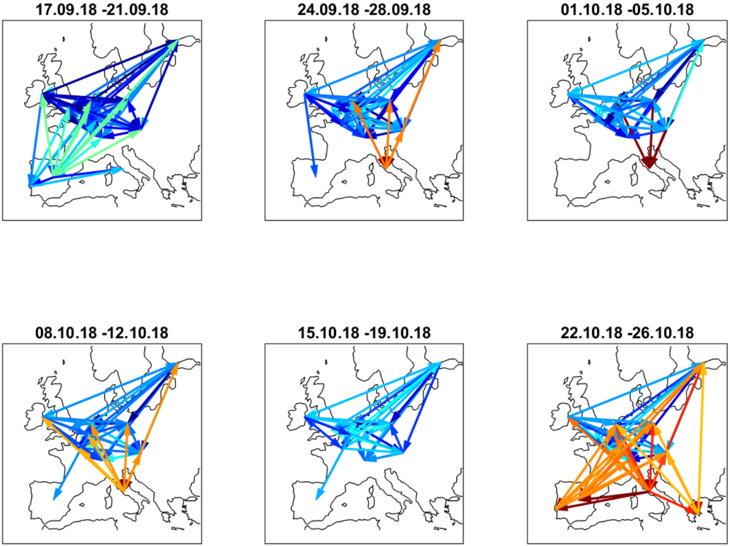
Filtered Correlation Influence Networks 2008 - 2013



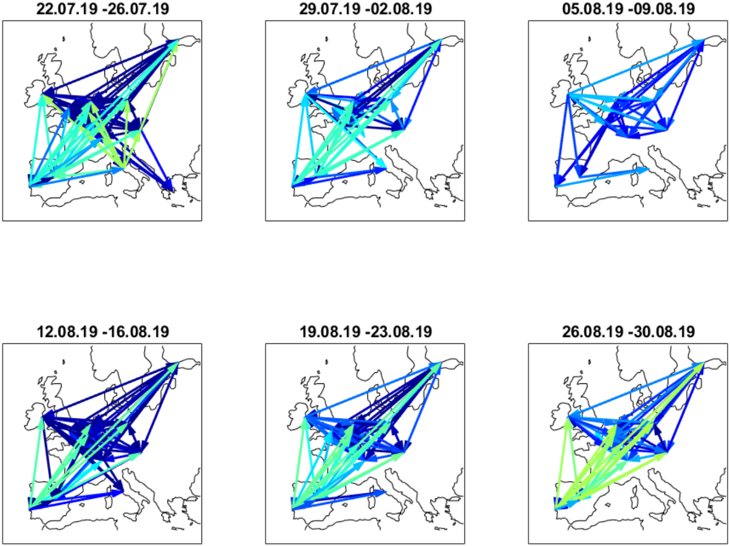
Filtered Correlation Influence Networks 2014 - 2019



Filtered Correlation Influence Networks October 2018

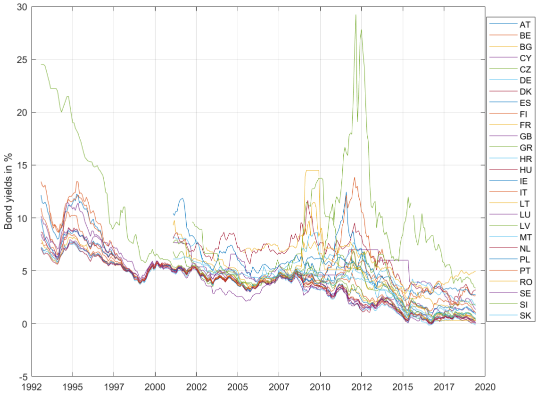


Filtered Correlation Influence Networks August 2019



Publicly available European Bond Yield data

- Source: ECB https://sdw.ecb.europa.eu
- Only monthly, but 27 EU countries (all but Estonia)



