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Unveiling Systemic Risk Spillover between Banks and the Broader Economy in Morocco

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ABSTRACT

This paper examines the growing importance of systemic risk transmission within financial systems, where cross-sectoral interdependencies can amplify financial instability, particularly during periods of economic and financial stress. This study investigates the systemic importance of the banking industry and identifies the sectors most susceptible to systemic contagion effects. To this end, it analyzes the network of interconnections between the banking sector and the Moroccan economy. A network-based methodological framework is employed. Tail risk is estimated using an Exponentially Weighted Moving Average Value at Risk approach, while dependency structures are captured through correlations among VaR series. These relationships are subsequently filtered using Triangulated Maximally Filtered Graphs and examined through the Louvain community detection algorithm and eigenvector centrality measures to characterize network topology, sectoral clustering, and systemic relevance across different periods. The findings reveal strong and persistent interconnections between the banking sector and key segments of the Moroccan economy. The results highlight the banking sector as a central node within the network, reflecting its critical role in the transmission and amplification of systemic risk. This study underscores the value of network-based approaches for macroprudential surveillance and the early detection of systemic vulnerabilities in emerging market economies.

Keywords: Network Theory; Cross-sectoral Dependencies; Casablanca Stock Exchange market; Banks; Systemic Risk.
JEL Classifications: C01, G01, C4, C5

1. INTRODUCTION

The emphasis on systemic risk has increased significantly, mainly due to the aftermath of the global financial crisis of 2007-2008, which made it a priority among decision-makers, regulators, and researchers (Brunnermeier, 2009). Systemic risk is distinct from typical forms of financial risks. Traditional metrics of risk detect the threats that single firms face, however, systemic risk is the result of the interdependence of linked agents in an economy (Berger et al., 2025). Thus, the crisis in one firm could be transmitted to the rest of the system, thereby threatening the stability of the financial sector (Danielsson et al., 2012; Admati and Hellwig, 2014). Hence, finding out how these effects occur is what regulators are mostly concerned with in their attempts to safeguard the financial systems.

In this regard, network theory has gained increasing prominence as a framework for analyzing the structure and dynamics of financial systems. By representing institutions as nodes and their relationships as links, network-based approaches provide a comprehensive view of how risks are transmitted across interconnected entities (Battiston et al., 2012; Allen and Babus, 2009; Allen & Gale, 2000). Empirical studies have demonstrated that financial linkages tend to intensify during periods of market stress, thereby reducing diversification benefits and increasing the potential for systemic disruptions (Bisias et al., 2018; Diebold and Yilmaz, 2014; Hilbers et al., 2005). To investigate these complex interdependencies, a variety of network-based techniques have been developed. In the field of network analysis, correlation-filtering methods have emerged as a prominent approach for extracting the most informative connections while preserving the essential structure of the network. (Mantegna and Stanley, 1999). A notable example of this is the triangulated maximally filtered graph (TMFG), which was first introduced by Tumminello et al. (2005) and further developed by Massara et al. (2016). Conversely, community detection algorithms, notably the Louvain method, have been shown to facilitate the identification of clusters of entities that are closely connected and which may serve as conduits for the transmission of financial shocks (Blondel et al., 2008). Collectively, these methodologies furnish valuable insights into the organization of financial networks and contribute to a more profound understanding of systemic risk propagation (Li et al., 2023; Long and Li, 2023; Wang et al., 2025; Wen et al., 2023).

Although literature on systemic risk is expanding, empirical evidence from emerging economies is still largely undiscovered. Addressing this gap is therefore essential for improving the understanding of systemic vulnerabilities and strengthening financial stability oversight in Morocco. This study aims to explore the transmission of systemic risk within the Casablanca Stock Exchange (CSE) market from 2008 to 2025. It considers three very major times of stress: the subprime crisis, the European debt crisis, and the COVID-19 crisis. The tail risk estimation is firstly done through an exponentially weighted moving average (EWMA) Value at Risk (VaR) framework. Subsequently, the signals from the VaR vectors are utilized for the construction of TMFGs that extract the main interconnections between institutions. Third, the Louvain algorithm identifies subsets of entities that have similar tail-risk dynamics, thereby, it enables the detection of a potential contagion across various sectors. Finaly, the eigenvector centrality indicator is applied to classify entities in each community according to their centrality importance (Bonacich, 1987).

This paper introduces several contributions to the current discourse on the topic of systemic risk. First, it presents a filtered topological representation of the tail-risk interconnections in the CSE market. Furthermore, it points out systemically crucial institutions and states that the banking sector is the central actor that configurates the network (Craig and von Peter, 2014; Levine, 2000, 2002). Moreover, it asserts the correlation of crisis-period extreme risks and affirms the effect of systemic fragility on emerging market environment. The results have significant suggestions for conducting macroprudential supervision, stress testing, and monitoring financial stability in Morocco.

