“Moroccan Stock Exchange market topology in crisis and non-crisis periods”

AUTHORS	Cherif El Msiyah Jaouad Madkour Younes Berouaga Ayoub Kyoud Ali Ait Lahcen

ARTICLE INFO	Cherif El Msiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud and Ali Ait Lahcen (2022). Moroccan Stock Exchange market topology in crisis and non-crisis periods. *Investment Management and Financial Innovations*, *19*(4), 274-284. doi:10.21511/imfi.19(4).2022.22
DOI	http://dx.doi.org/10.21511/imfi.19(4).2022.22
RELEASED ON	Thursday, 08 December 2022
RECEIVED ON	Thursday, 01 September 2022
ACCEPTED ON	Friday, 02 December 2022
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
35	**4**	**3**

© The author(s) 2022. This publication is an open access article.

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

Cherif El Msiyah (Morocco), **Jaouad Madkour** (Morocco), **Younes Berouaga** (Morocco), **Ayoub Kyoud** (Morocco), **Ali Ait Lahcen** (Morocco)

MOROCCAN STOCK EXCHANGE MARKET TOPOLOGY IN CRISIS AND NON-CRISIS PERIODS

Abstract

This paper seeks to investigate the dynamics within the Moroccan Stock Exchange (MSE) market topology in crisis and non-crisis periods using daily historical log returns of sectoral indices covering the period from January 4, 1993 to September 9, 2021. The study applies the Agglomerative Hierarchical Clustering (AHC) implemented on the Dynamic Time Warping (DTW) distance matrix over ten sub-periods covering numerous crises, from Subprime mortgage crisis to European debt crisis and finally COVID-19 crisis. The obtained clustering results are gathered into a network to display the cumulated interconnections between the sectoral indices. The findings showed that the Casablanca Stock Exchange (CSE) market clusters composition is dynamic during the studied period. Indeed, some sectoral indices demonstrated evidence of strong similarities by gathering in the same cluster over numerous sub-periods as the couples Electrical & Electronic Equipment and Transport or as Banks and Construction & Building Materials sectoral indices. Moreover, the interconnections of CSE sectoral indices are trend dependent. According to the obtained network, the Oil and Gas demonstrated its centrality.

Keywords clustering, network analysis, stock market topology, sectoral indices, financial crises

JEL Classification C38, D53, G11

Received on: 1st of September, 2022
Accepted on: 2nd of December, 2022
Published on: 8th of December, 2022

© Cherif El Msiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen, 2022

Cherif El Msiyah, Professor, National School of Commerce and Management, Moulay Ismail University, Morocco.

Jaouad Madkour, Professor, Department of Economics and Management, Faculty of Economics and Management, Abdelmalek Essaadi University, Morocco.

Younes Berouaga, Ph.D., National School of Commerce and Management, Ibn Tofaïl University, Morocco. (Corresponding author)

Ayoub Kyoud, Ph.D., National School of Commerce and Management, Ibn Tofaïl University, Morocco.

Ali Ait Lahcen, Ph.D., National School of Commerce and Management, Ibn Tofaïl University, Morocco.

This is an Open Access article, distributed under the terms of the Creative Commons Attribution 4.0 International license, which permits unrestricted re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

The adverse impacts of financial crises on the real economy are substantially significant, explained by a financial disorder that has two immediate consequences. Firstly, the supply of credit from banks is curtailed and interest rates are increased. This dissuades borrowers from taking on debt. Secondly, borrowers became unable to repay their loans due to the sudden devaluation of their assets. This credit crunch led to a decrease in growth and eventually a recession. These harmful consequences can cause a considerable drop in the performance of sectors within the capital market. Therefore, the collapse of one influential sector can lead to series of bankruptcies propagating through complex linkages within the capital market topological structure and endangering the global state of the economy. These economic upheavals have attracted much attention to the study of the sectoral index interrelations and their topological structure evolution. Despite this, there is a growing interest explained by the need of alternative ways to analyze the stock market structure as a complex interconnected system.

The first attempt to analyze the topology of financial markets was performed by Mantegna (1999), who proposed a novel approach to selecting topological space connecting financial market's stocks using the information present in time-series. Moreover, the interactions with-

http://dx.doi.org/10.21511/imfi.19(4).2022.22

in the capital market are studied by using a sufficient clustering method presented by Murtagh and Legendre (2011), in order to discover the inherent linkages within the capital market topological structure by creating a taxonomy classifying the capital market components based on their similarities.

The MSE market had experienced several crises during the last years, starting from the Subprime crisis to the European debt crisis and finally the Coronavirus pandemic crisis, which negatively affected the economy and especially sectoral activities. In such circumstances, it is crucial to understand the stock market topology dynamics and identify its corresponding behaviors.

