Network models to improve robot advisory portfolio management

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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, 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 **EFT returns** and **C** be their correlation matrix. The RMT matrix is given by:

$$\mathbf{C}' = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^{\mathbf{T}}, \tag{1}$$

where V is the eigenvector matrix and

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

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:

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

  with the distance between clusters being defined as:

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

  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:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} \hat{d_{i,j}} x_j \tag{2}$$

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:

$$\min_{\mathbf{w}} \mathbf{w}^{\mathbf{T}} \mathbf{COV}' \mathbf{w} + \gamma \sum_{i=1}^{n} x_i w_i$$

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 ETFs.

Application

- The data contains 92 time series of returns referred to ETFs traded over the period January 2006 to February 2018 (3173 daily observations)
- 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 balancing ETFs with the retrieved weights. Finally we connect each monthly portfolio performances from December 2006 to February 2018.

Data structure

	ETF class	Number of ETFs
1	Aggregate Bond	4
2	Commodity	8
3	Corporate-euro	11
4	Corporate-not euro	3
5	Corporate-high yield	2
6	Corporate-world	1
7	Emerging Equity-Asia	30
8	Emerging Equity-America	10
9	Emerging Equity-East Europe	4
10	Emerging Equity-world	17
11	Equity-Europe	1

Figure 1: **ETFs Compositions.**

Summary statistics

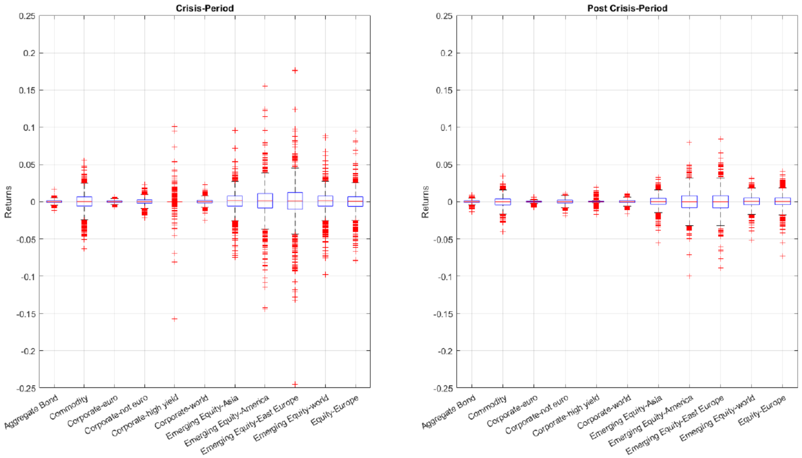


Figure 2: **Summary statistics for the returns of ETF classes considering two different period: crisis (2006-2012) and post crisis (2012-2013).**