2. MATERIALS AND METHODS

2.1. Value at Risk

This paper used the VaR methodology grounded on the EWMA volatility model. VaR provides a quantile-based measure of tail risk and captures the maximum expected loss over a given horizon at a specified confidence level. Formally, the -level VaR of entity at time is defined as the conditional lower quantile of the return distribution:

$$VaR_{i,t}^{\alpha} = inf\{x \in R : P(r_{i,t} \leq x \mid F_{i,t}) \geq \alpha\} \tag{1}$$

Where $F_{i,t}$ denotes the information set available at time $t-1$. Assuming conditional normality of logarithmic returns $r_{i,t}$, VaR can be expressed as:

$$VaR_{i,t}^{\alpha} = \mu_{i,t}^{EWMA} - z_{1-\alpha}\sigma_{i,t}^{EWMA} \tag{2}$$

Where $z_{1-\alpha}$ represents the $1-\alpha$ quantile of the standard normal distribution, $\mu_{i,t}^{EWMA}$ is the conditional mean, and $\sigma_{i,t}^{EWMA}$ is the conditional volatility. The EWMA model assigns exponentially declining weights to historical observations, reflecting the regularity of volatility clustering in financial daily time series. The conditional mean is presented as:

$$\mu_{i,t}^{EWMA} = \sum_{s=0}^{\infty} \lambda^{s} r_{i,t-s} \tag{3}$$

The decay parameter $\lambda \in (0,1)$ regulates the persistence of volatility shocks. In line with the RiskMetrics recommendation for daily data, λ is fixed at 0.94, implying a high degree of persistence while allowing the model to react swiftly to new information. The EWMA model can be interpreted as a restricted GARCH (1,1) specification with no mean-reversion term:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

For a tail probability of $\alpha = 1\%$, (equivalently, a confidence level of 99%), the critical value is $z_{0.99} = 2.33$, yielding:

$$VaR_{i,t}^{1\%} = \mu_{i,t}^{EWMA} - 2.33\sigma_{i,t}^{EWMA} \tag{5}$$

2.2. Triangulated Maximally Filtered Graph

To uncover the structural topology of systemic interdependencies, a filtered network is constructed using the TMFG methodology introduced by (Massara et al., 2016). The TMFG is a sparse network filtering technique designed to retain the most relevant information from a fully connected weighted graph while preserving planarity and clustering structures.

The building process of the structure starts with the identification of four nodes which will make a completely linked 4-clique (tetrahedron), chosen to maximize the total edge weight among all possible quadruplets. The initial configuration, therefore, results in four triangles and becomes the base of the planar structure. Then, the other vertices are added one after another. In every single loop, one vertex is positioned in the triangular face maximizing the weights between the candidate vertex and the three vertices that make up the face. The TMFG is constructed on the correlation matrix of VaR time series. As VaR captures the tail risk of entities, the correlation of VaR series demonstrates the tail risk co-movements. An important advantage of TMFG relative to alternative filtering methods is that it preserves local clustering structures through the formation of 3- and 4-cliques. These cliques capture tightly interconnected groups of institutions that may represent potential channels of joint vulnerability and amplification mechanisms.

Let $C = [c_{ij}]$ denote the correlation matrix, where c_{ij} measures the linear correlation between the VaR of entities i and j. Following (Mantegna, 1999), to transform similarity into a proper metric space, the correlation matrix is converted into a distance matrix $D = [d_{ij}]$ defined as:

$$D_{ij} = \sqrt{2\left(1 - C_{ij}\right)}, D_{ij} \in \left[0,2\right] \tag{6}$$

Strongly correlated VaR dynamics correspond to shorter distances, implying closer similarity in the tail-risk profile. Formally, if F_t denotes the set of triangular faces at iteration , and is a candidate node, the algorithm chooses the face $f \epsilon F_t$ that maximizes:

$$\sum_{j \epsilon f} C_{ij} \tag{7}$$

The filtered topology is represented by the adjacency matrix $A = [a_{ij}]$ defined as:

$$a_{ij} = \begin{cases} 1 & \text{if nodes } i \text{ and } j \text{ are connected in the TMFG} \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

2.3. Community Detection and Eigenvector Centrality

2.3.1. Louvain community detection algorithm

To uncover endogenous clustering patterns, this study implements the Louvain community detection algorithm, introduced by (Blondel et al., 2008; Fortunato, 2010). The Louvain method is a modularity-based optimization procedure that partitions the network into communities by maximizing the modularity function :

$$Q = \frac{1}{2m} \sum_{ij} [A_{ij} - \frac{k_i k_j}{2m}] \delta(c_i, c_j) \tag{9}$$

where A_{ij} denotes the element of the adjacency matrix representing the weighted connection between nodes i and j, k_i and k_j correspond to their respective degrees, and m represents the total number of edges in the network. The term $\delta(c_i,c_j)$ is the delta function, equal to 1 if nodes i and j belong to the same community and 0 otherwise.

