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**Article**

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## Systemic risk spillover effects within the Moroccan banking industry

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### ABSTRACT

This study reveals the hidden systemic risk spillover effects within Morocco's banking industry using marginal effects derived from Conditional Value at Risk, network theory, and systemic risk indicators. Our findings identify Banque Centrale Populaire and Attijariwafa Bank as key propagators of systemic risk, emphasizing their capacity to trigger systemic crises that threaten financial system stability and, consequently, the real economy. These revelations provide crucial insights to develop targeted policy interventions to enhance the resilience of Morocco's banking sector in the face of systemic crises.

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## 1. Introduction

The Moroccan banking sector has endured a series of crises, ranging from the Subprime crisis to the European debt crisis, and more recently, the COVID-19 crisis, highlighting significant threats to its stability. These crises have exposed the fragility of the Moroccan banking system, wherein the collapse of one financial institution during such tense periods heightens systemic risk, potentially triggering a chain of bankruptcies (Brunnermeier et al., 2009). Understanding systemic risk in the Moroccan banking sector is a crucial concern for both theoretical advancement and practical policymakers.

This article's focus is to unveil key contagion patterns, assess the evolution of systemic risk over time, and identifies banks' systemic importance within the Moroccan banking industry. By employing a multi-dimensional approach encompassing quantitative analysis, network theory, and systemic risk indicators, this article provides empirical evidence with major implications for financial stability and economic resilience. Despite the implications of a potential systemic crisis within Moroccan banking system, the attention given to this topic remains limited. Recent publications have investigated the impact of crises on Morocco's banking system, providing new perspectives on quantifying systemic risk. Firano (2015) studied systemic risk within the Moroccan banking industry, utilizing CoVaR and heteroscedasticity models. The author found that Attijariwafa Bank (AWB), Banque Marocaine du Commerce et Industrie (BMCI), and Bank of Africa (BOA) are the Global Systemically Important Banks (G-SIBs) within Morocco and that the systemic risk contagion is pro-cyclical. Nechba (2021) used CoVaR, Marginal Expected Shortfall (MES), and SRISK to measure the contribution of Moroccan banks' systemic risk and concluded that BOA and AWB contribute the most to systemic risk. Moreover, the author deducted that banks with a high level of capital inadequacy contribute more to systemic risk, and as capitalization increases, banks become less susceptible to systemic risk. Duan et al. (2021) used  $\Delta$  CoVaR, size of banking industries and confirmed COVID-19 cases in order to evaluate systemic risk and concluded that that COVID-19 increased systemic fragility within Morocco. Saidane et al. (2021) utilized Distance to Default (DD), K-Nearest Neighbors (KNN) and Consistent Information Multivariate Density Optimizing technique (CIMDO) in order to

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**Table 1.** Research gap analysis on systemic risk within Morocco's banking industry.

Authors	Methods	Time-varying systemic risk	Directional spillover effects
Firano (2015)	VaR, CoVaR, $\Delta$ CoVaR, GARCH	Yes	–
Nechba (2021)	VaR, CoVaR, $\Delta$ CoVaR, MES, SRISK	Yes	–
Duan et al. (2021)	VaR, $\Delta$ CoVaR, MES, SRISK	Yes	–
Saidane et al. (2021)	DD, KNN, CIMDO	Yes	–
This research	VaR, CoVaR, SFI, SNRI, Total Net Connectedness, Network theory indicators	Yes	Yes

investigate systemic risk and argued that a decline in the financial stability of large pan-African groups may trigger contagion effects that could harm the financial stability within countries of West African Economic and Monetary Union.

While existing research has focused on systemic risk exposure, it has overlooked critical aspects such as directional contagion spillovers between Moroccan banks, which provide regulators with crucial insights into the propagation sources and pathways of systemic risk. This gap represents a significant limitation. As summarized in Table 1, our study provides a more granular understanding of risk transmission paths within the Moroccan banking system. This not only enhances theoretical knowledge but also offers practical insights that inform regulatory measures to bolster financial stability and resilience in the face of future crises.

The research question guiding our study is: What are the key contagion paths observed among Moroccan banks, and how does systemic risk evolve within the Moroccan banking system? To address this question, this article utilizes several methodologies, combining statistical models, econometric techniques, and network theory allows for a multi-faceted evaluation of systemic risk, yielding robust insights. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are employed to estimate the Value at Risk (VaR) for each individual Moroccan bank. Building upon this, we utilize Quantile Regression Neural Network (QRNN) method to quantify the Conditional Value at Risk (CoVaR) in order to identify systemic risk contributors and assess their impact on the overall banking system. Leveraging network theory and quantitative network metrics, we analyze the topological importance of Moroccan banks, offering a network perspective on risk transmission. Moreover, we utilize Systemic Fragility Index (SFI), Systemic Network Risk Index (SNRI), and Total Net Connectedness to assess the evolution of systemic risk of the overall banking system.

The findings of this article offer a comprehensive response to the central question driving our study, highlighting the dynamic nature of systemic risk and the vulnerabilities of Morocco's banking system, particularly during times of economic turmoil. Notably, specific banks, such as Banque Centrale Populaire (BCP) and AWB, emerge as main contributors to systemic risk contagion, emphasizing their systemic importance and potential to trigger crises that threaten financial system stability and the real economy. In contrast, Crédit du Maroc (CDM) demonstrates its independence from the Moroccan banking system. In addition, our analysis reveals a significant increase in systemic risk and interconnectedness within the Moroccan banking industry during the Subprime and COVID-19 crises, indicating its vulnerability to economic downturns. Conversely, the impact of the European debt crisis on Morocco's banking system was relatively minor. These findings uncover the root of systemic risk transmissions, identify critical vulnerabilities within the banking system and underscore the necessity of implementing focused regulatory measures to mitigate the risk of systemic crises. Regulators should take targeted actions against these banks to address the potential threats they pose. This could involve imposing higher capital requirements or implementing transaction taxes between systemically important banks to reduce their interconnectedness.

This paper is organized as follows: Section 1 presents the literature review. Section 2 outlines the methods employed. Section 3 details the data utilized. Section 4 delves into the empirical findings and discusses the results. Section 5 highlights the main implications. Finally, Section 6 presents conclusions.

## 2. Literature review

Recent financial crises have emphasized the critical need to advance our understanding of systemic risk, which has become a crucial pillar in guaranteeing financial system stability and, consequently, the health

of the global economy. Due to their exposure and interconnections, the insolvency of a systemically significant financial institution holds the capacity to disrupt the regular operations of the financial system and thus trigger a wide systemic crisis that endangers the global economy.

Various models have been developed to assess systemic risk and assess the stability of financial systems. Chan-Lau (2010) used Co-Risk, network theory, and credit risk portfolio models to measure financial institutions' marginal contributions to risk. The author proposed to impose regulatory capital requirements based on the degree of their interconnections to mitigate in-dependencies and to avoid homogeneity. Brownlees and Engle (2017) introduced the Systemic RISK Index (SRISK), which represents a distinctive framework for quantifying financial institutions' contribution to systemic risk and evaluating the systemic risk within the overall system. SRISK is defined as a function of financial institutions' size, risk, and leverage. It offers a comprehensive analysis, enabling a granular understanding of the impact of individual institutions on systemic risk. Acharya et al. (2017) introduced the Systemic Expected Shortfall (SES) measure that quantifies financial institutions' losses during a broader financial system downturn. Incorporating the institution's leverage and the Marginal Expected Shortfall. The authors empirically demonstrated SES's capability to provide early warning of potential systemic risk during the Subprime crisis. Banulescu and Dumitrescu (2015) introduced the Component Expected Shortfall (CES) approach, which aggregates the *too big to fail* and the *too interconnected to fail* logics, allowing the assessment of financial institutions' contribution to systemic risk. The empirical results demonstrated the CES measure's effectiveness in identifying the Systemic Important Financial Institutions (SIFIs) within a network. Keilbar and Wang (2022) proposed a novel methodology for measuring systemic risk by utilizing QRNN, SFI and Systematic Hazard Index (SHI) to offer an effective evaluation of systemic risk during uncertain economic periods within the USA banking system through various crisis periods. The authors identified a significant systemic risk increase during the Subprime and European debt crises. Naeem et al. (2022) investigated the spillover of systemic risk among the top 10 USA industries from 2007 to 2021 using CoVaR, SFI, SHI, and SNRI. The authors identified the manufacturing industry as a central hub for risk, the telecommunications industry as a disconnected node, and the utilities industry as the most vulnerable during economic turmoil. These insights offer valuable implications for decision makers in mitigating systemic risk dynamics across industries during crisis periods. Zhang et al. (2023a) used DCC-GARCH-CoVaR to model the systemic risk of 33 listed Chinese financial institutions and found that the source of systemic risk is mainly the banking sector and that the leverage ratio is positively correlated with the systemic risk level, which shows that capital structure can effectively reduce systemic risk. Derindere (2023) investigated systemic risk from 2007 to 2022 within the Turkish banking industry. Utilizing the CES approach and the Markov Switching Vector Auto-regressive model, the author identified the major systemic risk sources and highlighted a distinct connection between the rise in systemic risk and the decline in economic growth in periods of financial stress.