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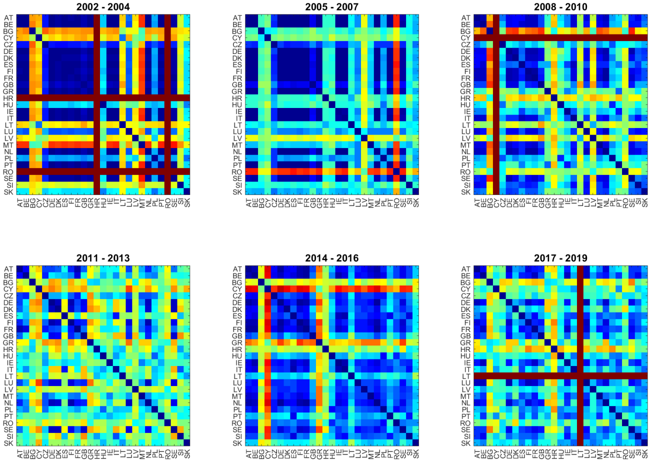
European Bond Return Correlations 2002 - 2019

- We define 3-year-windows as we only have monthly data



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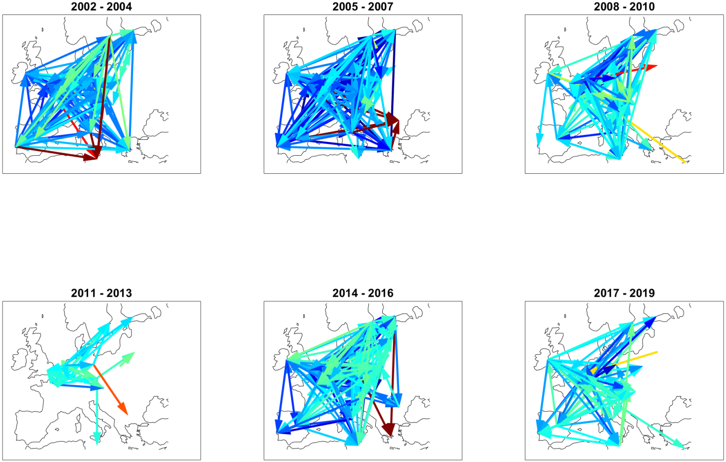
Filtered Correlation Influence Networks 2002 - 2019

- Also with monthly data, the networks replicate the core-periphery dynamics



Conclusions

- Since 2010, European bonds cluster into core and periphery groups according to their return correlations. We use filtered correlation influence networks to show the most significant drivers of convergence and divergence.
- During the European sovereign debt crisis 2010 - 2012, negative correlation influences between the core and periphery groups are the dominating force. Since 2013, the situation improved a lot.
- In 2015 during the negotiations between Greece and the Eurogroup and in 2018 during the Italian budget negotiations, the warning signals of negative correlation influences reappeared for short periods, although the absolute level of spreads is substantially smaller than during 2010 - 2012.
- The findings point to markets becoming more politically driven.

Full paper: ESM Working Paper #8 and JNTF (2015), "Sentiment Analysis of European Bonds 2016 - 2018" , Frontiers in AI (2019).

Use Case II: On the effectiveness of Portfolio Composition techniques to build stable and sound Robo Advisory Portfolios (Ronald Hochreiter, WU Vienna)

A short tale of Robo Advisory

As of 2019 many financial institutions already closed down their Robo Advisory business which was set up in the last few years - most recently in May 2019 Investec after having lost more than USD 32 million. To quote the CFO of one of the largest UK asset managers:

- Robo Advisors are a poor fit with the rest of the business because of the kind of customers that tend to use them, and
- it is difficult to sell investment products to people with no money.

Robo Advisory

- In general a Robo Advisor tries to extract/understand the risk behavior of its clients using questionnaires and/or simplified graphical tools. The clients are generally not wealthy and are financially not well-educated or even illiterate.
- Sometimes there is a mismatch between the behaviour data collected and the realization of Robo portfolios. This is mainly due to the inherent problem of simplified portfolio constructions as well as a non-adaptive process to changing market regimes.
- The aim of this case study is to apply a severely diverse set of Portfolio Construction techniques to understand their impact on different market regimes given certain objectives for Robo Advisory portfolios (e.g. minimizing drawdown or volatility, etc.)

