A review of two decades of correlations, hierarchies, networks and clustering in financial markets

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Abstract

This document is an ongoing review on the state of the art of clustering financial time series and the study of correlation and other interaction networks. This preliminary document is intended for researchers in this field so that they can feedback to allow amendments, corrections and addition of new material unknown to the authors of this review. The aim of the document is to gather in one place the relevant material that can help the researcher in the field to have a bigger picture, the quantitative researcher to play with this alternative modeling of the financial time series, and the decision maker to leverage the insights obtained from these methods. We hope that this document will form a basis for implementation of an open toolbox of standard tools to study correlations, hierarchies, networks and clustering in financial markets.

Keywords: Financial time series, Cluster analysis, Correlation analysis, Complex networks, Econophysics

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1. The standard and widely adopted methodology

The methodology which is widely adopted in the literature stems from Mantegna's seminal paper [1] (cited more than 1200 times as of 2017) and chapter 13 of the book [2] (cited more than 3600 times as of 2017) published in 1999. We describe it below:

- Let N be the number of assets.
- Let $P_i(t)$ be the price at time t of asset i, $1 \leq i \leq N$.
- Let $r_i(t)$ be the log-return at time t of asset i:

$$r_i(t) = \log P_i(t) - \log P_i(t-1).$$

- For each pair i, j of assets, compute their correlation:

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left(\langle r_i^2 \rangle - \langle r_i \rangle^2\right)\left(\langle r_j^2 \rangle - \langle r_j \rangle^2\right)}}.$$

- Convert the correlation coefficients ρ_{ij} into distances:

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

- From all the distances d_{ij}, compute a minimum spanning tree (MST) using, for example, Algorithm 1:

Algorithm 1 Kruskal's algorithm

procedure BuildMST($\{d_{ij}\}_{1 \leq i,j \leq N}$)
  $\triangleright$ Start with a fully disconnected graph $G = (V, E)$
  $E \leftarrow \emptyset$
  $V \leftarrow \{i\}_{1 \leq i \leq N}$
  $\triangleright$ Try to add edges by increasing distances
  for $(i, j) \in V^2$ ordered by increasing d_{ij} **do**
    $\triangleright$ Verify that i and j are not already connected by a path
    if not *connected*(i, j) **then**
      $\triangleright$ Add the edge (i, j) to connect i and j
      $E \leftarrow E \cup \{(i, j)\}$
  $\triangleright$ G is the resulting MST
  return $G = (V, E)$

Several other algorithms are available to build the MST [3].

The methodology described above builds a tree, i.e. a connected graph with $N - 1$ edges and no loop. This tree is unique as soon as all distances d_{ij} are different. The resulting MST also provides a unique indexed hierarchy [2] which corresponds to the one given by the dendrogram obtained using the Single Linkage Clustering Algorithm.

2. Methodological concerns and extensions

2.1. Concerns about the standard methodology

We list below the concerns that have been raised about the standard methodology during the last 20 years:

- The clusters obtained from the MST (or equivalently, the Single Linkage Clustering Algorithm (SLCA)) are known to be **unstable** (small perturbations of the input data may cause big differences in the resulting clusters) [4].
- The clustering instability may be partly due to the algorithm (MST/Single Linkage are known for the **chaining phenomenon** [5]).
- The clustering instability may be partly due to the correlation coefficient (**Pearson linear correlation**) defining the distance which is known for being **brittle to outliers**, and, more generally, not well suited to distributions other than the Gaussian ones [6].
- **Theoretical results** providing the statistical reliability of hierarchical trees and correlation-based networks are still **not available** [7].
- One might expect that the higher the correlation associated to a link in a correlation-based network is, the higher the **reliability** of this link is. In [8], authors show that this is **not always observed empirically**.
- Changes affecting specific links (and clusters) during prominent crises are of **difficult interpretation** due to the **high level of statistical uncertainty** associated with the correlation estimation [9].
- The standard method is somewhat **arbitrary**: A change in the method (e.g. using a different clustering algorithm or a different correlation coefficient) may yield a huge change in the clustering results [10, 4]. As a consequence, it implies huge variability in portfolio formation and perceived risk [10].

Notice that Benjamin F. King in his 1966 paper [11] (the first paper, to the best of our knowledge, about clustering stocks based on their historical returns; apparently unknown to Mantegna and his colleagues who

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reinvented a similar method) adds a final footnote which serves both as an advice and a warning for future work and applications:

> One final comment on the method of analysis: this study has employed techniques that rely on finite variances and stationary processes when there is considerable doubt about the existence of these conditions. It is believed that a convincing argument has been made for acceptance of the hypothesis that a small number of factors, market and industry, are sufficient to explain the essential comovement of a large group of stock prices; it is possible, however, that more satisfactory results could be obtained by methods that are distribution free. Here we are thinking of a factor-analytic analogue to median regression and non-parametric analysis of variance, where the measure of distance is something other than expected squared deviation. In future research we would probably seriously consider investing some time in the exploration of distribution free methods.

It is only but recently that researchers have started to focus on these shortcomings as we will observe through the research contributions detailed in the next section.

2.2. Contributions for improving the methodology

To alleviate some of the shortcomings mentioned in the previous section, researchers have mainly proposed alternative algorithms and enhanced distances. Some refinements of the methodology as a whole, alongside efforts to tackle the concerns about statistical soundness, have been proposed.

2.2.1. On algorithms

Several alternative algorithms have been proposed to replace the minimum spanning tree and its corresponding clusters:

- **Average Linkage Minimum Spanning Tree (ALMST)** [8]; Authors introduce a spanning tree associated to the Average Linkage Clustering Algorithm (ALCA); It is designed to remedy the unwanted chaining phenomenon of MST/SLCA.
- **Planar Maximally Filtered Graph (PMFG)** [12, 13] which strictly contains the Minimum Spanning Tree (MST) but encodes a larger amount of information in its internal structure.
- **Directed Bubble Hierarchal Tree (DBHT)** [14, 15] which is designed to extract, without parameters, the deterministic clusters from the PMFG.
- **Triangulated Maximally Filtered Graph (TMFG)** [16]; Authors introduce another filtered graph more suitable for big datasets.
- Clustering using **Potts super-paramagnetic transitions** [17]; When anti-correlations occur, the model creates repulsion between the stocks which modify their clustering structure.
- Clustering using **maximum likelihood** [18, 19]; Authors define the likelihood of a clustering based on a simple 1-factor model, then devise parameter-free methods to find a clustering with high likelihood.
- Clustering using **Random Matrix Theory (RMT)** [20]; Eigenvalues help to determine the number of clusters, and eigenvectors their composition.
- [21] proposes network-based community detection methods whose null hypothesis is consistent with RMT results on cross-correlation matrices for financial time series data, unlike existing community detection algorithms.
- Clustering using the **p-median problem** [22]; With this construction, every cluster is a star, i.e. a tree with one central node.