The network theory applied to systemic risk management has emerged. Yijun et al. (2023) investigated the influence of COVID-19 crisis on risk contagion among Chinese banks using transfer entropy and social network analysis. The findings reveal a significant increase in inter-bank systemic risk post-COVID-19, with notable shifts in key contagion nodes and an asymmetric contagion effect, especially affecting joint-stock and local financial institutions more than state-owned banks. The research emphasizes the importance of real data over simulations and offers valuable insights for risk prevention and control in the banking sector. Halaj and Hipp (2024) highlighted the dynamic nature of contagion within the banking system, demonstrating its variability over time. The study identifies a surge in contagion during significant crises, such as the Subprime crisis and the COVID-19 pandemic. Chan-Lau (2018) examined the effectiveness of network measures in identifying systemic communities within the USA financial market, utilizing 275 financial institutions' weekly equity returns, covering the period from January 1, 2001, to July 31, 2016. The author demonstrated that centrality measures correctly identify institutions exposed to systemic loss. Gong et al. (2019) proposed several systemic risk measurements combining both Granger causality tests and Principal Component Analysis to capture systemic risk and found that the increase in interconnections within the banking and insurance sectors can provide early warning of potential financial crises. Yang et al. (2020) used the Minimum Spanning Tree (MST) on 88 USA financial institutions' daily closing prices for the period from January 2006 to December 2018 and demonstrated that the insurance sector is systemically important. Furthermore, centrality measures show that J.P. Morgan Chase

is *too connected to fail* institution that dominates the network. Zhang et al. (2021) used the MST based on a time-varying copula function on 22 Chinese financial institutions covering the period from January 2, 2008 to August 20, 2018. The authors identified SIFIs based on network indicators.

### 3. Materials and methods

Utilizing Moroccan banks' log-returns from January 01, 2008, to December 31, 2022, this study follows a four-step methodology. Starting by estimating the VaR using GARCH approaches. Subsequently, the VaR results are used to measure the CoVaR calibrated using the QRNN approach for every Moroccan bank. Third, the effects between pairs of banks are deducted using the partial derivative of the banks' conditional quantiles. Fourth, indicators such as SFI, SNRI, Total Net Connectedness, out-degree centrality and, in-degree centrality were employed to quantify systemic risk. We begin by calculating the logarithmic returns of Moroccan banks listed on the Casablanca Stock Exchange market. Let  $r_{i,t}$  be the logarithmic return of  $i=1,\dots,N$  at time  $t$ , and  $P_{i,t}$  be the stock price of bank  $i$  at time  $t$ .

$$r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad (1)$$

#### 3.1. VaR

Introduced by JP Morgan Chase in 1993, the VaR concept was embraced in its basic form within the Basel II Accord. This method assesses the highest potential losses that a bank may face in severe situations at a chosen confidence level. This precaution ensures that financial institutions cover potential losses in their trading portfolios in 99% of the time (Fernandez, 2003). The literature offers diverse approaches and techniques for assessing VaR, with growing complexity in both the theoretical understanding and computational aspects of these methods. Engle and Manganelli (2004) introduced a new approach, Conditional Autoregressive Value at Risk (CAViaR), which specifies the evolution of the quantiles over time. McNeil and Frey (2000) proposed a novel method for estimating VaR by combining GARCH models and Extreme Value Theory to model volatility tails. Chao (2015) and Härdle et al. (2016) used linear Quantile Regression (QR) on state variables to measure VaR. This evolution underscores the vital role of VaR in strengthening financial institutions against market uncertainty. This study uses GARCH models to determine conditional volatility  $\check{\sigma}_t^2$  and conditional mean  $\check{\mu}_t$ , which are subsequently used in the VaR calculation. Note that  $q_\alpha$  refers to the quantile distribution; these parameters are typically modeled using auto-regressive processes.

$$VaR_{\alpha,t} = \check{\mu}_t + q_\alpha \times \sqrt{\check{\sigma}_t^2} \quad (2)$$

$$\check{\mu}_t = \beta_0 + \beta_1 \cdot r_{t-1} \quad (3)$$

$$\check{\sigma}_t = \omega + \alpha \cdot |r_{t-1}| + \beta \cdot \check{\sigma}_{t-1} \quad (4)$$

Despite being widely adopted in the financial sector, VaR, has been criticized for its perceived inability to effectively address the systemic nature of risk. This criticism stems from the VaR's exclusive focus on individual institutions in isolation. Consequently, there is a growing interest in alternative risk metrics that can overcome the limitations of VaR and provide systemic risk assessment.

#### 3.2. CoVaR

CoVaR emerges as a crucial metric in the financial risk management field, offering insight into the potential vulnerabilities of individual banks within the financial system during periods of market stress.

Numerous approaches have been used to calibrate CoVaR (Bernardi et al., 2013; Cao, 2013; Mainik & Schaanning, 2014). The CoVaR approach represents the VaR of a specific bank conditioned on other banks being at their VaR level. Moreover, the CoVaR for bank  $j$  given that other banks are at their VaR level  $\tau \in (0,1)$  at time  $t$ , is expressed by:

$$P(r_{j,t} \leq \text{CoVaR}_{j,t}^\tau \mid r_{-j,t} = \text{VaR}_{-j,t}^\tau = \tau) \quad (5)$$

This study uses the QRNN approach to calibrate the CoVaR. We begin by defining the neural network formula given by [Equation 6](#). Consider  $K$  vectors of features  $X_{-j,t}$  and a target variable  $X_{j,t}$  with  $t = 1, 2, \dots, n$ . Let  $\epsilon_t$  be the error term;  $\phi$  represents the sigmoid tangent activation function;  $\omega_{k,m}^h$  indicates the hidden layer weights connecting the input and hidden layers  $M$ ;  $b_m^h$  denotes the hidden-layer bias;  $\omega_m^o$  and  $b^o$  represent the weights of the output layer and output layer bias, respectively. We denote  $M_n$  as the number of nodes within a hidden layer. Cannon (2011) employed the R programming language to incorporate QRNN, integrating techniques such as bootstrap aggregation and left censoring. The author demonstrated that the QRNN overcome the performance of the baseline QR.

$$\begin{aligned} X_{j,t} &= h_\theta(X_{-j,t}) + \epsilon_{j,t} \\ &= \sum_{m=1}^{M_n} \omega_m^o \phi \left( \sum_{k \neq j}^K \omega_{k,m}^h X_{k,t} + b_m^h \right) + b^o + \epsilon_{j,t} \end{aligned} \quad (6)$$

The CoVaR is obtained by replacing  $X_{-j,t}$  vectors with their corresponding  $\text{VaR}_{-j,t}^\tau$  vectors, where  $\check{f}_\theta$  refers to the optimal estimate of the neural network:

$$\text{CoVaR}_{j,t}^\tau = \check{h}_\theta(\text{VaR}_{-j,t}^\tau) \quad (7)$$

The CoVaR provides insights into the risk of a specific institution by considering other institutions at their VaR level. To explore the risk spillover between pairs of banks and delve into the assessment of direct interconnections, we employ marginal derivatives to infer marginal effects.

