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ASSESSING SYSTEMIC RISK IN MOROCCO'S BANKING SECTOR: CONDITIONAL VALUE-AT-RISK APPROACH

Abstract

Systemic risk in the banking sector poses a major threat to financial stability, particularly in concentrated markets such as Morocco, where the failure of one institution may trigger widespread disruptions. Understanding the extent to which individual banks contribute to systemic risk and generate spillover effects is essential for sustaining financial system resilience. This study aims to assess the systemic risk contributions and spillover potential of six listed Moroccan banks, Attijariwafa Bank (ATW), Bank of Africa (BOA), Banque Marocaine pour le Commerce et l'Industrie (BCI), Banque Centrale Populaire (BCP), Crédit Immobilier et Hôtelier (CIH), and Crédit du Maroc (CDM), by applying the Conditional Value-at-Risk (CoVaR) methodology. The analysis uses daily return data covering the period from January 4, 2010 to January 10, 2025. Value-at-Risk (VaR) estimates at 99% and 95% confidence levels show that the three largest banks, ATW, BCP, and BOA, are the least individually risky banks under normal market conditions, suggesting greater stability. In contrast, the smallest banks, CDM, BCI, and CIH, exhibit higher individual risk exposure. CoVaR and ΔCoVaR (marginal CoVaR) results indicate that ATW, BCP, and BOA are the primary contributors to systemic risk, with a higher potential for spillover during times of distress, while the remaining banks are less systemically significant. These findings highlight the need for enhanced macroprudential oversight and regular stress testing for larger institutions, alongside improved internal risk controls for smaller banks. The study emphasizes the importance of data-driven regulatory strategies in mitigating systemic vulnerabilities and strengthening the long-term stability of Morocco's banking sector.

Keywords systemic risk, contagion, quantile regression, VaR, CoVar

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INTRODUCTION

In today's increasingly interconnected global economy, extreme financial events in one region can rapidly trigger contagion, impacting financial institutions across borders and leading to systemic crises with widespread economic and social consequences. Such contagion has been witnessed in events like the subprime mortgage crisis and sovereign debt defaults, which highlighted vulnerabilities within financial systems worldwide. Within national borders, the interconnectedness of banks creates channels through which distress in one institution can quickly propagate, risking broader instability in the banking sector.

Although widely adopted, traditional risk measures, such as Value-at-Risk (VaR), fall short in addressing the broader systemic risks embedded in financial systems. VaR primarily quantifies the risk faced by a single institution under normal market conditions but neglects the interconnectedness among institutions and the potential for risk to propagate through the system. This shortcoming limits the ability of regulators and policymakers to fully understand or respond to the collective threats posed by financial contagion and systemic crises.

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In Morocco, the growing interconnectedness of banks, both domestically and internationally, amplifies the potential for systemic risk and contagion within the national financial sector. However, there is currently a gap in understanding how individual Moroccan banks contribute to systemic risk and how distress may spill over across institutions. Without a precise characterization of these dynamics, the Moroccan banking system remains exposed to unforeseen shocks that could threaten economic stability.

Therefore, the scientific problem addressed in this study is the lack of effective measurement and understanding of systemic risk contributions and contagion mechanisms among Moroccan banks. Addressing this gap is essential for developing robust risk management frameworks and ensuring the resilience of Morocco's financial system amid increasing interconnectedness.

1. LITERATURE REVIEW

Systemic risk, the possibility that a disturbance at a single financial institution could trigger instability across the entire financial system, has become a major focus of financial stability policy, particularly since the 2008 global financial crisis. In response, academic research has increasingly centered on quantifying systemic risk contributions, contagion channels, and institutional vulnerabilities. One of the most influential tools in this domain is the Conditional Value at Risk (CoVaR) introduced by Adrian and Brunnermeier (2008, 2011, 2016), which estimates system-wide risk conditional on an individual institution under distress. The derivative, the Delta Conditional Value at Risk (ΔCoVaR), captures the marginal contribution of an institution to systemic risk. Alongside CoVaR, complementary measures such as Marginal Expected Shortfall (MES) and SRISK (Systemic Risk) have been widely adopted, offering multidimensional perspectives on systemic exposure, capital shortfall, and spillover effects.

This review organizes the literature into three broad themes:

(i) empirical applications of CoVaR across global financial systems;

(ii) integration with MES and SRISK as complementary systemic risk measures; and

(iii) methodological advancements, including machine learning, regime-switching, and backtesting frameworks.

Several studies have been conducted to measure systemic risk in banks from developed countries. For example, Drakos and Kouretas (2015) assessed systemic risk in the U.S. and the UK during the 2007–2009 financial crisis, using the CoVaR measure. They found that U.S. banks were the largest contributors to systemic risk, with foreign banks also playing a significant role. The study highlighted a rise in systemic risk across all sectors in post-2008. In European banks, Borri et al. (2012) found that bank size was a significant factor in systemic risk contribution, especially when using the marginal CoVaR (ΔCoVaR) methodology. Additionally, the study highlighted that banks operating in more concentrated banking systems contributed more to systemic risk. For Italian and major European banks, Bianchi and Sorrentino (2020) estimated ΔCoVaR from 2007 to 2018 using quantile regression, a closed-form formula, and a non-parametric method. They found that the closed-form formula produced results consistent with the other methods, offering greater robustness. Italian banks have been further analyzed by Bianchi and Sorrentino (2022), who affirmed the utility of ΔCoVaR in measuring systemic risk. Their study highlighted that factors such as higher capitalization helped mitigate risks, particularly those related to trading and investment banking activities. The research demonstrated how banks with better capitalization profiles were less vulnerable to systemic shocks. This finding supports the role of strong capital buffers in reducing a bank's systemic risk contribution, particularly in the context of market fluctuations.

In the Chinese banking sector, Zhang et al. (2021) analyzed systemic risk employing both quantile regression and the GARCH model to estimate VaR and CoVaR. Their results indicated that large commercial banks generally had higher systemic risk compared to smaller banks, although overall

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risk levels were relatively low. The study found that the CoVaR values derived from the GARCH model were significantly lower than those obtained from quantile regression, suggesting an underestimation of risk by the former method. Similarly, systemic risk has been measured by Roengpitya and Rungcharoenkitkul (2010) in the Thai banking sector using the CoVaR approach. They found that individual banks, especially during and after the Asian financial crisis, added significant risk to the system. While larger banks often contributed more to systemic risk, size alone was not the key determinant. The study also analyzed interbank financial linkages, showing that systemic connections varied over time and were influenced by specific bank characteristics. Always in Thailand's banking sector, Luangaram et al. (2024) examined how climate risks affect systemic risk, focusing on both transition and physical risks. Transition risks were assessed through a Brown-minus-Green (BMG) risk premium derived from the Fama-French model, while physical risks were measured using the Standardized Precipitation Evapotranspiration Index (SPEI). Systemic risk was quantified using CoVaR, and panel regressions revealed that both BMG and flood-related physical risks significantly increase systemic risk.

