International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2026, 16(4), 94-107.

From Sectoral Insights to Stock-Level Networks: Unveiling the Casablanca Stock Exchange Micro-Structure

Younes Berouaga[1]*, Mustapha Bouchekourte[2], Cherif El Msiyah[3], Jaouad Madkour[4]

[1]Research Laboratory in Management Sciences of Organizations, National School of Commerce and Management, Ibn Tofaïl University, Kenitra 14000, Morocco, [2]Research Laboratory in Management Sciences of Organizations, National School of Commerce and Manage-ment, Ibn Tofaïl University, Kenitra 14000, Morocco, [3]National School of Commerce and Management, Moulay Ismail University, Meknes 50000, Morocco, [4]Faculty of Economics and Management, Abdelmalek Essaâdi University, Tetouan 90000, Morocco. *Email: younes.berouaga@uit.ac.ma

Received: 01 February 2026 **Accepted:** 25 May 2026 **DOI:** https://doi.org/10.32479/ijefi.23288

ABSTRACT

This paper investigates the dynamics within the Casablanca Stock Exchange topology during crisis and non-crisis periods using daily historical log-returns of sectoral indices spanning the period from January 4, 1993, to September 9, 2021. The study applies Agglomerative Hierarchical Clustering to the Dynamic Time Warping distance matrix across ten sub-periods encompassing major financial crises, from the Subprime Mortgage Crisis to the European Debt Crisis and the COVID-19 pandemic. The resulting clustering outcomes are aggregated into a network representation to reveal the cumulative interconnections among sectoral indices. The findings indicate the interconnections among the Casablanca Stock Exchange sectoral indices appear to be trend-dependent, with the O&G sector emerging as a central hub within the network. Extending this analysis to a finer level, the study examines the dynamics of stocks composing the MASI index. Daily historical log-returns of stocks are collected for MASI constituents over the period from January 2, 2013, to October 27, 2022. Using a Granger causality–based topological approach, the study investigates the evolving interdependencies among stocks, providing deeper insights into the microstructure of the Casablanca Stock Exchange at the stock level.

Keywords: Market Structure, Financial Networks, Sectoral Interdependence, Stock-Level Interconnectedness, Systemic Risk
JEL Classifications: C32, C38, D53

1. INTRODUCTION

The negative impacts of financial crises on the real economy are considerably pronounced, mainly due to the financial disorder that produces two immediate consequences. First, banks' credit supply is severely restricted, while interest rates rise significantly. This situation discourages borrowers from taking on debt, leading to a period of stagnation. Second, borrowers are unable to repay their loans as a result of the sudden devaluation of their assets. This in turn triggers a tightening of credit, which reduces growth and ultimately leads to recession. These adverse effects directly affect the performance of stock market sectors, leading to major disruptions. The collapse of a key sector can trigger cascading failures through the complex interconnections of the market's topological structure, potentially endangering global economic stability.

The scale of such economic disruptions has generated significant interest in studying the interrelationships between sectoral indices and the evolution of the stock market's topological structure. Understanding how different sectors and stocks interact, particularly during crisis periods, is essential to assessing market resilience and predicting future behavior. Despite this growing interest, there remains a crucial need for alternative approaches to analyze stock market structure. These approaches should not view the market simply as a collection of financial instruments, but rather as an interconnected complex system, where relationships among participants are fundamental to understanding its overall functioning.

Economists, physicists, and mathematicians have extensively studied financial markets as complex systems. Early attempts to analyze the topology of financial markets were made by Mantegna and Stanley (1999), who proposed an innovative approach for selecting a topological space that connects financial market stocks using information contained in time series data. This pioneering study laid the groundwork for a new understanding of stock markets, not merely as collections of financial data, but as systems where interconnections between assets play a critical role. Later, the study of interactions within capital markets was further developed using clustering methods, as presented by Murtagh and Legendre (2011), who sought to identify underlying links within the topological structure of the stock market. By developing a taxonomy to classify market components according to their similarities, they highlighted the importance of viewing stock markets as complex networks, where relationships between stocks and sectors are key of understanding their dynamics.

The Casablanca Stock Exchange (CSE) has faced several economic crises over the past decades, each of which has negatively affected the national economy, particularly in terms of sectoral activities. These crises have included the subprime crisis, the European debt crisis, and, more recently, the COVID-19 pandemic, all of which disrupted financial markerts and various economic sectors. Each of these crises demonstrated the vulnerability of interconnected sectors, where a major disruption in one sector can quickly spread to others, causing widespread instability. Furthermore, these events underscored the need for analytical tools to better understand the underlying mechanisms of sectoral linkages and their evolution over time, particularly during crises.

In this context, the present study proposes a detailed analysis of the topological structure of the CSE, focusing on both crisis and non-crisis periods. Such analysis is crucial for portfolio managers, as it provides insights for optimizing investments by considering the dynamics of interrelations within the market topology during different phases. Moreover, this research may provide valuable insights for policymakers and decision-makers, assisting them in designing new economic synergies between sectors and creating integrated value chains based on cointegration relationships, thereby enhancing value creation within the economy. In addition, understanding these topological dynamics may help implement more effective regulatory mechanisms to minimize the impact of future crises on the national economy, while fostering greater market resilience to global disruptions. While traditional approaches of financial market analysis have provided important insights, they can be complemented by network analysis tools to capture the complexity of interactions among market participants more effectively. This study examines the dynamics of financial markets by considering the specific characteristics of the CSE and analyzing the evolution of its topological structure under different economic scenarios.

To understand stock market behaviors across different trends, this study highlights stock market topology and its evolution over time. Lahmiri (2016) examined the topological co-movement of the CSE as a complex network during different market regimes using the Agglomerative Hierarchical Clustering (AHC) algorithm based on Hurst exponents estimated to partition sectoral indices into groups. A key observation is that the Hurst exponent tends to be higher in bullish market periods than in bearish ones. Laha et al. (2020) applied topological data analysis techniques to the Indian Stock Market, demonstrating dependencies between stock prices and sectoral index variations. Huang et al. (2021) identified the determinants of market co-movement using daily prices of the CSI 300 index, finding that overall efficiency, average clustering coefficient, and network density could serve as early-warning indicators of potential future crises. Siudak (2021) analyzed the network topology of economic sectors using logarithmic returns of 496 stock prices from the S&P 500 index, identifying utilities, consumer cyclicals, and industrials as the central nodes of the U.S. stock market. Jaroonchokanan et al. (2022) explored the dynamics of the hierarchical tree structure of 37 stocks from the Stock Exchange of Thailand (SET) over 2008–2020, finding that dynamic hierarchical clustering led to less variable clustering and provided insights into stock market behavior during financial crises. Tsekeris (2017) evaluated sectoral relationships using network analysis of the input–output matrix of the Greek economy for 2010, identifying key sectors capable of influencing system stability. Lahmiri (2012) explored the topological dynamics of NASDAQ before, during, and after the subprime crisis using hierarchical clustering trees on sectoral return series, revealing that sectoral clusters depend on trends and that some sectors tend to form the same cluster throughout the study period, highlighting the dynamic nature of NASDAQ topology. Memon et al. (2020) applied the Minimum Spanning Tree (MST) method using cross-correlations computed from daily closing prices of 82 major Karachi Stock Exchange 100 index stocks, finding economic expansion in cement, fertilizer, and oil & gas sectors.

Numerous studies have investigated the mechanisms underlying the formation and evolution of complex networks, highlighting their structural and dynamic properties (Boguná et al., 2003; Dorogovtsev and Mendes, 2000; Barabási and Albert, 1999). These foundational works provided the theoretical basis for applying network theory to various domains, including finance. In the context of stock markets, network theory has become an increasingly popular analytical framework to capture and interpret the complex web of relationships among financial assets. By modeling stock markets as complex networks, researchers aim to uncover hidden topological structures and gain deeper insights into market behavior, especially during periods of volatility or systemic stress.

To better understand the dynamic behaviors and interdependencies of stock market components, numerous methodological approaches have been employed. For example, Huang et al. (2021) used Granger causality and Engle–Granger cointegration tests to analyze daily stock return data from the Chinese A-share market. Their results indicated that the level of interconnectedness among stocks tends to intensify in response to the spread of financial risk, suggesting that market shocks can amplify structural dependencies within the network. In another study, Li and Yang (2021) applied spectral clustering techniques to CSI 300 index data to identify central firms within the market and characterize the resulting financial network topology. Their approach facilitated the detection of key nodes whose positions may significantly influence market stability.