### 3.3. Marginal effects

To analyze the risk transmission channels among Moroccan banks, we conduct partial derivatives on the conditional quantile for each bank with respect to others. This procedure allows for a granular understanding of Moroccan banks' interconnections and their impact on the financial system.

$$\frac{\partial Q^\tau(X_{j,t} \mid X_{-j,t})}{\partial X_{i,t}} = \frac{\partial}{\partial X_{i,t}} \sum_{m=1}^{M_n} \omega_m^o \phi \left( \sum_{k \neq j}^K \omega_{k,m}^h X_{k,t} + b_m^h \right) + b^o \quad (8)$$

With the derivative of sigmoid tangent activation function in the QRNN:

$$\frac{\partial Q^\tau(X_{j,t} \mid X_{-j,t})}{\partial X_{i,t}} = \sum_{m=1}^{M_n} \omega_m^o \omega_{i,m}^h \phi' \left( \sum_{k \neq j}^K \omega_{k,m}^h X_{k,t} + b_m^h \right) \quad (9)$$

and,

$$\phi'(z) = \frac{2}{\left( \exp \frac{-z}{2} + \exp \frac{z}{2} \right)^2} \quad (10)$$

The marginal effects at extreme scenarios are presented as follows:

$$\frac{\partial Q^\tau(X_{j,t} | X_{-j,t})}{\partial X_{i,t}} \Big|_{X_{-j,t} = VaR_{-j,t}^\tau} = \sum_{m=1}^M \omega_m^o \omega_{i,m}^h \phi' \left( \sum_{k \neq j}^K \omega_{k,m}^h VaR_{k,t}^\tau + b_m^h \right) \quad (11)$$

The findings are employed to construct a network for several periods by aggregating the marginal effects observed. The directed marginal effects between banks are gathered into an adjacency matrix that represents the spillover effects.

$$A_t = \begin{bmatrix} 0 & a_{12,t} & \dots & a_{1K,t} \\ a_{21,t} & 0 & \dots & a_{2K,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{K1,t} & a_{K2,t} & \dots & 0 \end{bmatrix} \quad (12)$$

Self-effects are not considered by taking  $a_{j,t} = 0$  if  $j = i$ . For instance the adjacency matrix is used to construct a directed weighted network, highlighting the interconnections within the banking industry and investigating potential systemic risk propagation.

$$a_{ji,t} = \begin{cases} \left| \frac{\partial Q^\tau(X_{j,t} | X_{-j,t})}{\partial X_{i,t}} \right| X_{-j,t} = VaR_{-j,t}^\tau, & \text{if } j \neq i \\ 0, & \text{if } j = i \end{cases} \quad (13)$$

### 3.4. Systemic risk and spillovers analysis

To delve deeper into assessing the systemic risk of Morocco's banks. Various network metrics were used in this study. Diebold and Yilmaz (2014) presented the Total Net Connectedness at time  $t$  as the summation of marginal effects, which is a crucial indicator that provides a comprehensive assessment of the overall level of connections and dependencies among a financial network.

$$C_t = \frac{1}{K} \sum_{i=1}^K \sum_{j=1}^K a_{ji,t} \quad (14)$$

In addition, the SNRI is used to quantify the tail connectedness at lower quantile levels by combining the marginal spillover effects and the VaRs and CoVaRs levels, which provides a full picture of systemic risk evolution within a financial system. This method offers insights into the specific contributions of each bank to systemic risk and its potential impact on financial system stability.

$$SNRI_t = \sum_{i=1}^K \sum_{j=1}^K \left( 1 + |VaR_{i,t}^\tau| \right) \cdot \left( 1 + |CoVaR_{j,t}^\tau| \right) \cdot a_{ji,t} \quad (15)$$

The Total Net Connectedness and SNRI reflect the extent of the inter-linkages within a system. To assess the specific systemic risk vulnerability of each bank, it is necessary to employ the SFI, which helps evaluate each bank's isolated systemic exposure.

$$SFI_{j,t} = \sum_{i=1}^K \left( 1 + |VaR_{i,t}^\tau| \right) \cdot a_{ji,t} \quad (16)$$

Network measures provide information about the positions of the nodes within a network and serve in the identification of *too connected to fail* financial institutions (Gofman, 2017). The centrality measure represents a node's direct connections with other nodes in a network and serves as a metric to quantify

the influence of the node within the network (Freeman et al., 2002). This study uses out-degree centrality, which is a key indicator in systemic risk analysis, shedding light on how extensively a bank influences other entities within a financial network. In the context of systemic risk, it measures the number of connections from a specific bank to others. This metric assist regulators and policymakers in pinpointing institutions with significant out-degree centrality.

$$C_{\text{out}}(i) = \frac{\text{Outgoing Edges from Node } i}{\text{Total Number of Nodes} - 1} \quad (17)$$

Moreover, in-degree centrality has emerged as an essential metric in the assessment of systemic risk within financial networks, offering valuable insights into the vulnerability of individual banks. High in-degree centrality signifies that a bank is a central hub for systemic interactions, potentially making it more susceptible to external shocks or disturbances. Understanding in-degree centrality is essential for identifying key receivers of systemic influences.

$$C_{\text{in}}(i) = \frac{\text{Incoming Edges to Node } i}{\text{Total Number of Nodes} - 1} \quad (18)$$

#### 4. Data

This article focuses on the Moroccan banking institutions registered on the Casablanca Stock Exchange market as in [Table 2](#): Attijariwafa Bank, Banque Centrale Populaire, Bank of Africa, Banque Marocaine du Commerce et Industrie, Crédit Immobilier et Hotelier, and Crédit du Maroc. We consider the daily log returns from January 01, 2008 to December 31, 2022, covering the Subprime crisis (September 2008–August 2009), the European debt crisis (July 2011–June 2012), and the COVID-19 crisis (March 2020–May 2021).

[Table 3](#) summarizes the statistical descriptive of the data used. It is apparent that most kurtosis values exceed three. Furthermore, the Jarque-Bera (JB) test *p* values indicate that the does not follow a normal distribution. Additionally, the Augmented Dickey–Fuller (ADF) test *p* values display the stationarity of the data.

To ensure the robustness of the modeling process, this study employs a two-step validation approach. First, rigorous testing was conducted using the (Kupiec et al., 1995) test to evaluate the VaR model for each bank. The outcomes of these tests, summarized in [Table 4](#), demonstrate the adequacy of the VaR models. For all banks, the computed Probability of Failure (POF) values consistently met the critical value threshold, confirming the statistical robustness of each bank's VaR model.

Furthermore, the Diebold–Mariano (DM) test (Diebold & Mariano, 2002) was employed to compare the CoVaR performance of the QRNN model with that of a baseline linear QR model. The results in [Table 5](#)

**Table 2.** List of the Moroccan banks.

Bank	Symbol
Attijariwafa Bank	AWB
Banque Centrale Populaire	BCP
Bank of Africa	BOA
Banque Marocaine du Commerce et Industrie	BMCI
Crédit Immobilier et Hotelier	CIH
Crédit du Maroc	CDM

**Table 3.** Descriptive statistics.

	Max	Min	SD	Mean	Skew	Kurt	JB. <i>p</i> value	ADF. <i>p</i> value
AWB	6.04	-17.10	1.30	0.01	-0.86	13.03	0.00	0.00
BOA	9.50	-10.43	1.53	-0.01	-0.01	4.98	0.00	0.00
CIH	7.88	-10.49	1.87	-0.01	-0.09	2.35	0.00	0.00
BCP	9.53	-10.51	1.20	0.02	-0.21	8.96	0.00	0.00
BMCI	9.51	-22.50	2.04	-0.01	-0.48	7.53	0.00	0.00
CDM	9.51	-10.52	1.93	-0.01	-0.12	4.52	0.00	0.00

**Table 4.** Kupiec test results.

Bank	POF	Critical Value $\chi^2$	Test outcome
AWB	0.22	3.84	Accept
BCP	2.69	3.84	Accept
BOA	1.09	3.84	Accept
CIH	2.31	3.84	Accept
BMCI	3.41	3.84	Accept
CDM	3.70	3.84	Accept

**Table 5.** Diebold-Mariano test comparing the QRNN against the linear baseline QR model.

	AWB	BCP	BOA	CIH	BMCI	CDM
DM statistic	-2.73	-2.24	-3.30	-10.19	-3.82	-4.37
p value	0.01	0.02	0.00	0.00	0.00	0.00

indicate that the QRNN model significantly outperforms the baseline linear QR model for all the Moroccan banks at a 5% significance level. These findings affirm the robustness of the CoVaRs calibration.

The two-step validation process effectively ensures the robustness and accuracy of our modeling approach. Navigating into the Results section, our focus shifts toward a detailed exploration of the empirical findings. This phase involves meticulous examination of the data, aiming to uncover patterns and insights to understand systemic risk within the Moroccan banking system.