1. LITERATURE REVIEW

To understand the stock market behaviors across different tendencies, this paper sheds light on the stock market topology and its evolution over time. Lahmiri (2016) studied the CSE market topology co-movement as a complex network in different market regimes by using the AHC based on Hurst estimated exponents to partition sectoral indices into groups; one of the main findings is that the Hurst estimate rose during increasing regimes compared to decreasing regimes. Huang et al. (2021a) identified the determinant factors and the market co-movement using the complex network approach applied to the China Securities 300 index daily prices over the period from January 4, 2006 to December 31, 2019. This paper shows that global efficiency, average clustering coefficient and network density can bring an early warning for possible future crises. Siudak (2021) used the log-returns of 496 stock prices among the S&P 500 index to analyze the network topology of the economic sectors and found that the central nodes within the US stock market are utilities, consumer cyclical and industrials. Laha et al. (2020) used the Topological Data Analysis techniques on data from the Indian National Stock Exchange market and proved that there are dependencies between the stock prices and sectoral indices variations. Jaroonchokanan et al. (2022) explored the hierarchical tree structure dynamics of 37 stocks within the Stock Exchange of Thailand (SET) from 2008 to 2020 covering financial crises based on both Fisher information and correlation. This approach proved that the dynamic hierarchy leads to less-variant clustering, which can bring insights on stock market behavior in financial crisis periods. Tian et al. (2019) investigated the impact of sectoral dynamics on Chinese and American stock markets, especially during some extreme market events, and realized that impulsive events can develop the sectors' statistical causality and improve the connections across sectors in the long run. Tsekeris (2017) proposed an assessment of sectoral relationships using networks analysis to the input-output matrix of the intermediate transactions among the Greek economic sectors for 2010 and found the key sectors that have the ability to influence the stability of the economic system. Di Matteo et al. (2010) used the Minimum Spanning Tree on 300 most capitalized stocks data of the NYSE market and observed that is mostly influenced by the financial sector. Tabak et al. (2010) investigated the commodities topology based on the Minimum Spanning Tree and Ultrametric Hierarchical Tree using daily prices of 20 commodities covering the period from January 2, 1991 to February 8, 2008 and found that agriculture commodities are vital in the obtained network. Lahmiri (2012) investigated the topological dynamics of the NASDAQ index before, during and after the subprime crisis using the Hierarchical Clustering Trees on sectors returns series and found several results. The author proved that the sector clusters are trend dependent and that some sectors tend to form the same cluster during all the studied period. Huang et al. (2021b) used Granger Causality and Engle-Granger tests on the Chinese A-share market daily stock returns and found that the interconnections linking stocks can increase in response to the propagation of risk. Li and Yang (2021) applied the Spectral Clustering using the CSI 300 index data in order to analyze the network topology patterns and identified the key companies in the market. Li et al. (2019) built a complex network using information from the China Securities 300 and the S&P 500 indices to prove that the network periphery is an identification factor of optimal assets. Regarding numerous articles in this area, there is still a need for academic research to continuously explore the complex interrelations within the capital market topology in an uncertain world. This paper seeks to explore the dynamics of the MSE market topology and to highlight interrelations between its sectoral indices during various tendencies.

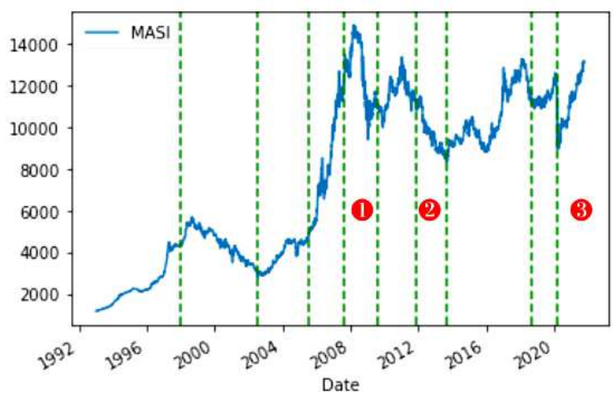
2. METHODOLOGY

2.1. Data

To study the complex dynamics of the MSE market topology, the daily historical log returns of sectoral indices covering the period from January 4, 1993 to September 9, 2021 are used. In this respect, the data set consists of the sectoral indices represented as follows: Forestry & Paper (PAP), Transport (TR), Telecommunications (TEL), Holding Companies (HOL), Investment Companies & Other Finance (FIN), Real Estate Participation & Promotion (PLA), Real Estate Investment Companies (IMM), Materials Software & Computer Services (INF), Transportation Services (STR), Mining (MIN), Utilities (COL), Oil & Gas (P&G), Food Producers & Processors (A&P), Insurance (ASS), Construction & Building Materials (BTP), Beverages (BOI), Chemicals (CH), Distributors (DIS), Electricity (ELC), Electrical & Electronic Equipment (ELQ), Pharmaceutical Industry (PHA), Engineering & Equipment Industrial Goods (EQI), Leisure & Hotels (L&H), Banks (BQ).

In this work, the time-series of sectoral indices are partitioned into sub-periods using the structural changes tests. Therefore, the Moroccan All Shares Index (MASI) time-series is split using the Bai and Perron (2003) Multiple Break-Point test and dates are obtained according to the structural changes in the MSE market. For 9 breaks equivalent to 10 sub-periods (Figure 1), the test statistic exceeds the critical value (respectively 8.53 and 5.20) so that the alternative hypothesis of a break is accepted. Next, these results are taken as a reference to split the time-series of all sectoral indices into periods. The studied period covers numerous crises, going from Subprime mortgage crisis to European debt crisis and finally COVID-19 crisis. Starting by the Subprime crisis that revealed interdependencies between financial markets worldwide. In Morocco, a return spillover effect was present in the MSE market in post-crisis period (El Ghini & Saidi, 2017). The international trade and the world demand of Morocco fell respectively by 11.9% and 10%. This drop has led to a 13.1% decline in the volume of Moroccan exports of goods and services. Thus, the decrease in final household consumption compared to its trend level reached 1.42% and the decline in exports of goods and services was 1.01%. For the year 2009, the drop is more pronounced, it is about 3.12% for consumption and 4.34% for exports, which negatively affected the demand and therefore the growth. GDP fell by 2.46% in 2009, compared to its trend level. The decline in growth led to a decrease in investment by around 3.57% in 2009.