Despite the substantial body of literature exploring these themes, there remains a clear need for ongoing empirical and theoretical research on the evolving and often nonlinear interrelationships that characterize financial markets. This is particularly relevant in light of heightened uncertainty and increasing complexity within global financial systems. The present study contributes to this discourse by focusing on the dynamics of the CSE, with a particular emphasis on the topology of its sectoral indices under different market conditions. Through this lens, we aim to uncover patterns of connectivity and interdependence that emerge across various economic scenarios.

Moreover, the use of Granger Causality, originally introduced by Granger (1969), plays a central role in our econometric investigation. This methodological tool enables the examination of causal relationships between time series variables by assessing whether the historical values of one variable contain predictive information about another. In financial applications, Granger Causality has proven particularly useful for identifying transmission channels, spillover effects, and directional influences among market participants. As noted in the broader literature, such methods are essential for quantifying the dynamic nature of inter-asset linkages and assessing the extent of systemic risk propagation across different market segments (Diebold and Yilmaz, 2009).

Graph theory provides a powerful mathematical framework for analyzing market structures. It enables the visualization and quantification of relationships among financial entities, revealing patterns and hierarchies that would otherwise be difficult to detect. Graphs can be used to represent various forms of interdependencies, such as correlations among stock returns, causal relationships, or even information flows. Key graph theory concepts, such as shortest paths, centrality measures, and communities, are directly applicable to financial analysis (Boguná et al., 2003; Dorogovtsev and Mendes, 2000).

In the context of stock markets, graph theory has been employed to construct MST and Planar Maximally Filtered Graph (PMFG) from correlation matrices. These graphical representations simplify the market's complex structure while preserving essential information on interdependencies. MSTs, for example, are particularly useful in identifying natural hierarchies and groupings of assets, which can assist in portfolio diversification and the detection of financial contagion (Di Matteo et al., 2010; Memon et al., 2020; Tabak et al., 2010). Analyzing the topology of such graphs, such as node degree distribution, average path length, and clustering coefficient, can reveal important market properties, including resilience, vulnerability to systemic shocks, and efficiency of information transmission (Huang et al., 2021).

Econometrics plays a crucial role in quantifying and modeling financial interconnections. While network theory provides the structural framework, econometrics offers the statistical tools to estimate the strength and direction of these links, as well as to test hypotheses on their dynamics. Econometric methods are essential to move from a simple description of networks toward an understanding of the mechanisms underlying financial interactions. Granger Causality, as previously mentioned, is a fundamental econometric tool for detecting directional relationships among financial variables. It allows one to determine whether past movements of an asset or sector can predict the future movements of another, providing valuable insights into shock transmission channels and risk propagation.

By combining these perspectives, network and graph theory for structural modeling, and econometrics for quantitative analysis of interdependencies, this study aims to provide a holistic understanding of the dynamics of the CSE. The goal is to move beyond traditional analyses by integrating the complexity of interconnections to better inform investment strategies and regulatory policies, particularly in the face of the recurrent challenges posed by financial crises. This multidisciplinary approach is essential for navigating an increasingly interconnected and volatile financial environment.

This paper is structured as follows: Section 2 introduces the data and methodology. Section 3 describes the materials and methods, while the empirical results are provided in Section 4, followed by the discussion in Section 5. Finally, Section 6 concludes the paper.

2. MATERIALS AND METHODS

To examine the intricate dynamics of the CSE network structure, this study uses daily logreturns of sectoral indices covering the period from January 4, 1993, to September 9, 2021, obtained from the official website of the Casablanca Stock Exchange. The dataset comprises the sectoral indices listed in Table 1. This

Table 1: Sectoral Indices of the CSE

Sector	Index Abbreviation
Banks	BK
Beverages	BVG
Chemicals	CHM
Construction and Building Materials	CBM
Distributors	DS
Electrical and Electronic Equipment	EEE
Electricity	ELC
Engineering and Industrial Equipment	EIG
Food Producers and Processors	FPP
Forestry and Paper	F&P
Holding Companies	HOL
Insurance	ISE
Investment Companies and Other Finance	IC
Leisure and Hotels	L&H
Materials, Software and Computer Services	MCS
Mining	MIN
Oil and Gas	O&G
Pharmaceuticals	PHA
Real Estate Investment Companies	REI
Real Estate Participation and Promotion	REP
Telecommunications	TEL
Transport	TR
Transportation Services	TRS
Utilities	UTL

period corresponds to the longest interval for which continuous and reliable sector index data are available at the Casablanca Stock Exchange, following the major market modernization in 1993. Sector indices are historically more stable and exhibit fewer missing observations or listing changes, making them suitable for long-term market topology analysis.

In addition to the sectoral approach, the study also investigates the dynamics of individual stocks composing the MASI index. Daily stock-level data are collected for MASI constituents over the period from January 2, 2013, to October 27, 2022. The analysis is conducted on a subset of 63 stocks for which continuous and complete time series are available throughout the sample period; firms that entered the Casablanca Stock Exchange during the horizon and exhibited incomplete data were excluded to ensure consistency and comparability. The complete list of selected stocks is reported in Table A1. This more recent interval reflects the modern phase of the Moroccan equity market, during which data quality improved significantly, and provides a reliable basis for econometric modeling and network construction.

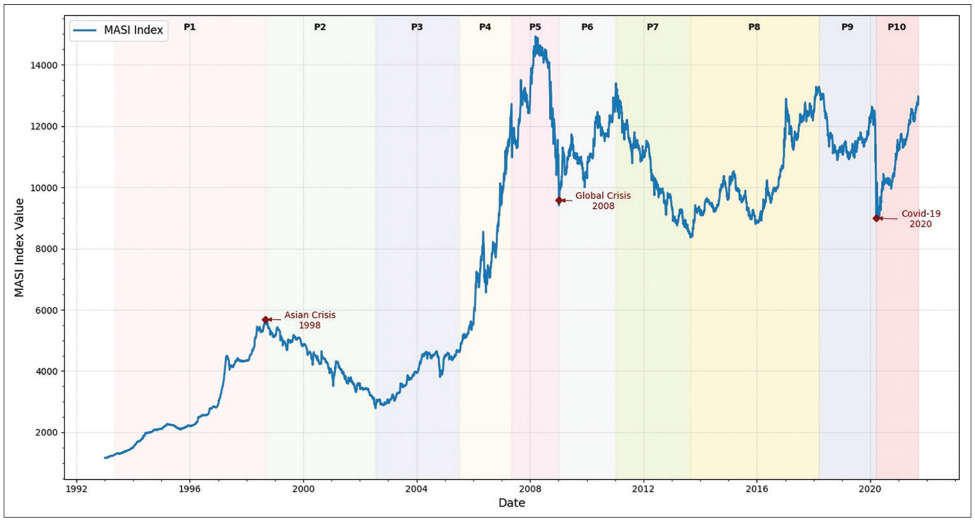
In this study, the sectoral index time series are examined using a methodology that divides the data into separate time windows. This process is carried out using structural change tests, which are designed to detect shifts in the underlying patterns of the data that may correspond to significant changes in the market conditions. Specifically, the MASI index, a key indicator of the performance of the CSE, is divided into several segments using a multiple break-point test. The Bai and Perron (2003) test, allows for the identification of dates that correspond to structural changes within the CSE.

The application of this multiple break-point test reveals a total of 9 breaks, which correspond to 10 distinct time windows, as illustrated in Figure 1. These break points serve as important reference points, dividing the MASI index time series into periods that reflect changing market conditions. Following the identification of these structural breaks in the MASI time series, the same approach is applied to the time series of all sectoral indices. Each sectoral index is thus partitioned into periods that align with the structural changes observed in the MASI index. The periods identified through this methodology are particularly relevant as they span a range of significant global and regional crises. Among these, the time series covers the Subprime Mortgage Crisis of 2007-2008, the European Debt Crisis of the early 2010s, and the unprecedented economic and financial disruptions caused by the Covid-19 pandemic. By segmenting the data in this way, the study ensures that the analysis of sectoral indices reflects the distinct market conditions that prevailed during each of these critical periods.