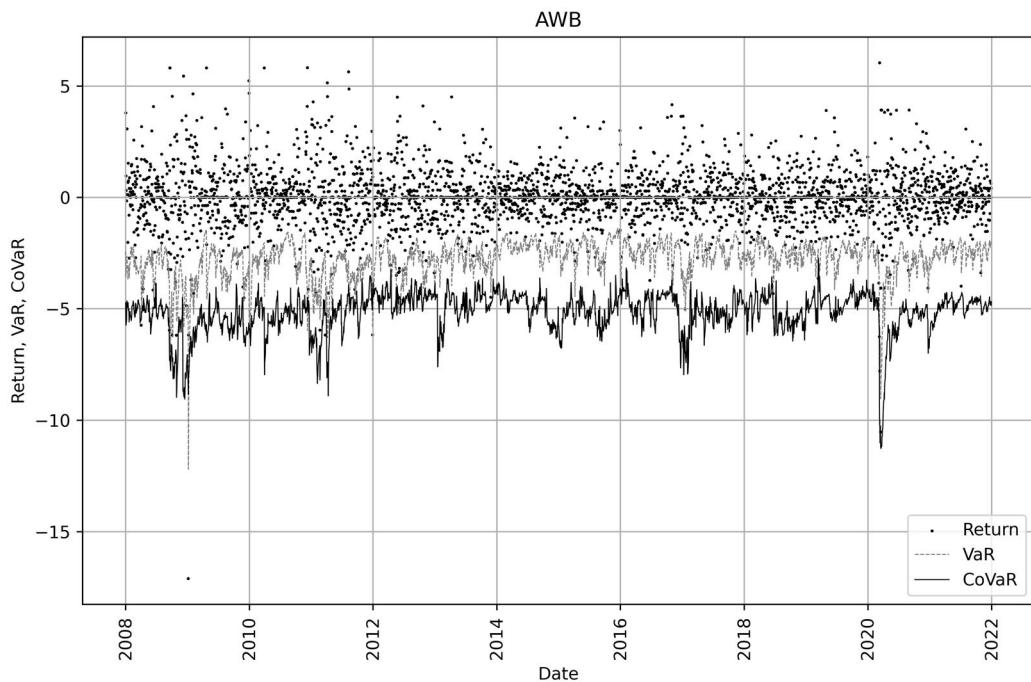
## 5. Results and discussion

To address the defined research question, this study employs an innovative methodology. Firstly, we measure the VaR for each Moroccan bank using GARCH models, providing a foundational understanding of individual bank risk. Subsequently, these VaRs are utilized in the CoVaR calibration, employing the QRNN method at the quantile level of  $\tau = 1$ . This step allows for a precise assessment of systemic risk by capturing the CoVaR and discerning the extent of risk transmission between pairs of banks. Thirdly, partial derivatives are computed on the quantile function derived from the QRNN, allowing the identification of contagion paths among Moroccan banks. Moreover, networking indicators are used allowing to assess the topological importance of banks within the Moroccan banking system. Finally, SFI, SNRI and Total Net Connectedness indicators are employed to evaluate the systemic risk evolution over time, providing a comprehensive analysis of the resilience and dynamics of the Moroccan banking system.

Using multiple risk measures (VaR, CoVaR) allows for a comprehensive evaluation of individual bank risk and systemic risk over time. Time series analysis using these metrics reveals notable spikes coinciding with major global financial crises. [Figure 1](#) illustrates the results for AWB, demonstrating a consistent pattern in both VaR and CoVaR throughout the observed period. During non-crisis periods, stability is evident, while the Subprime crisis and the COVID-19 crisis witness significant escalations in both risk measures, indicating a pronounced increase in systemic risk. Additionally, persistent spikes during 2011 reflects the impact of the European debt crisis. Importantly, this pattern is not unique to AWB; similar trends are observed across the majority of Moroccan banks, as depicted in [Figure 2](#).

The innovative aspect of our research lies in our comprehensive analysis of spillover effects within the banking industry, utilizing the directional pairwise effects of risk spillovers deduced from QRNN estimations. [Figure 3](#) illustrates the spillover effects matrix, highlighting the connections between different Moroccan banks. A higher value of the off-diagonal entries indicates a more significant spillover effect. This article provides graphical insight into the potential risk spillover between banks, allowing the identification of key relationships, evaluating risk exposures, and anticipating potential crises. Importantly, the findings reveal that spillover effects were more pronounced during the Subprime crisis and the COVID-19 crisis than during the entire study period. Meanwhile, during the European debt crisis, Moroccan banks experienced minimal marginal effects, marking a period characterized by the absence of significant impacts.

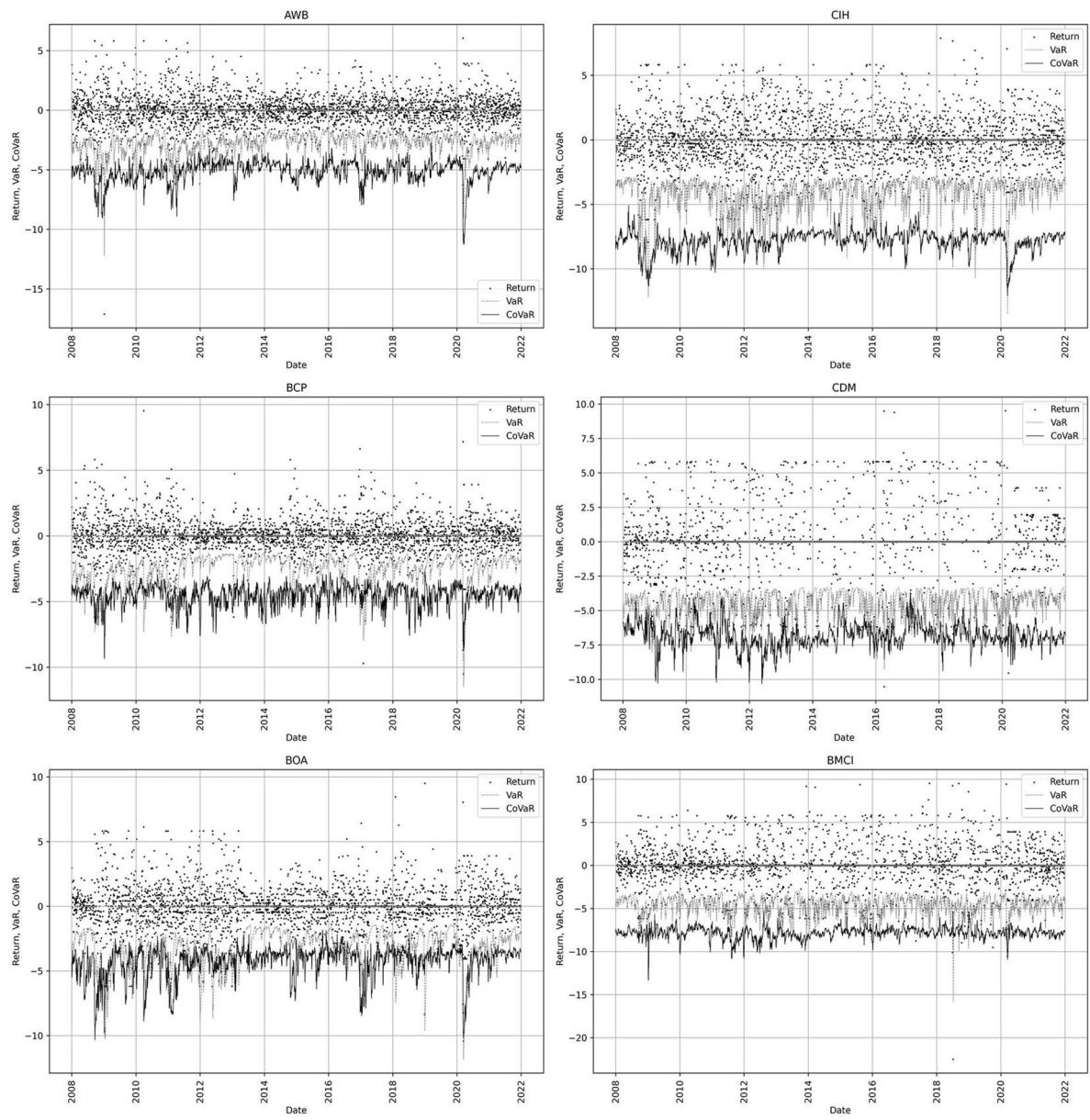
To delve further into the analysis, utilizing the derived mean of the marginal effects, a directed weighted network was constructed for each studied period, as shown in [Figure 4](#). Note that  $a_{j,i} > 0.4$  is considered to emphasize only significant spillovers. Additionally, the size of the nodes is determined by