Emerging markets present further validation of the CoVaR framework. For example, Khiari and Ben Sassi (2019) evaluated systemic risk among Tunisian listed banks using the CoVaR and ΔCoVaR frameworks. Their analysis showed that public banks, followed by the largest private banks, were the most systemically important. These banks not only contributed most to systemic risk but were also less sensitive to shocks from other institutions, highlighting their dominant systemic role. Similarly, de Mendonça and da Silva (2018) analyzed systemic risk in Brazil's banking sector using the ΔCoVaR methodology. The ΔCoVaR estimates aligned closely with stress periods identified by the Central Bank of Brazil. Key determinants of systemic risk included bank liquidity, profitability, leverage, and interest rates. In Pakistan, Hanif et al. (2019) assessed systemic risk in Pakistan's banking sector using the ΔCoVaR measure. They employed both static and dynamic models to analyze how firm-, sector-, and country-level factors – such as bank size, political stability, and industry concentration – affect systemic risk and firm valuation. The study found that sector-level characteristics like munificence and dynamism significantly influence systemic risk-taking behavior. In Indonesia, Raz (2018) investigated banking risk behavior in Indonesia using z-score and ΔCoVaR to measure idiosyncratic and systemic risks. The study found a significant negative relationship between bank capital and both types of risk, indicating that higher capital reduces risk exposure. It also revealed that banks increased capital in response to rising systemic risk, but not to idiosyncratic risk. The risk-mitigating effect of capital was stronger during normal times, while banks tended to take on more asset risk during financial distress.

In Latin American research, Arias et al. (2011) used CoVaR and quantile regressions to estimate market risk codependence among Colombian financial institutions. They emphasized that although market risk exposure had increased significantly since 2009, the interdependence of this risk had not been extensively explored. Their approach allowed for the assessment of systemic risk contributions across banks, pension funds, and other financial institutions. The findings indicated that risk codependence among these entities grew stronger during periods of financial distress.

While CoVaR captures the conditional dependence between institutions and the system, Marginal Expected Shortfall (MES) reflects an institution's expected losses in extreme downturns, and SRISK (Systemic Risk) estimates capital shortfall during systemic stress. Studies combining these metrics show they offer complementary insights into risk dynamics. For example, in the Korean banking sector, Yun and Moon (2014) analyzed systemic risk using CoVaR and MES. Both measures yielded similar rankings of banks' systemic risk contributions. They found that systemic risk contributions were strongly linked to bank-specific factors like VaR, size, and leverage, with differences noted between cross-sectional and time-series analyses. Systemic risk has also been assessed in China's banking sector by Huang et al. (2015), using CoVaR and MES. Their findings showed that systemic risk declined after the global financial crisis but began rising again around 2014. In Taiwan, Ender and Wong (2018) investigated systemic and individual bank risks using CoVaR and MES, based on a bivariate quantile autoregression model with asymmetric downside risk adjustments. They found that individual bank systemic risk showed significant external asymmetric downside risk, while systemic impacts were more uniform across institutions. Larger and more leveraged banks were more exposed to systemic risk. Foreign banks tended to propagate symmetric external risks, while domestic banks exhibited more asymmetric risk patterns.

In the Gulf Cooperation Council (GCC), Abedifar et al. (2017) studied the stability of banking systems combining Islamic and conventional finance in six GCC countries with dual banking systems. They compared systemic resilience across fully Islamic banks (IB), conventional banks (CB), and conventional banks with Islamic windows (CBw) using market-based measures like MES, SRISK, and CoVaR. They found that CBw banks were the least resilient, had the highest market synchronicity, and were the most interconnected during crises.

In the Colombian banking system, Rivera-Escobar et al. (2022) assessed systemic risk using CoVaR, MES, and SRISK. Their findings showed that despite economic losses from external shocks, the Colombian banking sector did not exhibit systemic risk.

In Turkey's banking sector, Sengul and Yilmaz (2019) measured systemic risk using CoVaR and MES for six Borsa Istanbul-listed banks. Although the two measures produced different risk rankings, they similarly explained cross-sectional variations in systemic risk across banks.

Similarly, Jin-Ping et al. (2020) examined how CEO overconfidence affects systemic risk in U.S. banks using CoVaR, MES, and SRISK measures. CEO overconfidence is measured through a stock options-based proxy. Their results show that banks with overconfident CEOs contribute more to systemic risk and have higher systemic risk exposure than those without. This effect is particularly strong during the 2008–2009 financial crisis.

The impact of high liquidity creation on systemic risk across 94 banks in 16 Western European countries has been studied by Louhichi et al. (2022). They measured systemic risk exposure with MES and systemic risk contribution with ΔCoVaR. Their results revealed that high liquidity creation increased systemic risk exposure during calm periods and even more so during financial crises. The systemic risk contribution from liquidity creation was significant primarily during the 2008–2009 crisis.

Similarly, the impact of macroeconomic variables on systemic risk for 24 European banks has been analyzed by Kurter (2022) using ΔCoVaR, MES, and SRISK measures. The study found that systemic risk increased after the global financial crisis and the Brexit referendum. It assessed individual banks' contributions to systemic risk during major stress periods. The results also showed a stable long-run relationship between systemic risk and variables like EU industrial production, inflation, Euribor, and US equity volatility.

ΔCoVaR and MES measures have also been applied by Wosser (2017) to examine systemic risk in European banks. The study found that a group of large banks in one country contributed the most to systemic risk when measured by ΔCoVaR, while another cluster of banks in a different jurisdiction was more affected by systemic shocks under MES. Factors such as institution size, maturity mismatch, non-performing loans, and income ratios were strongly linked to systemic risk.

The performance of CoVaR and SRISK as systemic risk measures during eight financial panics before FDIC insurance has been assessed by Brownlees et al. (2020). The results show that CoVaR and SRISK effectively identify systemic institutions in distress, detecting risks up to six months before panics. However, these measures proved to be only moderately effective in predicting financial crises on a broader scale.