2.2.2. On distances

At the heart of clustering algorithms is the fundamental notion of distance that can be defined upon a proper representation of data. It is thus an obvious direction to explore. We list below what has been proposed in the literature so far:

- Distances that try to quantify how one financial instrument provides information about another instrument:
  - Distance using **Granger causality** [23],
  - Distance using **partial correlation** [24],
  - Study of asynchronous, **lead-lag relationships by using mutual information** instead of Pearson's correlation coefficient [25, 26],
  - The correlation matrix is normalized using the affinity transformation: the correlation between each pair of stocks is normalized according to the correlations of each of the two stocks with all other stocks [27].
- Distances that aim at including non-linear relationships in the analysis:
  - Distances using mutual information, mutual information rate, and other **information-theoretic** distances [28, 26, 29, 30, 31, 32],
  - The Brownian distance [33],
  - **Copula-based** [34, 35, 36] and **tail dependence** [37] distances.
- Distances that aim at taking into account multivariate dependence:
  - Each stock is represented by a bivariate time series: its returns and traded volumes [38]; a distance is then applied to an *ad hoc* transform of the two time series into a symbolic sequence,
  - Each stock is represented by a multivariate time series, for example the daily (high, low, open, close) [39]; Authors use the **Escoufier's RV coefficient** (a multivariate extension of the Pearson's correlation coefficient).
- A distance taking into account both the **correlation** between returns **and** their **distributions** [6].

2.2.3. On other methodological aspects

Besides research contributions on algorithms and distances, other methodological aspects have been pushed further.

- Reliability and statistical uncertainty of the methods:
  - A **bootstrap** approach is used to estimate the statistical reliability of both hierarchical trees [40, 41] and correlation-based networks [8, 42],
  - **Consistency** proof of clustering algorithms for recovering clusters defined by nested block correlation matrices; Study of empirical **convergence rates** [41],
  - **Kullback-Leibler divergence** is used to estimate the amount of filtered information between the sample correlation matrix and the filtered one [43],
  - **Cophenetic correlation** is used between the original correlation distances and the hierarchical cluster representation [44],
  - Several measures between successive (in time) clusters, dendrograms, networks are used to estimate **stability** of the methods, e.g. cophenetic correlation between dendrograms in [45], adjusted Rand index (ARI) between clusters in [4], mutual information (MI) of link co-occurrence between networks in [9].
  - In [46], authors claim that clustering still cannot compete with "fundamental" industry classifications in terms of performance due to inherent out-of-sample instabilities, and thus propose to improve such given "fundamental" industry classification via further clustering large sub-industries at the most granular level.
- Preprocessing of the time series:
  - **Subtract the market mode** before performing a cluster or network analysis on the returns [47],

– Encode both **rank statistics** and a **distribution histogram** of the returns into a **representative vector** [6],

– Fit an ARMA(p,q)-FIEGARCH(1,d,1)-cDCC process (**econometric preprocessing**) to obtain dynamic correlations instead of the common approach of rolling window Pearson correlations [48],

– Use a clustering of successive correlation matrices to **infer a market state** [44].

- Use of **other types of networks**: threshold networks [49], influence networks [50], partial-correlation networks [24, 51], Granger causality networks [23, 52], cointegration-based networks [53], bipartite networks [54], etc.
- Understanding of the drivers of synchronous correlations using the properties of the collective stock dynamics at **shorter time scales** [55] by using **directed networks** of lagged correlations [55, 56].

3. Dynamics of correlations, hierarchies, networks and clustering

Many of the empirical studies are based on the whole period available from the data. Some researchers have started to investigate the dynamics of the empirical correlations, and also the hierarchies, networks and clusters extracted from them (cf. [57] as one of the earliest work). This dynamic setting which has the potential to track changes of the market structure is more interesting for practitioners (e.g. risk managers, traders, regulatory agencies). This research is still in its infancy and we think its results are still hardly exploitable in practice. For instance, an interesting but difficult question is the following: Are **changes** in the correlation structure due to statistical **noise** and data artifacts **or** do they provide a **real signal**?

No predominant methodology has emerged for now but the naive one which consists in:

- Computing Pearson correlations on a **rolling window of arbitrary length**,
- then independently computing a network or a clustering based on the rolling empirical correlation matrix.

Some promising avenue of research may be the use of temporal networks and temporal centrality measures [58].

Besides the shortcomings of Pearson correlation detailed above, this approach is brittle due to its strong **dependence *a priori* on:**

- the **sampling frequency** (e.g., intraday, daily, weekly),

  – Concerning the sampling frequency, authors in [59] notice that at intraday frequency level some time is needed before the cluster organization emerges completely. According to the paper, "the changes observed in the structure of the MST and of the hierarchical tree suggest that the intrasector correlation decreases faster than intersector correlation between pairs of stocks" when sampling frequency increases. In [47, 4], authors observe that the clusters obtained using daily returns are similar to the ones obtained with weekly timescales, and even to some extent to the ones using monthly returns. Most of the empirical studies focus on daily returns and only a few explore intraday data: [59, 60, 47, 61, 62, 55]. Working with higher frequencies (e.g. at the transaction or quote level) brings further difficulties such as coping with asynchronous data and the Epps effect [63].

- the **length** T of the rolling window,

  – What is the right length for the rolling window? No clear-cut answer has yet been proposed and, in most studies, its length is set somewhat arbitrarily. In [57], authors posit that "the choice of window width is a trade-off between too noisy and too smoothed data for small and large window widths, respectively" and that they "have explored a large scale of different values for both parameters, and the given values were found optimal". What are the proper criteria for setting the window length? The choice can be driven by the goal (e.g. time investment horizon), by regulatory rules (e.g. computing Value-at-Risk using 1-year historical data), by the stability of clusters [4], by a statistical convergence rate [41], by economic regimes or by a trade-off of the preceding criteria.

- the **number N of assets** studied.
  - The number of considered assets has also a significant impact on the results: the ratio T/N drives the precision of correlation estimation and ultimately the clustering [64, 41, 65, 66].