**Figure 1.** Plot of VaR (dashed grey line), CoVaR (black line), log-returns (black dots) of AWB.

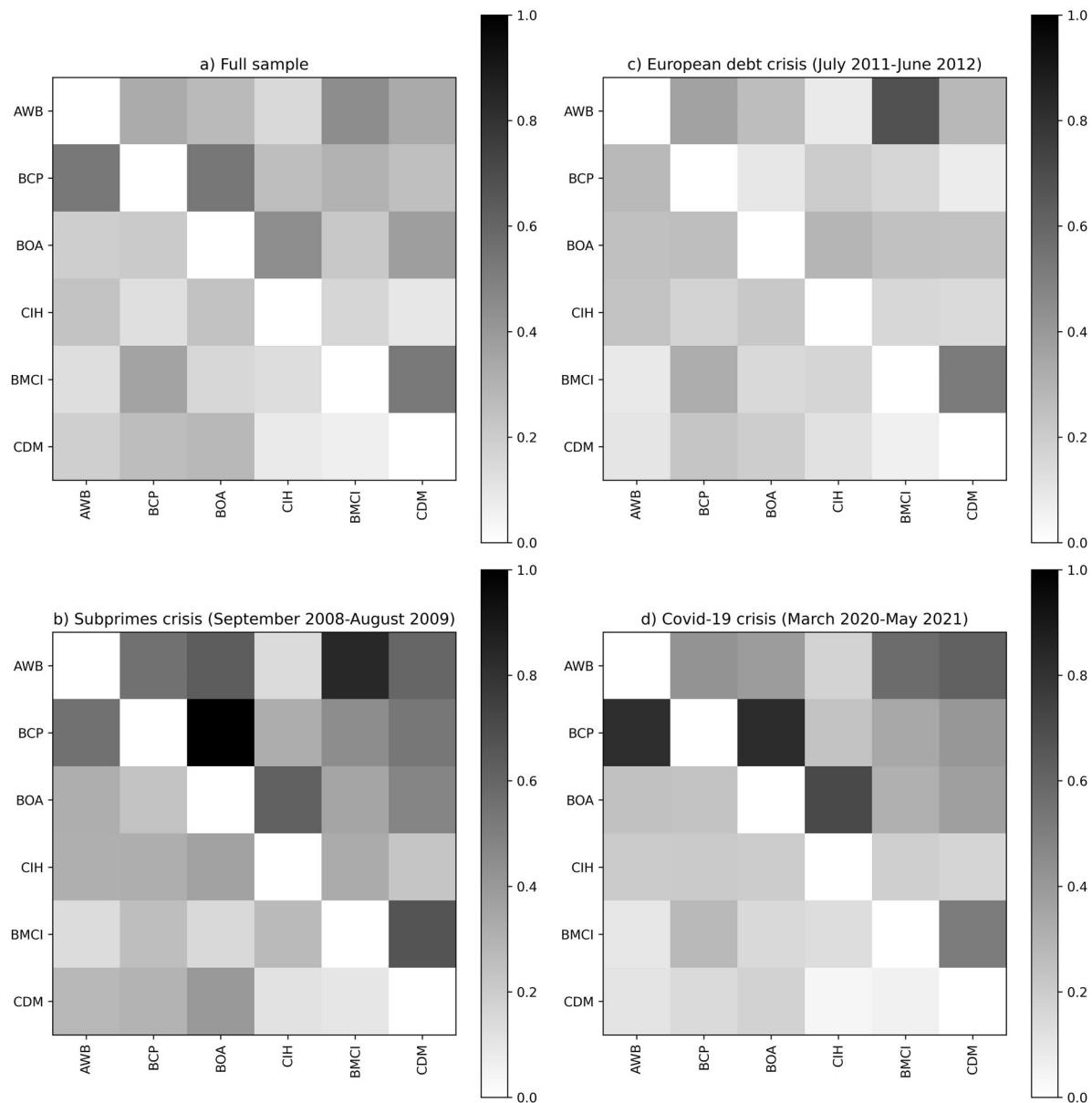
their outgoing effects; the greater the impact on the system, the larger is the node size. Furthermore, the widths of the edges are determined by their respective weights. The findings reveal a notable increase in inter-connectivity among banks during the Subprime crisis and the COVID-19 crisis, amplifying systemic risk spillover effects. Conversely, the European debt crisis had a limited impact on the Moroccan banking system. Notably, discernible clusters persist throughout the studied periods, indicating asymptotic dependencies between banks during extreme events.

First, examining the full sample network, our analysis reveals significant spillover effects from BCP toward AWB and BOA, underscoring their pivotal roles within the network. Notably, the impacts of BMCI on CDM, AWB on BMCI, and BOA on CIH are pronounced. Interestingly, BCP stands out as the only bank with no significant spillover effect pointing toward it. These inter-dependencies underscore the complexity of financial interactions within the observed network. Second, during the Subprime crisis, we observe a notable escalation in the influence of the BCP and the AWB, extending to a larger set of banks. Notable in this context is the continuous impact of AWB on BMCI, along with the influence of BCP on BOA and BMCI on CDM and BOA on CIH. These enduring dynamics emphasize the complexity of these interrelationships. The banking industry witnessed the development of numerous interconnections during this period. Third, during the European debt crisis, a consistent influence was observed between AWB and BMCI, as well as between BMCI and CDM. Simultaneously, the spillover effects involving other banks approach their minimum levels. Fourth, COVID-19 crisis underscored a notable surge in spillovers effects. The influence exerted by BCP on other Moroccan banks is particularly pronounced, along with the substantial impact of AWB on all banks. Noteworthy effects encompass the influence from BOA to CIH and from BMCI to CDM. The existence of asymptotic dependencies among numerous pairs of banks is discernible, indicating the absence of complete co-monotonicity of risks. Dependencies between the directed pairs BCP-AWB, BCP-BOA, AWB-BMCI, BOA-CIH, and BMCI-CDM were observed several times across the studied periods, highlighting their consistent connections. Moreover, the CIH and CDM are the only banks that do not have a significant direct influence on other banks, exhibiting neutral effects throughout the study period. This may help regulators monitor potential channels of transmission within the banking system. These asymmetric relations highlight the potential for a substantial loss in one bank that could lead to a significant loss in another bank. These findings are in the same order as the results of Said et al. (2023), mentioning that CDM indicates a lack of dependence on the system and the pairs BCP-ATW and ATW-BOA show a significant interdependence, highlighting that the loss of one of them can trigger a significant loss in the other.



**Figure 2.** Plot of VaR (dashed grey line), CoVaR (black line), log-returns (black dots) of the Moroccan banks.

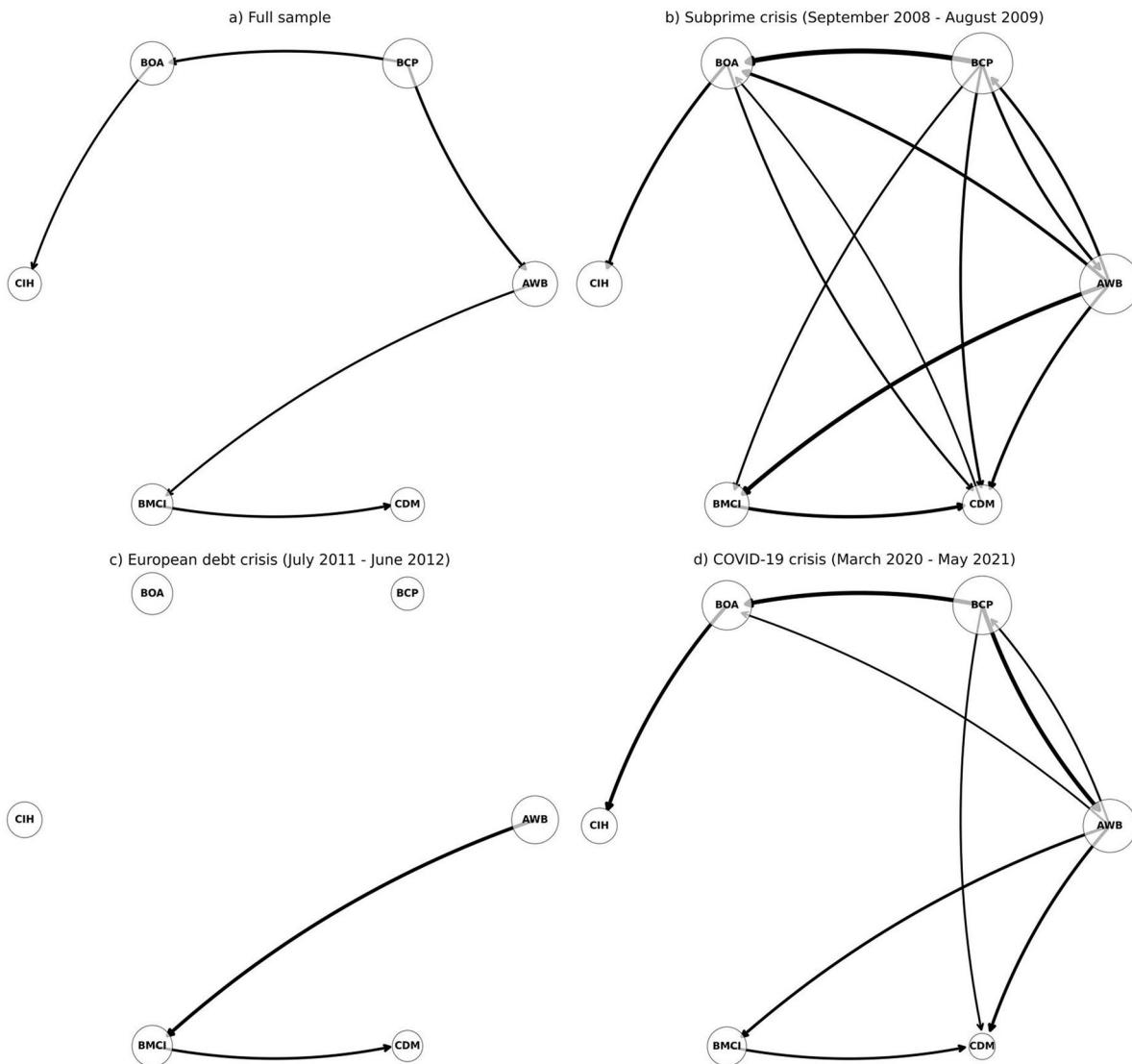
The systemic importance of an institution within a financial network is crucial, and our analysis focuses on assessing this importance through topological measures. Out-degree centrality serves as a robust approach for assessing the influence of individual banks on the interconnected network, capturing the extent to which a given bank transfers risk to other financial institutions. Our findings, as presented in [Table 6](#), highlight the remarkable out-degree centrality scores attributed to AWB and BCP, indicating their substantial influence on other banks. This influence is likely a result of their extensive financial linkages or strategic market positions, positioning them as pivotal nodes in the network. Additionally, [Table 7](#) illuminates the recipients of risk transmissions within the financial network. Notably, CDM and BOA consistently occupy top positions in in-degree centrality indicator, particularly during the Subprime and COVID-19 crises. This highlights their heightened susceptibility to the risk behaviors and activities of their counterparts in the system. While BCP and AWB are identified as influential in spreading risk to other banks, our findings underscore the distinct exposition of CDM and BOA to risks emanating from their peers in the Moroccan banking system. The observed increase in both out-degree centrality and in-degree centrality during the Subprime and COVID-19 crises provides valuable insights for regulators seeking to implement effective measures to improve the stability of the Moroccan banking system.



