INTERNATIONAL JOURNAL OF BANKING AND FINANCE
https://e-journal.uum.edu.my/index.php/ijbf

How to cite this article:
El Msiyah, C., & Madkour, J. (2022). Dynamics of the Moroccan industry indices network before and during the covid-19 pandemic. *International Journal of Banking and Finance*, *18*(1), 31-50. https://doi. org/10.32890/ ijbf2023.18.1.2

DYNAMICS OF THE MOROCCAN INDUSTRY INDICES NETWORK BEFORE AND DURING THE COVID-19 PANDEMIC

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Received: 28/7/2021 Revised: 18/10/2021 Accepted: 21/10/2021 Published: 5/1/2023

ABSTRACT

This paper studies the topological properties of the dynamics of the industry indices network at the Moroccan stock exchange by using network theory. The Minimum Spanning Tree (MST) was constructed from the metric distances which had been calculated for the different pairs of industrial indices. The dynamics of the MST were analysed over the period 2013 to 2020 using the sliding window technique. The period studied was divided into the pre-pandemic Covid-19 period and the pandemic Covid-19 period. Connectivity and centrality indicators were calculated to track the connectivity structure over time and to identify the positioning and the importance of the industry indices studied. The result of this study indicates that the network of industry indices was relatively stable during the pre-pandemic Covid-19 period before observing a sudden rapprochement between industries when the Covid-19 pandemic was officially announced. The formation of star-shaped networks was also observed. These networks were centred on the banking industry, essentially during the pandemic Covid-19 period. The banking industry was also positioned at the centre of the Moroccan industry indices network.

Keywords: Industry indices network, minimum spanning tree, covid-19, network connectivity, network centrality.

JEL Classification: C45, G01, G11, G23.

INTRODUCTION

The use of network theory to translate the financial taxonomy of stock markets has been adopted by many research studies. In addition to some seminal works (Mantegna, 1999; Bonanno et al., 2000; Bonanno et al., 2001; Onnela et al., 2003), a large body of the literature has confirmed that stock markets behave like complex network systems; and it is possible to study the topological properties of financial networks, which have an associated significant economic taxonomy (Tabak et al., 2010). For Arthur et al. (1997), financial markets can be characterized as complex evolving systems, therefore it is useful to use the tools of complex network systems to analyse the stock market dynamics. According to De Carvalho and Gupta (2018), the network representation of stock market asset returns not only retains the most essential and important features of a large set of asset return co-movements, but also helps to simplify the challenges for identifying the co-movement dynamics between assets, including those related to the number of assets and risk factors that must be assessed simultaneously and the non-stationarity of movement in the asset dynamics.

As the main tools of complex network theory, the clustering and filtering algorithms of the minimum spanning tree (MST) technique have been used to study the different topological and structural aspects of the stock markets, and also to illustrate their ability to transmit and exploit significant economic information. For example, Tumminello et al (2010) demonstrated the formation of clusters at different levels of trees and the possibility to define the taxonomy of stocks within the network by applying the different procedures for grouping and for filtering the correlation matrix of daily returns. Tola et al. (2008) used clustering algorithms to improve the reliability of portfolios in terms of the ratio of the expected risk to the realised risk. They showed that clustering portfolio optimization methods often outperforms the Markowitz or random matrix theory methods. Khashanah and Miao (2011) applied the MST to the entire financial system, consisting of typical markets (stocks, bonds, derivatives, currencies, and commodities) to study the changes in the structure of the financial system during the economic downturn.

With regard to the application of MST techniques on the stock market, a great deal of work has been done in both developed and emerging countries. For example, there has been work on certain emerging markets; Galazka (2011) used the MST to identify the stocks that strongly influenced the price dynamics of other stocks on the same Polish stock market, using a portfolio of 252 stocks in 2007. Majapa and Gossel (2016) applied the MST approach to study the topological evolution before, during and after the 2008-2009 crisis, by constructing a network map of the top 100 companies listed on the Johannesburg Stock Exchange. Sinha and Pan (2007) used data from 201 stocks over the period 1996–2006 to assess the strength of dominance of the largest companies in the Indian economy. Tabak et al. (2010) constructed the MST by using the weekly prices of the 47 stocks on the Brazilian stock exchange from January 7, 2000 to February 29, 2008, and by the correlation matrix for a variety of stocks of different industry indices. Moreover, the study showed that stocks tended to cluster by industry. Situngkir and Surya (2005) found that the Indonesian stock market became stable during the period from 2000 to 2004, just after the economic shock of the currency crisis. They also noted the dominance of several stocks in certain industries.