The Subprime crisis revealed the extent of interdependencies between financial markets at the global level. In Morocco, a return spillover effect was observed in the CSE during the post-crisis period (El Ghini and Saidi, 2017). International trade and global demand for Moroccan goods declined by 11.9% and 10%, respectively, which resulted in a 13.1% contraction in the export levels of goods and services. Household final consumption fell by 1.42% relative to its trend, while exports of goods and services decreased by 1.01%. The downturn intensified in 2009, with consumption shrinking by 3.12% and exports by 4.34%, exerting negative effects on both demand and growth. GDP contracted by 2.46% compared to its trend in 2009, while investment declined by around 3.57%. In 2011, the country's trade deficit widened by 25%, reaching 185.7 billion dirhams. During the same period, GDP growth slowed from 5.246% in 2011 to 3.01% in 2012.

The advent of the Covid-19 crisis led to a spectacular contraction in March 2020, with Moroccan economic activity shrinking by nearly 7%. The MASI index recorded a decline of -8.82%, marking a severe and sudden market downturn. Regarding the crisis impacts across sectors, the financial sector, including insurance companies, banks, and other financial institutions experienced a decline of 22.8%. The capital goods industry, real estate, building materials, and industrial engineering sectors also registered sharp contractions of -12.2%, -21.8%, -31.6%,

Figure 1: MASI index break points. Figure shows the historical evolution of the MASI Index over the period 1993–2023, with shaded regions indicating predefined market periods (windows) (P1–P10). Key financial crises, such as the Asian Crisis (1998), Global Financial Crisis (2008), and Covid-19 pandemic (2020), are highlighted to provide context for market stress periods



and -32.5%, respectively. The construction sector's market capitalization decreased from 78.812 billion dirhams in January to 59.764 billion dirhams in May. Likewise, the industrial sector's total market capitalization contracted from 119.957 billion dirhams at the start of the year to 100.691 billion dirhams by the end of May. This decline intensified in March, when the industrial sector recorded a notable drop of 21.10% following the rapid spread of COVID-19 in Morocco.

In this paper, the clustering tendency of the data is first examined using the Hopkins statistic (Hopkins and Skellam, 1954). Subsequently, the Dynamic Time Warping (DTW) method is applied to compute pairwise distances between time series. The resulting DTW distance matrix is then used within the AHC algorithm to form clusters of sectoral indices across multiple time windows (Ward Jr, 1963). To assess the robustness of the clustering structure, several cluster validity indices are employed (Arbelaitz et al., 2013). Finally, the clustering outcomes are represented as a network, emphasizing the overall relationships across the CSE's sectoral indices.

Following the clustering analysis, Granger Causality tests are performed to investigate the directional influence among the identified stocks data to assess the predictive relationships between individual stocks. This analysis helps identify how shocks in one stock may influence others, thereby contributing to a deeper understanding of the interdependencies within the market.

3. MATERIALS AND METHODS

3.1. Hopkins Test

Prior to applying the AHC algorithm, it is crucial to verify that the dataset is not uniformly distributed, which would indicate the existence of meaningful clusters. To evaluate the clustering tendency, the Hopkins test is employed. Let $X=\sum_{i=1}^{n} x_i$ and $Y=\sum_{j=1}^{m} y_j$ denote collections of n and m patterns, respectively, with $m \ll n$. Define u_j representing the least distance between y_j and its closest neighbor in X, and w_j corresponds to the smallest distance between a randomly generated pattern within X and its closest neighbor.

The Hopkins statistic is then given by:

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

The H statistic obtained serves to assess the degree to which the data exhibit a clustering structure. If H is close to 0, the data set does not have a clustering tendency. On the other hand, if H is approaching 1, it indicates a clustering tendency, suggesting that the data set is significantly clusterable.

3.2. Dynamic Time Warping

The DTW method measures the similarity between two time-series X and Y, which may be of different lengths. Each alignment of elements x_i and y_j is indicated by a grid point (i, j), where i and j denote their respective indices in sequences X and Y. DTW enables flexible matching in which multiple elements from one series can correspond to a single element of the other, as illustrated in Figure 2a. The method derives the optimal path that achieves the smallest possible distance between the two sequences. Formally, the warping path is defined as

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

where each w_k represents a correspondence point $(i, j)_k$, as presented in Figure 2b. Moreover, the warping path W must satisfy the set of constraints originally established by Sakoe and Chiba (2003).

Let $\delta(i, j)$ denote the dissimilarity measure between the elements x_i and y_j of the time-series X and Y. The DTW formulation seeks the optimal warping path $W=(w_1,\ldots,w_K)$ that minimizes the cumulative distance along the path:

$$DTW(X,Y)=\min\sum_{k=1}^{K}\delta(w_k) \tag{2}$$

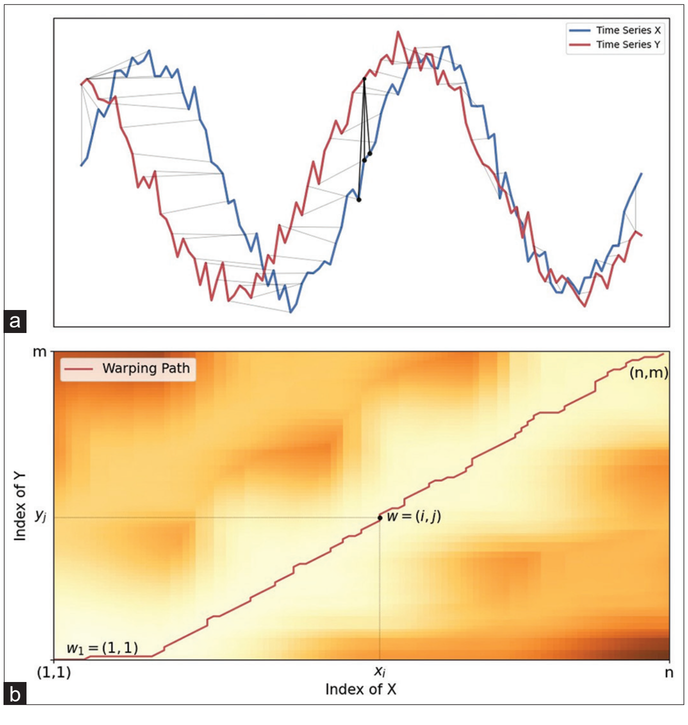
The dynamic programming method defines the cumulative distance $\Phi(i, j)$ through the following recursive relation:

$$\Phi(\mathrm{i},\mathrm{j})=\delta(\mathrm{i},\mathrm{j})+\min[\Phi(\mathrm{i}-1,\mathrm{j}),\Phi(\mathrm{i}-1,\mathrm{j}-1),\Phi(\mathrm{i},\mathrm{j}-1)]. \tag{3}$$

with appropriate boundary conditions (e.g., $\Phi(i, j) = \delta(i, j)$ and infinite values for out-of-bound indices).

The value $\Phi(i, j)$ represents the minimum accumulated distance to reach cell (i, j). Once the cumulative distance Φ is computed

Figure 2: Time-series alignment (a) and cumulative distance matrix (b)



through a forward pass, the optimal warping path can be retrieved by backtracking: starting from (I, J), one moves step by step to the preceding point among $\{(i-1, j), (i, j-1), (i-1, j-1)\}$ with the lowest cumulative distance, until reaching.

3.3. Agglomerative Hierarchical Clustering

The AHC algorithm is implemented using the distance matrix derived from the DTW analysis, with several linkage methods available for combining clusters (Murtagh and Contreras, 2012). The Ward.D linkage, implemented by the Lance–Williams algorithm, is used. This approach is integral to many AHC algorithms, which iteratively update inter-cluster distances at each merging step (Ward Jr, 1963; Murtagh and Legendre, 2011). In hierarchical clustering, each pair of merged clusters is chosen to produce the smallest possible increase in the sum of intraclass inertia, computed as the squared distance between the cluster centroids, weighted by their respective sizes. The Ward.D method, which reduces total intra-cluster variance, is applied to the DTW results to partition the data. Consider the merging of two clusters C_i and C_j, the recalculated distances between clusters after this combination are determined by a recursive formula. Here, d_{ij}, d_{ik}, and d_{jk} denote the distances between clusters C_i, C_j, and C_k, respectively, considering that the cluster distance function d_{Nk} calculates the separation between the merged cluster C_N and the existing cluster C_k.