2.3.2. Eigenvector centrality analysis

The eigenvector centrality not only counts the number of connections a node possesses but also counts the centrality of its neighbors. Formally, it is defined as:

$$C_E(i) = \frac{1}{\rho} \sum_{j=1}^{n} A_{ij} C_E(j) \tag{10}$$

where A_{ij} denotes the (i,j) entry of the adjacency matrix and ρ is the largest eigenvalue of A. Nodes with high eigenvector centrality are not only well-connected but are also connected to other highly influential nodes, making them critical hubs for contagion and propagation of systemic risk (Battiston et al., 2016).

3. RESULTS

This paper uses daily stock price data of companies listed on the CSE market from 2007 to 2025, covering major crises, namely, Subprime crisis, European debt crisis, COVID-19 pandemic. The data is publicly available on (Investing.com, s.d.). The paper focuses on entities that were continually listed on the CSE market, thus, removing the new listings and delisted companies. The input contains 61 entities from different sectors as presented in Appendix 1. The daily stock prices are then transformed into logarithmic returns $r_{i,t}$.

Before presenting the paper results, it is essential to assess the statistical significance of the modeling process. The VaR estimates are assessed by the Kupiec back-testing (Kupiec, 1995), to evaluate whether the observed frequency of VaR violations is aligned with the predetermined confidence level. The Kupiec test point of failure is fixed at the 99% percentile choice, representing the expected proportion in which losses may exceed the predicted VaR. This test ensures that the modeling framework is properly calibrated. According to Table 1, out of the 61 firms, only 30 successfully passed the Kupiec test. The subsequent analysis is therefore conducted on this reduced set of firms.

Following the validation of VaR models, the interdependencies among the retained firms are captured through a VaR-based correlation matrix, which reflects co-movements in extreme downside risk. Prior to interpreting the TMFG network topology and its systemic risk implications, the stability of the filtered network must be assessed. Accordingly, the robustness of the TMFG is evaluated using a bootstrap resampling procedure (Tumminello et al., 2005).

Let $G^{(0)} = (V,E^{(0)})$ denotes the TMFG constructed from the original sample and let $G^{(b)} = (V,E^{(b)})$ for $b = 1,\ldots,$B represents the networks obtained from bootstrap replications. Network stability is quantified using the Jaccard similarity index between the edge sets:

$$J^{(b)} = \frac{|E^{(0)} \cap E^{(b)}|}{|E^{(0)} \cup E^{(b)}|} \tag{11}$$

The overall robustness is summarized by the average bootstrap similarity:

Table 1: Kupiec back testing results for listed entities

Entity	LR	P-value	Pass	Entity	LR	P-value	Pass
IAM	1.777	0.1825	Yes	SBM	48.173	$<10^{-4}$	No
AUN	56.846	$<10^{-4}$	No	SND	0.066	0.7979	Yes
SNA	0.050	0.8228	Yes	STI	19.968	$<10^{-4}$	No
HPS	1.399	0.2370	Yes	MGM	1.948	0.1629	Yes
WFA	8.554	0.0034	No	IBC	1.063	0.3025	Yes
CTM	4.286	0.0384	No	CDM	2.387	0.1220	Yes
DPA	3.163	0.0753	Yes	FEB	1.948	0.1629	Yes
UNM	35.493	$<10^{-4}$	No	LAF	0.004	0.9501	Yes
AWB	0.009	0.9224	Yes	BCP	0.050	0.8228	Yes
ZLD	58.646	$<10^{-4}$	No	RIS	2.464	0.1165	Yes
MAO	15.093	0.0001	No	PRO	38.519	$<10^{-4}$	No
LBV	10.258	0.0014	No	ALC	0.781	0.3768	Yes
DLM	1.399	0.2370	Yes	CIH	2.464	0.1165	Yes
REB	16.154	0.0001	No	DIS	2.464	0.1165	Yes
BMCI	0.066	0.7970	Yes	JET	7.059	0.0079	No
ATS	2.464	0.1165	Yes	REM	15.093	0.0001	No
BOA	1.108	0.2925	Yes	EQD	46.506	$<10^{-4}$	No
LYD	8.554	0.0034	No	DRC	25.703	$<10^{-4}$	No
CIM	1.777	0.1825	Yes	AGMA	51.576	$<10^{-4}$	No
SNP	5.224	0.0223	No	SFN	15.093	0.0001	No
STH	20.699	$<10^{-4}$	No	ENN	5.224	0.0223	No
AFG	13.063	0.0003	No	CRD	0.009	0.9224	Yes
DEH	1.108	0.2925	Yes	MAG	51.576	$<10^{-4}$	No
LEA	32.567	$<10^{-4}$	No	SMM	0.781	0.3768	Yes
M2M	5.224	0.0223	No	AFI	5.563	0.0183	No
MIC	0.004	0.9501	Yes	CSM	9.389	0.0022	No
SMI	8.554	0.0034	No	TIM	32.567	$<10^{-4}$	No
ALM	23.145	$<10^{-4}$	No	OUL	77.789	$<10^{-4}$	No
CAS	2.660	0.1029	Yes	SNM	0.171	0.6792	Yes
INV	0.772	0.3797	Yes	LEC	3.705	0.0543	Yes
				MIT	0.066	0.7979	Yes

$$\bar{J} = \frac{1}{B}\sum_{b=1}^{B} J^{(b)} \quad (12)$$

Table 2 reports the mean Jaccard similarity values obtained from the bootstrap procedure applied to the TMFG networks across the studied periods. The highest average similarity is observed for the complete dataset (0.76), indicating strong structural stability over the full sample. The European debt crisis and Subprime crisis samples show mean values of 0.71 and 0.63, respectively, demonstrating that TMFG calibration frameworks are robust. The COVID-19 pandemic represents the lowest mean value (0.55). Overall, the TMFGs of the studied periods display Jaccard value above the threshold of 0.50, confirming that the topologies constructed are sufficient and the contributions of this paper are grounded on statistically significant results.