The world has already faced health crises (SARS, MERS and Ebola, among others) that impacted the stock markets and business activities, but less forcefully than the Covid-19 pandemic (Baker et al., 2020). Ashraf (2020) used the daily Covid-19 confirmed cases and death cases, as well as the stock markets returns data from 64 countries and found that stock markets quickly reacted to the Covid-19 pandemic. Liu et al. (2020) found that Asia experienced the most negative abnormal returns among the 21 leading stock market indices in most affected countries. Haroon and Rizvi (2020) found that the overwhelming panic generated by the news outlets has led to the increase in the volatility in the equity markets. Zhang et al. (2020) found that Covid-19 has led to an increase in the global financial market risk Aslam et al. (2020) examined the effects of Covid-19 on 56 global stock indices by using a complex network method and they revealed a structural change in the form of node changes, a reduced connectivity and significant differences in the topological characteristics of the network.

As in Yang et al. (2014), the present study aims to apply the MST technique directly to industry indices in order to analyse the structural change of the stock market and to identify the key sectors of the Moroccan economy. The study of the dynamic evolution of the industry indices network will then allow one to see the impact of the crisis on the industrial structure of the stock market. In the second section, of this paper, the MST model is presented and its usefulness shown in terms of simplifying the dependency structure between nodes. The next section presents the details of the study data and their uses for the construction of MSTs of the Moroccan industry indices. In the fourth section, the discussion will turn to the use of some indicators to analyse the dynamics of MSTs. The last section will present the results and draw the relevant conclusions.

METHODOLOGY

Minimum Spanning Tree Model

The use of the MST to translate the financial taxonomy consists in studying the financial assets connections through the evolution of their stock prices. In the context of the present study, the focus is on the industrial taxonomy of the Moroccan stock market. In this regard, the daily returns of the industry indices were used to calculate the correlation and distance matrix and to trace the MST for the Moroccan stock industries.

Let N be the number of industry indices studied. For an industry i $(i = 1, \dots, N)$, the rate of return on day t is:

$$R_i(t) = ln\left(\frac{P_i(t)}{P_i(t-1)}\right)$$

$P_i(t)$ is the closing price of i on day t .

The Pearson correlation coefficient between two industries i and j :

$$\rho_{ij} = \frac{\overline{R_i R_j} - \overline{R_i}\,\overline{R_j}}{\sqrt{\left(\overline{R_i^2} - \overline{R_i}^2\right)\left(\overline{R_j^2} - \overline{R_j}^2\right)}}$$

For an industry i , $\overline{R_i}$ represents the average of the log-returns $R_i(t)$ over the period studied. For T trading days studied $\overline{R_i} = \frac{1}{T}\sum_{t=1}^{T} R_i(t)$.

The correlation coefficients ρ_{ij} calculated for each pair of industry indices i and j form a symmetric correlation matrix C^t of $N \times N$ dimension and in which its diagonal elements equal to unity. In total, the correlation matrix contains $N(N-1)/2$ correlation coefficients fulfilling the condition $1 \leq \rho_{ij} \leq 1$.

The correlation coefficient of a pair of industry indices ρ_{ij} cannot be used as the distance between the two industries i and j because it does not fulfill the three axioms that define a metric (Mantegna, 1999). Indeed, to analyse the topological taxonomy of the industry indices network, a variable is needed that can function as distance, satisfying the three axioms of Euclidean distance:

$$\begin{cases} d_{ij} = 0 \text{ if and only if } i = j \text{ (positive definiteness)} \\ d_{ij} = d_{ji} \text{ (symmetry)} \\ d_{ij} \leq d_{ik} + d_{kj} \text{ (triangle inequality)} \end{cases}$$

The metric distance, introduced by Mantegna (1999), is determined from the Euclidean distance (Coelho et al., 2007), and it is permitted to relate the distance of two variables (i.e. industry indices) to their correlation coefficients, as in Equation (1):

$$d_{ij} = \sqrt{2\left(1 - \rho_{ij}\right)} \qquad (1)$$

The correlation coefficients are therefore, used to calculate the distances and to construct a matrix of the distances of the industry indices D^t of the same dimension as the correlation matrix $N \times N$.The small distances in the matrix imply the high correlations between industry indices.