An algorithm belongs to the Lance–Williams family if d_{Nk} can be computed recursively as follows:

$$d_{Nk} = \alpha_i d_{ik} + \theta_j d_{jk} + \beta d_{ij} + \gamma |d_{ik} - d_{jk}| \tag{4}$$

Where α_i, θ_j and β are determined by the choice of clustering algorithm. In the case of the Ward.D method, these parameters are defined as follows:

$$d(C_N, C_k) = \alpha_i d(C_i, C_k) + \theta_j d(C_j, C_k) + \beta(C_i, C_j) + \gamma |d(C_i, C_k) - d(C_j, C_k)| \tag{5}$$

$$ai = \frac{n_i + n_k}{n_i + n_j + n_k},\ \theta j = \frac{n_j + n_k}{n_i + n_j + n_k},\ \beta = \frac{-n_k}{n_i + n_j + n_k} \tag{6}$$

To provide a clearer understanding of the method, consider a set $C = \{e_i\ i = 1, \ldots, n\}$ of individuals with a centroid g. Suppose this set is divided into k clusters of sizes $n_1, n_2, \ldots, n_k$, denoted $C_1, C_2, \ldots, C_k$, each with its own centroid $g_1, g_2, \ldots, g_k$. The overall inertia of the entire dataset is expressed as:

$$It = \frac{1}{n}\sum_{i=1}^{n} d(e_i, g)^2 \tag{7}$$

with the between-cluster inertia given by:

$$Ie = \frac{1}{n}\sum_{i=1}^{k} n_i \times d(g_i, g)^2 \tag{8}$$

and the within-cluster inertia defined as:

$$Ia = \frac{1}{n}\sum_{i=1}^{k}\sum_{e \in Ci} d(e, g_i)^2 \tag{9}$$

The Ward.D method operates by successively merging clusters in an iterative process, where at each step the pair chosen is the one that produces the maximum increase in inter-class inertia.

The AHC algorithm proceeds through a sequence of steps. Initially, each observation is treated as its own cluster, leading to N clusters, each representing an individual. The pairwise distances between these clusters are then evaluated using the DTW approach. At each stage, the two closest clusters are identified and merged into a single cluster according to the Ward.D criterion. Following this, the distances between the newly formed cluster and the remaining clusters are recalculated. This iterative procedure continues until all individuals are grouped into a single cluster. In the literature, several studies have addressed the standardization of cluster evaluation through the Cluster Validity Index (CVI) (Sardá-Espinosa, 2017). In the present work, three indices are adopted, namely the Dunn index (DI), the Connectivity index (CI), and the Calinski Harabasz index (CHI), to assess the quality of the resulting partition (Dunn, 1973; Caliński and Harabasz, 1974; Tasdemir and Merényi, 2011).

3.4. Cluster Validity Index

Three clustering validity indices are employed to evaluate the quality of the clusters obtained in this study: the Dunn Index (DI), the Connectivity Index (CI), and the Calinski-Harabasz Index (CHI). The DI measures the ratio between the smallest inter-cluster distance and the largest intra-cluster distance, assessing cluster separation and compactness; higher values indicate better separation and cohesion. The CI measures the connectivity of points within each cluster, with lower values reflecting stronger intra-cluster connectivity and higher values indicating more dispersed clusters. The CHI evaluates the inter-cluster to intra-cluster dispersion, with higher values corresponding to more clearly separated and well-defined clusters. Together, these indices provide a comprehensive and objective assessment of cluster quality, ensuring that the observed groupings reflect meaningful structures rather than random noise (Arbelaitz et al., 2013).

3.5. Network Construction

Following the application of the AHC algorithm across several time windows, the resulting partitions are employed to build an undirected weighted network for the purpose of investigating the mechanisms underlying the observed complex structure. Formally, let $G = (R, F, \Omega)$ denote an undirected weighted graph, where $R = \{r_1, r_2, \ldots, r_n\}$ is the set of nodes and $F = \{f_1, f_2, \ldots, f_n\}$ the set of edges describing the connections between nodes. An edge f_{ij} is established if the elements (i, j) appear in the same cluster, and is absent otherwise. The weight set $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ encodes the strength of these connections, where each weight ω_{ij} corresponds to the number of times the pair (i, j) has been grouped within the same cluster throughout the considered windows.

3.6. Granger Causality Model

The Granger Causality model is a statistical hypothesis test employed to examine whether one time series can predict another time series (Granger, 1969). At its core, the Granger Causality framework relies on the principle that if a variable X Granger-causes another variable Y, then the historical values of X contain information that aids in improving the prediction of Y beyond what can be achieved using only the past values of *Y* alone. The formal mathematical representation of this relationship can be expressed as follows:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-1} + \sum_{j=1}^{q} \gamma_j X_{t-1} + \varepsilon_t \tag{10}$$

- Y_t is the dependent variable at time *t*,
- α is a constant term,
- β_i denotes the coefficients associated with the lagged values of *Y*,
- γ_j denotes the coefficients associated with the lagged values of *X*,
- ϵ_t is the error term,
- *p* and *q* are the maximum lag lengths for *Y* and *X*, respectively.

To test for Granger Causality, the procedure typically involves two key steps:

1. Estimate the Unrestricted Model: This model incorporates both past values of *Y* and *X*.
2. Estimate the Restricted Model: This model includes only past values of *Y*.

The null hypothesis asserts that *X* has no Granger-causal effect on *Y* (i.e., $\gamma_j = 0$ for all *j*). To assess this hypothesis, one can employ an F-test or a Wald test, comparing the goodness-of-fit of the two models.

In this paper, Granger Causality is employed to quantify the relationships and interdependencies between individual stocks within the market. Specifically, it helps identify whether past values of one stock can predict the future movements of another, thus providing insight into the directional flow of information between stocks. This method is particularly useful in understanding stock connectivity, as it reveals how price movements or shocks in one stock may influence the behavior of others. By applying Granger Causality, we can assess the degree to which stocks are interconnected and how these relationships contribute to sectoral performance and broader market dynamics. For instance, stocks that exhibit strong Granger Causality relationships are likely to respond similarly to market events or economic drivers, clustering within the same community or sector. This analysis not only aids in understanding the propagation of market signals but also highlights key stocks that play a pivotal role in the transmission of information across the market.

4. RESULTS AND DISCUSSION

This section presents the findings of our network analysis, structured across two distinct chronological periods and levels of granularity: the long-term dynamics of sectoral groupings (1993–2021) and the recent evolution of stock-level market microstructure (2013–2022). This dual perspective provides a comprehensive view of the market's structural evolution and its response to both historical and contemporary global shocks.

The first part of our analysis focuses on the Agglomerative Hierarchical Clustering applied to the Casablanca Stock Exchange sectoral indices over the extended period 1993 to 2021. This long-term view aims to understand how the market's fundamental structure reorganized in response to major economic shocks, including the 2008 Global Financial Crisis and the initial phase of the COVID-19 pandemic.

Prior to AHC application, the Hopkins and Skellam (1954) test (Table 2) confirms the suitability of the dataset for clustering, with values consistently close to 1, indicating a strong tendency for the data to form significant groups.

Figure 3 illustrates the temporal evolution of sectoral affiliations across the ten sub-periods (*P* 1–*P* 10) within this timeframe. Each row corresponds to a sectoral index, ordered according to the similarity of their clustering trajectories, while each column represents a specific subperiod. The colored cells denote the cluster affiliation of each index within a given period, with distinct colors assigned to different clusters. Crisis periods (*P* 5, *P* 7, and *P* 10) are shaded in red, thereby facilitating the identification of structural changes in market organization. A critical observation is the tendency for clusters to coalesce during these crisis periods, a phenomenon that reflects an increase in correlation and a loss of diversification benefits. Economically, this signifies that systemic shocks force sectors to behave homogeneously, reducing the market's ability to absorb risks in a differentiated manner.

To quantify the quality of these groupings and the structural health of the market during this period, we employ three clustering validity indices (Table 3): The Dunn Index (DI), the Connectivity Index (CI), and the Calinski-Harabasz Index (CHI). These metrics are interpreted as indicators of market resilience and fragmentation.