The work of Ziwei and Huang (2025) explored how intelligent algorithms improved systemic financial risk identification in Chinese banking, focusing on the gap between technology and risk management. They use AI implementation measures alongside systemic risk metrics, such as CoVaR, MES, and SRISK. Their findings showed that AI implementation reduced systemic risk exposure by 18.5%, with key improvements in risk identifi-

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cation efficiency, information processing, and decision-making. Larger banks benefited more from AI, but the research highlighted that the effects varied across bank types and market conditions.

Using ΔCoVaR and MES to measure systemic risk, Hanif et al. (2021) analyzed the systemic importance of financial institutions in Pakistan's banking sector. They found that MES and ΔCoVaR identified different systemically important institutions, with varying effects of factors like non-interest income, deposit ratio, and concentration depending on the measure used.

Several studies have pushed methodological boundaries in systemic risk modeling. For example, Karas and Szczepaniak (2017) developed an alternative method for estimating *CoVaR*, using market-based data instead of accounting values to better capture real-time systemic risk. They applied this approach to the Polish financial system, emphasizing the efficiency of Poland's stock market and the dominance of its banking sector. Similarly, Karimalis and Nomikos (2018) introduced a new methodology, Copula CoVaR, to estimate CoVaR using copula functions, which allowed for time-varying exposure of an institution's CoVaR to its VaR. They extended this method to other 'co-risk' measures like MES and applied it to a portfolio of large European banks to explore common market factors driving systemic risk. The impact of green finance on systemic risk has been explored by Chien-Chiang et al. (2025) in China's banking sector, focusing on the country's goals of peak emissions and carbon neutrality. They applied the CoVaR model and found that green credit policies effectively reduce systemic risk. The study also revealed that increasing the green credit scale lowers systemic risk, particularly for large state-owned and joint-stock banks, with banks mitigating risk through lower capital adequacy ratios and non-performing loan ratios while expanding green credit. A new approach to calibrating CoVaR using neural network quantile regression, modeling systemic risk spillovers in a network context through marginal effects, has been introduced by Keilbar and Wang (2022). Their out-of-sample analysis outperformed a linear baseline, emphasizing the importance of capturing nonlinear relationships in systemic risk modeling. They developed three network-based measures: the Systemic Network Risk Index (SNRI), Systemic Fragility Index (SFI), and Systemic Hazard Index (SHI), which proved effective in identifying systemically important firms, especially during the financial crisis. The CoVaR approach has been extended by Liu (2017) to a regime-switching framework, capturing nonlinearities in systemic risk by distinguishing between high-risk and normal-risk states. The study, focused on U.S. large bank [2]holding companies, shows that accounting for regime changes in tail risks helps capture both amplification and mean-reversion effects of adverse shocks on the banking system.

Backtesting tools have also evolved. For example, Banulescu-Radu et al. (2020, 2021) pioneered methods to validate systemic risk forecasts for ΔCoVaR, MES, and SRISK using statistical violation tests. Their early warning indicators offer actionable signals to regulators by quantifying forecast reliability in real time. Similarly, Löffler and Raupach (2013) provided a cautionary perspective, noting that CoVaR and MES may yield conflicting signals during contagion, especially when data quality is limited or idiosyncratic risk is misinterpreted.

The reviewed literature confirms that CoVaR provides robust tools for quantifying systemic contributions and exposures. Empirical studies have applied these tools across geographies, market structures, and crisis periods, consistently identifying key risk contributors and assessing interdependencies across banking systems. Nevertheless, regional disparities in research coverage persist. The North African and broader MENA banking systems remain understudied, especially when compared to Europe, Asia, and the Americas. In the Moroccan context, existing studies are narrow in scope and short in temporal coverage.

This study addresses these gaps by evaluating the systemic risk contributions and spillover effects of six listed Moroccan banks: Attijariwafa Bank (ATW), Bank of Africa (BOA), Banque Marocaine pour le Commerce et l'Industrie (BCI), Banque Centrale Populaire (BCP), Crédit Immobilier et Hôtelier (CIH), and Crédit du Maroc (CDM).

2. DATA AND METHODOLOGY

This section is dedicated to describing the data utilized and presenting the methods.

This study aims to assess the systemic risk contributions and spillover potential of six listed Moroccan banks, Attijariwafa Bank (ATW), Bank of Africa (BOA), Banque Marocaine pour le Commerce et l'Industrie (BCI), Banque Centrale Populaire (BCP), Crédit Immobilier et Hôtelier (CIH), and Crédit du Maroc (CDM), by applying the Conditional Value-at-Risk (CoVaR) methodology. The Moroccan banking index, referred to as BANK, consists of seven banking stocks, including CFG Bank. However, CFG Bank is excluded from this study due to the absence of data dating back to 2010. The analysis uses daily return data covering the period from January 4, 2010 to January 10, 2025. All data were downloaded from the website https://www.investing.com/equities/

By identifying systemic contributors and exposure pathways and evaluating their dynamics over 15 years, the study offers the first integrated, long-term analysis of systemic risk within Morocco's financial sector. This will contribute to a more informed approach to macroprudential regulation and financial stability policy in emerging market contexts.

Top Tier Moroccan banks include ATW, a leading institution with a strong presence in both retail and corporate banking; BCP, a major and well-established player in Morocco with regional expansion; and BOA, a prominent bank with a growing international presence, particularly in sub-Saharan Africa.

Mid-Tier Moroccan banks include BCI, a well-established bank offering a range of retail and corporate services and part of the BNP Paribas Group; CIH, which specializes in housing finance and commercial banking; and CDM, a bank that plays a significant role in providing financial services, with a focus on retail, corporate banking, and financing development projects, contributing to Morocco's economic growth.

In this section, the quantile regression method, the Value-at-Risk technique, and the CoVar method are described.

Quantile regression is a statistical method that extends traditional linear regression by focusing on the conditional quantiles of the response variable rather than just the conditional mean (Koenker & Bassett, 1978). It allows us to model the relationship between the independent variables (predictors) and different points (quantiles) of the distribution of the dependent variable.

Consider a random variable Y with its cumulative distribution function $F_Y(y)$. The quantile of order τ is typically defined as

$$q_\tau(Y) = \inf\{y / F_Y(y) \geq \tau\}. \tag{1}$$

If F_Y is continuous, then the following holds:

$$F_Y(q_\tau(Y)) = P(Y < q_\tau(Y)) = \tau \tag{2}$$

Quantile regression aims to evaluate how conditional quantiles $q_t(Y / X)$ defined as:

$$q_\tau(Y / X) = inf\{y / \ F_{Y/X}(y) \geq \tau\} \tag{3}$$

vary when the explanatory variables $X = (1, X_1, X_2, ...X_k)$ of Y vary. Unlike in linear regression, it does not assume that the effect of each explanatory variable remains constant across different quantiles.

