“Measuring systemic risk in the Moroccan banking system: A ΔCoVaR-based network approach”

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MEASURING SYSTEMIC RISK IN THE MOROCCAN BANKING SYSTEM: A ΔCOVAR-BASED NETWORK APPROACH

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Abstract

Systemic risk has emerged as a significant concern for financial stability, particularly in emerging markets that are susceptible to global financial disruptions. This paper examines the transmission channels of systemic risk within the Moroccan banking sector during significant crises, including the Subprime crisis, the European sovereign debt crisis, and the COVID-19 crisis. This study aims to characterize the Moroccan banking network, determine the key contributors to systemic risk, and analyze the mechanisms through which amplification loops exacerbate systemic risk under stressed market conditions. The complex dynamics of systemic risk transmission are captured by the ΔConditional Value at Risk approach, which is represented as a directed weighted network, with topology indicators capturing the network position of financial institutions. The results indicate a pronounced core–periphery network, in which Attijariwafa Bank (AWB), Bank of Africa (BOA), and Banque Centrale Populaire (BCP) consistently form significant triangular feedback loops that amplify systemic risk across all examined periods. In-strength and out-strength centrality measures confirm their dominant positions as primary transmitters and receivers of systemic risk. In contrast, peripheral institutions play a comparatively less pronounced role within the network. Overall, the results point to a marked structural concentration of systemic risk within Morocco's banking network and provide important implications for regulators and policymakers aiming to strengthen macroprudential oversight and safeguard financial stability.

Keywords systemic contagion, shock amplification, financial stability, network theory, crisis periods

JEL Classification G01, C32, C31, G21

INTRODUCTION

Financial stability has become a central concern in the aftermath of increasing global financial integration and interconnectedness. Banking systems have evolved into highly complex and interconnected structures, where rising interdependencies amplify the propagation and intensity of financial shocks. This evolution has raised important questions regarding the resilience of financial institutions in the face of systemic disturbances. In this context, understanding the mechanisms underlying systemic risk contagion has gained increased attention, alongside growing emphasis on the importance of strengthening the resilience of the banking sector to better withstand systemic shocks. The Subprime crisis demonstrated how the failure of a single bank can spread to the whole global financial system, causing economic downturn with far-reaching effects. Systemic risk, which is defined as the likelihood that a collapse of one institution could affect the whole financial system, has become a major concern for regulators, policymakers, and researchers (Acharya et al., 2010).

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Traditional systemic risk measurement approaches rely on idiosyncratic risk, size, or leverage to determine the systemic importance of an institution, which may underestimate the magnitude of the contagion channels that can transform isolated disturbances into systemic crises. In response, network theory has become essential for understanding systemic risk, as it represents the financial system as a set of interconnected institutions through which shocks can propagate and amplify. Within this framework, systemic risk is not solely determined by the inherent characteristics of individual financial institutions, but also by their topological properties (Allen & Gale, 2000). In such configurations, institutions occupying central positions play key roles as transmitters or amplifiers of systemic risk (Freixas et al., 2000). These insights highlight the need to move beyond micro-institutional analysis toward a network-based approach, enabling the identification of systemic risk amplification channels (Battiston et al., 2012).

Despite the growing adoption of network-based methodologies, empirical evidence remains heavily concentrated on advanced economies, leaving emerging banking systems comparatively underexplored. This imbalance limits the generalizability of existing findings and constrains our understanding of how banking network architecture in emerging contexts influences systemic fragility. This gap is particularly relevant in Morocco, where the banking sector plays an increasingly important role in the economy and serves as a central pillar of financial intermediation. Despite its growing significance, the structural features and interconnectedness of the Moroccan banking network remain insufficiently explored. These considerations underscore the need to investigate systemic risk contagion channels within Morocco to provide regulators with key insights for strengthening the banking sector stability.

1. LITERATURE REVIEW

Systemic risk phenomenon has evolved to be a highly challenging research field at the intersection of network theory and macroprudential regulation. Allen and Gale (2000) investigated the financial network configurations and stated that the network's completeness can either mitigate or intensify systemic risk. This early insight initiated a growing literature on the relationship between financial connectivity and systemic vulnerability. Building on this foundation, Haldane and May (2011) emphasized nonlinear amplification mechanisms and tipping-point dynamics, reinforcing the view that systemic risk is an endogenous feature of financial network topology rather than merely the aggregation of individual risks. Similarly, Battiston et al. (2012) demonstrated that systemic risk responses were inherently nonlinear, whereby small shocks could trigger disproportionately large effects, and their direction could vary depending on the underlying network connectivity. Moreover, Acemoglu et al. (2015) provided a formal characterization of the relationship between connectivity and stability, demonstrating that increased interconnection can reduce systemic risk. Beyond a certain threshold, however, additional connectivity amplifies fragility. This confirms the non-monotonic nature of financial stability in banking networks.