The results show that the DI values range from 0.884 (4th sub-period) to 0.973 (10th sub-period). Lower DI values during crisis

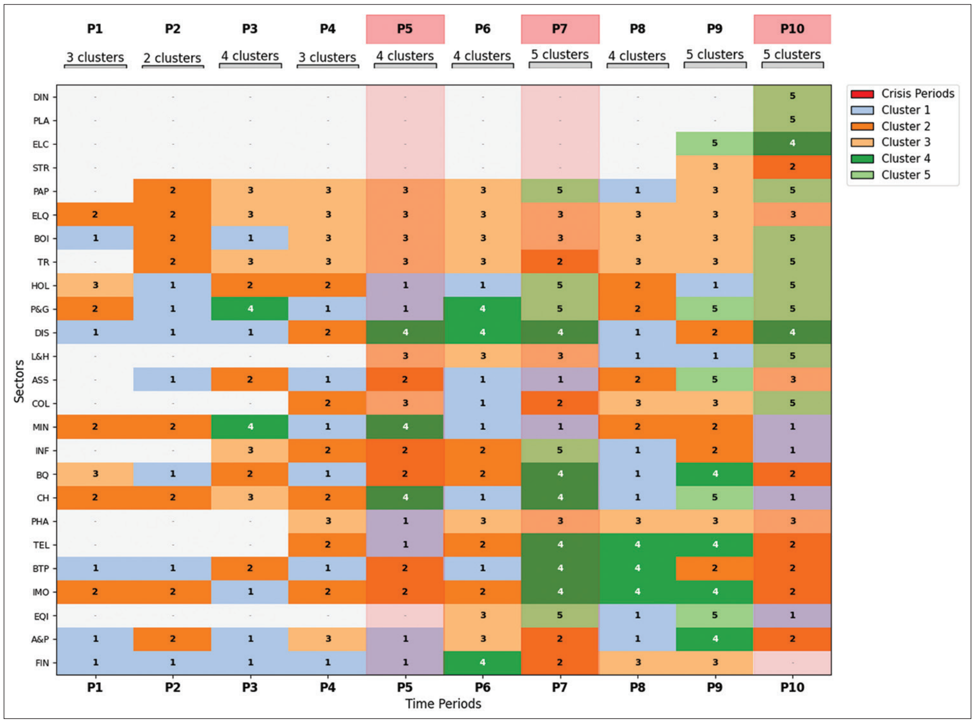
Table 2: Hopkins test values by window

Window	Hopkins test
w01	0.982
w02	0.868
w03	0.778
w04	0.691
w05	0.690
w06	0.727
w07	0.699
w08	0.782
w09	0.956
w10	0.720

Table 3: Validation metrics of sectoral index clusters

Window	DI	CI	CHI
w01	0.952	10.012	4.978
w02	0.971	3.029	2.112
w03	0.938	9.480	1.816
w04	0.884	8.612	1.509
w05	0.924	8.887	1.493
w06	0.908	13.789	1.578
w07	0.912	19.390	1.699
w08	0.932	12.431	1.849
w09	0.913	13.385	2.615
w10	0.973	9.123	2.755

Figure 3: Sectoral index clusters during crisis and non-crisis periods



Sectors	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
	3 clusters	2 clusters	4 clusters	3 clusters	4 clusters	4 clusters	5 clusters	4 clusters	5 clusters	5 clusters
DIN	-	-	-	-	-	-	-	-	-	5
PLA	-	-	-	-	-	-	-	-	-	5
ELC	-	-	-	-	-	-	-	-	5	4
STR	-	-	-	-	-	-	-	-	3	2
PAP	-	2	3	3	3	3	5	1	3	5
ELQ	2	2	3	3	3	3	3	3	3	3
BOI	1	2	1	3	3	3	3	3	3	5
TR	-	2	3	3	3	3	2	3	3	5
HOL	3	1	2	2	1	1	5	2	1	5
P&G	2	1	4	1	1	4	5	2	5	5
DIS	1	1	1	2	4	4	4	1	2	4
L&H	-	-	-	-	3	3	3	1	1	5
ASS	-	1	2	1	2	1	1	2	5	3
COL	-	-	-	2	3	1	2	3	3	5
MIN	2	2	4	1	4	1	1	2	2	1
INF	-	-	3	2	2	2	5	1	2	1
BQ	3	1	2	1	2	2	4	1	4	2
CH	2	2	3	2	4	1	4	1	5	1
PHA	-	-	-	3	1	3	3	3	3	3
TEL	-	-	-	2	1	2	4	4	4	2
BTP	1	1	2	1	2	1	4	4	2	2
IMO	2	2	1	2	2	2	4	4	4	2
EQI	-	-	-	-	-	3	5	1	5	1
A&P	1	2	1	3	1	3	2	1	4	2
FIN	1	1	1	1	1	4	2	3	3	-

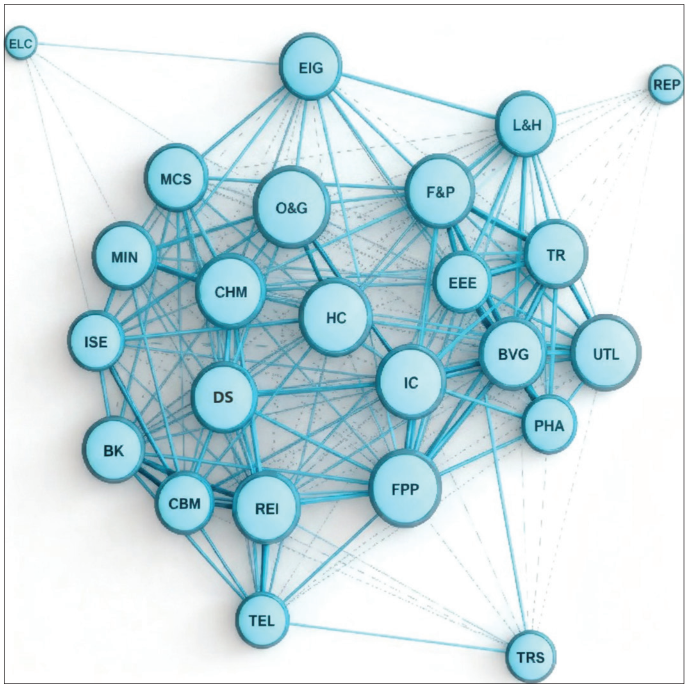
periods, such as in the 4th sub-period, indicate that clusters were less well separated and more dispersed, reflecting that financial market volatility tends to rise sharply in crisis periods such as the COVID-19 pandemic. In contrast, the 10th sub-period exhibits higher DI values, reflecting post-crisis stabilization, with clusters showing stronger separation and greater cohesion (Albulescu et al., 2020).

The CI values show substantial variation across sub-periods, with the lowest value of 3.029 observed in the 2nd sub-period, indicating strong intra-cluster connectivity, and the highest value of 19.390 in the 7th sub-period, reflecting weaker connectivity and higher dispersion. This suggests that sector cohesion was strongest in the 2nd sub-period and that clusters became more fragmented during the 7th sub-period, likely due to market instability associated with crises. Increased dispersion during turbulent periods is consistent with literature showing that financial markets tend to exhibit heightened connectedness and spillovers during crisis episodes, reflecting stronger co-movement and reduced structural distinction among groups of assets or sectors (Youssef et al., 2021).

The CHI values range from 1.493 (5th sub-period) to 4.978 (1st sub-period), providing a complementary view of cluster separation. High CHI values, as in the 1st sub-period, indicate well-defined and distinct clusters, typically corresponding to stable and predictable market conditions. Conversely, lower CHI values during crisis periods, such as the 5th sub-period, suggest less clear separation between clusters, reflecting the impact of increased volatility and uncertainty that occurs during turbulent markets and tends to strengthen connectedness across financial groups (So et al., 2021).

For a deeper understanding of the CSE topology, Figure 4 illustrates the undirected weighted network capturing the interconnections among sectoral indices. In contrast to conventional clustering methods that provide only a static partition, this network-based representation emphasizes the clustering outcomes by visualizing historical relationships between sectors. Edge widths reflect the strength of inter-sectoral dependencies, while node sizes are proportional to the number of connections associated with each sectoral index; node labels correspond to sector abbreviations.

Figure 4: Weighted Undirected Network of the CSE Sectoral Indices



The analysis of this network reveals that the Oil and Gas (O&G), FPP, and Holding Companies (HC) sectors exhibit the highest systemic importance. This long-term centrality is rooted in the real economy of the time. The O&G sector acts as a cross-sectoral cost hub; its high centrality (measured by Eigenvector Centrality EC) is explained by its role as an energy supplier, directly impacting the production costs of almost all other sectors. Any fluctuation in this sector propagates rapidly throughout the market, justifying its position as a critical bridge (high Betweenness Centrality BC). Similarly, the centrality of FPP underscores the market's dependence on agricultural cycles, while the centrality of HC indicates that large financial and industrial conglomerates act as contagion vectors by linking otherwise distinct sectors.