The standard quantile regression assumes that the quantiles of the conditional distribution have a linear form:

$$q_\tau(Y / X) = X'\beta_\tau, \tag{4}$$

where for each τ is associated a coefficient vector $\beta_\tau = (\beta_{1,\tau,}\beta_{2,\tau,...,}\beta_{k,\tau})$ corresponding to k explanatory variables (the constant included).

The last form can be expressed equivalently in the form:

$$Y = X'\beta_\tau + \varepsilon_\tau, \tag{5}$$

where ε_τ is the random variable representing the error that satisfies $q_t(\varepsilon_\tau / X) = 0$.

The parameter β_τ in the quantile regression:

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$$\begin{cases} Y = X'\beta_\tau + \varepsilon_\tau \\ q_\tau\left(Y / X\right) = X'\beta_\tau \end{cases}, \quad (6)$$

satisfies

$$\beta_\tau = \arg\min_\beta E\left[\rho_\tau\left(Y - X'\beta_\tau\right)\right], \quad (7)$$

where ρ_τ (.) is a test function defined by:

$$\rho_\tau\left(u\right) = u\left(\tau - \mathbb{I}_{(u<0)}\left(u\right)\right) \quad (8)$$

where the indicator function defined by:

$$\mathbb{I}_{(u<0)}\left(u\right) = \begin{cases} 1 & if\, u < 0 \\ 0 & esle \end{cases}. \quad (9)$$

The quantiles of the variable Y can be estimated from a sample $(Y_i)_{1 \le i \le n}$ of n i.i.d. variables. The quantile regression estimator (see Koenker & Bassett, 1978) is given by

$$\hat{\beta}_\tau = \arg\min_\beta \frac{1}{n}\sum_{i=1}^{n}\rho_\tau\left(Y_i - X_i'\beta_\tau\right). \quad (10)$$

Financial data can take various forms, such as Profit/Loss, Loss/Profit and Algebraic return.

The Profit/Loss variable PL_t of an asset in a time horizon of one period $[t - 1, t]$ is defined as ($PL_t = P_t - P_{t-1}$). The Loss/ Profit variable LP_t is given by ($LP_t = -PL_t = P_{t-1} - P_t$). The arithmetic return r_t is defined as

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{PL_t}{P_{t-1}}. \quad (11)$$

In its most literal sense, the Value At risk (VaR) of an asset or a portfolio over a horizon period $[t - 1, t]$, at a specific confidence level $(1 - \alpha)$ represents the maximum monetary loss that is likely to occur.

In terms of the loss-profit variable LP_t, VaR is defined by:

$$P\left(LP_t < VaR_{1-\alpha}\right) = 1 - \alpha. \quad (12)$$

This means that there is a probability of $(1 - \alpha)$ that LP_t will not exceed the monetary threshold $VaR_{1-\alpha}$. Since $VaR_{1-\alpha}$ represents a potential loss, it is typically a positive value. In essence, $VaR_{1-\alpha}$ corresponds to the $(1 - \alpha)$ quantile of the loss-profit variable LP_t:

$$VaR_{1-\alpha}\left(LP_t\right) = Quantile_{1-\alpha}\left(LP_t\right). \quad (13)$$

Equivalently, the relation (12) can be expressed as:

$$P\left(LP_t > VaR_{1-\alpha}\right) = \alpha. \quad (14)$$

This means that there is a probability of α that the Loss/Profit LP_t will exceed the monetary threshold $VaR_{1-\alpha}$.

To express the VaR in percentage terms, the arithmetic return r_t is used. In terms of r_t, the VaR can be defined as:

$$P\left(-r_t < \frac{VaR_{1-\alpha}\left(LP_t\right)}{P_{t-1}}\right) = 1 - \alpha. \quad (15)$$

The Value-at-Risk in percentage is defined by:

$$VaR_{1-\alpha}\left(in\ \%\right) = \frac{VaR_{1-\alpha}\left(LP_t\right)}{P_{t-1}} = Quantile_{1-\alpha}\left(-r_t\right). \quad (16)$$

This means that there is a probability of $(1 - \alpha)$ that $-r_t$ (the loss-profit in %) does not exceed $VaR_{1-\alpha}$(in %) (the Value-at-Risk in percentage).

Equivalently, the relation (15) can be expressed:

$$P\left(-r_t > \frac{VaR_{1-\alpha}\left(LP_t\right)}{P_{t-1}}\right) = \alpha. \quad (17)$$

This means that there is a probability of α that $-r_t$ exceeds $VaR_{1-\alpha}$(in %).

This is equivalent to:

$$P\left(r_t < -VaR_{1-\alpha}\left(in\ \%\right)\right) = \alpha. \quad (18)$$

This means that there is a probability of α that the algebraic return r_t does not exceed $VaR_{1-\alpha}$ (in %) (r_t).

Thus:

$$VaR_{1-\alpha}\left(in\ \%\right) = -Quantile_\alpha\left(r_t\right). \quad (19)$$

Alternatively, the relation (13) can be expressed:

$$P\left(r_t > -VaR_{1-\alpha}\left(in\ \%\right)\right) = 1 - \alpha. \quad (20)$$

This means that there is a probability of (1 – α) that r_t exceeds $-VaR_{1-\alpha}$ (in %).

Adrian and Brunnermeir (2008, 2011, 2016) developed a systemic risk measure called Conditional Value at Risk (*CoVaR*), which takes into account the contagion effect in risk management of financial systems. The fundamental idea behind *CoVaR* is to assess the conditional risk that a financial system (denoted as *j*) faces when an institution (denoted as *i*) is in distress, over a specific time horizon, and at a given confidence level. In other words, *CoVaR* measures the risk exposure of financial system *j*, given that financial institution *i* is undergoing a significant loss.

While *VaR* estimates the potential loss of an asset under normal conditions, *CoVaR* measures the risk to a system *j* when another institution *i* is in distress, at a specific confidence level. This helps evaluate how the failure or distress of one institution can impact the broader system, providing valuable insight into systemic risk.