Portfolio Composition Techniques

There are several heterogeneous types of Portfolio Composition techniques and it is known that many people only stick to a specific group of techniques without ever conducting a sound comparison. We apply and compare the results of the following techniques:

- A classical Markowitz Mean-Variance approach along with various methods to robustify the covariance matrix.
- Equal Risk Contribution (ERC) portfolios (again with robust convariance matrices)

Robustification approaches includes e.g. exponential weighting moving average covariance matrices, Harman's K-factor method and the Shrinkage models developed by Ledoit and Wolf.

Portfolio Composition Techniques

- Operations Research: Instead of using some covariance matrix the whole scenario set is used to build optimization models for certain coherent (statistical) risk measures, e.g. Expected Shortfall, MAD, Average Drawdown, Omega Ratio, ...
- Factor Models and Factor Ranking Portfolios: several factors are computed and after ranking assets by the respective factor value portfolios are built by using some consensus ranking (with or without additional constraints). Using ETFs restricts the set of available factors to rather technical ones (e.g. Momentum and Statistical Risk-based factors).

Portfolio Composition Techniques

- Technical Trading Rules and Portfolio Construction: Buy and Sell Signals of a set of technical trading strategies are combined to deduct a specific portfolio composition.
- Machine Learning: A set of features is extracted from time series (e.g. statistical measures) and based on this Design Matrix a predictive model is learned to create predictions that will be combined into a portfolio.
- Artificial Intelligence: Deep Learning models are applied, i.e.
  - Recurrent Neural Networks are used to forecast asset returns and based on the forecasts a portfolio composition is computed, and
  - Convolutional Neural Networks are used to build prediction models based on time series images.

Assets and Data

- The asset universe consists of slightly more than 50 ETFs that cover a wide range of countries and asset classes (e.g. equity sectors, commodities, ...). However the case study is designed such that the list of underlying assets can be easily exchanged.
- The effect of the different portfolio composition techniques is tested on certain pre-specified financial regimes (e.g. 2007-2009, 2011-2014, ...) to obtain an understanding how certain compositions behave in specific regimes to use this knowledge to build more stable and sound Robo Advisory portfolios.

Appendix: Selected ETFs (1/2)

	Symbol	Description
1	AGG	iShares Core U.S. Aggregate Bond ETF
2	DBC	PowerShares DB Commodity Index Tracking Fund
3	DFE	WisdomTree Europe SmallCap Dividend Fund
4	DIA	SPDR Dow Jones® Industrial Average ETF
5	DXJ	WisdomTree Japan Hedged Equity Fund
6	EEM	iShares MSCI Emerging Markets ETF
7	EFA	iShares MSCI EAFE ETF
8	EWG	iShares MSCI Germany ETF
9	EWH	iShares MSCI Hong Kong ETF
10	EWI	iShares MSCI Italy Capped ETF
11	EWT	iShares MSCI Taiwan ETF
12	EWU	iShares MSCI United Kingdom Index Fund
13	EWW	iShares MSCI Mexico Capped ETF
14	EWY	iShares MSCI South Korea Capped ETF
15	EWZ	iShares MSCI Brazil Capped ETF
16	EZU	iShares MSCI EMU ETF
17	FEZ	SPDR EURO STOXX 50 ETF
18	FXI	iShares China Large-Cap ETF
19	GDX	VanEck Vectors Gold Miners ETF
20	GLD	SPDR Gold Shares ETF
21	IAU	iShares Gold Trust ETF
22	IBB	iShares NASDAQ Biotechnology Index ETF
23	ITB	iShares U.S. Home Construction ETF
24	IVV	iShares Core S&P 500 ETF
25	IWD	iShares Russell 1000 Value ETF
26	IWM	iShares Russell 2000 ETF
27	IYR	iShares U.S. Real Estate ETF
28	KBE	SPDR S&P Bank ETF
29	KRE	SPDR S&P Regional Banking ETF
30	LQD	iShares iBoxx $ Investment Grade Corporate Bond ETF