As is evident in Figure 1, the topological structure based on the complete data sample shows the presence of seven unique communities. Community 1 is dominated by the banks AWB, BCP, and BOA linked by the shortest path in the network. The findings, looked at through the lens of network theory, reveal the tail risk joint movements of Moroccan banks, particularly those with considerable capital. This, in turn, can lead to the situation where negative consequences that affect one major bank may rapidly spread to others that are closely interconnected. Accordingly, these banks may take a lead role in the propagation of systemic risk throughout the CSE market. The rest of the banks, namely-CIH, BMCI, and CDM-are associated with different communities, which is a clear reflection of the tails risk profiles diversification. It was also a revealing observation that CIH is clustered with firms from other sectors, especially RIS (tourism), DPA (real estate), and ATS (insurance), which reflects the presence of significant tail dependencies across numerous industries. In the same manner, CDM is associated with mining sector firms such as MGM and MIT, which means that there is an inter-sectoral relationship beyond just that of banking. The getting of such result indicates the CSE network having cross-sectoral dependence channels.

Table 2: TMFG network robustness assessed via bootstrap Jaccard

Period	Mean Jaccard
Complete data	0.76
Subprime crisis	0.63
European debt crisis	0.71
COVID-19 crisis	0.55

The size of nodes is proportional to the eigenvector centrality within the community. Nodes outlined in black represent banking institutions.

Table 3 presents the ranking of nodes according to their eigenvector centrality within the detected communities over the global sample period. The table indicates that five out of six banks—AWB, BOA, BCP, BMCI, and CIH—occupy the top three positions in their respective communities. This pattern underscores the dominant role of the banking sector in shaping the network structure and governing the dynamics of tail-risk propagation across the CSE market. For instance, AWB leads community 1, while BOA and BCP follow closely, highlighting the clustering of highly capitalized banks within the same community. Moreover, the presence of other firms in the top ranks of certain communities suggests that non-banking institutions can also exert localized influence.

Figure 2 depicts the network topology that emerged during the Subprime crisis, a densely interconnected structure composed of

Figure 1: TMFG structure of the casablanca stock exchange market (Global Period)

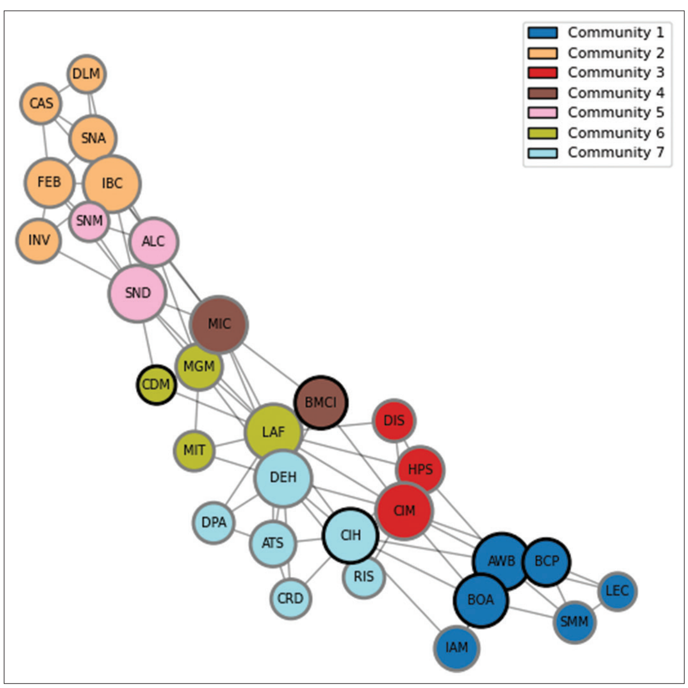

Figure 2: TMFG Structure of the casablanca stock exchange market (Subprime Crisis)