The empirical measurement of systemic risk has undergone a significant evolution over time. First, RiskMetrics (1996) introduced Value at Risk (VaR), a popular risk measure that assesses the probable maximum loss of a portfolio within a specific time horizon and pre-specified confidence level. VaR stands as one of the widely used tail risk metrics; despite its performance, it does not consider the interconnectedness between financial institutions but rather focuses on idiosyncratic risk exposure. In response, Adrian and Brunnermeier (2011) presented the Conditional Value at Risk (CoVaR) framework, which overcomes the VaR limitations by quantifying the risk exposure of an entity conditioned on the fact that the financial system is in a state of tail distress. In addition, ΔCoVaR proposed by Adrian and Brunnermeier (2016) quantifies the extent to which a bank contributes to systemic risk by comparing the system's VaR under the bank's median state and its stressed state. Other methodologies have been developed to capture systemic risk from different perspectives. Acharya et al. (2010) proposed the concept of marginal expected shortfall to assess an institution's contribution to systemic distress, while Brownlees and Engle (2017) introduced the SRISK measure based on capital shortfall under market stress. In addition, Diebold and Yilmaz (2014) developed spillover indices using variance decomposition techniques to quantify connectedness across financial institutions. Recently, progress in the modeling framework has integrated machine learning techniques to a better extent to unveil the complex interdependence structures. Within this framework, Keilbar and Wang (2022) used the Quantile Regression Neural Networks (QRNN), which allow for the estimation of conditional quantiles within a nonlinear framework, capturing complex dependencies in the data and improving the modeling of tail risk and systemic risk compared to traditional linear approaches. Collectively, these approaches shift from assessing the risks of each individually to assessing the systemic externalities and financial interconnectedness.

Adopting a network perspective, Billio et al. (2012) demonstrated that network centrality measures derived from return linkages provide early-warning indicators of systemic stress, highlighting the informational content embedded in financial networks. Extending this idea, Poledna et al. (2015) demonstrated within multilayer financial networks that a small subset of large banks accounts for a disproportionate share of aggregate systemic risk, and that neglecting network interdependencies leads to a systematic underestimation of potential systemic losses. In the European context, Aldasoro and Alves (2018) found that banks with higher interconnectedness are consistently more systemically important in transmitting shocks across the financial system. Similarly, Huang and Wang (2018) identified systemically important financial institutions through volatility spillover networks and demonstrated that a few large commercial banks concentrate risk transmission during crisis periods. Building on these results, Moratis and Sakellaris (2021) provided evidence that systemic importance is persistent over time and strongly associated with network centrality measures, particularly under stressed market conditions. Overall, these findings univocally point to the observation that systemic risk is largely concentrated in structurally central entities, suggesting that network centrality provides a fundamental extension to traditional size-based measures such as the "too big to fail" paradigm, giving rise to the notion of "too central to fail."

Despite these advances, research contributions are mostly focused on developed economies, while evidence on emerging banking systems is limited. This is especially the case for Morocco. Zakaria (2015) investigated procyclical contagion dynamics utilizing conditional correlations; meanwhile, Nechba (2021) claimed that bank capitalization is the essential factor affecting systemic vulnerability. Moreover, Said et al. (2023) identified systemically important banks using tail-risk indicators and actuarial risk measures.

This study seeks to characterize the structure of the Moroccan banking network, identify its main sources of systemic risk, and examine the mechanisms through which amplification loops intensify systemic risk during crisis periods. Additionally, it seeks to provide regulators with evidence-based insights to facilitate targeted interventions on key contagion channels, thereby safeguarding banking system stability.

Against this backdrop, this paper contributes to the literature along two main dimensions. First, it integrates tail-risk estimation with a network-based representation of financial interconnectedness by embedding ΔCoVaR within a directed and weighted network framework. Second, it provides new empirical evidence on systemic risk transmission in an emerging banking system by examining multiple crisis episodes.

2. METHODS

This paper focuses on Moroccan banks listed on the Casablanca Stock Exchange, namely Attijariwafa Bank (AWB), Banque Centrale Populaire (BCP), Bank of Africa (BOA), Crédit Immobilier et Hôtelier (CIH), Crédit du Maroc (CDM), and Banque Marocaine pour le Commerce et l'Industrie (BMCI). The dataset consists of daily stock prices transformed into logarithmic returns over the period from January 2008 to December 2022. The data are obtained from the publicly available database provided by Investing.com (n.d.). This time span is selected to capture major episodes of financial stress affecting global and domestic markets, including the Subprime crisis (September 2008 – August 2009), the European sovereign debt crisis (July 2011–June 2012), and the COVID-19 pandemic (March 2020–May 2021).