From the distance matrix, D^t, it can be seen that there is a directionless and fully connected graph G in which the nodes are industry indices and the links between them are measured by the distances d_{ij}.

The MST is then constructed by using $(N-1)$ direct links between the N nodes of G ,such that the sum of the $(N-1)$ distances of these links $\sum_{(i,j)\in \mathrm{MST}} d_{ij}$ is minimal. In this way, the MST is constructed progressively by linking all the nodes together with the smallest distances. It can be started by linking the two closest (most correlated) nodes, the next node is added to the MST, with the condition that the added distance must be the smallest and also the addition of that node should not close the loop with the nodes that are already added to the MST. Kruskal's algorithm is used for this purpose. A detailed approach to constructing MSTs using Kruskal's algorithm is presented in Yang et al. (2014).

The number of links between nodes is considerably reduced by using the minimum spanning tree (MST). The present study therefore, will go from the $N \times (N-1)/2$ distances in the distance matrix D^t to only $(N-1)$,the shortest distances in the MST.

Data

The data for the study were the prices of $N = 21$ industry indices of the Moroccan stock exchange from January 23, 2013 to November 30, 2020, i.e. a total of 1,945 trading days $t = 1,2,...,1945$.

As in Onnela et al. (2003), Tabak et al. (2010) and Yang et al. (2014), and for analysis and smoothing purposes, the data were divided into $w = 1.2 \ldots .89$ windows of width $W = 185$ .The step between two consecutive windows was set at 20 trading days $dW = 20$ .The choice of $W = 185$ was motivated by the fact that the period of the Covid-19 pandemic studied was 185 days (between March 01, 2020 to November 30, 2020); this period corresponded roughly to the time between the official announcement of the pandemic and the announcement of the vaccine availability. The step of $dW = 20$ corresponded roughly to the average number of trading days per month. Thus, this distribution of data consisted of studying the evolution of 89 MSTs, each corresponding to a window of 185 stock market prices with a 20-day shift (overlap) from one window to another. The last window studied corresponded to the entire period of the Covid-19 pandemic (March 01, 2020 to November 30, 2020). This choice was arbitrary with the fact that the choice of window width had been a compromise between too noisy and too smoothed data for small and large window widths, respectively (Onnela et al., 2003). Similarly, for the overlap step, the choice of very small dW might cause concerns related to its inability to identify the episodic changes in the networks because the network carried a huge portion of the observations between the successive windows (De Carvalho & Gupta, 2018).

The constructed MSTs for different time windows were not independent of each other (two successive MSTs share 165 trading days over an analyzed MST period of 185 trading days), but form a series over time. Therefore, this multitude of trees was interpreted as a sequence of evolutionary steps of a single dynamic asset tree (Onnela et al., 2003)

The 21 stock market industry indices studied are classified as in Table 1. The MSTs corresponding to the two periods, the pre-pandemic period (January 23, 2013 to February 29, 2020) and the pandemic period (March 1, 2020 to April 30, 2020) are as given in Figure 1.

Table 1

Industry Indices Included in the Study and their Tickers

Index (1)	ticker symbol (1)	industry indice (1)	index (2)	ticker symbol (2)	industry indice (1)
1	FP	Food / production	12	H&SS	Hardware, software and services
2	INSUR	Insurance	13	MINES	Mines
3	BANK	Banks	14	RE	Real estate participation and development
4	B&CM	Building and construction materials	15	O&G	Oil and gas
5	DRINK	Drinks	16	UTIL	Utilities
6	CHEM	Chemistry	17	FC&OF	Funding company and other financial activities
7	DISTR	Distributors	18	PC&H	Portfolio companies and Holding companies
8	EEE	Electronic and electrical equipment	19	F&P	Forestry and paper
9	PHARM	Pharmaceutical industry	20	TCOM	Telecommunication
10	EIE	Engineering and industrial equipment	21	TRANS	Transport
11	L&H	Leisure and hotels			