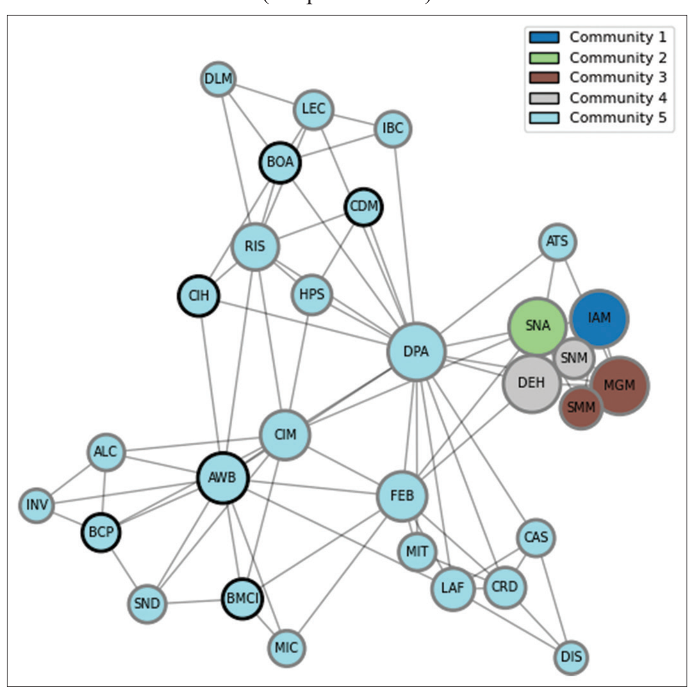

Table 3: Ranking of nodes by eigenvector centrality across detected communities (Global period)

Rank/community	1	2	3	4	5	6	7
1	AWB	IBC	CIM	MIC	SND	LAF	DEH
2	BOA	FEB	HPS	BMCI	ALC	MGM	CIH
3	BCP	SNA	DIS	—	SNM	MIT	ATS
4	IAM	INV	—	—	—	CDM	RIS
5	SMM	CAS	—	—	—	—	DPA
6	LEC	DLM	—	—	—	—	CRD

five communities, with community 5 characterizing the greatest number of linked nodes, which underscore the remarkable increase of interconnections during stressed market conditions and the most important cross-tail co- movements between financial and non-financial sectors. The extremely connected concentration of nodes reveals the highest level of systemic integration during this crisis in line with Acharya et al. (2010).

The size of nodes is proportional to the eigenvector centrality within the community. Nodes outlined in black represent banking institutions.

Table 4 also illustrates that community 5, the core of the network, is dominated by DPA, an important real estate firm in Morocco, occupying the top position in terms of eigenvector centrality. DPA is followed by AWB, and FEB, the presence of these firms signals the importance of their role in amplifying and transmitting extreme risks across the real and financial sectors during the Subprime crisis. DPA's eigenvector centrality clearly indicates that the real estate sector in Morocco is highly vulnerable to global shocks, including the indirect effects of the Subprime crisis because these spread from the U.S. to emerging markets via financial linkages, reduced foreign investments, and diminished demand for real estate (Shiller, 2012).

The TMFG network during the European debt crisis period is depicted in Figure 3, on the contrary of the global sample period and the Subprime crisis period, BMCI and CDM are members of the same community, as are BCP and CIH, but AWB and BOA instead are found in different communities, implying heterogeneous sensitivity to the European debt crisis. Overall, this redistribution signals a substantial topological reconfiguration of the network.

The size of nodes is proportional to the eigenvector centrality within the community. Nodes outlined in black represent banking institutions.

Table 5 reports the ranking of nodes according to eigenvector centrality within the six detected communities during the European debt crisis. The results show the consistent centrality of AWB, which ranks highest in its community, while BCP and BOA obtain the lowest rankings. On the other hand, BMCI and CIH appear to be central within their communities. Moreover, it is apparent that the increasing role of insurance companies (ALC and ATS) within their communities.

During the COVID-19 period, the network structure exhibited seven distinct communities, as illustrated in Figure 4. Unlike the global and Subprime periods, banks are more evenly distributed across these communities, indicating a substantial reconfiguration of the network under crisis conditions.

Table 4: Ranking of nodes by eigenvector centrality across detected communities (Subprime crisis)

Rank/community	1	2	3	4	5
1	IAM	SNA	MGM	DEH	DPA
2	—	—	SMM	SNM	AWB
3	—	—	—	—	FEB
4	—	—	—	—	CIM
5	—	—	—	—	RIS
6	—	—	—	—	LAF
7	—	—	—	—	CRD
8	—	—	—	—	CIH
9	—	—	—	—	BOA
10	—	—	—	—	BMCI
11	—	—	—	—	HPS
12	—	—	—	—	LEC
13	—	—	—	—	BCP
14	—	—	—	—	MIT
15	—	—	—	—	SND
16	—	—	—	—	CAS
17	—	—	—	—	CDM
18	—	—	—	—	ALC
19	—	—	—	—	ATS
20	—	—	—	—	MIC
21	—	—	—	—	IBC
22	—	—	—	—	INV
23	—	—	—	—	DLM
24	—	—	—	—	DIS

Table 5: Ranking of nodes by eigenvector centrality across detected communities (European debt crisis)

Rank/community	1	2	3	4	5	6
1	HPS	FEB	DPA	ALC	ATS	CIH
2	IAM	SNA	AWB	DEH	MIT	LEC
3	SND	BMCI	LAF	IBC	CRD	CAS
4	-	MIC	-	DLM	DIS	SMM
5	-	INV	-	BOA	SNM	MGM
6	-	CDM	-	-	CIM	BCP
7	-	-	-	-	RIS	-

The size of nodes is proportional to the eigenvector centrality within the community. Nodes outlined in black represent banking institutions.