Mathematically, the $CoVaR^{j/i}_{1-\alpha}$ of a system *j* conditional on the distress of a financial institution *i* is defined as the Value-at-Risk of system *j* in a given time horizon of one period and at a specific confidence level (1 – α), conditional on institution *i* being in distress. The failure of institution *i* means that $LP_i = VaR_{1-\alpha}(LP_i)$, which is equivalent to

$$r_i = -VaR_{1-\alpha}(in\ \%) = Quantile_\alpha(r_i), \tag{21}$$

where LP_i and r_t are respectively the Loss/Profit and the algebraic return of the financial institution *i*. Thus, the *CoVar* is defined as a Value-at-Risk:

$$\begin{aligned} CoVaR^{j/i}_{1-\alpha} &= VaR_{1-\alpha}\left(LP_j / LP_i = VaR_{1-\alpha}(LP_i)\right) \\ &= Quantile_{1-\alpha}\left(LP_j / LP_i = Quantile_{1-\alpha}(LP_i)\right). \end{aligned} \tag{22}$$

Equivalently, in terms of the algebraic returns, this can be expressed:

$$\begin{aligned} &CoVaR^{j/i}_{1-\alpha} \\ &= Quantile_\alpha\left(r_j / r_i = Quantile_\alpha(r_i)\right). \end{aligned} \tag{23}$$

To estimate the *CoVar*, the quantile regression method is used.

2.1. Estimation of the CoVaR

Since $CoVaR^{j/i}_{1-\alpha}$ is the α-order quantile of r_j conditionally to r_i, the $CoVaR^{j/i}_{1-\alpha}$ can be estimated using the quantile regression method:

$$\begin{aligned} &r_j = \beta^i_\alpha + \gamma^i_\alpha . r_i + \varepsilon, \\ &CoVaR^{j/i}_{1-\alpha} = Quantile_\alpha\left(r_j / r_i\right) \\ &= \hat{\beta}^i_\alpha + \hat{\gamma}^i_\alpha \cdot r_i. \end{aligned} \tag{24}$$

Therefore:

$$\begin{aligned} &CoVaR^{j/r_i = Quantile_\alpha(r_i)}_{1-\alpha} \\ &= Quantile_\alpha\left(r_j / r_i = Quantile_\alpha(r_i)\right) \\ &= \hat{\beta}^i_\alpha + \hat{\gamma}^i_\alpha \cdot Quantile_\alpha(r_i). \end{aligned} \tag{25}$$

Additionally, if the institution *i* is in the median (normal) state, meaning that $LP_i = VaR_{0.50}(LP_i)$, or equivalently $r_i = Quantile_{0.50}(r_i)$, then:

$$\begin{aligned} &CoVaR^{j/r_i = Quantile_{0.50}(r_i)}_{1-\alpha} \\ &= Quantile_\alpha\left(r_j / r_i = Quantile_{0.50}(r_i)\right) \\ &= \hat{\beta}^i_\alpha + \hat{\gamma}^i_\alpha \cdot Quantile_{0.50}(r_i). \end{aligned} \tag{26}$$

2.2. Definition of Δ*CoVaR*

To assess the contribution of each bank to systemic risk, Adrian and Brunnermeir (2011) defined the Δ*CoVaR* as the difference between the *CoVaR* conditionally the institution *i* is distressed and the *CoVaR* conditionally the institution *i* is in the median state:

$$\begin{aligned} \Delta CoVaR^{j/i}_{1-\alpha} &= CoVaR^{j/r_i = Quantile_\alpha(r_i)}_{1-\alpha} \\ &- CoVaR^{j/r_i = Quantile_{0.50}(r_i)}_{1-\alpha}, \end{aligned} \tag{27}$$

which is reduced to:

$$\Delta CoVaR^{j/i}_{1-\alpha} = \hat{\gamma}^i_\alpha \cdot \begin{pmatrix} Quantile_\alpha(r_i) \\ -Quantile_{0.50}(r_i) \end{pmatrix}. \tag{28}$$

3. RESULTS AND DISCUSSION

This section presents the results obtained from applying the CoVaR method to the Moroccan financial system.

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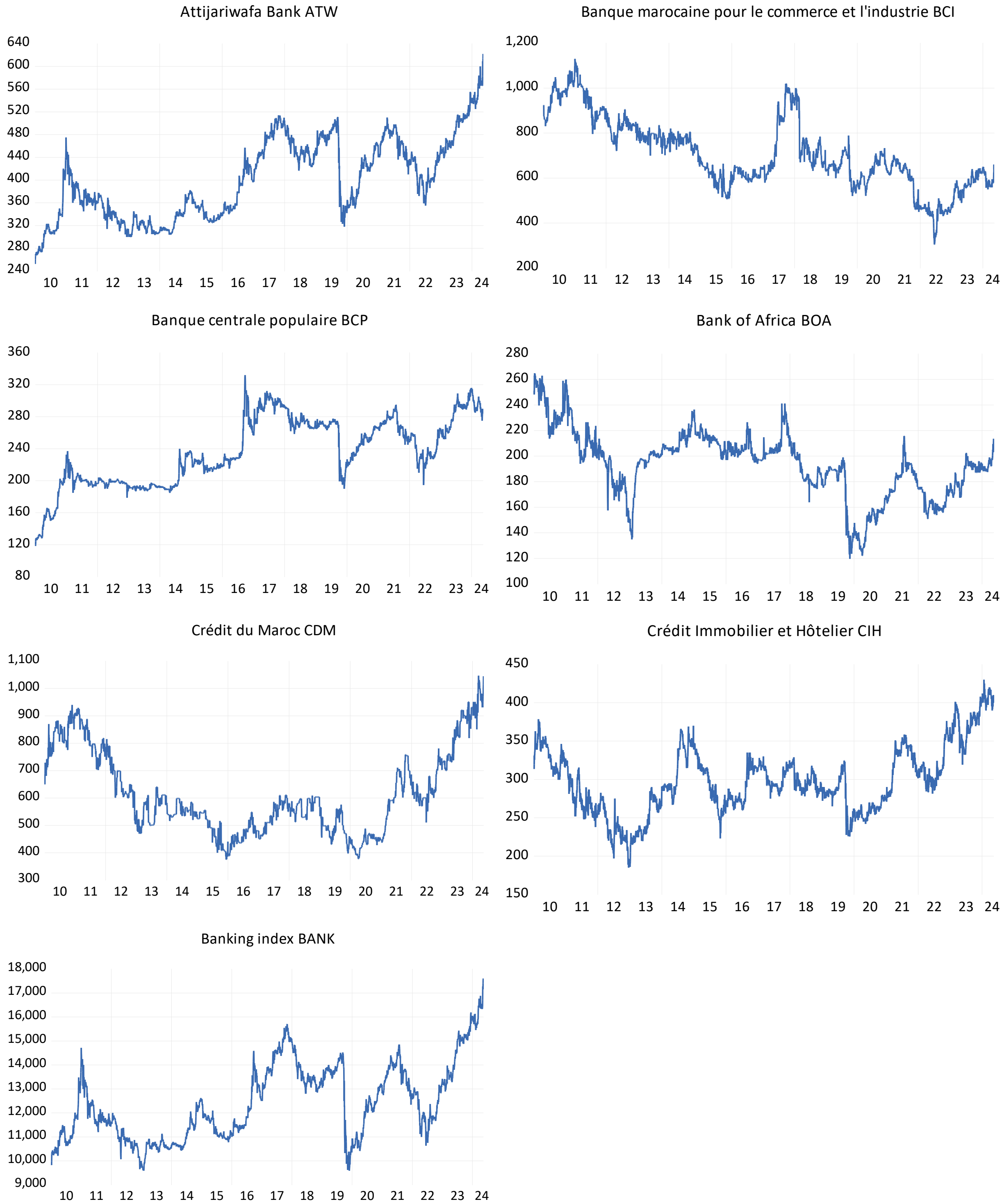

Figure 1. Graphical representations of the six banks and the banking index

Figure 1 presents the graphical representations of the six banks and the banking index.