Appendix: Selected ETFs (2/2)

	Symbol	Description
31	OIL	iPath S&P GSCI Crude Oil Total Return Index ETN
32	SDS	UltraShort S&P500 ETF
33	SH	Short S&P500 ETF
34	SLV	iShares Silver Trust ETF
35	SPY	SPDR S&P 500 ETF
36	USO	United States Oil Fund
37	VGK	Vanguard FTSE Europe ETF
38	VNQ	Vanguard REIT ETF
39	VTI	Vanguard Total Stock Market ETF
40	VWO	Vanguard FTSE Emerging Markets ETF
41	XHB	SPDR Homebuilders ETF
42	XLB	Materials Select Sector SPDR Fund
43	XLE	Energy Select Sector SPDR Fund
44	XLF	Financial Select Sector SPDR Fund
45	XLI	Industrial Select Sector SPDR Fund
46	XLK	Technology Select Sector SPDR Fund
47	XLP	Consumer Staples Select Sector SPDR Fund
48	XLU	Utilities Select Sector SPDR Fund
49	XLV	Health Care Select Sector SPDR Fund
50	XLY	Consumer Discretionary Select Sector SPDR Fund
51	XME	SPDR S&P Metals & Mining ETF
52	XOP	SPDR S&P Oil & Gas Exploration & Production ETF

Use Case III: Network models to enhance automated cryptocurrency portfolio management (Paolo Giudici, Paolo Pagnottoni, Gloria Polinesi, UNIPV and POLITECNICA)

Robot advisors, intro

- **FinTech** innovations are increasing exponentially, for the evolving technology on the supply side and for the shifting of consumer preferences on the demand side
- The total masses managed by the automatic consultancy are estimated around 980 billion dollars in 2019, and 2,552 billion in 2023

Robot advisors and financial automation, Pros&Cons

- **Advantages**:
  - Improved financial inclusion
  - Lower fees
  - High speed of service
  - Customized user experience
- **Disadvantages**:
  - User may not understand portfolio construction
  - Portfolio models may be too simple
  - Contagion between asset returns increases
  - Portfolio allocation may not be complaint with investors' risk profile

Our contribution

- Build **similarity network models** from the available asset return data
- Models that can incorporate multiple correlations (contagion) between asset returns in porfolio allocation.
- The ultimate goal is to improve portfolio allocation and risk compliance, taking systemic risk into account

Two main original contributions

- We extend the application of similarity networks from stock returns to **Exchange Traded Fund** returns
- We propose **an extension to Markowitz' portfolio allocation** that takes network centrality and, therefore, contagion, explicitly into account

The Random Matrix approach

- **RMT** separates the "sistematic" part of a signal embedded into a return correlation matrix from the "noise"
- Tests the eigenvalues of the correlation matrix: $\lambda_k < \lambda_{k+1}; k = 1, \ldots, n$, against the null hypothesis that they are from a random Wishart matrix $\mathbf{R} = \frac{1}{T}\mathbf{A}\mathbf{A}^\mathbf{T}$

Let r_i, for $i = 1, \ldots, n$, be a time series of **Cryptocurrency returns** and $\mathbf{C}$ be their correlation matrix. The RMT matrix is given by:

$$\mathbf{C}^* = \mathbf{V}\mathbf{L}\mathbf{V}^\mathbf{T}, \tag{4}$$

where V is the eigenvector matrix and

$$\mathbf{L} = \begin{cases} 0 & \lambda_i < \lambda_+ \\ \lambda_i & \lambda_i \geq \lambda_+ \end{cases}$$

Similarity Network

- In a similarity network **nodes** represent asset returns and **edges** the distance between adjacent nodes.
- There exist different metrics to build **distances** between nodes: we apply the Euclidean distance

$$d_{ij} = \sqrt{2 - 2c'_{ij}},$$

- There exist different algorithms to simplify a similarity network: we apply the **Minimum Spanning Tree**, that reduces the number of edges from $N*(N-1)/2$ to $N-1$.
- In the MST, at each step, two cluster nodes l_i and l_j are merged into a single cluster if:

$$d(l_i, l_j) = \min\{d(l_i, l_j)\}$$

with the distance between clusters being defined as:

$$d(l_i, l_j) = \min\{d_{rq}\}$$

with $r \in l_i$ and $q \in l_j$.