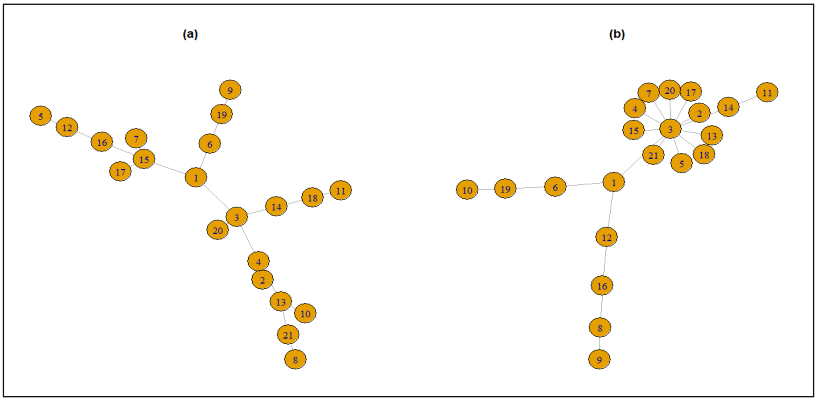
Notes. Index and ticker symbols are given by the authors and the industry indices correspond to that of the Casablanca Stock Exchange.

Data Analysis

A simple comparison of the two MSTs allows us to see that the industries were much more centred on the banking industry during the period of the covid-19 pandemic than during the period before the covid-19 pandemic. It should also bevpointed out that the industries linked directly to the banking industry before the pandemic were also linked during the pandemic period; this is the case for "*Real estate participation and development*" industry (link 3-14), "*Building and construction materials*" industry (link 3-4), "*Food/ production*" industry (link 3-1) and "*Telecommunication*" industry (link 3-20). This result is consistent with that of Musmeci et al. (2015) who, using filtered correlations between US stocks over the period from January 1997 to December 2012, showed a pattern of clustering that changes radically with the outbreak of the financial crisis of 2007. The change in structure is analysed in more detail below using some of the connectivity and centrality indicators.

Figure 1

Minimum Spanning Trees (MST) of the Industry Indices of the Covid-19 Pandemic Period (b) and the Covid-19 Pre-pandemic Period (a)



RESULTS AND ANALYSIS

Network Connectivity Dynamics of Industry Indices

In addition to the calculation of the overall distance of MSTs, the present study used some key indicators to identify the most important connections between the industry indices, and to analyse their evolution over the period under review.

For the 20 distances d_{ij} of the links belonging to MST, the size of MST is calculated by Equation (2):

$$MST - Distance = \sum_{d_{ij} \in \mathrm{MST}} d_{ij} \tag{2}$$

For 89 MSTs generated between January 23, 2013 and November 30, 2020, the last 9 MSTs (MST 81 to MST 89) had part of the period covered (185 trading days) during the Covid-19 pandemic. Specifically, the 81st MST covered 160 days before the pandemic period (before March 1, 2020) and 25 trading days during the pandemic period (from March 1). The 82nd MST covered 140 days before the pandemic period and 45 trading days during the pandemic period and so on until the last MST (89th) which covered the pandemic period from March 1, 2020 to November 30, 2020.

It can be seen that the MST size (MST-Distance) of the last 9 MSTs decreased on average from 25.03 before the pandemic period to 19.5 during the pandemic period. It was also noted that from the 81st MST and for only 25 covered trading days, there was practically the same level of decline. Indeed, the size of the 81st MST, which covered the period from September 21, 2019 to March 25, 2020, showed a comparable decline with the MSTs covering a larger fraction of the pandemic period. This can be explained by the brutal reaction of the stock market from the first days of the official announcement of the pandemic.