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This research employs a multistep methodology. Firstly, the VaR is calculated using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Engle, 1982; Bollerslev, 1986). The VaR results are then validated through the Kupiec back-testing (Kupiec, 1995). Second, CoVaRs are computed using VaRs vectors based on the QRNN and linear quantile regression frameworks (Cannon, 2011; Koenker, 2005). The CoVaRs resulting from QRNN and linear quantile regression are compared through the Diebold–Mariano test (Diebold & Mariano, 2002) to select the model that provides the most accurate estimates. Third, the obtained CoVaR calibrations are used to measure ΔCoVaRs, which in turn are adopted for the establishment of a directed weighted network representing the systemic contributions among Moroccan banks. Fourth, edges, cycles, and centrality measures are utilized to analyze the Moroccan banking network structure and to identify global systemically important banks.

2.1. Value at risk

The concept of VaR, initially formalized by JP Morgan, measures the maximum potential loss of a portfolio over a given horizon at a specified confidence level. It ensures that financial institutions are sufficiently capitalized to absorb adverse market movements (Fernandez, 2003). Several improvements have been proposed to upgrade the accuracy of this measure. For instance, McNeil and Frey (2000) combined GARCH processes with Extreme Value Theory to better capture tail risk, while Engle and Manganelli (2004) developed a time-varying quantile approach to improve VaR estimation. Linear quantile regression has been employed by Chao et al. (2015) and Härdle et al. (2016). These contributions highlight the central role of VaR in modern risk management. Formally, let X_t denote the return of an asset at time t, which can be decomposed as:

$$X_t = \mu_t + \varepsilon_t, \quad \varepsilon_t = z_t \sigma_t, \quad z_t \sim i.i.d.(0,1) \tag{1}$$

where μ_t is the conditional mean, σ_t^2 is the conditional variance, ε_t denotes the unexpected return or innovation at time t, and z_t are standardized innovations. The conditional variance σ_t^2 is modeled using a Gaussian GARCH (1,1) specification:

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

where ω > 0 is a constant, $\alpha \geq 0$ captures the short-term impact of shocks, and β ≥ 0 reflects the persistence of volatility. Under this framework, the VaR at τ = 1% is given by:

$$VaR_t^{\tau} = \mu_t + q_{\tau}\, \sigma_t, \tag{3}$$

where $q_\tau = F_z^{-1}(\tau)$ denotes the τ-quantile of the standardized innovation distribution, typically assumed to follow a standard normal distribution.

VaR has been criticized for its institution-specific focus, which neglects interdependencies within the financial system. To overcome this limitation, CoVaR has been developed as a key measure to capture systemic risk.

2.2. Conditional value at risk

CoVaR captures the risk of a given institution j conditional on another institution i being in distress. It is based on the concept of conditional quantiles. Formally, the τ-th conditional quantile of the return of institution j at time $t(X_{j,t})$ given the return of institution i at time $t(X_{j,t})$ is defined as:

$$Q_{X_j}^{\tau}\left(X_{i,t}\right) \tag{4}$$
$$= \inf\left\{x \in \mathbb{R} : P\left(X_{j,t} \leq x \middle| X_{i,t}\right) \geq \tau\right\}.$$

In its linear specification, the conditional quantile function can be approximated as:

$$Q_{X_j}^{\tau}\left(X_{i,t}\right) = \delta_\tau + \gamma_\tau X_{i,t}, \tag{5}$$

where δ_τ denotes the intercept and γ_τ sensitivity of X_j to X_i at quantile τ.

To capture nonlinear dependence structures between institutions, the conditional quantile function is approximated using a Quantile Regression Neural Network (QRNN), specified as:

$$X_{j,t} = f_\theta\left(X_{i,t}\right) + \varepsilon_{j,t}, \tag{6}$$

where $\varepsilon_{j,t}$ is an error term and $f_\theta(.)$ is a nonlinear function parameterized by a neural network. For a feedforward neural network with one hidden layer, the conditional quantile function is approximated as:

$$f_\theta\left(X_{i,t}\right)=b^0+\sum_{m=1}^{M}\omega_m^0\,\phi\left(b_m^h+\omega_{i,m}^h X_{i,t}\right), \quad (7)$$

where $\varphi(.)$ denotes a sigmoid activation function, $b_m^{\ h}$ represents the bias of the hidden layer, $\omega_{i,m}^{\ h}$ are the weights connecting the input to the hidden layer, and $\omega_m^{\ 0}$ together with b^0 correspond to the weights and bias of the output layer. The parameter set is denoted by θ, and M is the number of hidden neurons. The QRNN is estimated by minimizing the quantile loss function:

$$\hat{\theta}=\arg\min_\theta\sum_t\rho_\tau\left(X_{j,t}-f_\theta\left(X_{i,t}\right)\right), \quad (8)$$

where the check function is defined as $\rho_\tau\left(u\right)=u(\tau-\mathbb{I}(u<0))$, u denotes the quantile residual. This approach directly targets the τ-th conditional quantile and allows for a flexible estimation of dependence structures.