Centrality measures

- To measure the importance of each node, we can use the **eigenvector centrality**.
- The importance of a node depends on the importance of the nodes to which it is connected:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} \hat{d_{i,j}} x_j \tag{5}$$

Portfolio Construction

- Differently from previous works which employ centrality measures as an alternative measure of diversification risk, we extend Markowitz' approach using RMT and MST in the optimisation function itself:

$$\min_{\mathbf{w}} \mathbf{w}^{\mathbf{T}} \mathbf{C}^{*} \mathbf{w} + \gamma \sum_{i=1}^{n} x_i w_i$$

subject to

$$\begin{cases} \sum_{i=1}^{n} w_i = 1 \\ \mu_P \geq \frac{\sum_{i=1}^{n} \mu_i}{n} \\ w_i \geq 0 \end{cases}$$

- A high risk propensity (represented by a high value of γ) translates in a portfolio composed by more systemically risky assets, that lay in the central body of the network, avoiding isolated cryptocurrencies.

Application

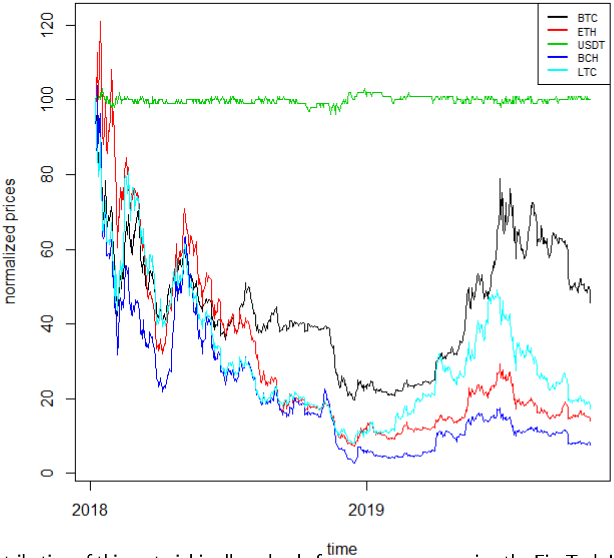
- The data contains 10 time series of returns referred to cryptocurrencies traded over the period 14 September 2017 - 17 October 2019 (764 daily observations)
- Cryptocurrencies were selected in terms of market capitalization
- Portfolio returns are computed using the last month of each time window
- We use eleven months of observations as a look-back period computing asset centrality and the consequent portfolio weights
- Then we calculate the return of each portfolio over the next month rebalancing cryptocurrencies with the retrieved weights. Finally we connect each monthly portfolio performances from January 2018 to October 2019