The seventh sub-period was characterized by numerous events, the European sovereign debt crisis affected the Moroccan economy due to their commercial ties, knowing that 51.4% of Moroccan exports are destined to Euro zone, Morocco's trade deficit increased by 25% during 2011 to 185.7 billion dirhams, and the growth of GDP went from 5.246% in 2011 to 3.01% in 2012.



Notes: The dashed line is used to represent the breaks, each break corresponds to a date, the line corresponds to the MASI time-series. (1) represents the Subprime crisis period, (2) represents the European debt crisis period, and (3) represents the COVID- 19 crisis period.

Figure 1. MASI break points

http://dx.doi.org/10.21511/imfi.19(4).2022.22

The advent of the COVID-19 crisis caused a spectacular drop during March 2020 with a contraction in the Moroccan economic activity of nearly 7%, the MASI had reached a record level of -8.82% never recorded since the creation of the MSE market, which experienced a brutal and unprecedented fall. Regarding the crisis impacts on some sectors, the financial sector (insurance, banks and finance companies) achieved a downward trend of -22.8%. However, the sectoral performance of the capital goods industry, building materials, real estate and industrial engineering are, respectively, -12.2%, -21.8%, -31.6% and -32.5%. Thus, the capitalization of the construction sector went from a significant capitalization of 78.812 billion in January to 59.764 billion dirhams in May. Furthermore, the total capitalization of the industrial sector went from 119.957 billion dirhams in January to 100.691 billion dirhams by the end of May; with a sharp decline of 21.10% in March due to the spread of the Coronavirus in Morocco.

In this paper, one must check the clustering ability of the data by the Hopkins test (Hopkins & Skellam, 1954). Then, the DTW method is used to calculate the distances spacing time-series (Berndt & Clifford, 1994). Next, the DTW results are employed on the AHC method to construct clusters of sectoral indices over multiple sub-periods (Ward Jr, 1963). Then, to prove the validity of the clustering results, various cluster validity indicators are called (Arbelaitz et al., 2013). The obtained clustering results are gathered into a network to display the cumulated interconnections between the sectoral indices in the MSE market.

2.2. Hopkins test

Before applying the AHC, one must make sure that the data set is not generated by a uniform distribution, which means a presence of meaningful clusters within the data. For this purpose, the Hopkins test is used to collect information about the clustering tendency. Let

$$X = \sum_{i=1}^{n} x_i \text{ and } Y = \sum_{j=1}^{m} y_j, \tag{1}$$

respectively a collection of n and m patterns, where m is much less than n. Let u_j and w_j be defined respectively as the minimum distance between y_j and its nearest point in X; and w_j as the minimum distance spacing a random pattern in X and its nearest point. The Hopkins statistic is defined by formula (2):

$$H = \frac{\sum_{j=1}^{m} u_j}{\sum_{j=1}^{m} u_j + \sum_{j=1}^{m} w_j} \tag{2}$$

The interpretation of the Hopkins test is based on the H statistic; the data set does not have the clustering tendency if H is close to 0. On the other hand, if H is close to 1, it indicates a clustering tendency, which means that the data set is significantly clusterable.

2.3. Dynamic time warping

The DTW consists in comparing the distance separating two time-series X and Y (unequal-length), each alignment between x_i and y_j is represented by a grid point (i, j). Moreover, the DTW computes the pattern in such many-to-one or one-to-many points as pointed in Figure 2(a) and determines the optimal warping path between them. The warping path

$$W = \sum_{k=1}^{K} w_k, \tag{3}$$

maps the X and Y time-series elements while checking that the distance between them is minimized. It should be noted that each w_k corresponds to a point $(i, j)_k$, as shown in Figure 2(b). In addition, the warping path W needs to fulfill some sets of conditions as in Sakoe and Chiba (1978).

Aiming to formulate a dynamic programming problem, let $\delta(i, j)$ be the distance measure spacing two elements x_i and y_j from each time-series and define the DTW problem as a minimization of the warping paths according to a cumulative distance for each path.

$$DTW(X,Y) = \min_{w}\left[\sum_{k=1}^{K} \delta(w_k)\right]. \tag{4}$$

The cumulative distance $\Phi(i, j)$ can be defined referring to the dynamic programming formulation given by formula (5):

$$\Phi(i,j) = \delta(i,j) + \\ + \min\left[\Phi(i-1,j), \Phi(i-1,j-1), \Phi(i,j-1)\right]. \tag{5}$$

The cumulative distance is represented as the total of the minimum of accumulated distances of the surrounding points and the distance between the time-series elements. By using a backward, the optimal warping path can be found choosing at each step the previous points according to the lowest cumulative distance.

2.4. Agglomerative hierarchical clustering

To implement the AHC based on the DTW results, there are different methods for clustering (Murtagh & Contreras, 2012). The Ward linkage implemented by the algorithm of Lance-Williams is used, which is a part of numerous AHC algorithms that consist of adjusting the cluster distances at each phase where the cluster pairs are merged (Ward Jr, 1963; Murtagh & Legendre, 2011). Each pair of the merged clusters must result in minimum raise in the sum of the intra-class inertia; obtained by the weighted squared distance calculated between the centers of the clusters. The Ward method that minimizes the total intra-cluster variance is applied on the DTW results to partition the data. Suppose two clusters C_i and C_j are combined, the updated distances spacing clusters are given by a recursive formula. Noting that, d_{ij}, d_{ik} and d_{jk} are the distances separating, respectively, the clusters C_i, C_j and C_k, where the cluster distance function d_{Nk} represents the distance between C_N (newly created cluster) and C_k.