RMT filtering

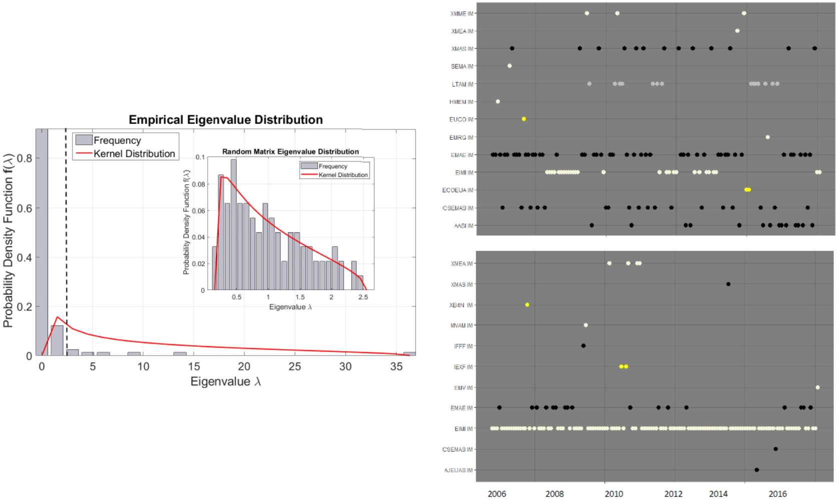


Figure 3: **Random Matrix Analysis**

MST networks

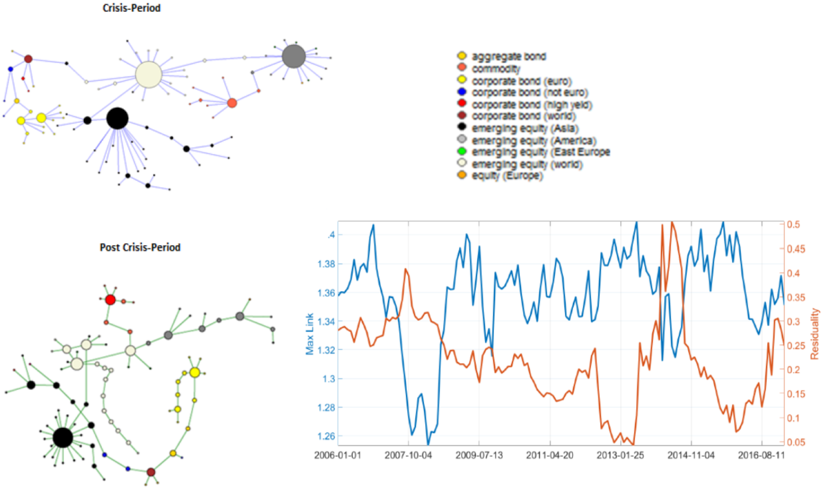
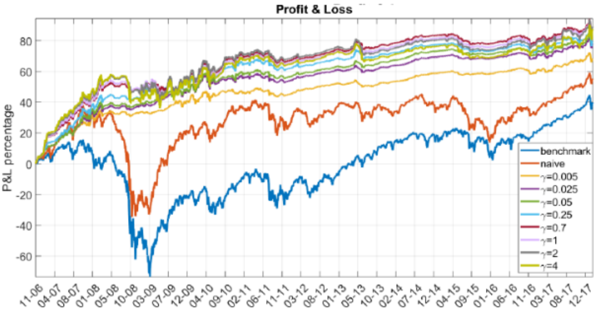
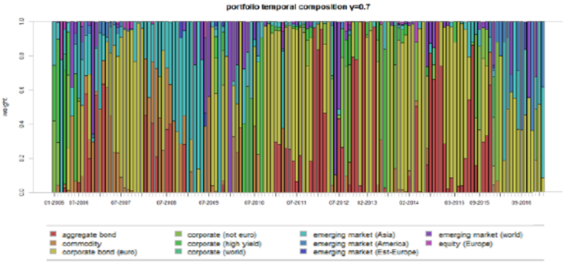


Figure 4: **Network Analysis**

Portfolio Results





Portfolio Results - II

year	naive	$\gamma = 0.005$	$\gamma = 0.025$	$\gamma = 0.05$	$\gamma = 0.25$	$\gamma = 0.7$	$\gamma = 1$	$\gamma = 2$	$\gamma = 4$
2006	0.12	0.18	0.18	0.18	0.16	0.17	0.17	0.17	0.16
2007	0.09	0.08	0.09	0.10	0.11	0.13	0.13	0.14	0.15
2008	-0.09	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02
2009	0.12	0.03	0.04	0.03	0.02	0.01	0.00	0.02	0.02
2010	0.03	0.01	0.02	0.03	0.03	0.04	0.04	0.04	0.04
2011	-0.03	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
2012	0.02	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03
2013	-0.06	-0.00	0.00	0.00	-0.00	-0.00	-0.01	-0.03	-0.03
2014	-0.00	0.02	0.03	0.03	0.02	0.03	0.03	0.03	0.03
2015	-0.04	-0.00	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.03
2016	0.02	0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.02
2017	0.04	0.01	0.01	0.00	0.00	0.00	0.00	-0.00	-0.01
2018	0.03	-0.01	-0.01	-0.02	-0.07	-0.05	-0.03	0.05	0.14

Figure 6: **Portfolio Extra-returns**