For a given MST and a knowledge of N, i.e., the number of industry indices studied, the mean and the standard deviation of the link distances in MST is as expressed in Equation (3) and Equation (4):

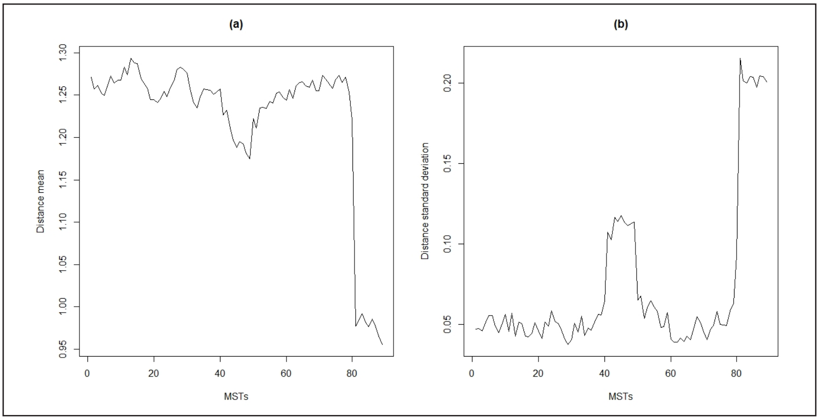
$$\overline{d} = \frac{1}{N-1} \sum_{d_{ij} \in \mathrm{MST}} d_{ij} \tag{3}$$

$$\sigma_d = \frac{1}{N-1} \sum_{d_{ij} \in \mathrm{MST}} \left(d_{ij} - \overline{d}\right)^2 \tag{4}$$

Where $N - 1$ is the number of links in the MST.

Figure 2

Distance Mean (a) and Distance Standard Deviation (b) of MST Links



The mean and standard deviation of the link distances in the MST are represented as a function of time for the different MSTs generated in Figure 2. The average distance of links in the MSTs decreased from 1.25 during the pre-pandemic period to 0.97 for MSTs in the pandemic period. This represents a decrease of about 22 percent from one period to the next, the industry indices were thus 22 percent closer on average during the pandemic period (indicating more correlation between indices). The decrease in the average distance of links is in line with the results of several studies, which have shown an increase in the mean correlation (decrease in average distance of links) during market crashes (see Onnela et al. (2003), Drozdz et al. (2000), and Majapa and Gossel (2016). The result is also partly consistent with that of Ang and Chen (2010) who, in studying the correlations between US equities and the overall US market, found that correlations increased following downside moves, particularly for extreme downside moves than for upside moves. This asymmetry of correlation movement was also demonstrated by Longin and Solnik (2001) who also found that correlations were higher during bear markets than in bull markets.

The decrease in the average distance of links was accompanied by a very high variation in the distance standard deviation of links between the two periods (Figure 2b). The standard deviation increased from 0.057 on average during the pre-pandemic period to 0.204 during the pandemic period (for a minimum of 0.63 and a maximum of 1.32); which was an increase of 255 per cent. According to Khashanah and Miao (2011), this clearly visible jump in the distance standard deviation could be explained by the intensification of systemic risk; correlations thus, appeared more uncertain due to unexpected and urgent responses to market events.

As for the distance standard deviation of links, the variability was also remarkable. For the pre- pandemic period, the minimum distance was 1.13 and the maximum distance was 1.34, whereas during the pandemic period, the minimum distance was 0.63 and the maximum distance was 1.32. The combined effect was reflected in the strengthening of the links between industries (nodes), as can be seen in Figure 1b. This may occur either because of the strengthening of existing links in MST, as is the case for some industries whose linkage has become closer to the banking industry, or because weaker links (of high distance) are deactivated from the MST.

For a better visualization of the successive topological changes in MSTs and in particular, the links with the banking industry, the survival rate of direct links in MSTs were calculated (Onnela et al., 2003). In a single step, the simple survival rate calculates the percentage of links (between each 2 industry indices) that survive from one MST to another. For two consecutive MSTs at times t and $t-1$ $(t = 2, \dots, 89)$, the simple survival rate is given by Equation (5):

$$\sigma_t = \frac{1}{N-1} \times \left| E_t \cap E_{(t-1)} \right| \tag{5}$$

Where E_t is the set of MST links at time, t, $\cap$ is the intersection operator and $|\cdots|$ gives the number of elements in the set.