**Figure 3.** Marginal effect between the Moroccan banks.

To individually assess the systemic risk exposure of Moroccan banks, we utilized SFI as a key metric in our analysis. This allowed for a granular evaluation of each bank's vulnerability to systemic shocks and its potential contribution to overall financial instability. Figure 5 reveals two notable spikes corresponding to the Subprime crisis and the COVID-19 crisis across almost all Moroccan banks, which refer to an increase in the Moroccan banks' systemic risk fragility. These results align with the empirical findings in the literature. Louati et al. (2022) used network theory and Markov chains to demonstrate that systemic risk increased significantly during the COVID-19 crisis, especially after the lockdown. Belcaid and El Ghini (2019) demonstrated an increase in connectedness within the Morocco banking system during the Subprime crisis and returning to a stable pattern in the aftermath. Beraich and El Main (2022) utilized the DY approach on Morocco's financial institutions' daily stock prices. They observed that the COVID-19 crisis increased the volatility spillover index. Furthermore, they identified varying degrees of spillover effects between every Moroccan bank and the sectoral banking index both before and after the COVID-19 crisis.

Table 8 displays the SFI average for every crisis period, offering insights into the tail effects within the banking system. Notably, the analysis reveals that AWB stands out as the primary source of systemic risk,



**Figure 4.** Time average of risk spillover effects across Moroccan banks.

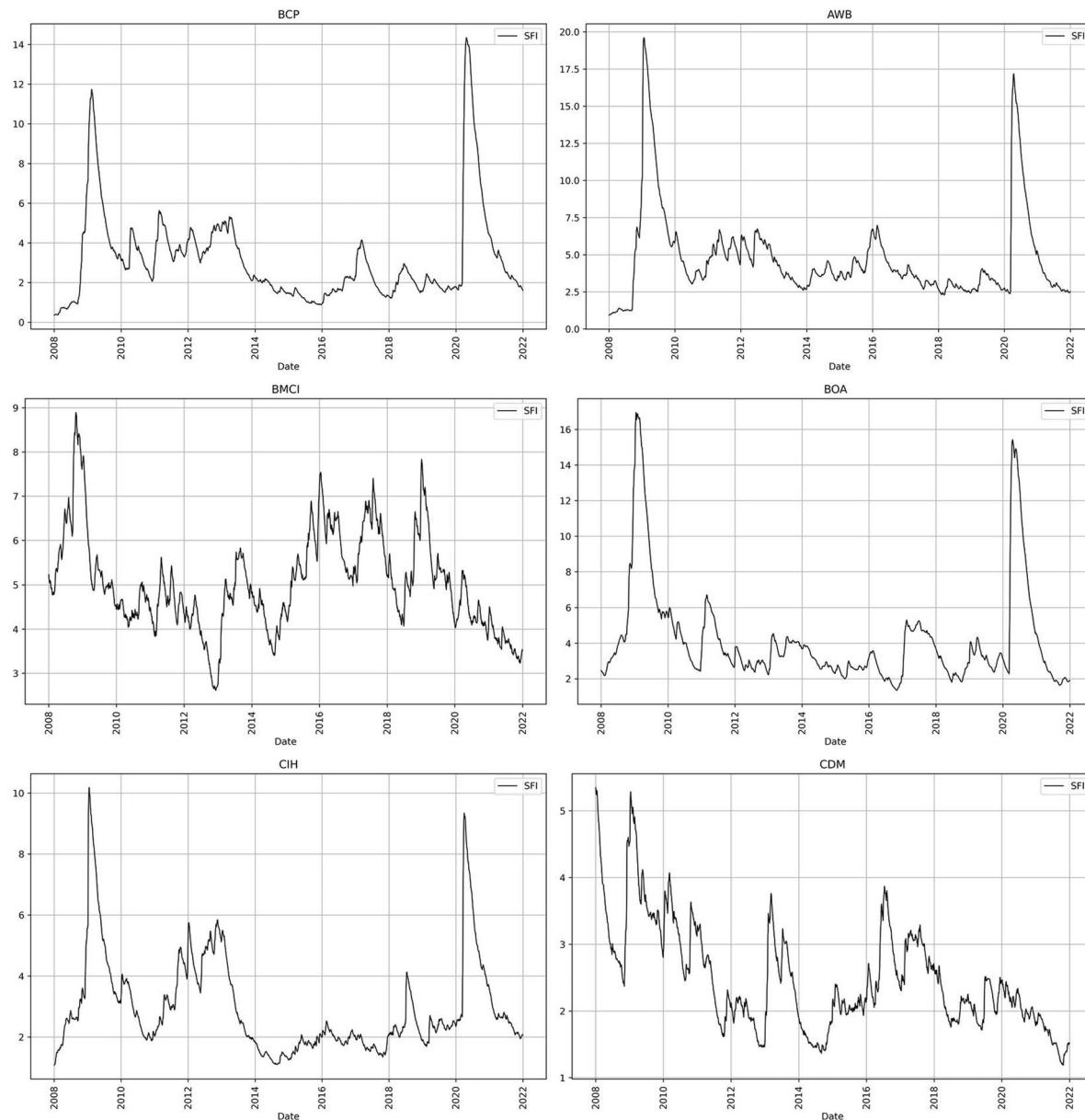
**Table 6.** Out-degree centrality across Moroccan banks.