Focusing on the significance of each sector within the broader financial network, Figure A1 in Appendix presents the rankings of sectoral indices based on multiple network indicators. These rankings illustrate the relative centrality and interconnections of each sector, providing an overview of their position and influence within the overall market network structure.

Building upon the macro-level insights derived from the long-term sectoral analysis, this section transitions to a more granular examination of the Casablanca Stock Exchange microstructure at the individual stock level, covering the period 2013 to 2022. This period is critical as it captures the market's response to recent global events, including the US-China trade tensions and the full impact of the COVID-19 crisis.

The analysis of market microstructure is based on Granger Causality at the stock level. Figure 5 provides a snapshot of the market's causality structure at the beginning of our study period (2013-2016). It clearly illustrates the influences between various stocks during this early phase, setting a baseline for comparison with later periods. The causality network for this first window is notably characterized by its low density, which strongly suggests a limited degree of market integration.

Moving to the latter part of our study, Figure 6 presents the market structure at the end of the analysis period (2019-2022), notably encompassing the critical COVID-19 crisis. The comparison reveals a major structural transformation. The network shifts from low density in 2013–2016 to a significantly increased density in 2019–2022. This densification is a classic marker of crisis periods, but it is exacerbated here by global uncertainty. The focus on the 2013–2022 period allows us to capture the impact of the COVID-19 pandemic and, crucially, the US-China trade tensions. These tensions, by disrupting global supply chains, introduced political and economic uncertainty that translated into an increase in market connectivity on the local exchange. Sectors dependent on imports (such as Construction and Building Materials, linked to CSM, a new central player) became more sensitive to external shocks, forcing greater price synchronization.

The centrality analysis at the stock level (PageRank for received influence and Out-degree for emitted influence) reveals the study's most novel finding: a marked asymmetry between the capacity to receive information and the capacity to emit it. To further understand this dynamic, Figures 7 and 8 present only the top 10 stocks with the highest average centrality for readability. Figure 7 shows the temporal evolution of influence received, whereas 8 illustrates each stock's capacity to exert influence on others.

Figure 5: Causality Network - First Window (2013–2016)

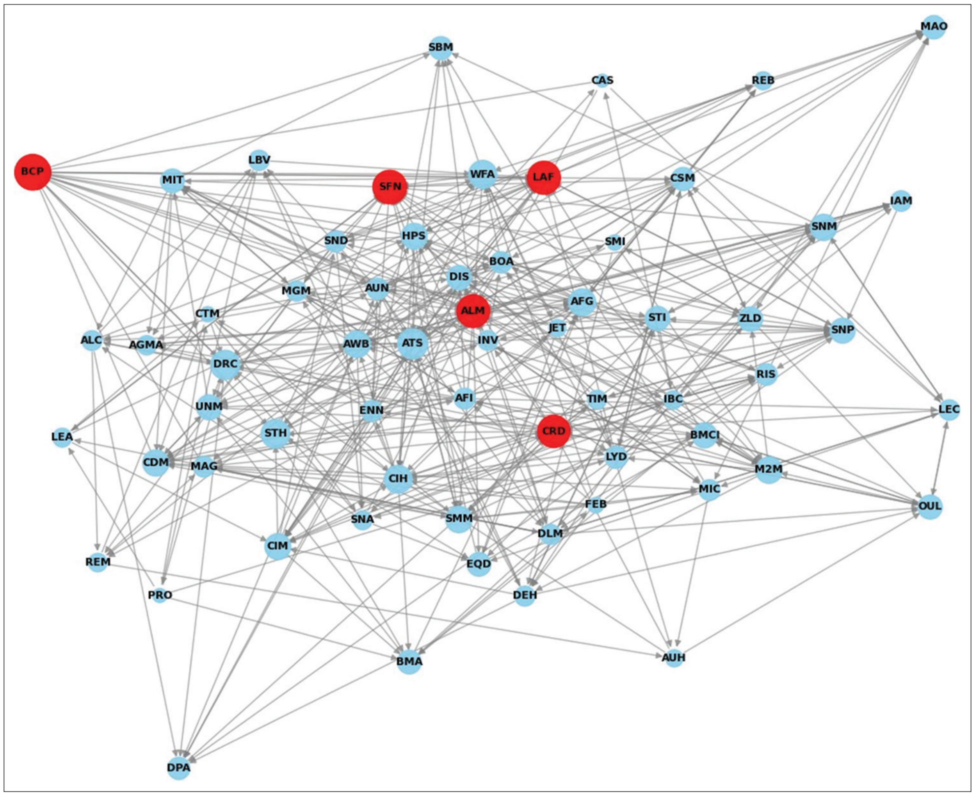


Figure 6: Causality Network - Last Window (2019–2022)

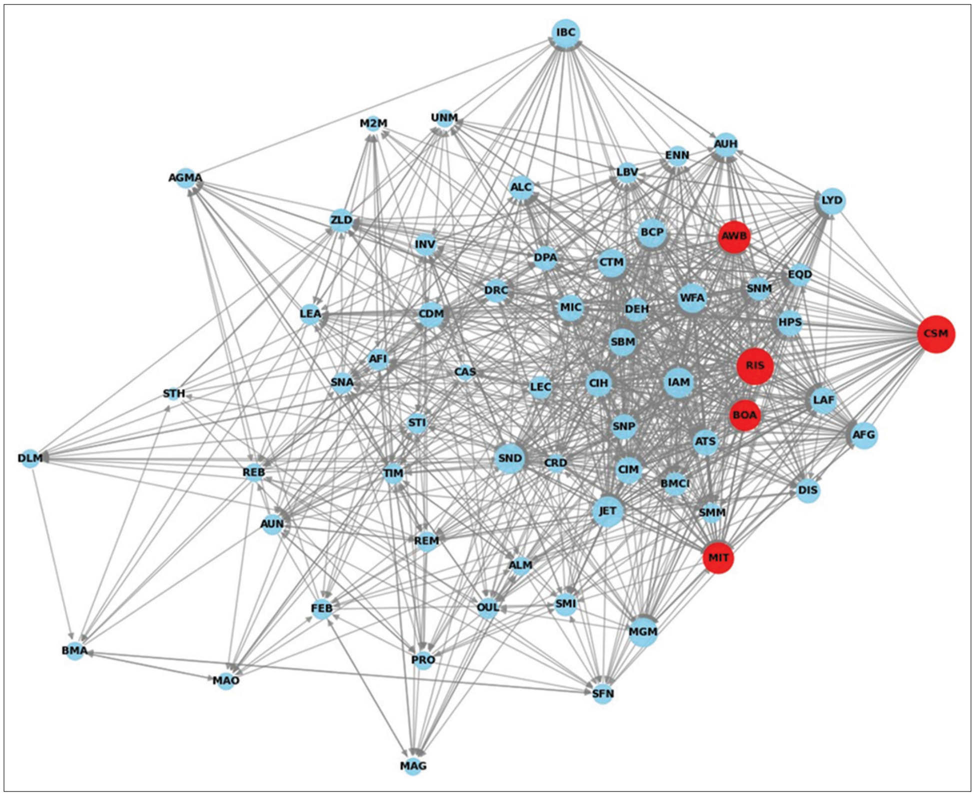
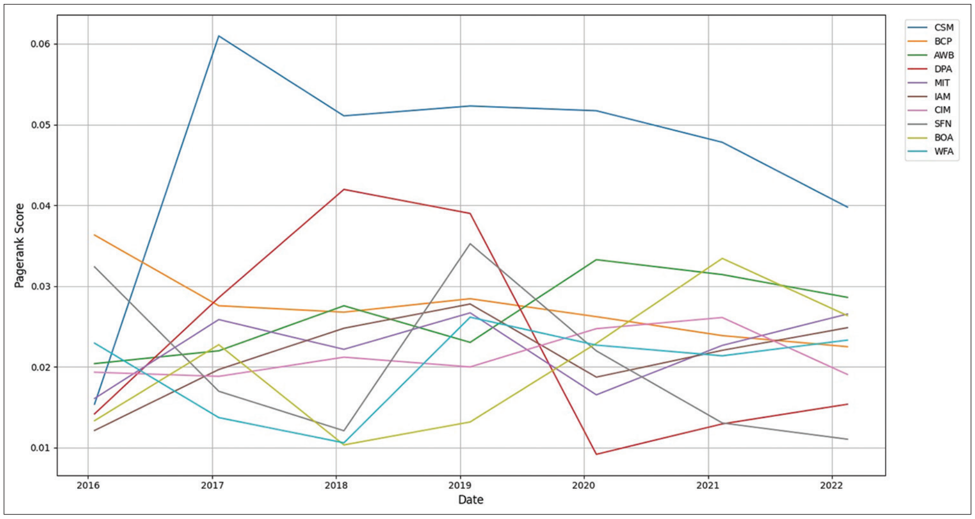