Table 6 shows that among the six banks, five are ranked in the top 3 of their respective communities, whereby AWB, BCP, and CIH have occupied the first positions. It is important to mention that CIH is linked with companies from the real estate related industries, thereby pointing out the emergence of cross-sector tail-risk linkages. Compared to the previous crises, the observed network fragmentation is indicating a more dispersed

Figure 3: TMFG structure of the casablanca stock exchange market (European Debt Crisis)

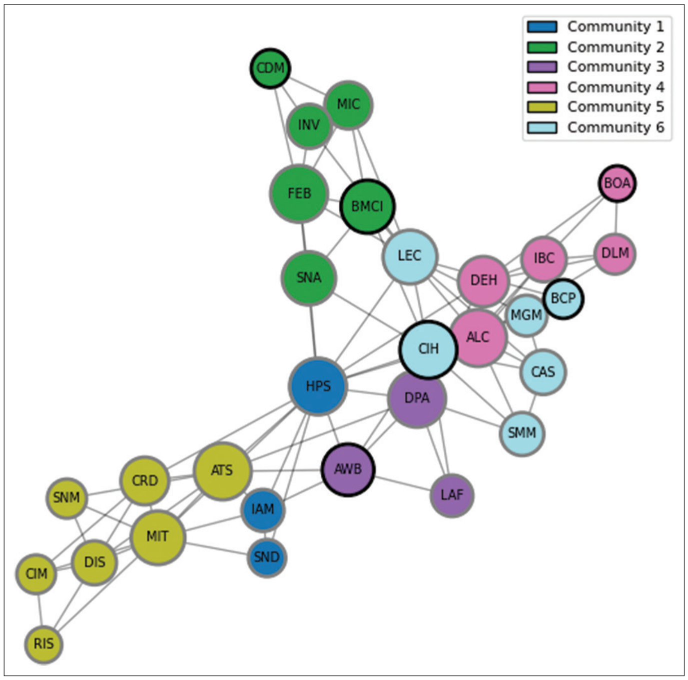

Figure 4: Triangulated maximally filtered graph structure of the Casablanca stock exchange market (COVID-19 crisis)

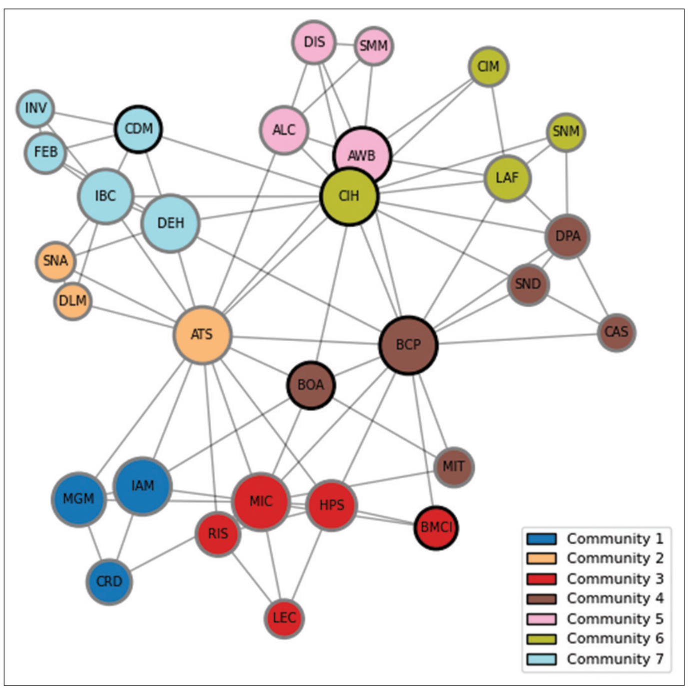

Table 6: Ranking of nodes by eigenvector centrality across detected communities (COVID-19 crisis)

Rank/ community	1	2	3	4	5	6	7
1	IAM	ATS	MIC	BCP	AWB	CIH	DEH
2	MGM	SNA	HPS	BOA	ALC	LAF	IBC
3	CRD	DLM	RIS	DPA	DIS	CIM	CDM
4	-	-	BMCI	SND	SMM	SNM	FEB
5	-	-	LEC	MIT	-	-	INV
6	-	-	-	CAS	-	-	-

risk structure, thus the transmission of shocks through several channels is possible, which would have the effect of amplified systemic risk in a more distributed manner (Glasserman and Young, 2016). Besides, ATS and ALC insurance companies are occupying important rank within their communities, demonstrating the potential systemic role of insurance in shaping the systemic risk transmission channels.