Summary statistics

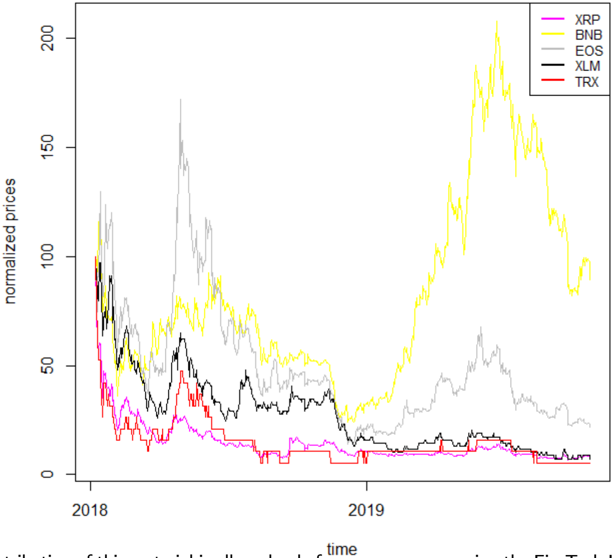
	mean	std.	kurtosis
BTC	0.0009	0.04	3.35
ETH	-0.0007	0.05	2.90
XRP	0.0004	0.07	15.73
USDT	0.0000	0.01	4.28
BCH	-0.0011	0.08	6.47
LTC	-0.0003	0.06	8.02
BNB	0.0033	0.07	7.74
EOS	0.0017	0.07	3.93
XLM	0.0021	0.10	26.19
TRX	0.0021	0.15	13.15

Cryptocurrency summary statistics over the period 14 September 2017 - 17 October 2019

Prices - I


BTC
ETH
USDT
BCH
LTC
normalized prices
0
20
40
60
80
100
120
2018
2019
time

Prices - II


XRP
BNB
EOS
XLM
TRX
normalized prices
0
50
100
150
200
2018
2019
time

MST networks

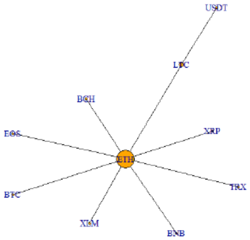


Figure 1: **MST September 2017- January 2018**. The figure shows the MST representation relative to the period of the speculative bubble.

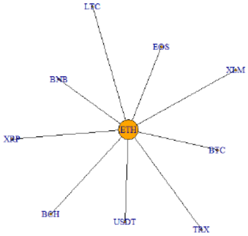


Figure 2: **MST June 2019- October 2019**. The figure shows the MST relative to the period June 2019- October 2019.

Portfolio Results - I

Period	CRIX	GM	EW	CM	NW	$\gamma = 0.005$	$\gamma = 0.025$	$\gamma = 0.05$	$\gamma = 0.15$	$\gamma = 0.7$	$\gamma = 1$
Jan-2018	-0.14	-0.13	-0.16	0.04	-0.22	-0.21	-0.26	-0.27	-0.36	-0.43	-0.43
May-2018	-0.67	-0.62	-0.60	-0.12	-0.79	-0.78	-0.73	-0.66	-0.83	-1.08	-1.10
Sep-2018	-1.37	-1.37	-1.43	-0.88	-0.83	-1.02	-1.24	-1.23	-1.40	-1.60	-1.64
Jan-2019	-1.85	-1.78	-1.78	-1.32	-0.87	-1.50	-1.86	-1.98	-2.19	-2.29	-2.31
May-2019	-1.35	-1.25	-1.27	-1.01	-0.74	-1.22	-1.33	-1.29	-1.44	-1.55	-1.57
Sep-2019	-0.99	-1.45	-1.49	-1.02	-0.54	-1.19	-1.34	-1.44	-1.86	-2.13	-2.15

Cumulative profit & losses

Portfolio Results - II

Period	GM	EW	CM	NW	$\gamma = 0.005$	$\gamma = 0.025$	$\gamma = 0.05$	$\gamma = 0.15$	$\gamma = 0.7$	$\gamma = 1$
Jan-2018	0.74	0.75	0.63	0.64	0.69	0.77	0.79	0.78	0.77	0.99
May-2018	0.73	0.75	0.95	0.83	0.74	0.77	0.83	0.87	0.87	0.55
Sep-2018	0.81	0.84	0.87	0.61	0.80	0.75	0.76	0.80	0.80	0.48
Jan-2019	1.16	1.11	1.47	1.24	1.34	1.36	1.39	1.40	1.40	1.26
May-2019	0.80	0.80	1.05	0.97	0.93	0.84	0.75	0.72	0.72	0.98
Sep-2019	0.75	0.78	1	1.14	0.43	0.38	0.38	0.38	0.37	0.78