Figure 7: Evolution of Stock PageRank



Stocks like CSM, RIS, and AWB emerge as the most central nodes (high PageRank) in the last window (2019–2022). These stocks act as barometers that absorb and reflect diffuse market information. Their ascent is an indicator of the post-COVID market transformation, where companies sensitive to domestic demand and real estate shocks (CSM, RIS) become the primary receivers of uncertainty. Conversely, the Influence Factor (Out-degree) remains low and ephemeral for the majority of stocks. The CSE market lacks clear and persistent opinion leaders capable of actively disseminating information to the entire network.

To provide a consolidated visual summary, Figure 9 presents a centrality heatmap for the last window, which visually corroborates these observations. The PageRank line within the heatmap displays several hot spots (CSM, RIS, AWB), while the Influence Factor line is almost entirely dark, reinforcing the conclusion regarding the absence of strong influence emitters.

This asymmetry is a structural characteristic of the CSE, suggesting a market dominated by collective reaction (high information absorption) rather than proactive dissemination (low influence emission). This finding makes a significant contribution to the literature by characterizing the information dynamics of the CSE. These findings carry important implications for portfolio optimization: the high centrality of CSM, for instance, positions it as a potentially risky stock in terms of systemic risk, whereas

Figure 8: Evolution of Stock Influence

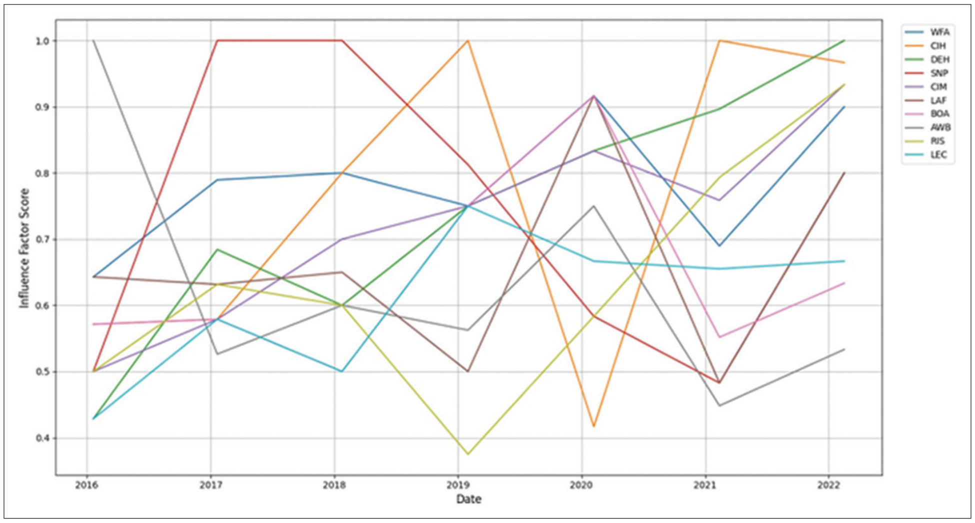
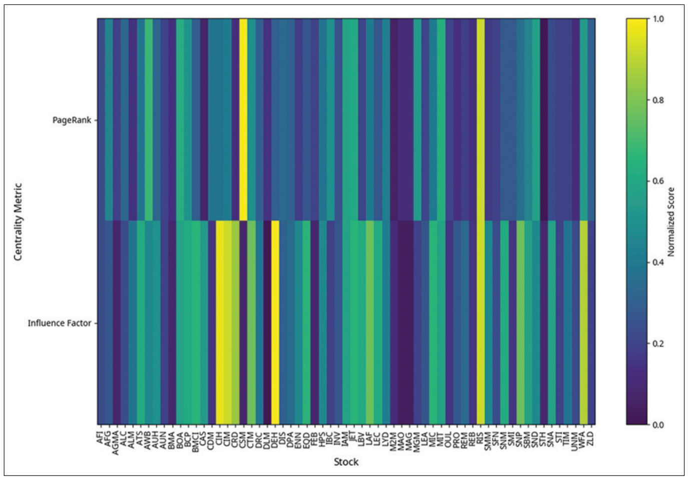


Figure 9: Centrality Heatmap - Last Window



peripheral stocks with low PageRank and Influence Factor scores could offer superior diversification benefits.

The methodology employed provides a dual-perspective analysis: a long-term view of systemic sectoral vulnerability (1993–2021) and a recent, granular view of information flow asymmetry (2013–2022). This comprehensive approach yields important implications for both academics and practitioners.

For portfolio managers, the results have direct implications for risk management and diversification. The long-term centrality of sectors like O&G (1993–2021) and the recent centrality of stocks like CSM (2013–2022) position them as potential sources of systemic risk. For investors seeking to minimize exposure to market shocks, it is prudent to avoid overweighting these securities. Conversely, network analysis provides an objective basis for optimal diversification: stocks that consistently exhibit low PageRank and Influence Factor scores are the most peripheral and thus offer the best diversification benefits, as they are less correlated with the market's core.

For regulators, the identification of "barometers" (CSM, RIS) and "cost hubs" (O&G) allows for targeted surveillance. The network densification observed during crisis periods (in both timeframes) is an early warning sign of increased vulnerability to contagion. Understanding the "Barometers vs. Leaders" asymmetry is essential for evaluating the effectiveness of transparency and information dissemination policies in the market.

Our analysis demonstrates that the CSE's dynamics have shifted from a fragmented to an integrated state, characterized by a structural asymmetry in information flow. This characterization, supported by a rigorous economic interpretation of network metrics and contextualized by both historical shocks and recent global events, provides significant added value by offering a framework for risk and diversification analysis tailored to the specificities of emerging markets.

5. CONCLUSION

This paper has undertaken a multi-dimensional topological analysis of the CSE, dissecting its structure at both the macroscopic level of sectors and the microscopic level of individual stocks. By combining clustering techniques and directional causality analysis, we have successfully mapped the dynamic architecture of the market and its evolution across various periods of crisis and stability. The results obtained are not mere statistical observations; they reveal the functional anatomy of the CSE and provide crucial insights into its resilience, vulnerabilities, and shock propagation mechanisms.

Our sectoral analysis highlighted a non-trivial and evolving community structure. The persistence of certain groupings, such as the (TR-F&P) pair or the (BKReal EstateCBM) trio during crises, demonstrates that market interdependencies extend beyond traditional industry classifications. More importantly, the centrality analysis identified the O&G sector as a cornerstone of the network, systematically dominating the rankings for influence (EC), proximity (CC), and intermediation (BC). This sector is not merely well-connected; it acts as a primary conduit for the flow of information and shocks throughout the economy, a finding corroborated by studies in other emerging markets.

Transitioning to the individual stock level, the Granger Causality analysis revealed a major structural transformation of the market between 2013 and 2022. We observed a shift from an initially fragmented, sparsely connected state to a significantly more integrated and systemic network, a metamorphosis catalyzed by the COVID-19 crisis. This network densification during a crisis is a canonical result in the financial networks literature, confirming that the CSE, despite its frontier status, is not immune to this phenomenon of systemic nervousness.

A key contribution of this granular analysis is the identification of a fundamental asymmetry between received influence (PageRank) and emitted influence (Out-degree). The CSE possesses clear barometers, stocks like CSM that absorb and reflect the general market state, but it lacks clear leaders that actively and concertedly disseminate information. This market of followers structure has profound implications: it suggests a dynamic where shocks are rapidly integrated by a few sentinel stocks, but where proactive influence is diffuse, which may both dampen certain shocks and make the market more difficult to anticipate.