The CoVaR of institution j, conditional on institution i being in distress, captures the potential loss of institution j when institution i is experiencing extreme adverse conditions:

$$CoVaR_{j|i,t}^{\tau}=\hat{f}_\theta\left(X_{i,t}=VaR_{i,t}^{\tau}\right). \quad (9)$$

2.3. ΔConditional value at risk

To assess the marginal contribution of institution i to systemic risk, Adrian and Brunnermeier (2016) introduced the ΔCoVaR measure, defined as:

$$\Delta CoVaR_{j|i,t}^{\tau}=CoVaR_{j|i,t}^{\tau}-CoVaR_{j|i,t}^{median}, \quad (10)$$

where $CoVaR_{j|i,t}^{median}$ is computed when institution i is in a normal state (median level). This measure captures the additional risk transmitted to institution j due to the distress of institution i, and is widely used as an indicator of systemic risk contribution. Pairwise $\Delta CoVaR_t^{\tau}$ values are then mapped into a directed, weighted network, where the edge from i to j represents the magnitude of systemic spillover. The resulting ΔCoVaR network is analyzed using network indicators offering a detailed view of risk propagation.

2.4. Network construction and analysis

Let $G = (V, E, W)$ denote a directed weighted network, where $|V| = N$ is the number of banks, $W = [w_{ij}]$ is the weighted adjacency matrix, and E represents the set of directed links between banks. Each element w_{ij} captures the systemic impact of bank i on bank j and is constructed from the ΔCoVaR measure. Specifically, the adjacency matrix is defined as:

$$w_{ij}=\frac{1}{T}\sum_{t=1}^{T}\left|\Delta CoVaR_{j|i,t}\right|, \quad (11)$$

where T is the number of observations, $w_{ij} > 0$ indicates that distress in bank i increases the systemic risk of bank j, while $w_{ij} = 0$ reflects the absence of a direct systemic risk link. To understand the propagation of systemic risk within the banking sector, this paper introduces the structural properties of the ΔCoVaR network using network measures, allowing the identification of the banks that play central roles in transmitting shocks throughout the system.

The weighted in-strength centrality of node i captures the cumulative systemic risk received by bank i from all other institutions. A high weighted in-strength centrality indicates that a bank is highly exposed to systemic spillovers from other institutions:

$$k_i^{in}=\sum_{j\neq i}w_{ji}, \quad (12)$$

In addition, the weighted out-strength centrality of node i reflects the cumulative systemic risk transmitted from bank i to the rest of the system. A high weighted out-strength centrality indicates that a bank is a major contributor to systemic spillovers:

$$k_i^{out}=\sum_{j\neq i}w_{ij}. \quad (13)$$

The total number of directed systemic links is defined as:

$$E=\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\mathbb{I}(w_{ij}>0). \quad (14)$$

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Feedback loops are captured by identifying directed closed cycles. Using the binary adjacency matrix $A = [a_{ij}]$, where $a_{ij} = \mathbb{I}(w_{ij} > 0)$, the number of closed systemic risk contagion cycles of length c is given by:

$$c - cycle = \frac{Tr\left(A^c\right)}{c}, \quad c \geq 2, \tag{15}$$

where $Tr(A^c)$ counts closed contagion cycle of length c, and the division by c corrects for rotational symmetry.

3. RESULTS

The results of the modeling framework are subject to a two-stage validation process. First, the VaR estimates are assessed by the Kupiec back-testing (Kupiec, 1995) to evaluate whether the observed frequencies of VaR violations are aligned with the theoretical failure rate implied by the VaR confidence level (99%). The null hypothesis states that the proportion of violations equals 1%. Table 1 reports the test outcome for each bank. The results show that, in all cases, the null hypothesis cannot be rejected at the 5% significance level, as the test statistics remain below the critical value of 3.84. This confirms that the VaR models are adequately calibrated.

Table 1. Kupiec test results

Bank	POF	Critical Value	Test Outcome
AWB	0.19	3.84	Accept
BCP	2.41	3.84	Accept
BOA	1.17	3.84	Accept
CIH	2.55	3.84	Accept
BMCI	3.31	3.84	Accept
CDM	3.62	3.84	Accept

Second, the test by Diebold and Mariano (2002) is applied to compare CoVaR forecasts obtained from the QRNN model with those from the linear quantile regression model. The null hypothesis assumes equal predictive accuracy. Table 2 reports the Diebold–Mariano (DM) statistics and corresponding p-values for each bank. At the 5% significance level, the null hypothesis of equal predictive accuracy is rejected in all cases, indicating that the QRNN model provides superior forecasting performance relative to the linear benchmark.