This dependence makes it difficult to fully understand and analyze results. Once these 'parameters', i.e. the sampling frequency, T, and N, are chosen, one can study

- the **dynamics of correlations**:
  - In [27], authors are using a sliding window of $T = 22$ days to measure and monitor the eigenvalue entropy of the stock correlation matrices (estimated using daily returns, for $N = 25$ (Tel-Aviv stock market), and $N = 455$ (from S&P500)). They also propose a 3D visualization to monitor the configuration of stocks using a 3D PCA.
  - [67] notices three regime shifts during the period 1989-2011 by monitoring eigenvalues and eigenvectors of the empirical correlation matrices (estimated using quarterly recorded prices from the US housing market; $T = 60$, $N = 51$, the number of US states).
- the **dynamics of the MST** and other hierarchical trees:
  Using summary statistics:
  - The MST which evolves over time is monitored using summary statistics (also called topological features) [68] such as the normalized tree length [57], the mean occupation layer [57], the tree half-life [57], a survival ratio of the edges [69, 60, 48], node degree, strength [48], eigenvector, betweenness, closeness centrality [48], the agglomerative coefficient [70].
  - Using these statistics, [57] notices that:
    - the MST strongly shrinks during a stock market crisis,
    - the optimal Markowitz portfolio lies practically at all times on the outskirts of the tree,
    - the normalized tree length and the investment diversification potential are very strongly correlated.
  - And [48] notices that in the Asia-Pacific stock market:
    - the DST (dynamic alternative of the MST, built from dynamic correlations) shrinks over time,
    - Hong Kong is found to be the key financial market,
    - the DST has a significantly increased stability in the last few years,
    - the removal of the key player has two effects: there is no clear key market any longer and the stability of the DST significantly decreases.
  - In [71], authors observe that for the Japanese and Korean stock markets, there is a decrease of grouping by industry categories.

  Using distances or similarity measures between successive dendrograms:
  - Cophenetic correlation coefficient. In [70], authors propose a cophenetic analysis of public debt dendrograms in the European Union ($N = 29$ countries) computed using Pearson correlation of quarterly debt-to-GDP ratios between 2000 Q1 and 2014 Q1 ($T = 57$) with a sliding window of size $w = 15$.
- the **dynamics of clusters**:
  - The paper [22] finds that the cluster structures are more stable during crises (using the p-median problem, an alternative clustering methodology).

- Authors in [60] notice that there is an "ecology of clusters": They "can survive for finite periods of time during which time they may evolve in some identifiable way before eventually dissipating or dying".
- In [44], the authors track the merging, splitting, birth, death, contraction, and growth of the clusters in time.

4. Financial applications

Though many of the academic studies focus on the MST or the clusters *per se*, some papers try to extend their use beyond the filtering of empirical correlation matrices. It has been proposed to leverage them for making financial policies, optimizing portfolios, computing alternative Value-at-Risk measures, residualizing expected returns, grouping and selecting quantitative trading alphas, etc.

4.1. Portfolio Design and Trading Strategies

- [57] finds that the Markowitz portfolio layer in the MST is higher than the mean layer at all times.
- As the stocks of the minimum risk portfolio are found on the outskirts of the tree [72, 57], authors expect larger trees to have greater diversification potential.
- In [73, 45], authors compare the Markowitz portfolios from the filtered empirical correlation matrices using the clustering approach, the RMT approach and the shrinkage approach.
- [74, 75] propose to invest in different part of the MST depending on the estimated market conditions.
- Authors show that there is no inner-mathematical relationship between the minimum variance portfolio from Markowitz theory and the portfolios designed from the minimum spanning tree [76]. Empirical evidence of such relations found by previous studies is essentially a stylized fact of financial returns correlations and time series, not a general property of correlation matrices.
- It appears that a large number of stocks are unnecessary for building an index of market change [11].
- The paper [77] describes methods for index tracking and enhanced index tracking based on clusters of financial time series.
- [37] introduces a procedure to design portfolios which are diversified in their tail behavior by selecting only a single asset in each cluster.
- [78] investigates several network and hierarchy based active portfolio optimizations, and find their out-of-sample performance competitive with respect to conventional ones.
- [79] presents the performance of seven portfolios created using clustering analysis techniques to sort out assets into categories and then applying classical optimization inside every cluster to select best assets inside each asset category.
- In [44], they suggest that tracking the merging, splitting, birth, and death of the clusters in time could be the basis for pairs-like reversal trading strategies but with pairs corresponding to clusters.
- One can build a simple mean-reversion statistical arbitrage strategy whereby one assumes that stocks in a given industry move together, cross-sectionally demeans stock returns within said industry, shorts stocks with positive residual returns and goes long stocks with negative residual returns [46].
- Earnings per share forecasts prepared on the basis of statistically grouped data (clusters) outperform forecasts made on data grouped on traditional industrial criteria as well as forecasts prepared by mechanical extrapolation techniques [80].
- [81] suggests that one may design a new set of Ricci network curvature based-strategies in statistical arbitrage (e.g. for mean-reverting portfolios).
- In [82], authors apply the TMFG for building sparse forecasting models and for financial applications such as stress-testing and risk allocation.
- [83] finds the existence of significant relations between past changes in the market correlation structure and future changes in the market volatility.
- In [46], authors suggest the use of clustering to build statistical classification of quantitative trading alphas for which there is no analog of "fundamental" industry classifications such as the GICS, BICS, ICB, NAICS, SIC, etc.

- [84, 85] describe a behavioral bias: investors overly rely on the standard industry classifications (e.g., SIC, NAICS). Corporate managers can exploit this behavioral bias to steer their company towards a more favorable industry and therefore benefit from a lower cost of capital. The article [84] does not discuss this behavioral bias from the investor point of view, but it can pay to have a different (statistical) view of the standard industry classification to avoid such opportunistic window dressing. In [85], authors claim that long-short strategies exploiting mispricing due to the industry categorization bias generate statistically significant and economically sizable risk-adjusted excess returns.
- In [86], authors show that considering alternative industry classifications (for example, text-based ones) can enhance the returns of well-known quantitative strategies such as the industry momentum one which is driven, according to the paper, by inattention to less visible horizon peers.

4.2. Risk Management

How much money a given portfolio can lose? in normal market conditions? in stressed market conditions? in the presence of systemic risk?

To answer these questions, the use of clusters and networks can help. As presented previously, the clustering hierarchy can be used to filter a correlation [73, 87] or a tail dependence [37] matrix, which helps to measure the risk in normal and stressed market conditions respectively. The systemic risk as defined by the Bank for International Settlements is the risk that a failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties. Networks seem thus a particularly relevant tool to study this kind of risk.

- Study of **systemic risk**:
  - In [88], authors assert that the diminution of regulation has removed barriers between sectors and regions allowing bank to diversify their risk, but it also increased the economic risk through increased interdependencies.
  - The paper [89] is focused on energy derivative markets, and their market integration which can be seen as a necessary condition for the propagation of price shocks. The MST is used to "identify the most probable and the shortest path for the transmission of price shocks".
  - Authors in [67] focus on the US housing market. According to the paper, "dramatic increases in the systemic risk are usually accompanied by regime shifts, which provide a means of early detection of housing bubbles." They find a sharp increase in housing market correlations over the past decade, indicating that systemic market risk has also greatly increased; They observe that prices diffuse in complex ways that do not require geographical clusters unlike worldwide stock markets which exhibit clear geographical clustering [9].
  - The paper [33] is focused on the shipping market. Authors explore the connections between the shipping market and the financial market: The shipping market can provide efficient warning before market downturn. Alike many economic systems which have been exhibiting an increase in the correlation between different market sectors, a factor that exacerbates the level of systemic risk, the three major world shipping markets, (i) the new ship market, (ii) the second-hand ship market, and (iii) the freight market, have experienced such an increase. Authors show it using the MST, Granger causality analysis, and Brownian distance on the prices of the real shipping market, and the stock prices of publicly-listed shipping companies.
  - [23] investigates the monthly returns of hedge funds, banks, broker/dealers, and insurance companies. They find that all four sectors have become highly interrelated over the past decade, likely increasing the level of systemic risk.
  - [81] shows that Ricci curvature may serve as an indicator of fragility in the context of financial networks.
  - [44] detects distinct correlation regimes between 1998 and 2013. These correlation regimes have been significantly different since the financial crisis of 2008 than they had been previously. Cluster

tracking shows that asset classes are now less separated. Correlation networks help the authors to identify "risk-on" and "risk-off" assets.