This paper has demonstrated that the topology of the CSE is neither random nor static. It is structured, dynamic, and responds predictably to macroeconomic shocks. We have identified the sectors and stocks that constitute the market's systemic core, as well as those that populate its periphery. This structural map is not a mere academic curiosity; it provides an indispensable empirical foundation for rethinking portfolio management in this specific context.

The analysis conducted in this paper has illuminated an unavoidable reality: the market is a complex network whose structure influences the behavior of its components. We have identified a systemic core and a less-connected periphery. This structural dichotomy raises a fundamental and eminently practical question for any investor: how can this topological knowledge be exploited to build more efficient and resilient portfolios?

Traditional diversification methods, which rely on a dense and noisy correlation matrix, ignore this underlying architecture. They treat the market as a fully connected system where every asset is linked to every other, an assumption that our analysis calls into question. If, as our findings suggest, central stocks act as concentrators of systemic risk and peripheral stocks as potential islands of diversification, then a portfolio strategy that fails to distinguish between these two categories is fundamentally suboptimal.

This is precisely the challenge that the future study aims to address. Having mapped the territory, it is now time to use it to navigate more intelligently. The future study will therefore move from descriptive analysis to prescriptive application. We will employ a well-established techniques from graph theory to filter the noise from the correlation matrix and extract its structural backbone: the Minimum Spanning Tree (MST). By constructing portfolios based not on the full set of correlations, but on this essential market structure, we will seek to answer a crucial question: can portfolios informed by network topology significantly outperform traditional approaches, particularly in the context of the CSE?

6. AUTHOR CONTRIBUTIONS

All multi-authored papers should include an Author contributions section to describe each author's specify contributions using the relevant CRediT roles. Please refer to the CRediT taxonomy for more information.

7. USE OF AI TOOLS DECLARATION

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

8. ACKNOWLEDGMENTS

The authors received no financial support for the research, authorship, and/or publication of this article.

9. CONFLICT OF INTEREST

All authors declare no conflicts of interest in this paper.

REFERENCES

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.

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.

Bai, J., Perron, P. (2003), Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18, 1-22.

Barabási, A.L., Albert, R. (1999), Emergence of scaling in random networks. Science, 286(5439), 509-512.

Boguná, M., Pastor-Satorras, R., Vespignani, A. (2003), Absence of epidemic threshold in scale-free networks with degree correlations. Physical Review Letters, 90(2), 028701.

Caliński, T., Harabasz, J. (1974), A dendrite method for cluster analysis. Communications in Statistics-Theory and Methods, 3(1), 1-27.

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.

Diebold, F.X., Yilmaz, K. (2009), Measuring financial asset return and volatility spillovers, with application to global equity markets. Economic Journal, 119(534), 1224-1228.

Dorogovtsev, S.N., Mendes, J.F.F. (2000), Evolution of networks with aging of sites. Physical Review E, 62(2), 1842.

Dunn, J.C. (1973), A fuzzy relative of the isodata process and its use in detecting compact well-separated clusters. Journal of Cybernetics, 3, 32-57.

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.

Granger, C.W.J. (1969), Investigating causal relations by econometric models and cross- spectral methods. Econometrica, 37, 424-438.

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.

Huang, C., Deng, Y., Yang, X., Cao, J., Yang, X. (2021), A network perspective of comovement and structural change: Evidence from the Chinese stock market. International Review of Financial Analysis, 76, 101782.

Huang, C., Wen, S., Li, M., Wen, F., Yang, X. (2021), An empirical evaluation of the influential nodes for stock market network: Chinese a-shares case. Finance Research Letters, 38, 101517.

Jaroonchokanan, N., Termsaithong, T., Suwanna, S. (2022), Dynamics of hierarchical clustering in stocks market during financial crises. Physica A: Statistical Mechanics and its Applications, 607, 128183.

Laha, S., Majumdar, K. (2020), Clustering and classification of time series using topological data analysis with applications to finance. Expert Systems with Applications, 162, 113868.

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.

Lahmiri, S. (2016), Clustering of Casablanca stock market based on hurst exponent estimates. Physica A: Statistical Mechanics and its Applications, 456, 310-318.

Li, B., Yang, Y. (2021), Undirected and directed network analysis of the Chinese stock market. Computational Economics, 60, 1155-1173.

Mantegna, R.N., Stanley, H.E. (1999), Introduction to Econophysics: Correlations and Complexity in Finance. Cambridge: Cambridge University Press.

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, 1-14.

Murtagh, F., Contreras, P. (2012), Algorithms for hierarchical clustering: An overview. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 2(1), 86-97.

Murtagh, F., Legendre, P. (2011), Ward's Hierarchical Clustering Method: Clustering Criterion and Agglomerative Algorithm. arXiv preprint arXiv:1111.6285.

Sakoe, H., Chiba, S. (2003), Dynamic programming algorithm optimization for spoken word recognition. IEEE Transactions on Acoustics, Speech, and Signal Processing, 26(1), 43-49.

Sardá-Espinosa, A. (2017), Comparing time-series clustering algorithms in r using the dtwclust package. R Package Vignette, 12, 41.

Siudak, D. (2021), Sectoral analysis of the US stock market through complex networks. European Research Studies Journal, 24, 951-966.

So, M.K., Chan, L.S., Chu, A.M. (2021), Financial network connectedness and systemic risk during the covid-19 pandemic. Asia-Pacific Financial Markets, 28(4), 649-665.

Tabak, B.M., Serra, T.R., Cajueiro, D.O. (2010), Topological properties of stock market networks: The case of brazil. Physica A: Statistical Mechanics and its Applications, 389(16), 3240-3249.

Tasdemir, K., Merényi, E. (2011), A validity index for prototype-based clustering of data sets with complex cluster structures. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 41(4), 1039-1053.

Tsekeris, T. (2017), Network analysis of inter-sectoral relationships and key sectors in the Greek economy. Journal of Economic Interaction and Coordination, 12, 413-435.

Ward, J.H. Jr. (1963), Hierarchical grouping to optimize an objective function. Journal of the American Statistical Association, 58(301), 236-244.

Youssef, M., Mokni, K., Ajmi, A.N. (2021), Dynamic connectedness between stock markets in the presence of the covid-19 pandemic: Does economic policy uncertainty matter? Financial Innovation, 7(1), 13.

APPENDICES

Table A1: List of stocks included in the analysis with their ticker symbols

Company Name	Ticker	Company Name	Ticker
Afriq Industries SA	AFI	Afriquia Gaz	AFG
AGMA Lahlou-Tazi	AGMA	Aluminium du Maroc	ALM
Atlanta Sanad Assurance	ATS	Alliances Développement Immobilier	ALC
Attijariwafa Bank	AWB	Auto Hall	AUH
Auto Nejma	AUN	Bank of Africa	BOA
Balima	BMA	Banque Centrale Populaire	BCP
BMCI	BMCI	Cartier Saada	CAS
Crédit du Maroc	CDM	CIH Bank	CIH
Ciments du Maroc	CIM	Colorado	CRD
Cosumar	CSM	CTM	CTM
Dari Couspate	DRC	Delattre Levivier Maroc	DLM
Delta Holding	DEH	Diac Salaf	DIS
Douja Promotion Addoha	DPA	Ennakl Automobiles	ENN
Eqdom	EQD	Fenie Brossette	FEB
HPS	HPS	IB Maroc.com	IBC
Involys	INV	IAM	IAM
Jet Contractors	JET	Label Vie	LBV
Holcim Maroc	LAF	Lesieur Cristal	LEC
Lydec	LYD	M2M Group	M2M
Maghreb Oxygène	MAO	Maghrebail	MAG
Managem	MGM	Maroc Leasing	LEA
Microdata	MIC	Minière de Touissit	MIT
Oulmès	OUL	Promopharm SA	PRO
REM	REM	Rebab Company	REB
Risma	RIS	S2M Monétique	SMM
Salafin	SFN	Sanlam Maroc	SNM
SMI	SMI	SNEP	SNP
SBM	SBM	Sonasid	SND
Sothema	STH	SNA	SNA
Stroc Industrie	STI	Timar	TIM
Unimer	UNM	Wafa Assurance	WFA
Zellidja SA	ZLD		

Source: Casablanca Stock Exchange official listings

Figure A1: Sectoral Rankings Across Network Indicators