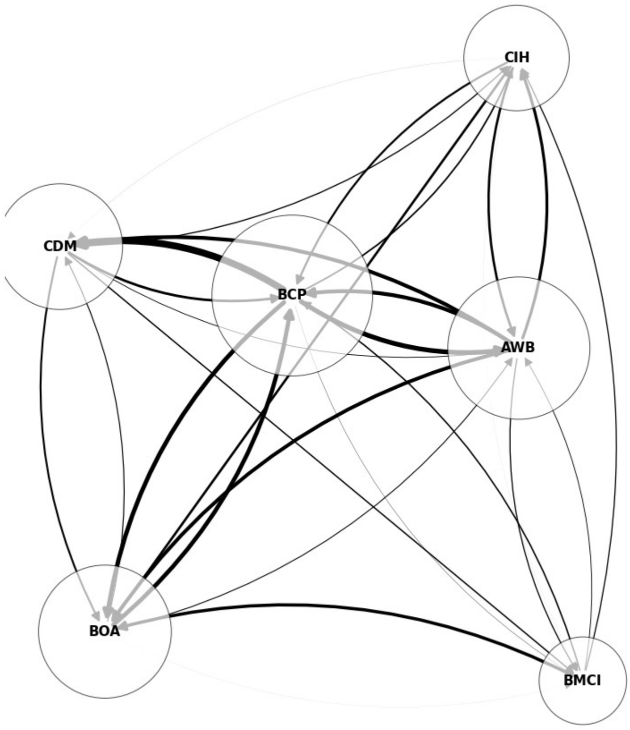
Table 2. Diebold-Mariano test results

Bank	DM statistics	p value
AWB	–2.21	0.03
BCP	–2.24	0.02
BOA	–3.19	0.00
CIH	–9.09	0.00
BMCI	–3.60	0.00
CDM	–4.00	0.00

Overall, this two-step validation procedure verifies that the VaR calibrations provide a sufficient base while the CoVaRs obtained through the QRNN model demonstrate the ability to capture more effectively the nonlinear systemic risk, which ensures that the result implications of this paper are grounded on statistically significant information.

The Moroccan banking network is investigated as a weighted directed graph in which nodes correspond to individual banks while edges are the ΔCoVaR-based systemic risk spillovers to comprehend the overall structure, it is essential to examine cycles, which are closed contagion pathways through which systemic risk originating from bank A can spill over to other institutions and eventually return to its origin (bank A), thereby disseminating and exacerbating the severity of financial crises. A loop of 2-cycle shows that there is a reciprocal relationship between two banks (for example, Bank A → Bank B → Bank A). Longer cycles like 3-cycle are formed with triangular feedback loops (Bank A → Bank B → Bank C → Bank A), while 4-cycle and further on recognize more complex chains of propagation which involve four, five, or six institutions respectively. It should be noted that 6-cycles are considered the longest in this study.

In a directed network, a cycle can be represented in several forms, depending on the orientation and the order of edges. For example, the directed cycle Bank A → Bank B → Bank C → Bank A forms a cycle of length three. If the directional structure additionally enables the chain Bank C → Bank A → Bank D → Bank C, then this would imply a distinct cycle based on a different chain and order of institutions. Therefore, cycles stand hereby as potential propagation pathways, pointing out the fact that systemic risk can be distributed across different banks before returning to their original source.



Note: Nodes correspond to banks and edges represent systemic risk spillovers measured by ΔCoVaR. Edge thickness indicates the intensity of transmitted systemic risk, while node size reflects weighted out-strength centrality.

Figure 1. ΔCoVaR-based interbank network for the Subprime crisis period

As displayed in Figure 1, during the Subprime crisis, the Moroccan banking network exhibited a highly interconnected core dominated by AWB, BOA, and BCP. These three banks formed closed contagion cycles, underscoring their critical role in systemic risk propagation. The directional arrows between them reveal strong reciprocal linkages, creating a self-reinforcing structure that amplifies systemic risk across the network and threatens the stability of the Moroccan financial system and, consequently, the broader economy. This configuration suggests that even small disturbances at the core may trigger cascading effects capable of disrupting the entire banking system.