  – In [90], authors study the clusters' composition evolution, and their persistence. They observe that the clustering structure is quite stable in the early 2000s becoming gradually less persistent before the unfolding of the 2007-2008 crisis. The correlation structure eventually recovers persistence in the aftermath of the crisis, settling up a new phase which is distinct from the pre-crisis structure one, where the market structure is less related to industrial sector activity.
  – [91] finds that financial institutions which have, in the correlation networks, greater node strength, larger node betweenness centrality, larger node closeness centrality and larger node clustering coefficient tend to be associated with larger systemic risk contributions.
  – [92, 93] discuss the detection of early-warning signals of the 2008 crisis via the analysis of the properties of interbank networks.
  – In [94], authors highlight that the underlying financial network required to study systemic risk is only partially observable in general. They propose a method to reconstruct such a network, i.e. to build a set of (directed and weighted) dependencies among the constituents of a complex system.

- Risk management **methods**:
  – In [95], authors design clusters that tend to be comonotone in their extreme low values: To avoid contagion in the portfolio during risky scenarios, an investor should diversify over these clusters.
  – As far as diversification is concerned, portfolio managers should probably focus on the most stable parts of the graph [89].
  – In [96], authors postulate the existence of a hierarchical structure of risks which can be deemed responsible for both stock multivariate dependency structure and univariate multifractal behaviour, and then propose a model that reproduces the empirical observations (entanglement of univariate multi-scaling and multivariate cross-correlation properties of financial time series).
  – Industries (e.g. clusters as statistical industry classification) can be used as risk factors in multi-factor risk models [46].
  – Clusters (statistical industry classification) can be an alternative to sometimes unavailable "fundamental" industry classifications (e.g. in emerging or small markets) [46].

We found that the risk literature using correlation networks and clusters consists essentially in descriptive studies. For now, there are only too few propositions in the academic literature to build effective network-based or cluster-based risk systems.

4.3. Financial Policy Making

Clusters and networks can help designing financial policies. Several papers propose to leverage them to detect risky market environments, develop indicators that can predict forthcoming crisis or economic recovery [61], improve economic nowcasting [97], or find key markets and assets that drive a whole region, and on which stimulus can be applied effectively.

- Authors of [88] claim that "separation prevents failure propagation and connections increase risks of global crises" whereas the prevailing view in favor of deregulation is that banks, by investing in diverse sectors, would have greater stability. To support their argument, using financial networks, they study the aftermath of the Glass-Steagall Act (1933) repeal by Clinton administration in 1999. They find that erosion of the Glass–Steagall Act, and cross sector investments eliminated "firewalls" that could have prevented the housing sector decline from triggering a wider financial and economic crisis:

> Our analysis implies that the investment across economic sectors itself creates increased cross-linking of otherwise much more weakly coupled parts of the economy, causing dependencies that increase, rather than decrease, risk.

- According to [23], bank and insurance capital requirements and risk management practices based on VaR, which are intended to ensure the soundness of individual financial institutions, may amplify aggregate fluctuations if they are widely adopted:

  > For example, if the riskiness of assets held by one bank increases due to heightened market volatility, to meet its VaR requirements the bank will have to sell some of these risky assets. This liquidation may restore the bank's financial soundness, but if all banks engage in such liquidations at the same time, a devastating positive feedback loop may be generated unintentionally. These endogenous feedback effects can have significant implications for the returns of financial institutions, including autocorrelation, increased correlation, changes in volatility, Granger causality, and, ultimately, increased systemic risk, as our empirical results seem to imply.

- In [89], authors find that the move towards integration started some time ago and there is probably no way to stop or refrain it. However, regulation authorities may act in order to prevent prices shocks from occurring, especially in places where their impact may be important.

5. Practical Fruits of Clusters, Networks, and Hierarchies[1]

5.1. Stylized facts

Stylized facts can be described as follows [99]:

> A set of [statistical] properties, common across many instruments, markets and time periods, [which] has been observed by independent studies.

From the papers we reviewed, we can list the following stylized facts:

- Elements belonging to some economic sectors are strongly connected within themselves, whereas others are much less connected.
- The Energy and Financial sectors are examples of strong connections whereas elements belonging to the Conglomerates, Consumer cyclical, Transportation, and Capital Goods sectors are weakly connected.
- General Electric is at the center of US stocks networks (for several centrality criteria) [1, 59, 57, 38].
- The Energy, Technology, and Basic Materials sectors are sectors of elements significantly connected among them but weakly interacting with stocks belonging to different economic sectors.
- The Financial sector is strongly connected within, but also to others.
- The assets of the classic Markowitz portfolio are always located on the outer leaves of the tree [57, 72, 75].
- The maximum eigenvalue of the correlation matrix, which carries most of the correlations, is very large during market crashes [100] (increased value of the mean correlation).
- The MST shrinks during market crashes [57] and contains a low number of clusters [70].
- The MST provides a taxonomy which is well compatible with the sector classification provided by an outside institution [2, 57].
- Scale free (i.e. the degree of vertices is power law distributed $f(n) \sim n^{-\alpha}$) structure of the MST [101, 102, 57, 103], but the scaling exponent depends on market period and window width [69].
- The MST obtained with the one-factor model is very different from the one obtained using real data [103]. This invalidates the Capital Asset Pricing Model which is based on the one-factor model $r_i(t) = \alpha_i + \beta_i r_M(t) + \epsilon_i(t)$.

