MUNI
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SUPTECH WORKSHOP III

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Network models to enhance automated cryptocurrency portfolio management

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

Contribution

- Build **similarity network models** from the available asset return data
- Models that can incorporate multiple correlations (contagion) between asset returns in portfolio 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 "systematic 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:

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

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

$$d_{ij} = \sqrt{2(1 - c_{ij})}$$

- 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:

$$x_i = \frac{1}{\lambda}\sum_{j=1}^{N}\hat{d}_{i,j}x_x$$

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:

$$
\begin{aligned}
&\min_{\mathbf{w}} \mathbf{w}^T \mathbf{C}^* \mathbf{w} + \gamma \sum_{i=1}^{n} x_i w_i \\
&\sum_{i=1}^{n} w_i = 1 \\
&\mu_p \geq \tfrac{1}{n} \sum_{i=1}^{n} \mu_i \\
&w_i \geq 0
\end{aligned}
$$

- 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

MST networks

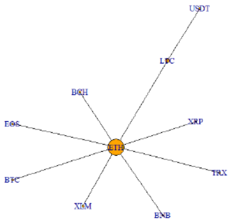


Figure 1: **MST September 2017- January 2018**. The figure shows the MST representation relative to the period of the speculative bubble.

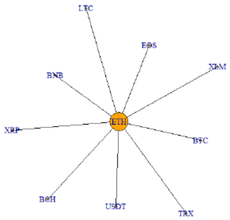


Figure 2: **MST June 2019- October 2019**. The figure shows the MST relative to the period June 2019- October 2019.

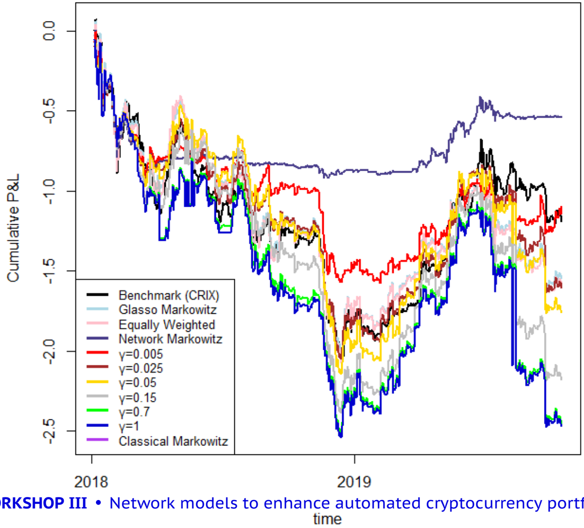
Portfolio Results - I, Cumulative P & L

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

Portfolio Results - II, Value at Risk (VaR)

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

Portfolio Results - III, cumulative returns



Portfolio Results - IV, highlights