In the short term, it can be said that the high level of simple survival rates reflected a certain topological stability in the configuration of the industry indices network. Indeed, compared to a total number of direct links $(N-1=20)$, an average survival rate of 67.56 per cent (13.51 links from one MST to another over the pre- pandemic period) was noted. This was in comparison to the average survival rate of 80 per cent (16 links from one MST to another) during the pandemic period. Thus, one could conclude that the strengthening of the links between industries (nodes) in successive MSTs occurred, to a large extent, as a result of the strengthening of already existing links.

In both the pre- pandemic and pandemic periods, the banking industry was the most surviving node (see Figure 3).

Figure 3

Number of Times the Nodes have Survived both during the Covide-19 Pandemic Period and before the Covide-19 Pandemic Period

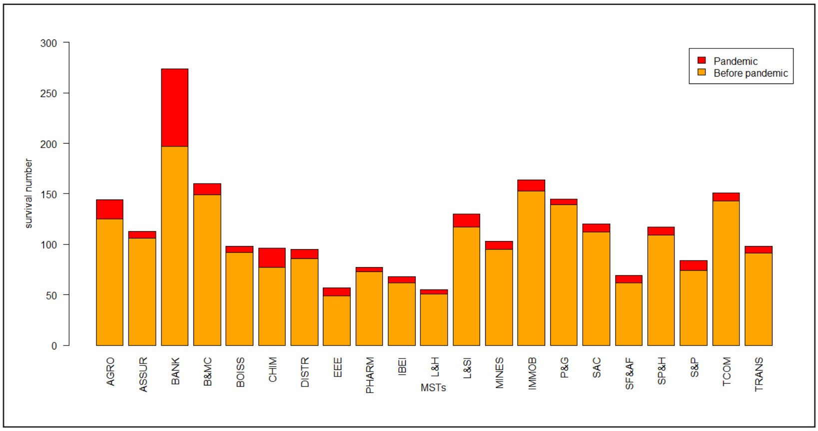
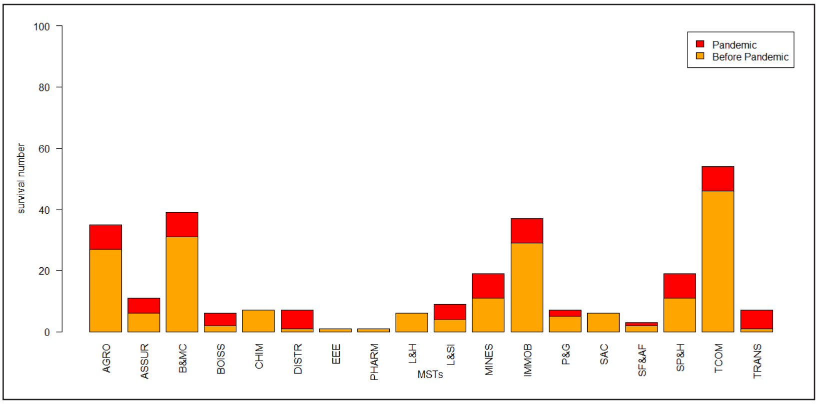


Figure 4

Number of Times the Nodes have Survived together with BANK node, both during the Covide-19 Pandemic Period and before the Covide-19 Pandemic Period



During the pre- pandemic period, the banking industry survived 197 times, of which 46 times with the "*Telecommunication*" node (link 3-4), 31 times with the "*Building and construction materials*" node (link

3-4), 29 times with the "*Real estate participation and development*" node (link 3-14). During the pandemic period (for the last 9 MSTs), the banking industry survived 77 times, including 8 times (out of the 8 MSTs) with 6 nodes including the nodes "*Telecommunication*", "*Building and construction materials*" and "*Real estate participation and development*" (see Figure 4).

Dynamic Analysis of Network Centrality

In addition to the connectivity indicators discussed above, centrality indicators contained very useful additional information about the structure of the network topology.

The node degree is the basic indicator for measuring the clustering and the centrality in a network, it is equal to the number of direct links connecting a given node to other nodes in the network. For N nodes of the MST, the degree of node j is given by the Equation (6):

$$Deg_j = \sum_{k=1}^{N} I_{jk} \qquad (6)$$

Where I_{jk} denotes the indicator function that gives 1 in a condition that the node j is directly linked to k, and 0 otherwise.