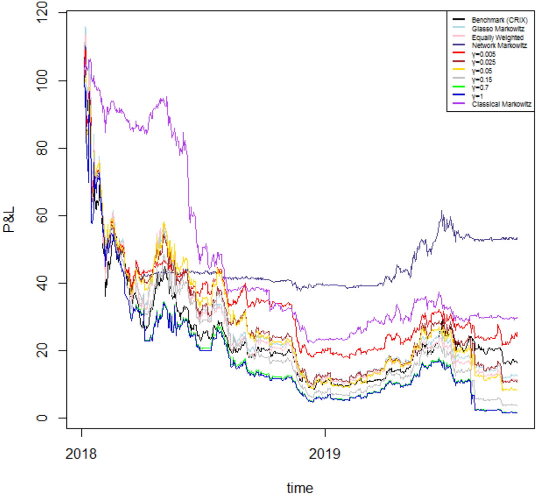
Rachev ratio

Portfolio Results - III

Period	CRIX	EW	NW	GM	CM
Jan-2018	0.11	0.13	0.15	0.14	0.03
May-2018	0.04	0.05	0.02	0.05	0.03
Sep-2018	0.11	0.11	0.10	0.12	0.02
Jan-2019	0.07	0.10	0.05	0.07	0.01
May-2019	0.04	0.02	0.03	0.02	0.04
Sep-2019	0.05	0.05	0.02	0.05	0.01

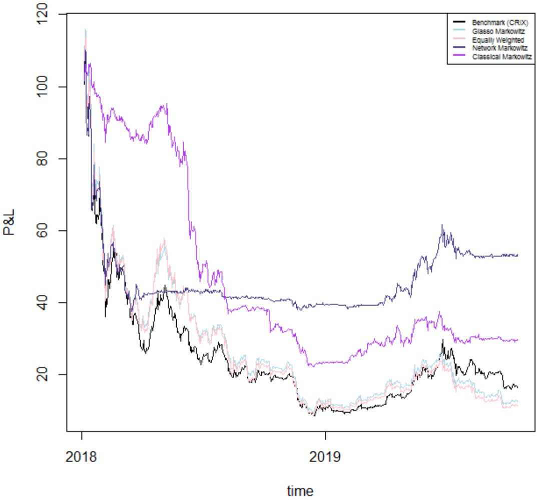
Value at Risk (VaR)

Portfolio Results - IV



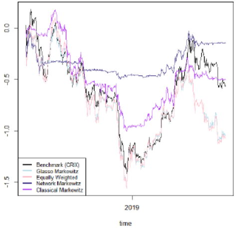
Portfolio returns

Portfolio Results - V



Highlight of portfolio returns

Sensitivity



(a)

(b)

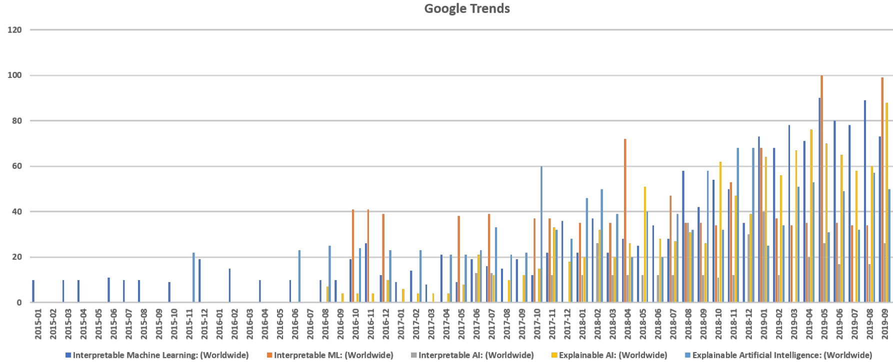
(c)

Sensitivity analysis with respect to different rolling windows

Use Case IV: eXplainable AI in credit scoring and portfolio construction (Dimitri Marinelli, Jochen Papenbrock, Niklas Bussmann, Paolo Giudici; FIRAMIS and UNIPV)