Table 1 and Table 2 present the results of the Augmented Dickey-Fuller Test of stationarity applied to the series representing the prices and the algebraic returns of the six banks and the banking index.

According to Table 1, the t-statistics of the prices of the six banks and the banking index do not exceed the tabulated critical values at the 1%, 5% and 10% levels. It is concluded that all the prices are not stationary.

According to this table, the t-statistics of the algebraic returns of the six banks and the banking in-

Table 1. Augmented Dickey-Fuller applied to the prices

Bank	BANK	ATW	BCI	BCP	BOA	CDM	CIH
t-stat	–1.152	–1.266	–2.282	–2.674	–3.093	–1.104	–2.020

Note: Level 1%: –3.432; Level 5%: –2.862; Level 10%: –2.567.

Table 2. Augmented Dickey-Fuller applied to the algebraic returns

Bank	RBANK	RATW	RBCI	RBCP	RBOA	RCDM	CIH
t-stat	–60.53237	–64.91214	–40.87513	–64.74274	–40.02306	–29.91377	–53.20319

Note: Level 1%: –3.432; Level 5%: –2.862; Level 10%: –2.567.

dex exceed the tabulated critical values at the 1%, 5% and 10% levels. It is concluded that all the algebraic returns are stationary.

The application of the quantile regression of the algebraic return *RBank* of the banking index on the algebraic return $RBank_i$ of the Bank *i* gives:

$$CoVaR_{1-\alpha}^{RBANK/RBank_i} = Quantile_\alpha\left(RBANK / RBank_i\right) = \hat{\beta}_\alpha^i + \hat{\gamma}_\alpha^i \cdot RBank_i, \quad (29)$$

where $\hat{\beta}_\alpha^{\,i}$ and $\hat{\gamma}_\alpha^{\,i}$ are the estimated coefficients of the quantile regression method.

The *CoVar* values when $Bank_i$ is in distress and normal (median) states are deduced by:

$$CoVaR_{1-\alpha}^{RBANK/RBank_i=Quantile_\alpha(RBank_i)} = \hat{\beta}_\alpha^i + \hat{\gamma}_\alpha^i . Quantile_\alpha\left(RBank_i\right), \quad (30)$$

$$CoVaR_{1-\alpha}^{RBANK/RBank_i=Quantile_{0.5}(RBank_i)} = \hat{\beta}_\alpha^i + \hat{\gamma}_\alpha^i . Quantile_{0.50}\left(RBank_i\right). \quad (31)$$

The ΔCoVaR is then deduced by the difference between the two *CoVar*:

$$\Delta CoVaR^{RBANK/RBank_i} = \hat{\gamma}_\alpha^i \cdot \begin{pmatrix} Quantile_\alpha\left(RBank_i\right) \\ -Quantile_{0.50}\left(RBank_i\right) \end{pmatrix}. \quad (32)$$

The Value-at-Risk $VaR_{1-\alpha}$ (in %) at confidence levels (1 – α = 99%), (1 – α = 95%), and (1 – α = 50%) are calculated using the quantiles of orders 1%, 5% and 50%. They are presented in Table 3.

Table 3. Value-at-Risk $VaR_{1-\alpha}$ (in %) at confidence levels (1 – α = 99%), 95%, 50%

i	$Bank_i$	$VaR_{0.99}$ (in %) $= -Q_{0.01}$*	$VaR_{0.95}$ (in %) $= -Q_{0.05}$**	$VaR_{0.50}$ (in %) $= -Q_{0.50}$***
1	ATW	3.32%	1.77%	0%
2	BCI	5.97%	3.93%	0%
3	BCP	3.27%	1.63%	0%
4	BOA	3.97%	2.22%	0%
5	CDM	5.98%	3.72%	0%
6	CIH	5.17%	2.96%	0%

Note: * 1 – α = 99%; ** 1 – α = 95%; *** 1 – α = 50%.

Table 3 shows that for Bank ATW, the VaR is 3.32% at the 99% confidence level, indicating a 1% likelihood of incurring a loss greater than this amount within the specified period, while at the 95% level, it stands at 1.77%, implying a 5% chance of exceeding this loss. Bank BCI shows a VaR of 5.97% at the 99% confidence level, corresponding to a 1% chance of a loss greater than this amount, and 3.93% at the 95% level, reflecting a 5% probability. Bank BCP reports a VaR of 3.27% at the 99% level and 1.63% at the 95% level, indicating respective chances of losses exceeding these values of 1% and 5%. For Bank BOA, the VaR is 3.97% at the 99% confidence level and 2.22% at the 95% confidence level, signaling similar probabilities of greater-than-these-losses. Bank CDM exhibits a *VaR* of 5.98% at the 99% level and 3.72% at the 95% level, reflecting a 1% and 5% likelihood of losses beyond these thresholds. Finally, Bank CIH shows a VaR of 5.17% at the 99% level and 2.96% at the 95% level, corresponding to the same probabilities of higher losses.

In summary, BCP exhibits the lowest risk, followed by ATW and BOA. Conversely, CDM, BCI, and CIH are the most exposed to potential losses. These findings are illustrated in Figure 2.