Table 2 summarizes the degrees of the main nodes over the entire pre-pandemic and the entire pandemic periods (see Figure 1). It can be seen that the banking industry dominates the dynamics of the industry indices mainly during the pandemic period. The other industries have a lower weight in the network. The case of the "*Oil and Gas"* industry shows a disconnected evolution possibly due to the deep price drop.

Table 2

Degrees of the Main Nodes

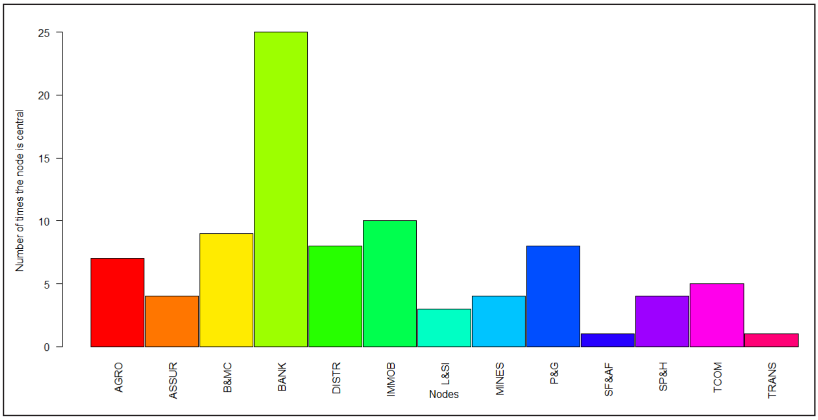
	BANK	FP	O&G	B&CM	RE
January 23, 2013 to February 29, 2020	4	3	4	3	2
March 1, 2020 to November 30, 2020	12	3	1	1	2

Notes. Table 2 uses the tickers defined in Table 1

Dynamic monitoring of the time sequence of MSTs allows us to identify the central node for the 89 MSTs and the degree of centrality of the different industries. From Gilmorea et al. (2008), the central node was defined as the node (industry) with the greatest number of direct links (the maximum degree of node). In the cases where the two nodes have the same number of direct links, the node with the lowest sum of distances of its links is selected. This is the same principle used in the construction of MSTs because the short connections link the node more closely to its neighbourhood than long connections (Onnela et al., 2003).

Figure 5

MSTs Central Nodes



During the whole period studied in Figure 5, the banking industry dominated the share of central nodes of MSTs (28.09 percent), followed by "*Building and construction materials*" industry and "*Real estate participation and development*" industry with shares equal to 11.236 per cent. These three industries together constituted 50 percent of the central nodes. During the pandemic period, the banking industry monopolized almost half of the direct links (9 to 12, out of 21) while the average for the pre- pandemic period was 4,737 direct links. Thus, the banking industry positioned itself as the central node for all MSTs during the pandemic period. The network connecting the BANK node during the pandemic period demonstrates the formation of a very star-like network structure (see Figure 1b) compared to the shape of the network before the pandemic period (see Figure 1a). The formation of star-shaped networks was directly related to a higher maximum node degree (De Carvalho & Gupta, 2018).

For a more global measure of centrality, Onnela et al. (2003) has proposed to calculate mean occupation layer (MOL), which is the average number of links crossed by the centre of the tree (central node) to reach the various other nodes. This is expressed as Equation (7).

$$MOL(cn_t) = \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}[n_i(t)] \tag{7}$$

Where $MOL(cn_t)$ is the MOL for the central node of MST during period t and $\mathcal{L}[n_i(t)]$ denotes the level of node n_i (other than the central node) in relation to the central node. This level is 1 if n_i is linked to cn by a direct link, 2 if n_i passes through another node before reaching cn and so on.

The average MOL during the pandemic period dropped significantly to 1.76 compared to a pre-pandemic average of 2.88. Moreover, the average distance of MOL links also decreased by almost 28 per cent (from 1.23 to 0.89). This shows that the banking industry became very close to other industries during the pandemic period, both in terms of the decrease in the number of links crossed on average (MOL) and the average distance per link crossed. This double effect explains the topological shrinkage of MST during the pandemic period, initially explained by the *MST-Distance* indicator and confirmed in several studies such as in Onnela et al. (2003) and Majapa and Gossel (2016).