In this respect, an algorithm is affiliated to the Lance-Williams family if d_{Nk} can be calculated recursively by formula (6):

$$d_{Nk} = \alpha_i d_{ik} + \theta_j d_{jk} + \beta d_{ij} + \gamma \left| d_{ik} - d_{jk} \right|. \tag{6}$$

The parameters α_i, θ_j, β, and γ change depending on the clustering algorithm chosen. The Ward method implemented by the Lance-Williams formula is used, where C_i, C_j, C_k, and n_i, n_j, n_k are, respectively, the disjoint clusters and clusters sizes.

$$\begin{aligned} d\left(C_N, C_k\right) &= \alpha_i d\left(C_i, C_k\right) + \theta_j d\left(C_j, C_k\right) + \\ &+ \beta\left(C_i, C_j\right) + \gamma \left| d\left(C_i, C_k\right) - d\left(C_j, C_k\right) \right|. \end{aligned} \tag{7}$$

For better understanding, one must present how it works. Let $C = e_i : I = \{1 : n\}$ a group of individuals with the gravity center g, partitioned in k classes

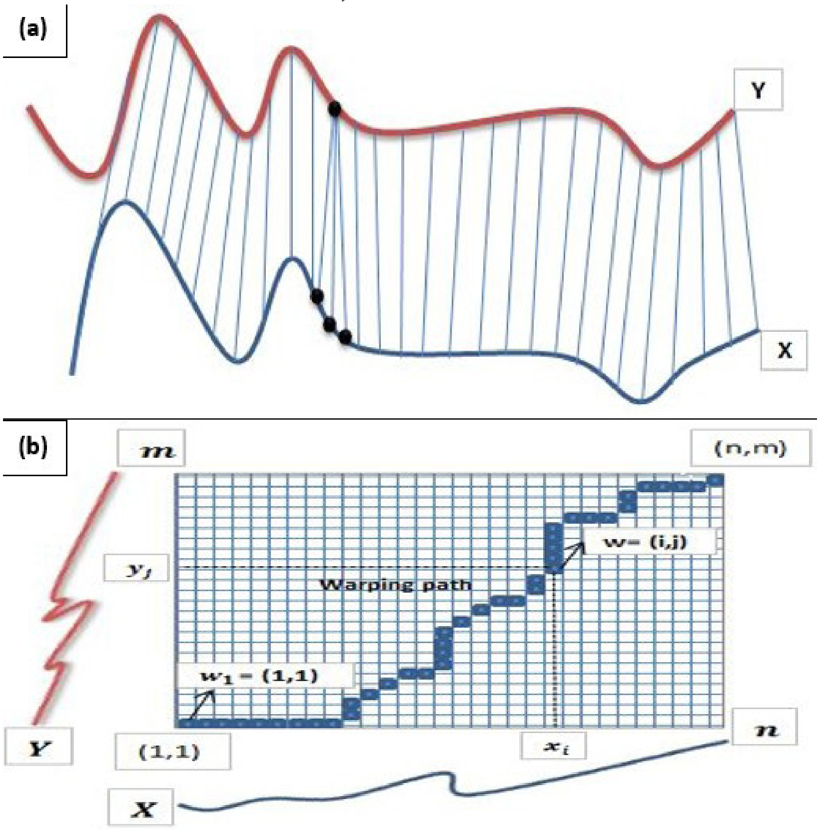


Figure 2. An example of time-series alignment (a) and cumulative distance matrix (b)

of size $n_1, n_2, ..., n_k$ presented as $C_1, C_2, ..., C_k$, with gravity centers $g_1, g_2, ..., g_k$. The total cloud's inertia is given by:

$$I_t = \frac{1}{n}\sum_{i=1}^{n} d\left(e_i, g\right)^2, \tag{8}$$

where the inter-class inertia is equal to

$$I_e = \frac{1}{n}\sum_{i=1}^{k} n_i \cdot d\left(g_i, g\right)^2, \tag{9}$$

and the intra-class inertia is equal to

$$I_a = \frac{1}{n}\sum_{i=1}^{k}\sum_{e \in C_i} d\left(e, g_i\right)^2. \tag{10}$$

The Ward method consists of grouping the classes so that the increase in inter-class inertia is maximal.

The AHC algorithm performs numerous steps. Starting by considering each individual as a cluster and getting N clusters for N individuals, the distances between the clusters are calculated by the DTW method. Then comes the step of determining the closest clusters so that they can be combined into a single cluster using the Ward method. Next, the distances spacing the new cluster and the old clusters are calculated. One must repeat these steps until all elements are clustered. Several works studied the standardization of cluster scoring metrics using the Cluster Validity Index (CVI) (Sardá-Espinosa (2017). In this work, three indices are used, Dunn index, Connectivity index, and Calinski Harabasz index, to determine the quality of the obtained partitioning (Dunn, 1973; Caliński & Harabasz, 1974; Tasdemir & Merényi, 2011).