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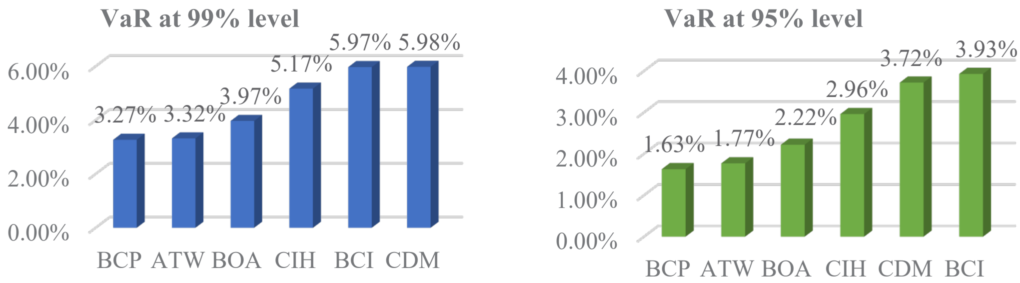

Figure 2. Value-at-Risk of the six Moroccan banks at (1 – α = 99%) and (1 – α = 95%)

The following results illustrate the systemic risk in the event of distress for each bank at α = 1% and at α = 5%. Table 4 presents the *CoVaR* and *CoVaR* at the 99% confidence level.

Table 4. *CoVaR* and *ΔCoVaR* at the (1 – α = 99%) confidence level

i	$Bank_i$	$\hat{\beta}^i_{0.01}$	$\hat{\gamma}^i_{0.01}$	$CoVaR_{0.99}$	$\Delta CoVa_{R0.9}9$
1	ATW	–0.0115	0.7112	–3.51%	–2.36%
2	BCI	–0.0238	0.2027	–3.59%	–1.21%
3	BCP	–0.0178	0.5874	–3.70%	–1.92%
4	BOA	–0.0212	0.4366	–3.85%	–1.73%
5	CDM	–0.0239	0.1220	–3.12%	–0.73%
6	CIH	–0.0228	0.2200	–3.42%	–1.14%

1. *Interpretation of the CoVaR at* (1 – α = 99%):

If ATW experiences a 1% loss (as per its VaR), the CoVaR for the Moroccan banking system is –3.51%, indicating potential losses of up to 3.51%. For BCI, a 1% loss results in a CoVaR of –3.59%, suggesting a potential loss of the same magnitude, while BCP's *CoVaR* of –3.70% implies a possible loss of 3.70%. BOA's distress with a 1% loss results in a *CoVaR* of –3.85%, indicating potential losses of up to 3.85%. When CDM faces a 1% loss, the *CoVaR* is –3.12%, with potential losses of up to 3.42%. Lastly, CIH's 1% loss results in a *CoVaR* of –3.42%, suggesting a potential loss of 3.59%. BOA Bank poses the highest systemic risk to the Moroccan banking system, as a 1% loss by BOA could trigger losses of up to 3.85% across the entire system.

2. *Interpretation of the* ΔCoVaR *at* (1 – α = 99%):

ATW has the highest ΔCoVaR at –2.36%, indicating that it contributes the most to systemic risk in Morocco when transitioning from a normal state to distress. BCP, with a ΔCoVaR of –1.92%, also contributes significantly to systemic risk, though slightly less than ATW. Similarly, BOA's ΔCoVaR of –1.73% shows a considerable contribution to systemic risk, albeit lower than that of ATW and BCP. CDM contributes the least to systemic risk with a ΔCoVaR of –0.73%, followed by CIH with a ΔCoVaR of –1.14%, and BCI with a ΔCoVaR of –1.21%.

Table 5 presents the *CoVaR* and *ΔCoVaR* at the 95% confidence level.

Table 5. *CoVaR* and *ΔCoVaR* at the (1 – α = 95%) confidence level

i	$Bank_i$	$\hat{\beta}^i_{0.05}$	$\hat{\gamma}^i_{0.05}$	$CoVaR_{0.95}$	$\Delta CoVaR_{0.95}$
1	ATW	–0.0065	0.6684	–1.84%	–1.18%
2	BCI	–0.0125	0.1064	–1.67%	–0.42%
3	BCP	–0.0103	0.5204	–1.88%	–0.85%
4	BOA	–0.0107	0.3624	–1.88%	–0.80%
5	CDM	–0.0124	0.0794	–1.54%	–0.30%
6	CIH	–0.0119	0.1796	–1.72%	–0.53%

1. *Interpretation of the CoVaR at* (1 – α = 95%)*:*

If ATW experiences a 5% loss, the Moroccan banking system's *CoVaR* is estimated at –1.84%, implying a potential loss of the same magnitude. A 5% loss by BCI results in a *CoVaR* of –1.67%, while both BCP and BOA lead to a *CoVaR* of –1.88%, suggesting similar risks. CDM's 5% loss produces a *CoVaR* of –1.54%, and CIH's loss of 5% would cause the system to face a potential loss of 1.72%, as indicated by its *CoVaR*.

BCP and BOA exhibit the highest systemic risk in the event of a 5% loss, with ATW following closely behind. In contrast, CIH, BCI, and CDM pose comparatively lower systemic risk than the three largest banks, BCP, BOA, and ATW.

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2. *Interpretation of the ΔCoVaR at* (1 – α = 95%):

ATW has the highest ΔCoVaR at –1.18%, indicating its leading contribution to systemic risk in Morocco during a shift from a normal state to distress. BCP follows with a *ΔCoVaR* of –0.85%, reflecting a notable yet smaller impact. BOA, with a ΔCoVaR of –0.80%, also contributes significantly, though to a lesser extent than ATW and BCP. CDM has the smallest impact on systemic risk, with a ΔCoVaR of –0.30%. BCI follows with a ΔCoVaR of –0.42%, while CIH shows a slightly higher contribution at –0.53%.

The contribution of each bank to system risk in Morocco at (1 – α = 99%) and (1 – α = 95%) confidence levels is illustrated in Figure 3 below.

As illustrated in Figure 3, ATW emerges as the largest contributor to systemic risk in Morocco, whereas CDM represents the smallest risk contributor.

In summary, at both (1 – α = 99%) and (1 – α = 95%) confidence levels, banks ATW, BCP, and BOA emerge as the most systemically important institutions, as their distress would exert the greatest impact on the overall banking system. Conversely, CDM, BCI, and CIH are the least systemically significant, with their distress having a comparatively smaller effect on the system.

Therefore, regulators could prioritize monitoring ATW, BCP, and BOA more closely, ensuring these banks maintain higher capital buffers or adopt precautionary measures to mitigate their systemic risk potential. While CDM, BCI, and CIH also contribute to systemic risk, their impact is comparatively smaller. This insight could guide capital adequacy requirements, risk mitigation policies, and stress tests conducted by Moroccan financial regulators.

This study concludes that large banks contribute more significantly to the systemic risk of the Moroccan banking market.