AI methods in credit scoring

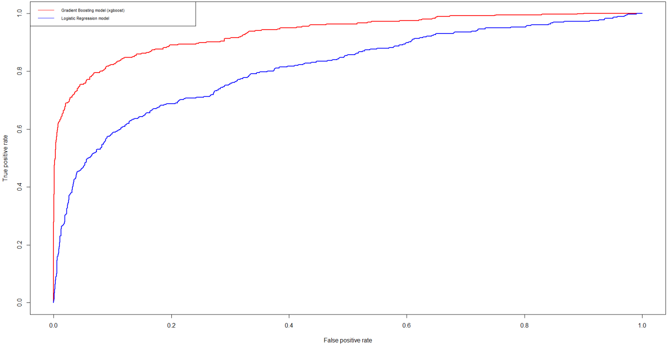
- Computationally intensive AI models can beat classic logistic regression scoring models
- However, they are not interpretable (black-boxes)
- Explainable AI models can help interpretability maintaining high predictive accuracy



Explainable AI and Interpretable AI are trending

AI methods in credit scoring: application

- We consider about 15,000 SME companies, which have received a loan, out of which about 11% have defaulted. The data contains 20 explanatory variables
- We apply the XGboost algorithm on a training dataset (80%) and compare the predictions with the best logistic regression model on the test set (20%)



The AUROC improves from 0.81 to 0.93.

To interpret the model, we propose to apply to Shapley values:

$$\phi_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!} \left[f_x(z') - f_x(z' \setminus i) \right] \qquad (6)$$

correlation network models obtained from minimum spanning tree.

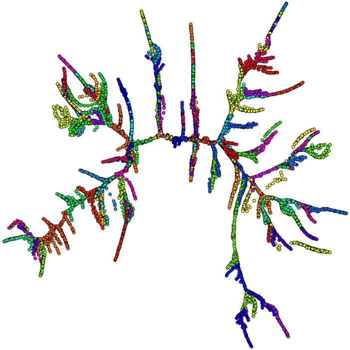


Figure 1: Minimal Spanning Tree representation of the borrowing companies. Clustering has been performed using the standardized Euclidean distance between institutions. Companies are colored according to their cluster of belonging.

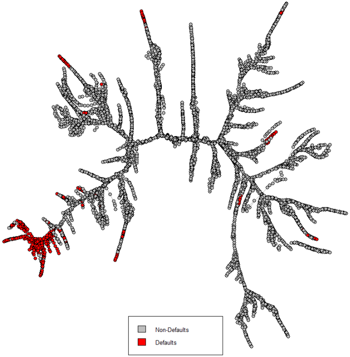


Figure 2: Minimal Spanning Tree representation of the borrowing companies. Clustering has been performed using the standardized Euclidean distance between institutions.Companies are colored according to their default status: red= defaulted; grey= not defaulted.

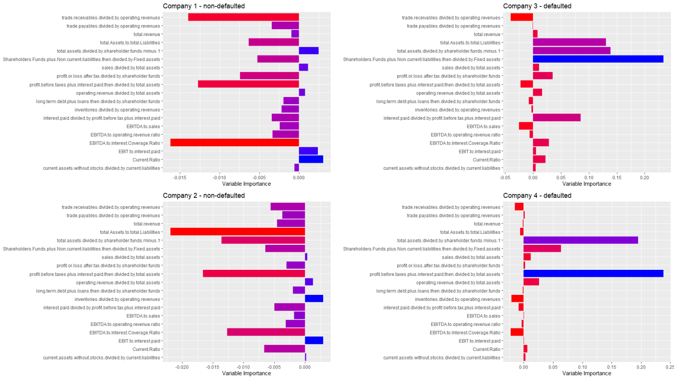


Figure 3: Contribution of each explanatory variable to the Shapley's decomposition of four predicted default probabilities, for two defaulted and two non defaulted companies. A red color indicates a low variable importance, and a blue color a high variable importance.