[1] reference to the book *Practical Fruits of Econophysics* [98]

- Stocks compose a hierarchical system progressively structuring as the sampling time horizon increases [104, 47].
- The correlation among market indices presents both a fast and a slow dynamics. The slow dynamics is a gradual growth associated with the development and consolidation of globalization. The fast dynamics is associated with events that originate in a specific part of the world and rapidly (in less than 3 months) affect the global system [9, 67].
- Removing the dynamics of the center of mass decreases the level of correlations, but also makes the cluster structure more evident [47].
- Scale invariance of correlation structure (by subtraction of the market mode) might have important implications for risk management, because it suggests that correlations on short time scales might be used as a proxy for correlations on longer time-horizons [47].
- The MST is star-like in low-volatility segments, and chain-like in high-volatility segments [61].
- Volatility shocks always start at the fringe and propagate inwards [61].
- The "post-subprime" regime correlation matrix shows markedly higher absolute correlations than the others [44].
- In [44], authors find far less asset class separation in the post-subprime period.
- One can distinguish three types of topological configurations for the companies: (i) important nodes, (ii) links and (iii) dangling ends [101].
- A node keeps the majority of its neighbours. The non-randomness of the stock market topology is thus a robust property [101].
- The largest eigenvector of the correlation matrix is strongly non-Gaussian, tending to uniform - suggesting that all companies participate. Authors find indeed that all components participate approximately equally to the largest eigenvector. This implies that every company is connected with every other company. In the stock market problem, this eigenvector conveys the fact that the whole market "moves" together and indicates the presence of correlations that pervade the entire system [20].
- The measure of the average length of shortest path in the PMFG shows a small world effect present in the networks at any time horizon [104].
- Among the 100 largest market capitalization stocks in the NYSE, the auto and lagged intraday correlations play a much more prominent role in 2011-2013 than in 2001-2003 [55].
- Authors in [55] find striking periodicities in the validated lagged correlations, characterized by surges in network connectivity at the end of the trading day.
- At short time scales, measured synchronous correlations among stock returns tend to be lower in magnitude [63], but lagged correlations among assets may become non-negligible [105, 56].
- Banks may be of more concern than hedge funds from the perspective of connectedness [23].
- A lack of distinct sector identity in emerging markets [106]; Few largest eigenvalues deviate from the bulk of the spectrum predicted by RMT (far fewer than for the NYSE) [106].
- Emergence of an internal structure comprising multiple groups of strongly coupled components is a signature of market development [106].

5.2. Moot points and controversies

Though most of the conclusions of empirical studies do agree, we find some claims that seem to be contradictory:

- [107] finds that eccentricity-based risk budgeting portfolios have improved return to risk ratios, hence better invest in centrality (of the minimum spanning tree). On the contrary, [57, 72, 75] conclude that it is better to invest in the peripheries (of the minimum spanning tree).
- Volatility shocks always start at the fringe and propagate inwards [61], but in [108], authors assert that the credit crisis spreads among affected stocks from more centralized to more outer ones, as spread the news about the extent of damage to the global economy.
- One might expect that the higher the correlation associated to a link in a correlation-based network is, the higher the reliability of the link is. The paper [8] shows that it is not always observed empirically.

However, the Cramér–Rao lower bound (CRLB) for correlation [109] points out that the higher the correlation, the easier its estimation, i.e. less statistical uncertainty for high correlations.

- For filtering the correlation matrix, SLCA is more stable than ALCA according to [7], but ALCA is more stable and appropriate than SLCA according to [73, 44].
- During a crisis period, is there an increase or decrease of clusters stability? Most papers find a decrease (e.g. [89, 90]), but at least one [22] (using an alternative clustering methodology, the p-median problem) advocates for an increase.

Acknowledgments

Many thanks to the researchers which have contributed to improve this review (in chronological order): David Matesanz, Tiziana Di Matteo, Diego Garlaschelli, Damiano Brigo, Fabrizio Lillo.

Appendix A. The Ecosystem of Correlations, Networks, and Hierarchies in Econophysics

Appendix A.1. A brief history

In 1966, Benjamin F. King asserts in [11] that "a desired result is the separation of the large set of individual series into a smaller set of clusters of security price changes that tend to move as homogeneous groups". For him,

> the most dramatic indication of industry comovement to be found, however, is provided by the following "quick and dirty" method of factor analysis. We shall refer to this technique as "cluster analysis" [...]. One begins by transforming the residual covariance matrix, G_1, to a residual correlation matrix by pre- and post-multiplying by the square root of the inverse of the diagonal. Then this matrix is searched for the highest positive pairwise correlation coefficient. When the highest correlation is found, the two variables are added together to form a new, combined variable, reducing the total number of variables from 63 to 62. Next, the correlation matrix is recomputed in order to include the correlation between the combined variable and the remaining variables. (The correlations involving the individual variables that merged are blanked out; in sum, the order of the residual correlation matrix is reduced by one.) Then, moving on to Pass 2, the search for the maximum pairwise correlation is repeated, followed by all of the necessary combining and modification of the correlation matrix that has just been described. At each pass after the second it is possible for either single variable to join another variable, a single variable to join a group of other variables, or else, two groups to merge in order to form a larger group. One can see that at the end of 62 passes, all of the variables will have joined to form one group, unless the routine stops because of exhaustion of positive correlation coefficients.

Through this verbose description, one can recognize the description of the Single Linkage clustering algorithm put forward by Sneath in *The Application of Computers to Taxonomy*, 1957. However, it seems that the author was not aware of this technique as the following footnote from his paper suggests:

> After hearing a presentation at the 1964 meeting of the Econometric Society by Walter Fisher, I believe that the computational procedure described in this section is very similar to, if not the same as, Fisher's procedure for aggregating multivariate observations. A more detailed comparison awaits the publication of Fisher's most recent work. It is interesting also to consider this technique as an example of "hierarchical grouping to optimize an objective function" (Ward).

Benjamin F. King ends his paper with a final footnote that acts both as a warning and some suggestions for future research:

> One final comment on the method of analysis: this study has employed techniques that rely on finite variances and stationary processes when there is considerable doubt about the existence of these conditions. It is believed that a convincing argument has been made for acceptance of the hypothesis that a small number of factors, market and industry, are sufficient to explain the essential comovement of a large group of stock prices; it is possible, however, that more satisfactory results could be obtained by methods that are distribution free. Here we are thinking of a factor-analytic analogue to median regression and non-parametric analysis of variance, where the measure of distance is something other than expected squared deviation. In future research we would probably seriously consider investing some time in the exploration of distribution free methods.

Though this paper has received more than 1033+ citations (as of Jan. 2017) essentially from journals of finance, accounting and business, it seems that it has not received much follow-up in the following years. A noticeable exception is the paper [45] which investigates the dendrogram and its temporal stability between weekly stock market index rates of return for the world's 12 major international equity markets between 1963 and 1972.