Table 3 presents the potential systemic risk closed contagion cycles from which a shock may propagate to escalate into a systemic crisis. The analysis focuses on persistent connections at high percentiles, underscoring the most significant edges. At 85% percentile, the remaining 2 cycles are AWB → BCP → AWB, and BOA → BCP → BOA reflect the most significant bilateral links, while the last remaining 3-cycle at 75% percentile is AWB → BOA → BCP → AWB, capture robust multilateral feedback mechanisms. In addition, the strongest systemic risk contagion edge, observed at the 99% percentile, occurs along the directional link BCP → CDM, indicating that distress in BCP had the most pronounced propagation to CDM.

Table 3. Distribution of network metrics of the Moroccan banking network (Subprime crisis)

Metric	0%	5%	10%	25%	50%	75%	85%	90%	95%	99%
2-cycle	13	11	10	6	4	2	2	0	0	0
3-cycle	32	27	24	14	4	1	0	0	0	0
4-cycle	67	51	43	20	2	0	0	0	0	0
5-cycle	100	68	54	21	0	0	0	0	0	0
6-cycle	78	46	34	12	0	0	0	0	0	0
Edge	28	26	25	21	14	7	5	3	2	1

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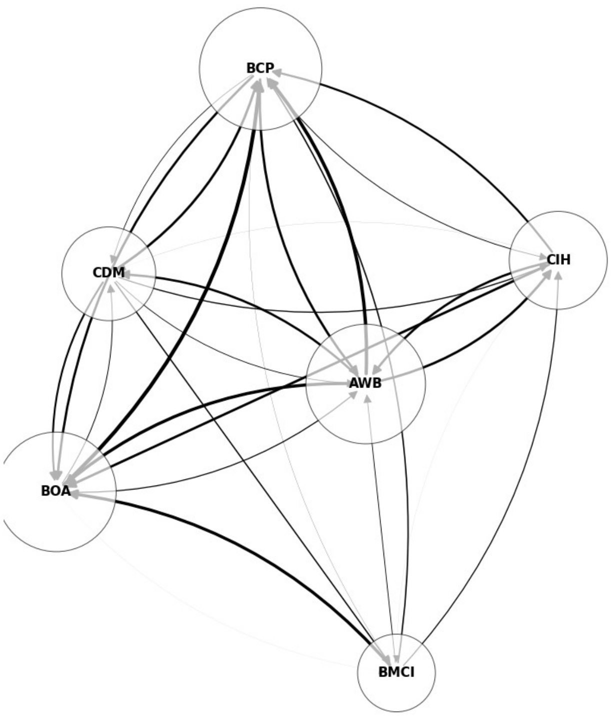
Table 4 presents the node-level centrality metrics, which reaffirm the prominence of AWB, BCP, and BOA as the principal transmitters of systemic risk, as indicated by their elevated weighted out-strength centrality ranks. Furthermore, BCP, BOA, and CDM occupy the top positions in terms of weighted in-strength centrality during the Subprime crisis, implying that BCP and BOA functioned simultaneously as major sources and recipients of systemic risk within the network.

Table 4. Node-level centrality ranking of Moroccan banks across different crisis periods

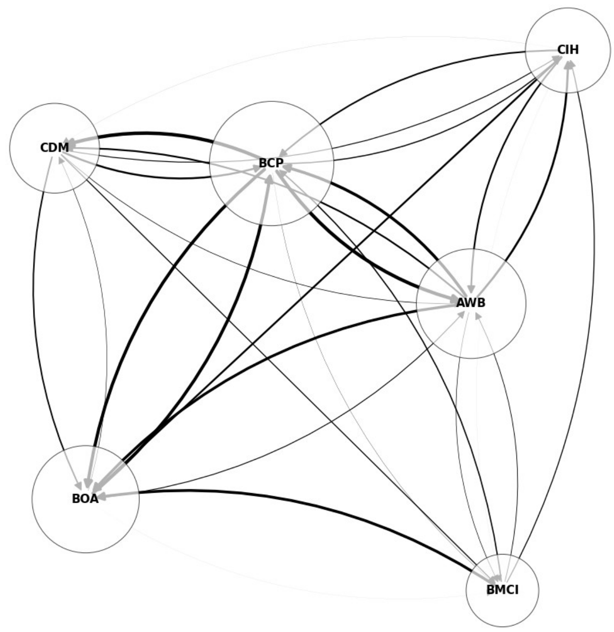
Rank	Subprime crisis		European Debt Crisis		COVID-19 crisis	
	k^{out}	k^{in}	k^{out}	k^{in}	k^{out}	k^{in}
1	BCP	BOA	AWB	BCP	BCP	CDM
2	AWB	BCP	BOA	BMCI	AWB	BCP
3	BOA	CDM	BMCI	CDM	BOA	BOA
4	CIH	AWB	CIH	AWB	BMCI	BMCI
5	BMCI	CIH	BCP	BOA	CIH	AWB
6	CDM	BMCI	CDM	CIH	CDM	CIH