2.5. Network construction

After applying the AHC over multiple sub-periods, the obtained results are used to construct an undirected weighted network in order to explore potential mechanisms underlying complex network. Start by assuming $G = (R, F, \Omega)$ an undirected weighted network that includes a set of vertices $R = r_1, r_2, ..., r_n$ and a set of edges $F = f_1, f_2, ..., f_n$, representing the interconnections between vertices for which an edge f_{ij} exists if (i, j) individuals co-existed in the same cluster and does not otherwise, and a set of edge weights $\Omega = \omega_1, \omega_2, ..., \omega_n$, representing the strength of the interconnections between individuals for which the weight ω_{ij} indicates the number of co-existences between the couple (i, j) in the same cluster over the studied sub-periods.

3. RESULTS

Table 1 displays the Hopkins statistics, which shows that the used data set partitioning is possible, it can be seen that all statistics of the whole studied sub-periods are close to 1. The next step is to implement the DTW method on the AHC algorithm.

Table 1. Hopkins test results

Sub-periods	Hopkins test	Sub-periods	Hopkins test
01	0.9817530	06	0.7269325
02	0.8677797	07	0.6991124
03	0.7778100	08	0.7819251
04	0.6912362	09	0.9559426
05	0.6897632	10	0.7200521

Figure A1 shows the application of multiple AHC, where every heptagon represents a sectoral index, every rectangle with rounded corners represents a sub-period from P1 to P10, and every group within rectangles with rounded corners constitutes a cluster. Table 2 represents the three clustering validity indices used in this paper to evaluate and judge the quality of the obtained clusters. Starting with the first indicator, the Dunn index, which is an internal cluster metric that quantifies the ratio of the smallest distance between points in different clusters (better separation), and the largest distance within any of the clusters (more compact clusters). This measure lies between 0 (the worst classification) and +∞ (the best classification). The Dunn index ranges from 0.8840, which is the lowest level returning, to the 4th sub-period to 0.9726, which is the highest level according to the 10th sub-period. Secondly, the Connectivity index corresponds to the degree of connectedness of each cluster by evaluating its degree at each of all the nearest data points within the same cluster. The connectivity index fluctuates between 0 and +∞ (should be minimized); the results shows that it varies between 3.0290 returning to the second sub-period, which is clearly the best result over the studied sub-periods and

19.3901 relative to the 7th sub-period. Finally, the Calinski-Harabasz index represents the relationship between the sum of inter-clusters and intra-cluster dispersion, the measure lies between 0 (the worst classification) and +∞ (the best classification). One can clearly notice that the values obtained are included between 1.492466 and 4.977875, which corresponds, respectively, to the 5th and 1st sub-period. Referring to the clustering validity indices, one can conclude that the partitioning results are acceptable.

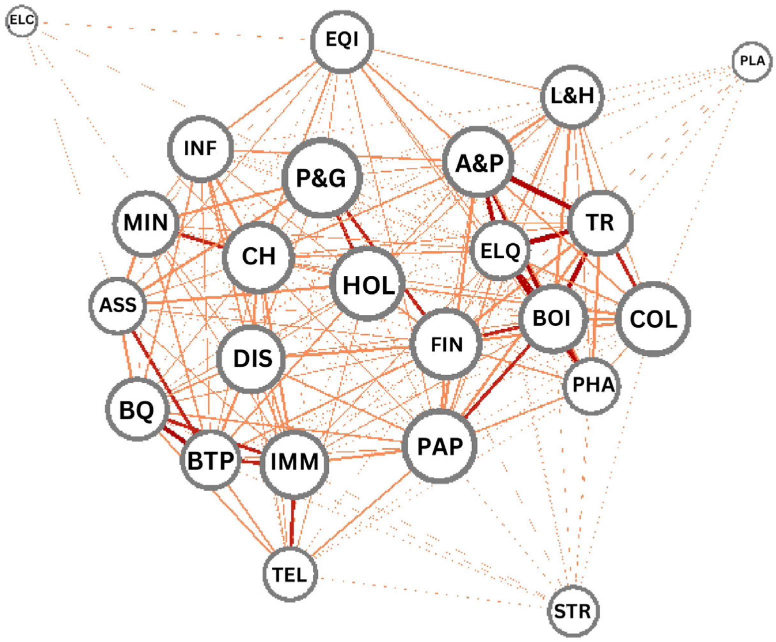
Table 2. Validation indices of sectoral index clusters

Sub-periods	Dunn index	Connectivity index	Calinski-Harabasz index
01	0.9519	10.0115	4.977875
02	0.9709	3.0290	2.111882
03	0.9380	9.4798	1.815822
04	0.8840	8.6119	1.509191
05	0.9241	8.8869	1.492466
06	0.9079	13.7893	1.578263
07	0.9123	19.3901	1.698532
08	0.9315	12.4306	1.848694
09	0.9131	13.3849	2.615046
10	0.9726	9.1230	2.754604

Figure 3 shows the undirected weighted network G that maps the interrelations between the sectoral indices. Unlike classical cluster analysis, which relies on a static overview of the partitioning, this network puts light on the previous results of clustering by drawing edges that highlight historical interrelations between sectoral indices for better understanding of coalitions and interconnections between sectors.

Table 3 reports the rankings of the sectoral indices in terms of network indicators. Starting by Eigenvector Centrality (Bonacich, 2007), which measures the influence of a node within a network while giving consideration to the importance of its neighbors. The oil and gas, food producers & processors and holding companies are connected to numerous sectors; themselves acquire high values of connectivity, which make them the most influential sectors in the network. Looking at Closeness Centrality (Cohen et al., 2014) and the Harmonic Closeness Centrality (Rochat, 2009), the oil and gas sector is the best placed to influence the entire network most quickly. Betweenness Centrality (Barthelemy, 2004) demonstrates that oil and gas sector represents a bridge between all nodes in the network.