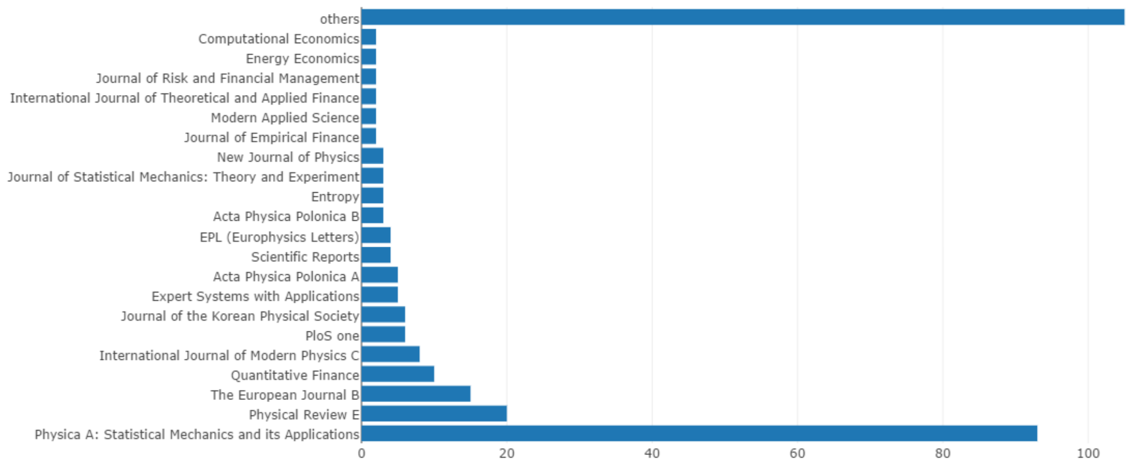


Figure A.1: Number of papers in the main journals from the bibliography

In [80], authors present an alternative methodology using clustering: Unlike many other ones that are based on the correlations between the log-returns of stock prices, their clustering is used to group firms based on a set of variables which are deemed relevant for the problem under study. In their case, they want to forecast earnings. To do so, they propose to use measures of the type and size of sources of funds, measures of uses of funds, measures of profitability, measures of historical growth rates, and measures of liquidity.

Very few other papers have been published until the 'seminal' work of Mantegna in 1999. This work has determined the standard methodology followed by many studies in the following two decades.

Appendix A.2. Journals of interest

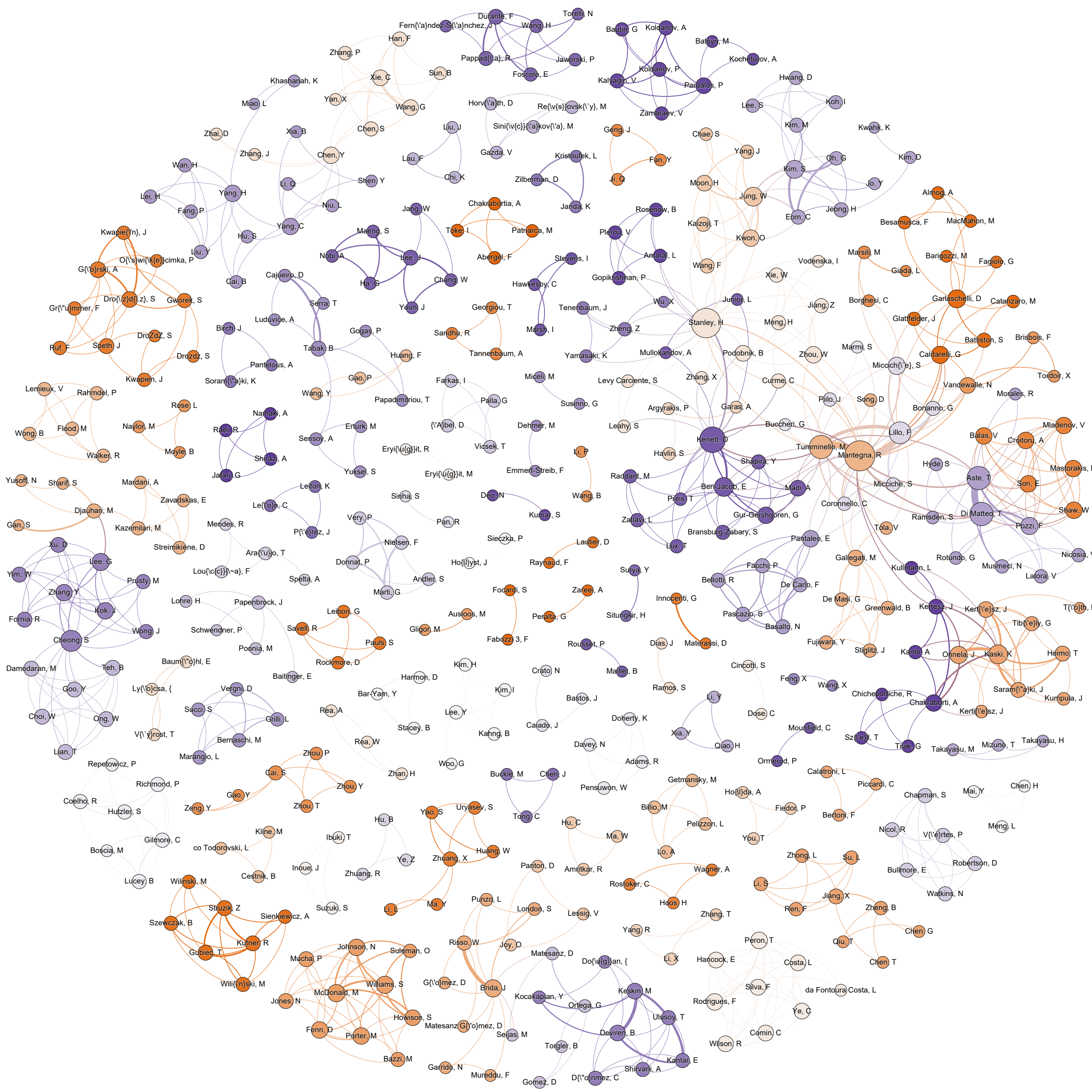
Articles are most often published in Physics journals; Some others in Finance and Economics journals. Most of the literature is available on arXiv `https://arxiv.org/`. Considering the bibliography in this review, the journals displayed in Figure A.1 amount to more than 200 articles (about 2/3 of the bibliography), and *Physica A: Statistical Mechanics and its Applications* alone amounts to nearly 1/3 out of the whole bibliography. The remaining 1/3 of the publications are scattered in disparate journals and venues: machine learning [4], pattern recognition [6] and data mining [3], statistics [110], systems and computations journals [111, 112], business journals [11], economics and finance [113], computational finance [114], cognitive and socio-economic studies [115, 116], natural and social sciences journals [117], planning and development policies [118].

Appendix A.3. Community detection of the authors

In Figure A.2, we display the co-author network built from the bibliographic record. The size of the nodes corresponds to the number of co-authors (degree in this graph). Mantegna has 26 co-authors, followed by Stanley with 25 co-authors. The size of the edges corresponds to the number of co-authored papers between two given authors. Notice the strong co-authorship triangle between Mantegna, Tumminello, Lillo: (Mantegna, Tumminello, 16), (Mantegna, Lillo, 16) and (Lillo, Tumminello, 9); And also (Aste, Di Matteo, 18). Then, we apply the minimum spanning tree methodology to this network. Since there are several connected components, it yields a minimum spanning forest of the authors. The resulting network is displayed in Figure A.3.