During the European debt crisis, the Moroccan banking network kept a core-periphery structure with prominent edges linking AWB, BOA, and BCP (Figure 2). As presented in Table 5, at 50% percentile threshold, three significant 2-cycle remain, namely AWB → BCP → AWB, AWB → CIH → AWB, and BOA → BCP → BOA. The existence of reciprocal structures is indicative of robust bilateral contagion mechanisms, thus indicating the presence of reinforced feedback effects among systemically significant institutions. Furthermore, 3-cycle configurations persisted at 50% percentile, thus serving to emphasize the multilateral dimension of systemic risk transmission. The cycles AWB → BOA → BCP → AWB, AWB → CIH → BCP → AWB, and CDM → BCP → AWB → CDM reveal interconnected triads through which shocks may propagate. Such triangular structures amplify systemic vulnerability by enabling contagion to circulate beyond simple pairwise exposures. In contrast to the Subprime crisis, the identified amplification cycles extend beyond the core institutions (AWB, BCP, and BOA) to include CDM and CIH. Moreover, the strongest systemic risk contribution edge (observed at 99% percentile) is BOA→BCP. The weighted in-strength and out-strength centrality measures show the constant core, AWB, and BOA, systemic risk transmitter, with BMCI



Note: Nodes correspond to banks and edges represent systemic risk spillovers measured by ΔCoVaR. Edge thickness indicates the intensity of transmitted systemic risk, while node size reflects weighted out-strength centrality.

Figure 2. ΔCoVaR-based interbank network for the European debt crisis period



Note: Nodes correspond to banks and edges represent systemic risk spillovers measured by ΔCoVaR. Edge thickness indicates the intensity of transmitted systemic risk, while node size reflects weighted out-strength centrality.

Figure 3. ΔCoVaR-based interbank network for the COVID-19 crisis period

Table 5. Distribution of network metrics of the Moroccan banking network (European Debt Crisis)

Metric	0%	5%	10%	25%	50%	75%	85%	90%	95%	99%
2-cycle	12	10	9	6	3	0	0	0	0	0
3-cycle	29	24	21	12	3	0	0	0	0	0
4-cycle	59	43	36	18	2	0	0	0	0	0
5-cycle	85	53	42	17	0	0	0	0	0	0
6-cycle	64	32	24	8	0	0	0	0	0	0
Edge	27	25	24	20	14	7	4	3	2	1

having a more pronounced role, occupying the weighted out-strength centrality third rank (Table 5). Overall, the European debt crisis network exhibits relatively homogeneous systemic risk contributions across institutions, as amplification cycles disappear beyond the 50th percentile threshold, indicating the absence of major contributors. However, the reduction of multilateral channels highlighted the limited impact of this crisis on the Moroccan banking system.

During the COVID-19 crisis, the Moroccan banking network maintained a pronounced core–periphery structure, with AWB, BOA, and BCP forming a tightly connected central cluster that dominates systemic risk propagation (Figure 3). This core is characterized not only by its central position in the network but also by the intensity and persistence of bilateral linkages among its members. The arrows linking these three banks reveal strong and mutually reinforcing exposures, indicating that shocks originating in one institution are rapidly transmitted to the others and may subsequently reverberate back to the source. Such reciprocal relationships give rise to a robust feedback loop, amplifying systemic risk through endogenous contagion mechanisms.

As presented in Table 6, at 85% percentile threshold, the cycles AWB → BOA → AWB, and BOA → BCP → BOA reflect the most significant bilateral dependencies, while the 3-cycle observed at 75% percentile is AWB → BOA → BCP → AWB, which captures the persistence of multilateral feedback mechanisms. The presence of these structures at high percentiles highlights the significance of

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Table 6. Distribution of network metrics of the Moroccan banking network (COVID-19 Crisis)

Metric	0%	5%	10%	25%	50%	75%	85%	90%	95%	99%
2-cycle	13	11	10	6	4	2	2	0	0	0
3-cycle	32	27	24	13	4	1	0	0	0	0
4-cycle	67	51	43	18	2	0	0	0	0	0
5-cycle	100	68	54	17	0	0	0	0	0	0
6-cycle	78	46	34	8	0	0	0	0	0	0
Edge	28	26	25	21	14	7	5	3	2	1

these multilateral contagion channels. Moreover, the observed edge at 99% percentile is BCP → CDM.

The in-strength and out-strength centrality measures further confirm the dominance of BCP, BOA, and AWB as key transmitters of systemic risk; notably, CDM occupies the first rank in terms of in-strength centrality measures (Table 4).