Rank	Subprime		European debt		COVID-19	
	Symbol	Out-degree	Symbol	Out-degree	Symbol	Out-degree
1	BCP	2.98	AWB	1.74	BCP	2.73
2	AWB	2.88	BOA	1.33	AWB	2.26
3	BOA	2.09	BMCI	1.29	BOA	1.95
4	CIH	1.62	CIH	0.96	BMCI	1.21
5	BMCI	1.55	BCP	0.84	CIH	1.01
6	CDM	1.24	CDM	0.73	CDM	0.54

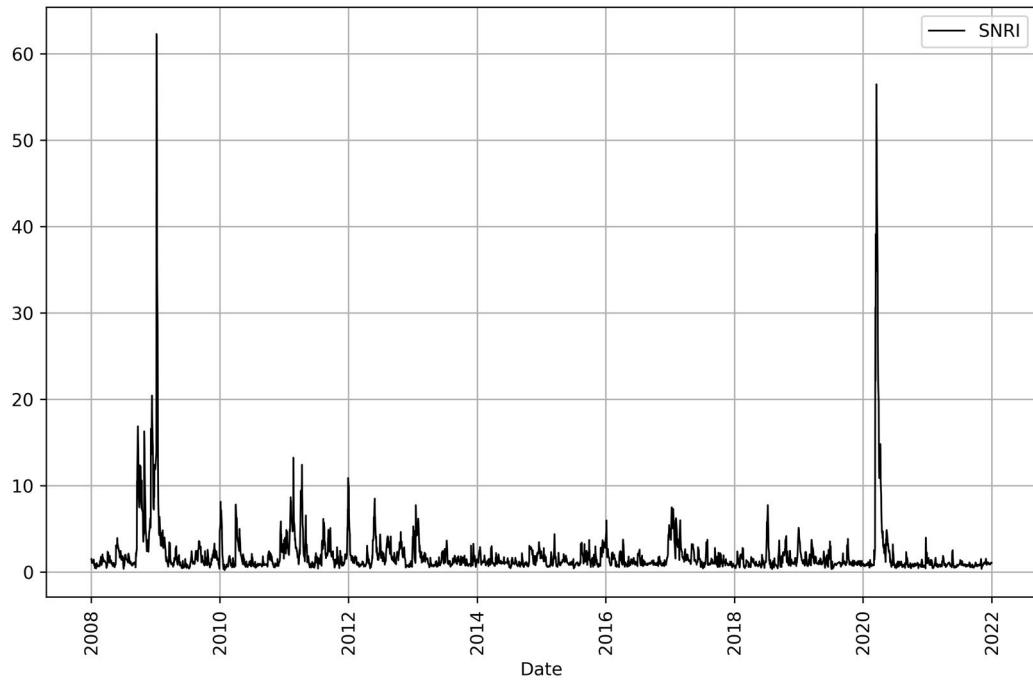
consistently maintaining the highest fragility levels across different periods. Conversely, the CDM demonstrates a level of independence from the system, indicating that the bank is less likely to trigger a crisis within the banking system. The significant risk emanating from AWB underscores the necessity of specific regulatory measures designed to mitigate its relative risk. To provide a comprehensive understanding of the banking system's resilience, we investigated additional metrics. The SNRI, as introduced by Keilbar and Wang, (2022), emerged as a crucial metric capturing lower tail connectedness and offering nuanced insights into time-varying systemic risks confronting the entire system. Figure 6 displays the smoothed SNRI of the Moroccan banking system, revealing important spikes during the Subprime and COVID-19 crises, along with moderate spikes during the European debt crisis, emphasizing the interdependent nature of the Moroccan banking system with global financial system changes. Notably, the

**Table 7.** In-degree centrality of the Moroccan banks.

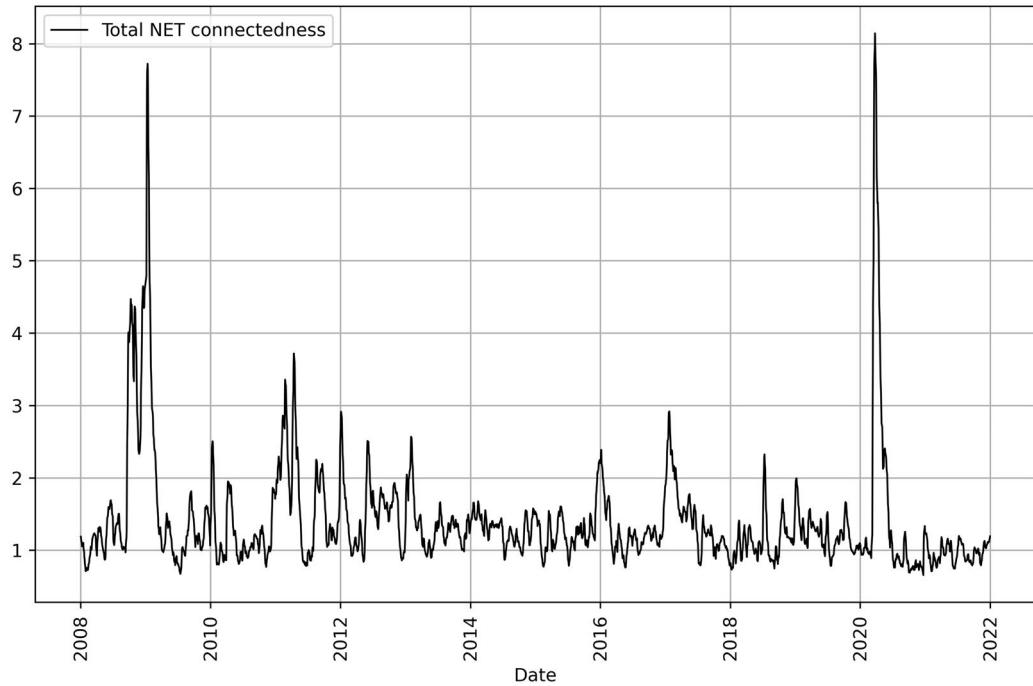
Rank	Subprime		European debt		COVID-19	
	Symbol	In-degree	Symbol	In-degree	Symbol	In-degree
1	BOA	2.66	BCP	1.39	CDM	2.16
2	CDM	2.61	BMCI	1.36	BOA	1.81
3	BMCI	2.15	CDM	1.31	BMCI	1.81
4	BCP	1.72	AWB	0.99	AWB	1.58
5	AWB	1.67	BOA	0.96	BCP	1.34
6	CIH	1.53	CIH	0.89	CIH	1.33

**Figure 5.** Time varying SFI of the Moroccan banks.**Table 8.** Average SFI across Moroccan banks.

Rank	Subprime		European debt		COVID-19	
	Symbol	SFI	Symbol	SFI	Symbol	SFI
1	AWB	8.82	AWB	6.02	AWB	7.75
2	BOA	8.61	CIH	4.47	BOA	7.13
3	BMCI	6.09	BMCI	4.40	BCP	7.08
4	BCP	5.05	BCP	3.99	CIH	4.62
5	CIH	5.05	BOA	3.55	BMCI	4.21
6	CDM	3.24	CDM	1.93	CDM	1.85



**Figure 6.** Time varying SNRI of Morocco's banking system.



**Figure 7.** Time varying total net connectedness of Morocco's banking system.

pattern remains stable during non-crisis periods, suggesting a robust underlying structure that undergoes fluctuations in response to economic turmoil, further highlighting its susceptibility to external shocks.

Figure 7 illustrates the time-varying smoothed Total Net Connectedness indicator, revealing three significant spikes that correspond to the Subprime crisis, European debt crisis, and COVID-19 crisis. The results demonstrate that the Moroccan banking system tends to enhance interrelations and increase connectivity during periods of crisis. The positive correlation between interconnectedness and systemic

risk underscores the need for a deeper understanding of the complex inter dependencies within the Moroccan banking system. Indeed, connectivity is closely associated with the stability of the financial system. This association is grounded in the hypothesis that financial connectivity enhances risk-sharing among interconnected financial institutions, promoting the overall stability of the system. Acemoglu et al. (2015) argued that banks are inclined to foster closer interrelations to share risk and fortify their collective resilience during extreme events. Similarly, the authors noted that financial interconnections do not guarantee financial system stability. Rather, in the presence of large shocks, these interconnections may facilitate the spread of the financial contagion within the network. Martinez-Jaramillo et al. (2019) emphasized the importance of interconnectedness in comprehending systemic risk and deliberated on the optimal level of connectivity to improve the stability of the financial system. Haldane (2013) demonstrated that highly interconnected financial networks may serve as shock absorbers during crises and that connectivity triggers stability; however, beyond a certain level, these interconnections may amplify the propagation of risk. The observed surge in systemic risk and interconnections within the banking system during extreme events is not unique to Moroccan banks; rather, it is a phenomenon well documented across numerous countries and regions (Zhang et al., 2023b; Keilbar & Wang, 2022; Baumöhl et al., 2022; Zhou et al., 2020).