Appendix A.4. Asset classes

Assets considered in the empirical studies come from different regions and markets, often from the publication authors' own geographical area. For example, Asian and Chinese researchers focus on Chinese



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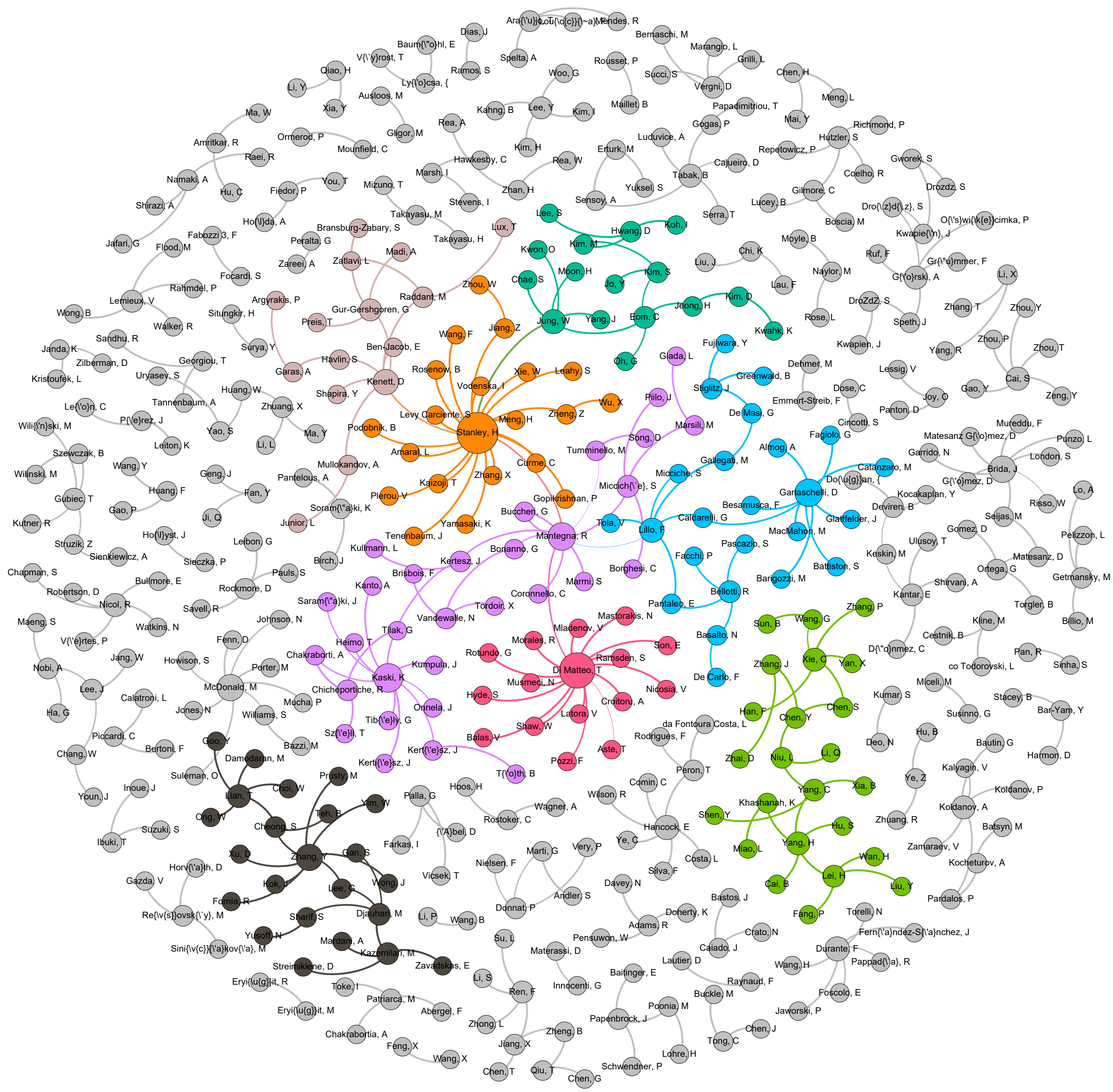

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Raynaud, F
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Ren, F
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Foscolo, E
Poonia, M
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Jiang, X
Zheng, B
Chen, J
Tong, C
Lohre, H
Feng, X
Wang, X
Chen, T
Qiu, T
Schwendner, P
Chen, G

stocks [119, 3, 120, 121, 122, 53, 123, 124, 50, 125]. Besides the Chinese markets, some other Asian markets are investigated: Japan [71, 126, 127], Korea [128, 129, 130, 62, 131, 132], India [106, 133], Malaysia [134, 135], Indonesia [136]. And also emerging markets such as Brazil [137, 138, 139, 140, 141, 142], Turkey [143, 144, 145], Poland [146, 147]. Yet, many studies focus on S&P500 (even from non-US authors) which can be considered as the reference dataset. Some European researchers have investigated particular European markets [148, 149, 150, 151, 152, 153, 154, 155], but many others simply use the S&P500 to illustrate their methodological concerns and developments. A study on all the European stocks, for example, is tricky because of the problem of correlation spillover due to the different closing hours and closing days of the different European market places [156]. It may be an explanation why these papers focus on a regional market at a time: UK companies [157, 26], Italian companies [150, 158, 159], German companies [160, 154, 161].

Several classes of assets have been investigated through the clustering and network methodology: market indices (especially stocks) [45, 162, 163, 9, 127, 164, 156], equities [165], currencies [60, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185], commodities [186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196], housing market [67, 197], bonds and interest rates [198, 199, 200, 201, 139, 153], funds and ETFs [202, 23, 203, 204], credit default swaps [205, 6, 4].

Appendix B. Illustrations of some stylized facts

Appendix B.1. Hierarchical structure of correlations

In Figures B.7, B.11, B.15, B.19, we display each time the same three correlations matrices but reordered using the dendrograms obtained from Ward, Single, Complete, Average Linkages respectively. Below the diagonal we can observe the estimated (Spearman) correlation coefficients, above we can observe the mean values of the blocks defined by the clusters (obtained by a flat-cut in the dendrogram). For illustration purpose, we have chosen an arbitrary number of cluster that we keep constant for all the methods. We can notice the known issue of Single Linkage: it tends to produce a lot of small clusters and a large one.