4. DISCUSSION

The empirical results indicate that the Moroccan banking system exhibits a core-periphery structure across all analyzed crisis periods, with AWB, BCP, and BOA at its core, acting as global systemically important banks. From a network theory perspective, such stable structures can lead to an apparent endogenous amplification mechanism, whereby stresses are magnified through feedback loops in the core of the system. These results lend empirical support to network contagion models (Battiston et al., 2012), which posit that densely connected core structures amplify shocks and exacerbate systemic vulnerability. This is consistent with the findings of Said et al. (2023), who identified AWB and BCP as systemically important banks exhibiting systemic risk with the potential to trigger a systemic crisis. Furthermore, the persistent systemic risk edge, BCP → CDM, highlights the potential role of BCP in transmitting systemic risk to CDM and creating an influence bridge between the core and the periphery of the network.

The presence of persistent 2 cycles and 3 cycles provide strong empirical evidence of the systemic risk amplification mechanisms. These findings align with the theoretical framework of Acemoglu et al. (2015), which suggests that densely connected core structures amplify systemic vulnerability. However, this study builds on their work by demonstrating that such contagion mechanisms are not confined to large-scale financial systems but are also present in emerging banking systems. Moreover, the findings indicate that the Moroccan system experienced a less pronounced systemic risk impact during the European debt crisis. This may reflect differences in exposure composition or indirect transmission channels rather than direct balance-sheet contagion. Another important result concerns BMCI, which becomes more central during the European debt crisis. This finding aligns with the literature on foreign bank ownership and cross-border systemic risk transmission (Cetorelli & Goldberg, 2012; Claessens & Van Horen, 2015), which shows that internationally affiliated banks may act as conduits for external shocks.

From a policy perspective, these findings suggest that a shift from size-based regulation to a network-based macroprudential framework is necessary, given that network theory provides additional insight into the systemic risk propagation. The persistence of feedback loops indicates that financial distress can be rapidly amplified through a limited number of transmission channels, which provides regulators with valuable information in targeting significant channels by mechanisms such as macroprudential capital buffers, sector-specific exposure limits, countercyclical capital requirements, and tighter interbank exposure constraints. Therefore, these results support incorporating network centrality and contagion metrics into sensibility and cross-border contagion stress-testing frameworks to improve monitoring and anticipation of systemic vulnerabilities.

Overall, this study contributes to existing literature in three main dimensions. First, it shows that Morocco's global systemically important banks exhibit systemic risk that is structurally persistent across crisis episodes. Second, it highlights that AWB, BCP, and BOA play a dominant role in the transmission of systemic risk and may act as potential sources of widespread contagion, thereby affecting the stability of the entire banking system. Third, it documents the heterogeneous impact of different crisis episodes, with the Moroccan banking system displaying relatively greater resilience during the European sovereign debt crisis compared to the Subprime and COVID-19 crises.

CONCLUSION

Adopting a ΔCoVaR-based directed weighted network framework, this research investigates systemic risk in the Moroccan banking system, with emphasis on the function of network structure in shaping the systemic risk contagion dynamics in various crisis episodes.

The results consistently reveal a stable core–periphery architecture in which banks, namely AWB, BCP, and BOA, occupy structurally dominant positions across all the studied periods. Beyond their individual importance, these banks form a tightly interconnected core characterized by persistent systemic risk feedback loops. The presence of these structural characteristics serves as substantial proof of the endogenous amplification mechanisms, where the shocks are not just transmitted but also intensified within the core before spreading to the rest of the system. Apart from that, it implies that the systemic risk in Morocco is also due to the network interdependencies rather than solely the institutional exposures.

A key contribution of this study is to demonstrate that such contagion dynamics, previously emphasized in large advanced financial systems, are also present in an emerging banking system. Moreover, the analysis highlights heterogeneous crisis effects, with relatively weaker systemic amplification during the European sovereign debt crisis, and a notable increase in centrality for certain foreign-linked institutions such as BMCI, reinforcing the role of cross-border transmission channels.

From a policy perspective, this evidence argues against traditional balance-sheet-based regulatory approaches and supports the adoption of a network-based macroprudential policy. The core of transmission mechanisms implies that systemic risk may arise due to a few transmission channels, implying that targeted regulatory actions, such as institution-specific capital buffers, interbank exposure constraints, and network-informed stress testing, on the source of systemic risk amplification tend to mitigate systemic crisis.

This study makes three distinct contributions to existing literature. First, it provides evidence that systemic risk in Morocco is structurally persistent and concentrated within a stable core of systemically important banks. Second, it shows that these institutions act as both individual risk centers and collective amplifiers of financial distress through recursive network effects. Third, it reveals that crisis transmission mechanisms differ across global shock episodes, emphasizing the significance of cross-border linkages and heterogeneous exposure channels in shaping systemic vulnerability.

AUTHOR CONTRIBUTIONS

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