This study incorporates a forward-looking analysis wherein the CoVaR of each bank is computed, considering a – 20% decline in other banks (unprecedented scenario in Morocco). By forecasting potential spillover effects, this article reveals systemic risk spillover paths and sheds light on the relative significance of each bank. It anticipates implications and provides actionable recommendations for regulators to mitigate these risks during tense scenarios. Figure 8 illustrates the systemic risk spillover effects among Moroccan banks during the stress period, highlighting their interconnected nature and contagion pathways. This analysis delves deeply into these interconnections, emphasizing their implications for financial stability and risk management. Among the banks, BCP and AWB are identified as the most influential, followed by BMCI, CIH, CDM, and BOA, based on out-degree centrality rankings. BCP

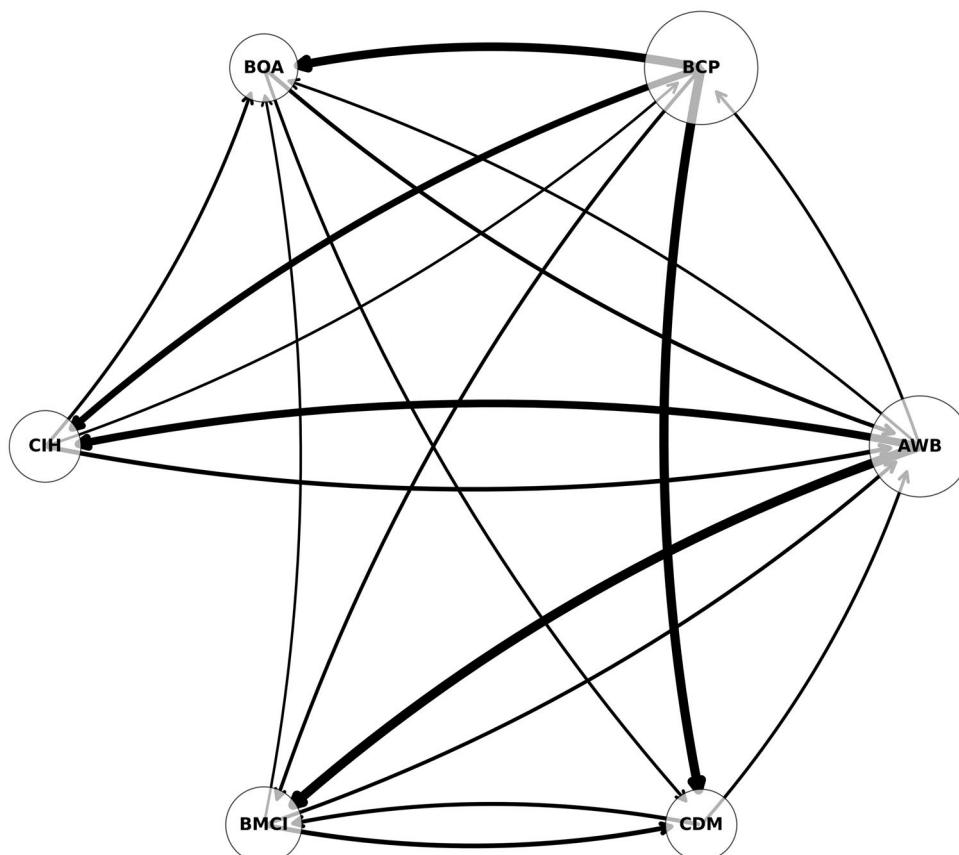


Figure 8. Network of systemic risk spillovers during the stress period.

and AWB emerge as pivotal nodes in the network, exhibiting the highest out-degree centrality, which signifies their substantial influence within the system. In contrast, BMCI, CIH, CDM, and BOA exhibit lower out-degree centrality, suggesting a relatively lesser role in the network. BCP and AWB are particularly crucial as they exert substantial spillover effects on the Moroccan banking system, capable of propagating financial stress extensively. Their central roles imply that any adverse developments affecting BCP and AWB could potentially escalate into a systemic crisis. While BMCI, CIH, CDM, and BOA also contribute to the network dynamics, their spillover effects are generally less pronounced compared to BCP and AWB.

While this study offers valuable insights, it is important to acknowledge its limitations. One key constraint is our reliance on stock market data, which may not fully capture the multifaceted nature of systemic risk. Systemic risk can manifest in various forms beyond what is observable through stock prices, given its inherent complexity. This reliance may overlook critical factors such as interbank operations, off-balance-sheet activities, and market sentiment, which also contribute to systemic risk. Furthermore, the exclusive focus on Moroccan banks limits the generalizability of the findings. Systemic risk extends beyond the banking sector and can affect other financial institutions, such as insurance companies, investment firms, and non-bank financial entities. This narrow focus may not provide a comprehensive picture of systemic risk within the broader financial ecosystem. To address these limitations, future research could incorporate a broader range of data sources, such as interbank lending data, and macroeconomic indicators, to provide a more granular view of systemic risk. Additionally, expanding the scope of the study to include other types of financial institutions and sectors would offer a more comprehensive understanding of systemic risk. Methodological advancements, such as the use of deep learning and more complex networks, could enhance the analysis of systemic risk and its implications. By integrating diverse data and methodologies, researchers can deepen the understanding of systemic risk.

## 7. Implications

The findings of this study hold important implications for both theoretical and managerial practices within the systemic risk management field. By employing a robust methodology, this research contributes to the existing body of knowledge in several key ways. This study explores the spillover effects and network dynamics within Morocco banking industry, which provide valuable insights into the systemic risk propagation path and complex interrelations among Moroccan banks. Furthermore, this study enhances our understanding of systemic risk dynamics within the Moroccan banking sector, particularly during times of economic turbulence.

From a practical perspective, this study offers actionable insights for regulatory bodies. The identification of specific banks, notably AWB and BCP, as potential triggers for systemic crises underscores the urgency for targeted regulatory measures. In light of these findings, regulatory authorities should consider implementing higher capital and liquidity buffers to enhance these banks' capacity to absorb shocks without transmitting risk throughout the entire network. Enhancing transparency and reporting is also critical for improved risk assessment and management. Requiring comprehensive disclosure of risk exposures, particularly for AWB and BCP, will empower regulators to make more informed decisions. Furthermore, it is imperative to recognize the increasing connectivity during crises. Regulators can leverage this insight to implement proactive measures aimed at maintaining a delicate equilibrium of connectedness to increase stability (Hussain et al., 2023). This may include conducting periodic stress testing exercises to assess the resilience of the banking system to various shock scenarios, imposing limits on excessive interconnectedness, and implementing financial transaction taxes between G-SIBs to limit their interconnections. By adopting these measures, regulators can reduce the likelihood of contagion and systemic collapse, thereby safeguarding the stability of the Moroccan banking system.

This study builds upon existing research by extending empirical findings on systemic risk dynamics. By analyzing systemic risk evolution and contagion spillovers, it advances our understanding of systemic risk transmission mechanisms within Moroccan banking system.

## 8. Conclusion

This study delved into the systemic risk inherent to the Moroccan banking system. Initially, we employ GARCH models to calibrate the VaR measure for each bank. Following this, the VaR vectors are utilized to calibrate the CoVaR measure of each bank using the QRNN approach. Finally, this study employed the SFI, SNRI, Total Net Connectedness, out-degree centrality, and in-degree centrality to understand the systemic importance of Moroccan banks during crisis periods. The major findings are presented as follows:

First, this study provides evidence of the widespread impact of both the Subprime crisis and the COVID-19 crisis on Moroccan banks, underscoring the significant repercussions these global financial events had on the Moroccan banking sector. Moreover, this study reveals that the European debt crisis had a limited impact on Moroccan banks relative to other crises. Second, out-degree centrality sheds light on the pivotal role played by AWB and BCP, as leaders in transmitting risk within the financial network. In contrast, the CDM, recognized for its elevated in-degree centrality, emerges as a recipient of risk transmissions, highlighting the complex interaction of influence within the system. Third, parallel insights arose from the SFI indicator, leading to the conclusion that AWB has the capacity to trigger a potential systemic crisis. Conversely, CDM is relatively independent of the banking system. Fourth, an examination of SNRI and Total Net Connectedness provides insights into the responses of the Moroccan banking sector during crisis periods. The escalation of lower-tail connectivity indicates an increase in systemic risk. However, it is imperative to note that these intensified interconnections may serve to fortify system stability and risk sharing but simultaneously elevate the likelihood of systemic risk propagation within the banking system.

The findings carry crucial implications for regulatory bodies and banks in Morocco. Identifying AWB and BCP as potential triggers for a systemic crisis underscores the necessity for tailored regulatory interventions. Strengthening capital requirements and bolstering the high-quality liquid assets of these banks could improve overall financial system stability. Additionally, the observed rise in connectivity during crises underscores the importance of carefully managing interconnections. Incorporating connectivity as a monitoring indicator is essential for mitigating systemic risk within the Moroccan banking system.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## Authors contribution

Ayoub Kyoud, conception and design, analysis and interpretation of the data, writing – original draft, revising content, final approval. Cherif EL Msiyah, conception and design, analysis and interpretation of the data, writing – original draft, revising content, final approval. Jaouad Madkour, conception and design, analysis and interpretation of the data, writing – original draft, revising content, final approval. All authors agree to be accountable for all aspects of the work.

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## Data availability statement

The data that support the findings of this study are openly available on the website of the Moroccan Stock Exchange Market. The authors performed further calculations. The data and necessary code are available upon request.

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