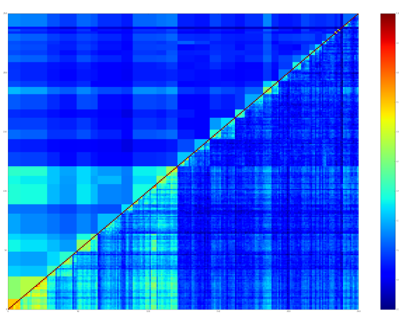

Figure B.4: Correlation matrix for 3-year maturity CDS of the underlying of CDXIG series 28 and ITXEB series 27 - returns from 2010/04/01 to 2017/08/04

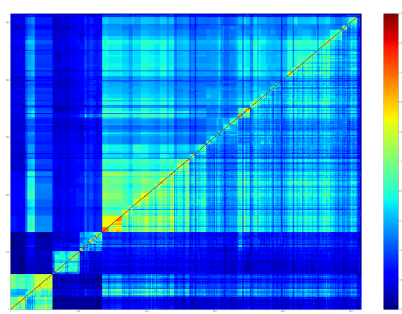

Figure B.5: Correlation matrix for 5-year maturity of all the worldwide (Europe, US, Japan, Asia, Emerging) liquid CDS - returns from 2010/04/01 to 2017/08/04

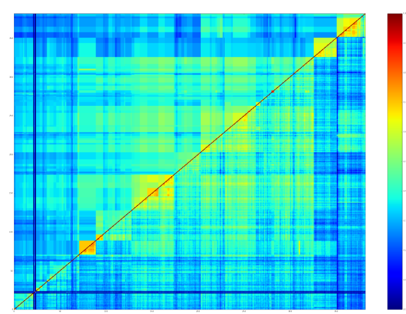

Figure B.6: Correlation for most of the S&P500 stocks (only including those which have complete history) - returns from 2001/08/03 to 2016/08/01

Figure B.7: Correlation matrices whose rows and columns have been ordered by the dendrogram obtained using Ward method

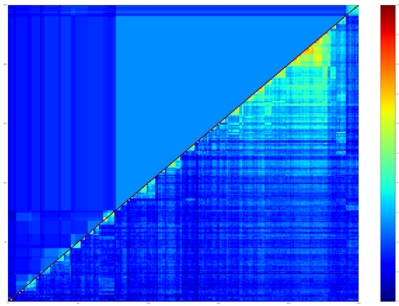

Figure B.8: Correlation matrix for 3-year maturity CDS of the underlying of CDXIG series 28 and ITXEB series 27 - returns from 2010/04/01 to 2017/08/04

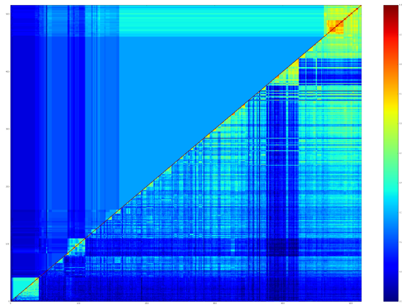

Figure B.9: Correlation matrix for 5-year maturity of all the worldwide (Europe, US, Japan, Asia, Emerging) liquid CDS - returns from 2010/04/01 to 2017/08/04

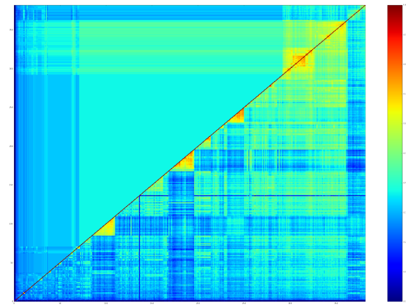

Figure B.10: Correlation for most of the S&P500 stocks (only including those which have complete history) - returns from 2001/08/03 to 2016/08/01

Figure B.11: The same matrices, but in these figures rows and columns have been ordered by the Single Linkage dendrogram

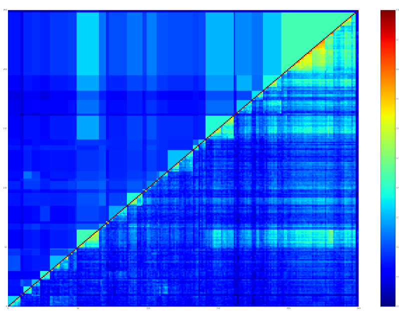

Figure B.12: Correlation matrix for 3-year maturity CDS of the underlying of CDXIG series 28 and ITXEB series 27 - returns from 2010/04/01 to 2017/08/04

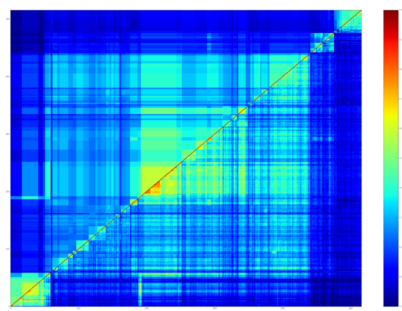

Figure B.13: Correlation matrix for 5-year maturity of all worldwide (Europe, US, Japan, Asia, Emerging) liquid CDS - returns from 2010/04/01 to 2017/08/04

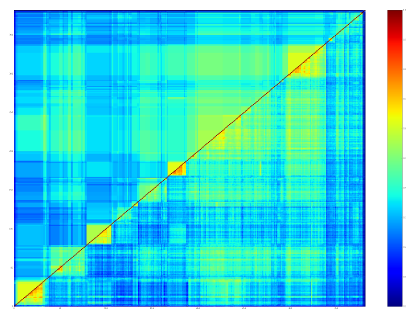

Figure B.14: Correlation for most of the S&P500 stocks (only including those which have complete history) - returns from 2001/08/03 to 2016/08/01

Figure B.15: The same matrices, but in these figures rows and columns have been ordered by the Complete Linkage dendrogram

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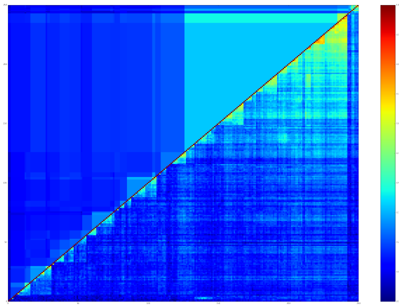

Figure B.16: Correlation matrix for 3-year maturity CDS of the underlying of CDXIG series 28 and ITXEB series 27 - returns from 2010/04/01 to 2017/08/04

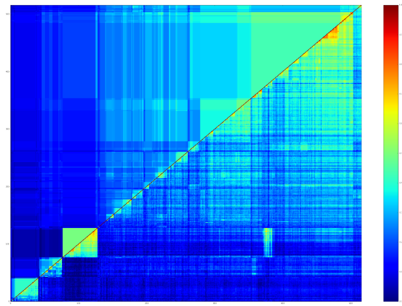

Figure B.17: Correlation matrix for 5-year maturity of all worldwide (Europe, US, Japan, Asia, Emerging) liquid CDS - returns from 2010/04/01 to 2017/08/04

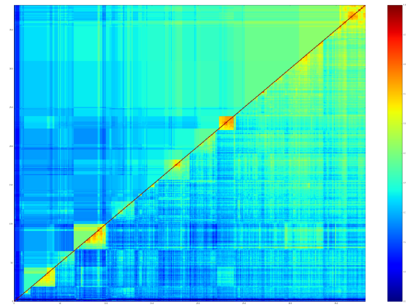

Figure B.18: Correlation for most of the S&P500 stocks (only including those which have complete history) - returns from 2001/08/03 to 2016/08/01

Figure B.19: The same matrices, but in these figures rows and columns have been ordered by the Average Linkage dendrogram

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