The results reveal that tail risk in the Moroccan financial network is primarily driven by the banking, real estate related upstream and downstream industries and insurance companies, with banks exerting the most pronounced influence. AWB dominates the network with high eigenvector centrality across the studied periods. It is interesting to note that the Subprime crisis forms a distinct network with a rather unique structure, featuring five different communities, and one community gathering almost all nodes. This configuration indicates both the strong influence that the Subprime crisis had on the CSE market and the increased interconnectedness during this period, potentially creating systemic risk propagation channels. The findings are consistent with previous studies that focused on the significance of inter-sectoral ties in risk transmission due to externally induced crises (Battiston et al., 2016). Studies on developing markets also reported similar concentrations of systemic importance during crisis periods (Glasserman and Young, 2016).

From a regulatory and macro-prudential perspective, these findings emphasize the need for proactive and dynamic supervision. Institutions that persistently occupy central network positions, particularly AWB, BCP, and BOA, and especially AWB warrant enhanced capital and liquidity requirements in line with Global Systemically Important banks framework. Moreover, the structural nexus between banks, real estate related industries underscore the importance of monitoring sectoral credit concentrations and incorporating real estate related sectors stress scenarios into macro-prudential stress tests. Tightening default criteria for real estate exposures and encouraging higher provisioning can reduce systemic vulnerability by ensuring that banks are better prepared to absorb losses from property-related shocks. As interconnectedness tends to increase during crises, regulatory intensity should be adjusted accordingly, with time-varying tools deployed to counteract pro-cyclical integration and mitigate the amplification of systemic risk (Billio et al., 2012). The network's topology shifts sharply during crises. The Subprime episode, for instance, witnesses a modularity decrease with most institutions falling into a single dominant community (Hautsch et al., 2015). The proximity and the cohesion of institutions tend to rise under stress which implies that the system becomes more vulnerable (Haldane, 2011).

4. CONCLUSION

The empirical findings offer a solid ground for arguing that the Moroccan banks and the key economic sectors, especially those related to real estate, have a mutual connection that is persistent and substantial. These inter-sector linkages build a very well interrelated financial core within which the shocks from one sector can easily disseminate into other sectors by means of direct and indirect channels. The observations verify the fact that AWB acts as too interconnected to fail node, its failure or distress could generate substantial contagion effects across sectors and potentially spill over to the wider economy.

Additionally, the insurance sector occupies a position of systemic importance in the CSE market, which indicates a non-banking source of potential threats to stability. Thus, Morocco's systemic risk should be viewed as a multi-dimensional sectoral problem, which is primarily constituted by interconnected nodes of the network, rather than just by the size of the institution itself. Looking from the macro-prudential angle, these findings point to the necessity of attending the cross-sector exposures and of including the network indicators to the financial stability frameworks to foresee the situation and mitigate the ripple effects associated with systemic shocks.

REFERENCES

Acharya, V.V., Cooley, T., Richardson, M., Walter, I. (2010), Manufacturing tail risk: A perspective on the financial crisis of 2007--2009. Foundations and Trends in Finance, 4, 247-325.

Admati, A., Hellwig, M. (2014), The Bankers' New Clothes: What's Wrong with Banking and What to Do about It: With a New Preface by the Authors. United States: Princeton University Press.

Allen, F., Babus, A. (2009), Networks in finance. In: The Network Challenge: Strategy, Profit, and Risk in an Interlinked World. New York: Pearson Prentice Hall. p367.

Allen, F., Gale, D. (2000), Financial contagion. Journal of Political Economy, 108, 1-33.

Battiston, S., Caldarelli, G., May, R.M., Roukny, T., Stiglitz, J.E. (2016), Complexity theory and financial regulation. Science, 351, 818-819.

Battiston, S., Gatti, D.D., Gallegati, M., Greenwald, B., Stiglitz, J.E. (2012), Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. Journal of Economic Dynamics and Control, 36, 1121-1141.

Berger, A.N., Peydró, J.L., Sedunov, J., Taboada, A.G. (2025), Systemic Risks, Crises, and Connections of the Real Economy, Banking Sector, and Financial Markets. Oxford: Oxford University Press.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L. (2012), Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics, 104, 535-559.

Bisias, D., Flood, M., Lo, A.W., Valavanis, S. (2018), A survey of systemic risk analytics. NMIMS Management Review, 4, 255-296.

Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, É. (2008), Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 2008, 10008.

Bonacich, P. (1987), Power and centrality: A family of measures. American Journal of Sociology, 92, 1170-1182.

Brunnermeier, M.K. (2009), Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives, 23, 77-100.

Cao, Y. (2022), Extreme risk spillovers across financial markets under different crises. Economic Modelling, 116, 106026.

Craig, B., Von Peter, G. (2014), Interbank tiering and money center banks. Journal of Financial Intermediation, 23, 322-347.

Danielsson, J., Shin, H.S., Zigrand, J.P. (2012), Balance sheet capacity and endogenous risk. IMF Economic Review, 565-608.

Diebold, F.X., Yilmaz, K. (2014), On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182, 119-134.

Fortunato, S. (2010), Community detection in graphs. Physics Reports, 486, 75-174.

Glasserman, P., Young, H.P. (2016), Contagion in financial networks. Journal of Economic Literature, 54, 779-831.