Another indicator given by Barthélemy (2004) to measure the centrality of nodes is the Betweenness centrality which is the fraction of shortest paths passing through a given node. For a node, the Betweenness centrality is given by Equation (8):

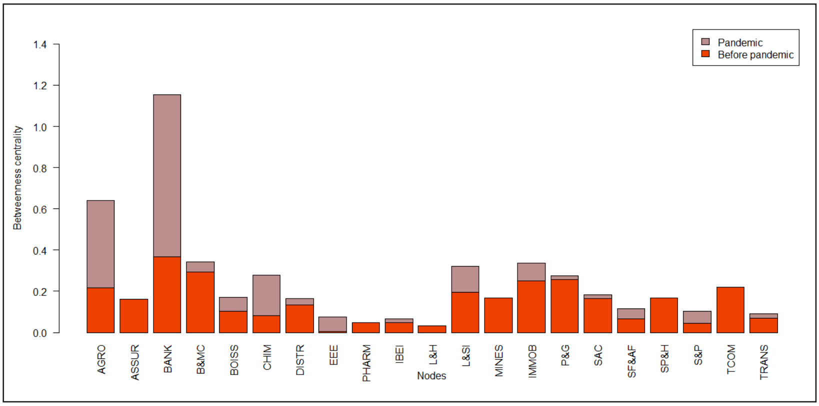
$$BC(i) = \sum_{j\neq k} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{8}$$

Where σ_{jk} is the total number of shortest paths from node j to node k and $\sigma_{jk}(i)$ is the number of shortest paths from node j to node k through i.

The usefulness of the Betweenness centrality is that some less connected nodes can be very central, i.e.,the fact that they link different parts of the network together. Again, the banking sector was the most central (see Figure 6); it had 36.85 per cent of the shortest paths in the pre-pandemic period and 78.47 per cent in the pandemic period. This shows a particular importance both in terms of the centrality and the systemic risk that may result.

Figure 6

Betweenness Centrality of MST Nodes



This central weight of the banking industry underscored its importance in the Moroccan economy, and even at the African level where Moroccan banks are among the most solid and most visible. Things may be different in other countries. Yang et al. (2014) found that durable consumer goods were at the heart of the Chinese stock market. Coelho et al. (2007) found that the financial industry was located as a central node in the London Stock Exchange. On the Brazilian stock market, Tabak et al. (2010) showed that telecommunications was positioned at a central location, followed by the materials industry and the finance industry.

CONCLUSION

This study has provided useful information on how different industry indices have reacted together in light of the pandemic events like that of Covid-19. This reaction was reflected in a sudden rapprochement between industries from the beginning of the Covid-19 pandemic. The construction of the minimum spanning trees (MST) for the pandemic and pre- pandemic periods effectively shows a considerable shrinkage of the tree from the first days of the announcement of pandemic measures.

The study of the dynamic evolution of the Moroccan industry indices network shows that the network was relatively stable during the pre-pandemic period, before observing great volatility from the start of the pandemic. This is valid for all the indicators used to study this dynamic. The results show that from one period to another (before pandemic to pandemic), the mean distance dropped by 21.9 per cent, the standard deviation increased by 255 per cent and the mean proximity to the centre of the MST (MOL) decreased to 1.76 links, instead of 2.88 before the pandemic.

The other important result is the noted importance of certain industries, and the central role played by the banking industry. In addition to the observed importance of certain industries ("*Real estate participation and development*", "*Building and construction materials*", "*Telecommunication*", " *Food / production*") due to their central weight and their survival in MSTs, the banking industry was positioned as the most central node throughout the period studied. This centrality is perfectly reinforced from the point that it became the only central node during the period of the Covide-19 pandemic. This was also the industry that has survived in all of the MSTs studied.

Considering that financial systems in low-income countries tend to be more bank-based than stock market-based, the Moroccan case study is interesting for two reasons. Firstly, for a modest income country like Morocco and with the observed importance of banks as a very central industry in the industry indices network, it can be concluded that it is rather the banking system that is still at the centre of the financial system. Secondly, the importance given by the economic policy in Morocco to the banking industry as a lever for financing and development is compatible with the role that this industry plays in the evolution of the industry indices network.

ACKNOWLEDGMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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