Source: Own calculations. The graphs are generated using Gephi Force Atlas 2 layout.



Notes: The width of the edges depends on the strength of the interrelation, the inner nodes represent the sectoral indices, the node size is related to the number of edges incident on it, the strings mentioned in the nodes are the abbreviations of the sectoral indices.

Figure 3. Undirected weighted network of sectoral indices of the MSE market

http://dx.doi.org/10.21511/imfi.19(4).2022.22

Table 3. Networking indicators analysis

Rank	Eigenvalue Centrality	Closeness Centrality	Harmonic Closeness Centrality	Betweenness Centrality
1	P&G	P&G	P&G	P&G
2	A&P	HOL	HOL	CH
3	HOL	A&P	A&P	COL
4	COL	COL	COL	FIN
5	A&P	FIN	FIN	DIS
6	CH	CH	CH	HOL
7	FIN	A&P	A&P	EQI
8	IMM	IMM	IMM	IMM
9	BOI	BOI	BOI	BOI
10	DIS	DIS	DIS	A&P
11	MIN	MIN	MIN	ASS
12	INF	TR	TR	TR
13	TR	INF	INF	IMM
14	L&H	BQ	BQ	BQ
15	BQ	L&H	L&H	L&H
16	EQI	EQI	EQI	INF
17	ELQ	BTP	BTP	PHA
18	BTP	ELQ	ELQ	MIN
19	PHA	ASS	ASS	ELQ
20	ASS	PHA	PHA	BTP
21	TEL	TEL	TEL	TEL
22	STR	STR	STR	STR
23	PLA	PLA	PLA	ELC
24	ELC	ELC	ELC	PLA

4. DISCUSSION

The composition of the clusters shows that their structure changes over time demonstrating the dynamic of the interrelations between the sectoral indices. From the clustering results, some sectoral indices demonstrated strong similarity by gathering in the same cluster during most of the studied sub-periods, the couples (TR; PAP), (TR; BOI), (TR; ELQ) and (BOI; ELQ) persisted in the same cluster during 7 sub-periods. Moreover, (PHA; ELQ), (IMM; TEL), (PAP; BOI), (PAP; ELQ) and (BTP; BQ) persisted in the same cluster during 6 sub-periods. In addition, the couples of sectoral indices that matched 5 times in the same cluster are (BOI; FIN), (BOI; PHA), (BOI; A&P), (BTP; ASS), (COL; TR), (P&G; HOL), (P&G; FIN), (BQ; IMM) and (CH; MIN).

In addition, it can be noted that from the first introduction of the insurance index to the MSE market, it pertained to the same cluster with the bank sector through the sub-periods preceding the 2008 crisis. Conversely, during all the sub-periods posterior the Subprime crisis, these sectoral indices are not combined into one group, which indicates a change in the behavior of the bank-insurance activity post-subprime crisis. On top of that, the trio of banking, real estate investment companies and its upstream sector (construction and building materials) are gathered in the same cluster only during crisis sub-periods, meaning that negative shocks cause an interrelation between the real estate value chain and the banking sector. In addition, both leisure & hotels and its sub-sector beverages match each other consistently during and post Subprime crisis, during the Euro Debt crisis and the pandemic crisis of COVID-19, which explains the strong interdependence between the two sectoral indices in decreasing regimes (Aratuo & Etienne, 2019). Knowing that, the cyclical relationship between the real estate with its upstream & downstream industries and banking activity is not novel in the empirical finance literature. Albulescu et al. (2020) studied the relationship between the US banking and real estate markets using a quantile causality framework and nonlinearity tests to provide evidence of dual causality present in the tail areas only. Considering the complex linkages between real estate and bank sectors, the bank stock market is likely affected by shocks in real estate prices. Besides the findings discussed above, the pharmaceutical industry and transport sectoral indices are grouped in the same cluster only in non-crisis windows. In addition, the analysis of results showed that during crisis periods, multiple sectors are gathered in the same clusters, like a pair of oil & gas and holding companies or transport and utilities, which belong to the same clusters during crisis periods. Contrary to the findings discussed above, the pharmaceutical industry and transport sectors are regrouped in the same cluster in non-crisis periods.

Indeed, both electrical & electronic equipment and transport proved strong similarity. The arrival of new sectoral indices on the MSE market is presented in the periphery of the network with small size nodes, like electricity and real estate participation & promotion. According to the networking indicators analysis, the node of oil & gas sector always dominates the very advanced ranking, which allows us to conclude that the oil & gas sector plays an important influential role in the network, which is in line with the findings of Memon et al. (2020), who proved an economic expansion in the cement, fertilizers and oil & gas sectors using networking indicators analysis.

CONCLUSION

This paper investigates the topology of sectoral indices of the MSE market using daily log-return observations covering the period from January 4, 1993 to September 9, 2021. First, AHC integrated with DTW distance measure over multiple sub-periods is performed to partition the data into clusters. Then, these results are used to construct a network representation to display the interrelations between the sectoral indices. Three major subtracted findings are presented as follows. Firstly, the clustering results show that the number and the composition of clusters changed frequently over time, which indicates that the MSE market topology is dynamic. Secondly, some sectoral indices provided evidences of specific behavior over crisis and non-crisis periods. Thirdly, the network analysis clearly demonstrates that the oil and gas sector mostly occupies a very advanced ranking in terms of the importance of each sectoral index in the MASI network using networking indicators. This allows us to conclude that the MSE market influential and potential leader sector is the oil and gas sector.