Haldane, A.G. (2011), Systemic risk in banking ecosystems. Nature, 469, 351-355.

Hautsch, N., Schaumburg, J., Schienle, M. (2015), Financial network systemic risk contributions. Review of Finance, 19, 685-738.

Hilbers, P., Otker-Robe, I., Pazarbasioglu, C., Johnsen, G. (2005), Assessing and Managing Rapid Credit Growth and the Role of Supervisory and Prudential Policies. [IMF Working Paper]. p5-151

Investing.com. (s.d.), Available from: https://fr.investing.com/equities

Kupiec, P.H. (1995), Techniques for verifying the accuracy of risk measurement models. In: Division of Research and Statistics, Division of Monetary Affairs, Federal. Berlin: An Academic Publisher. p73-84.

Levine, R. (2000), Are bank-based or market-based financial systems better? Journal Economía Chilena, 3, 25-55.

Levine, R. (2002), Bank-based or market-based financial systems: Which is better? Journal of Financial Intermediation, 11, 398-428.

Li, Y., Chen, S., Liu, J.W. (2023), Sectoral spillovers and systemic risks: Evidence from China. Finance Research Letters, 55, 104018.

Long, S., Li, Z. (2023), Dynamic spillover effects of global financial stress: Evidence from the quantile VAR network. International Review of Financial Analysis, 90, 102945.

Mantegna, R.N. (1999), Hierarchical structure in financial markets. The European Physical Journal B-Condensed Matter and Complex Systems, 11, 193-197.

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

Massara, G.P., Di Matteo, T., Aste, T. (2016), Network filtering for big data: Triangulated maximally filtered graph. Journal of Complex Networks, 5, 161-178.

Shiller, R.J. (2012), The Subprime Solution: How Today's Global Financial Crisis Happened, and what to do about it. United States: Princeton University Press. p1-224.

Tumminello, M., Aste, T., Di Matteo, T., Mantegna, R.N. (2005), A tool for filtering information in complex systems. Proceedings of the National Academy of Sciences, 102, 10421-10426.

Wang, G., Zhao, H., Shu, L., Song, L. (2025), Understanding risk spillover in multi-layer financial networks: The role of bank-firm connections. International Review of Financial Analysis, 105, 104404.

Wen, B., Bi, S., Yuan, M., Hao, J. (2023), Financial constraint, cross-sectoral spillover and systemic risk in China. International Review of Economics and Finance, 84, 1-11.

APPENDIX

Appendix 1: Considered listed entities on the casablanca stock exchange market

Ticker	Firm Name	Ticker	Firm Name
AFI	AFRIC INDUSTRIES	AFG	AFRIQUIA GAZ
AGMA ALM	AGMA	ALC ATS AUH	ALLIANCES
AWB AUN BOA	ALUMINIUM DU MAROC ATTIJARIWAFA	BMA BCP CAS	ATLANTASANAD ASSURANCE
BMCI CDM CIM	BANK	CIH CRD CTM	AUTO HALL
CSM DRC DEH	AUTO NEJMA	DLM DIS ENN	BALIMA
DPA EQD HPS	BANK OF AFRICA	FEB IBC IAM	BANQUE CENTRALE POPULAIRE CARTIER
INV	BANQUE MAROCAINE POUR LE	LBV LEC M2M	SAADA
JET LAF LYD	COMMERCE ET L'INDUSTRIE	MAG LEA MIT	CREDIT IMMOBILIER ET HOTELIER
MAO MGM MIC	CREDIT DU MAROC	PRO REB SMM	COLORADO
OUL REM RIS	CIMENTS DU MAROC COSUMAR	SNM SNP SND	COMPAGNIE DE TRANSPORTS AU MAROC
SFN SMI SBM	DARI COUSPATE DELTA HOLDING	SNA	DELATTRE LEVIVIER MAROC
STH STI UNM	DOUJA PROMOTION GROUPE ADDOHA	TIM	DISWAY
ZLD	EQDOM	WFA	ENNAKL AUTOMOBILES
	HPS INVOLYS		FENIE BROSSETTE
	JET CONTRACTORS LAFARGEHOLCIM		IB MAROC COM
	MAR		ITISSALAT AL MAGHRIB LABEL VIE
	LYDEC		LESIEUR CRISTAL
	MAGHREB OXYGENE MANAGEM		M2M Group MAGHREBAIL
	MICRO DATA OULMES MUTANDIS SCA		MAROC LEASING MINIERE TOUISSIT
	RISMA		PROMOPHARM
	SALAFIN		REBAB COMPANY S.M.MONETIQUE SAHAM
	SOCIETE METALLURGIQUE D'IMITIER		ASSURANCE
	SOCIETE DES BOISSONS DU MAROC		SOCIETE NATIONALE D'E×LECTROLYSE ET
	SOTHEMA		DE PETROCHIMIE
	STROC INDUSTRIE		SONASID
	UNIMER		STOKVIS NORD AFRIQUE TIMAR
	ZELLIDJA		WAFA ASSURANCE