AUTHOR CONTRIBUTIONS

Conceptualization: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Data curation: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Formal analysis: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Investigation: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Methodology: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Project administration: Cherif Elmsiyah, Jaouad Madkour.
Resources: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Software: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Supervision: Cherif Elmsiyah, Jaouad Madkour.
Validation: Cherif Elmsiyah, Jaouad Madkour.
Visualization: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Writing – original draft: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.
Writing – review & editing: Cherif Elmsiyah, Jaouad Madkour, Younes Berouaga, Ayoub Kyoud, Ali Ait Lahcen.

REFERENCES

1. Albulescu, C. T., Bouri, E., Tiwari, A. K., & Roubaud, D. (2020). Quantile causality between banking stock and real estate securities returns in the US. *The Quarterly Review of Economics and Finance, 78,* 251-260. https://doi.org/10.1016/j.qref.2020.03.005
2. Aratuo, D. N., & Etienne, X. L. (2019). Industry level analysis of tourism-economic growth in the United States. *Tourism Management, 70,* 333-340. https://doi.org/10.1016/j.tourman.2018.09.004
3. Arbelaitz, O., Gurrutxaga, I., Muguerza, J., Pérez, J. M., & Perona, I. (2013). An extensive comparative study of cluster validity indices. *Pattern Recognition, 46*(1), 243-256. https://doi.org/10.1016/j.patcog.2012.07.021
4. Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics, 18*(1), 1-22. https://doi.org/10.1002/jae.659
5. Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*(5439), 509-512. https://doi.org/10.1126/science.286.5439.509
6. Barthelemy, M. (2004). Betweenness centrality in large complex networks. *The European Physical Journal B, 38*(2), 163-168. https://doi.org/10.1140/epjb/e2004-00111-4
7. Berndt, D. J., & Clifford, J. (1994). Using dynamic time warping to find patterns in time series. *KDD workshop, 10*(16), 359-370. Retrieved from https://www.aaai.org/Papers/Workshops/1994/WS-94-03/WS94-03-031.pdf
8. Bonacich, P. (2007). Some unique properties of eigenvector centrality. *Social Networks, 29*(4), 555-564. https://doi.org/10.1016/j.socnet.2007.04.002
9. Caliński, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. *Communications in Statisticstheory and Methods, 3*(1), 1-27. https://doi.org/10.1080/03610927408827101
10. Cohen, E., Delling, D., Pajor, T., & Werneck, R. F. (2014). Computing

classic closeness centrality, at scale. *In Proceedings of the second ACM Conference on Online Social Networks,* 37-50. https://doi.org/10.1145/2660460.2660465

11. Di Matteo, T., Pozzi, F., & Aste, T. (2010). The use of dynamical networks to detect the hierarchical organization of financial market sectors. *The European Physical Journal B, 73*(1), 3-11. https://doi.org/10.1140/epjb/e2009-00286-0
12. Dunn, J. C. (1973). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *Taylor \& Francis,* 32-57. https://doi.org/10.1080/01969727308546046
13. El Ghini, A., & Saidi, Y. (2017). Return and volatility spillovers in the Moroccan stock market during the financial crisis. *Empirical Economics, 52*(4), 1481-1504. https://doi.org/10.1007/s00181-016-1110-8
14. Hopkins, B., & Skellam, J. G. (1954). A new method for determining the type of distribution of plant individuals. *Annals of Botany, 18*(2), 213-227. https://doi.org/10.1093/oxfordjournals.aob.a083391
15. Huang, C., Deng, Y., Yang, X., Cao, J., & Yang, X. (2021a). A network perspective of comovement and structural change: Evidence from the Chinese stock market. *International Review of Financial Analysis, 76,* 101782. https://doi.org/10.1016/j.irfa.2021.101782
16. Huang, C., Wen, S., Li, M., Wen, F., & Yang, X. (2021b). An empirical evaluation of the influential nodes for stock market network: Chinese A-shares case. *Finance Research Letters, 38,* 101517. https://doi.org/10.1016/j.frl.2020.101517
17. Jaroonchokanan, N., Termsaithong, T., & Suwanna, S. (2022). Dynamics of hierarchical clustering in stocks market during financial crises. *Physica A: Statistical Mechanics and its Applications, 128183.* https://doi.org/10.1016/j.physa.2022.128183
18. Laha, S., Majumdar, & K, A. (2020). Clustering and classification of time series using topological data analysis with applications to finance. *Expert Systems with Applications, 162,* 113868-113868. https://doi.org/10.1016/j.eswa.2020.113868
19. Lahmiri, S. (2012). A clustering approach to examine the dynamics of the NASDAQ topology in times of crisis. *Management Science Letters, 2*(6), 2113-2118. https://doi.org/10.5267/j.msl.2012.06.008
20. Lahmiri, S. (2016). Clustering of Casablanca stock market based on hurst exponent estimates. *Physica A: Statistical Mechanics and its Applications, 456,* 310-318. https://doi.org/10.1016/j.physa.2016.03.069
21. Li, B., & Yang, Y. (2021). Undirected and Directed Network Analysis of the Chinese Stock Market. *Computational Economics,* 1-19. https://doi.org/10.1007/s10614-021-10183-w
22. Li, Y., Jiang, X. F., Tian, Y., Li, S. P., & Zheng, B. (2019). Portfolio optimization based on network topology. *Physica A: Statistical Mechanics and its Applications, 515,* 671-681. https://doi.org/10.1016/j.physa.2018.10.014
23. Mantegna, R. N. (1999). Hierarchical structure in financial markets. *The European Physical Journal B-Condensed Matter and Complex Systems, 11*(1), 193-197. https://doi.org/10.1007/s100510050929
24. Memon, B. A., Yao, H., & Tahir, R. (2020). General election effect on the network topology of Pakistan's stock market: network-based study of a political event. *Financial Innovation, 6*(1), 1-14. https://doi.org/10.1186/s40854-019-0165-x
25. Murtagh, F., & Contreras, P. (2012). Algorithms for hierarchical clustering: an overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 2*(1), 86-97. https://doi.org/10.1002/widm.53
26. Murtagh, F., & Legendre, P. (2011). Ward's hierarchical clustering method: clustering criterion and agglomerative algorithm. *arXiv preprint arXiv, 1111.6285.* https://doi.org/10.48550/arXiv.1111.6285
27. Rochat, Y. (2009). Closeness centrality extended to unconnected graphs: The harmonic centrality index. *ASNA, EPFL-CONF-200525.*
28. Sakoe, H., & Chiba, S. (1978). Dynamic programming algorithm optimization for spoken word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing, 26,* 43-49. https://doi.org/10.1109/TASSP.1978.1163055
29. Sardá-Espinosa, A. (2017). Comparing time-series clustering algorithms in r using the dtwclust package. *European Research Studies Journal, 24*(3B), 951-966. Retrieved from https://cran.r-hub.io/web/packages/dtwclust/vignettes/dtw-clust.pdf
30. Siudak, D. E. (2021). Sectoral analysis of the us stock market through complex networks. *European Research Studies Journal, 24.* https://doi.org/10.1007/s11403-015-0171-7
31. Tabak, B. M., Serra, T. R., & Cajueiro, D. O. (2010). Topological properties of commodities networks. *The European Physical Journal B, 74*(2), 243-249. https://doi.org/10.1140/epjb/e2010-00079-4
32. Tasdemir, K., & Merényi. (2011). A validity index for prototype-based clustering of data sets with complex cluster structures. *IEEE Transactions on Systems, Man, and Cybernetics, 41*(4), 1039-1053. https://doi.org/10.1109/TSMCB.2010.2104319
33. Tian, H., Zheng, X., & Zeng, D. D. (2019). Analyzing the dynamic sectoral influence in Chinese and American stock markets. *Physica A: Statistical Mechanics and its Applications, 536,* 120922. https://doi.org/10.1016/j.physa.2019.04.158
34. Tsekeris, T. (2017). Network analysis of inter-sectoral relationships and key sectors in the Greek economy. *Journal of Economic Interaction and Coordination, 12*(2), 413-435. https://doi.org/10.1007/s11403-015-0171-7
35. Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association, 58*(301), 236-244. https://doi.org/10.1080/01621459.1963.10500845

APPENDIX A

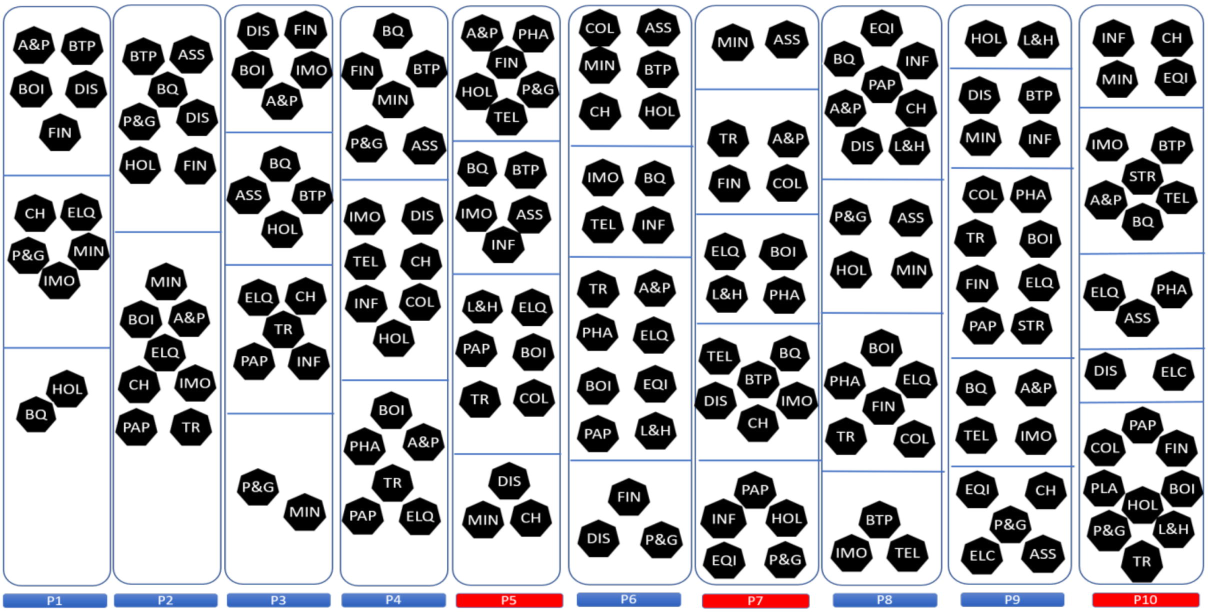


Figure A1. Sectoral index clusters during crisis and non-crisis periods

http://dx.doi.org/10.21511/imfi.19(4).2022.22