CoVaR analysis offers valuable information for authorities, such as Bank Al-Maghrib, to identify institutions posing the greatest systemic risks and adjust regulations accordingly. Banks with high ΔCoVaR may face stricter capital requirements or be subject to enhanced stress-testing protocols. The CoVaR results provide essential data for designing stress testing scenarios, allowing regulators to simulate the impact of one institution's distress on the entire system.

In conclusion, CoVaR is a powerful tool for assessing how individual banks contribute to systemic risk in Morocco. By leveraging VaR, CoVaR, and ΔCoVaR metrics, policymakers can identify systemically important institutions, understand risk spillovers, and implement preventive measures to safeguard the financial system.

4. DISCUSSION

This study finds that larger Moroccan banks, specifically Attijariwafa Bank (ATW), Banque Centrale Populaire (BCP), and Bank of Africa (BOA), contribute more significantly to systemic risk than smaller institutions such as Crédit du Maroc (CDM), Banque Marocaine pour le Commerce et l'Industrie (BCI), and Crédit Immobilier et Hôtelier (CIH). This

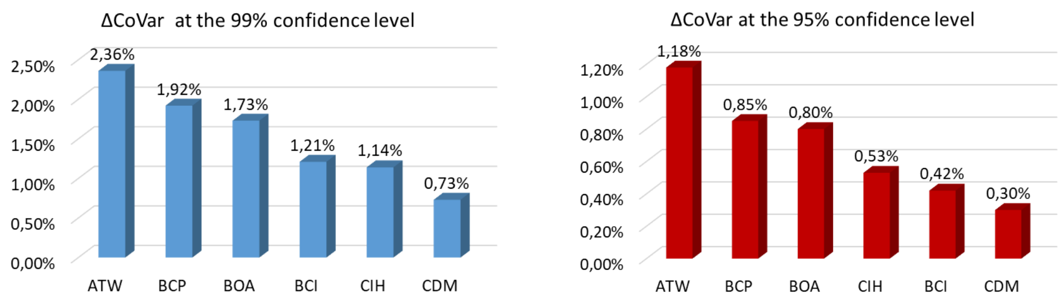

Figure 3. ΔCoVaR for the six banks at (1 – α = 99%) and (1 – α = 95%) confidence levels

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observation is consistent with the broader literature, where bank size, market dominance, and interconnectedness often correlate with heightened systemic risk contributions.

Our findings align closely with those of Borri et al. (2012), who demonstrated that bank size and market concentration significantly increase systemic risk in European banking systems. Similarly, Roengpitya and Rungcharoenkitkul (2010), studying the Thai banking sector, concluded that larger banks were the main transmitters of systemic risk, especially during periods of financial instability. Like these studies, our analysis using *CoVaR* and *ΔCoVaR* reveals that distress in larger Moroccan banks has disproportionate spillover effects on the financial system.

However, not all empirical evidence supports a direct link between size and systemic risk. For instance, López-Espinosa et al. (2012) found no strong correlation between size and systemic risk in international banks. This discrepancy may be due to differences in institutional structures, regulatory regimes, or the presence of global diversification among larger banks – factors less pronounced in the Moroccan context, where the financial system is more concentrated and bank-centric.

Closer to our context, Kyoud et al. (2024) confirmed that BCP and ATW were key transmitters of systemic risk in Morocco, especially during major crises. Our findings extend their conclusions by identifying BOA as an additional significant contributor, suggesting that systemic importance in Morocco may not be solely driven by absolute size but also by factors such as business model, exposure to specific markets, and network centrality.

Furthermore, our results diverge slightly from Nechba (2021), who emphasized AWB (Attijariwafa Bank) and BOA, but did not rank BCP as highly. The variation may stem from different time frames, data granularity, or methodological specifications. Zakaria (2015), by contrast, identified BCI as a key systemic risk contributor – a result we only partially confirm, as BCI ranks as moderately systemic in our study but not among the top three.

Evidence from other emerging markets offers additional insight. Civan et al. (2020) and Sengul and Yilmaz (2019), examining Turkish banks, reported that large private banks posed greater systemic risks than public institutions. This mirrors our conclusion in the Moroccan case, where the largest private banks dominate systemic risk rankings.

Our results also align with cross-country findings that CoVaR-based measures effectively capture the asymmetric effects of distress propagation, as observed in both developed and emerging market contexts. For example, the CoVaR-based ranking of systemic risk contributors in our study parallels that of Manguzvane and Mwamba (2017) in South Africa and Anghelache and Oanea (2014) in Romania, who found that systemic importance is concentrated in a few large institutions.

While most studies identify large banks as primary risk contributors, some counterexamples exist. Muharam and Erwin (2017) in Indonesia and Jiang and Zhang (2020) in China found instances where smaller or regionally focused banks exhibited higher systemic risk due to specific vulnerabilities or digital exposure. Although we do not observe this in the Moroccan market during our sample period, these findings suggest that size may be a proxy, but not a sufficient explanation for systemic importance.

In summary, this study confirms and extends the existing literature on systemic risk in bank-dominated financial systems. By applying the *CoVaR* framework to Moroccan banks, we show that systemic importance is concentrated in the largest institutions, echoing patterns observed in other national contexts. However, the results also point to local particularities – such as the emerging systemic relevance of BOA – that warrant further investigation and underscore the importance of context-specific analysis in systemic risk research.

CONCLUSION

This study assessed the systemic risk contributions of six Moroccan banks using the CoVaR approach over 2010–2025 to identify which institutions pose the greatest threat to financial stability.

The results show that Attijariwafa Bank (ATW), Banque Centrale Populaire (BCP), and Bank of Africa (BOA) exhibit the highest systemic risk contributions, reflecting their size, interconnectedness, and dominance within the Moroccan banking sector. In contrast, Crédit du Maroc (CDM), Banque Marocaine pour le Commerce et l'Industrie (BCI), and Crédit Immobilier et Hôtelier (CIH) display comparatively limited systemic impact. These findings indicate that systemic vulnerabilities are concentrated among the largest and most influential institutions.

From these findings, several conclusions can be drawn. First, regulatory authorities should prioritize stricter oversight of systemically important banks through enhanced capital requirements, stress testing, and liquidity provisions. Second, intervention strategies should be differentiated according to each bank's risk profile, focusing on systemic containment for large banks and internal risk mitigation for smaller ones. Finally, CoVaR-based measures prove to be valuable tools for identifying systemic vulnerabilities and guiding macroprudential policy.

Future research should consider expanding the scope to include non-bank financial institutions, assess cross-border risk spillovers, and incorporate climate and geopolitical risks into the CoVaR framework. Additionally, exploring the dynamic behavior of systemic risk over shorter time intervals could yield insights into crisis detection and real-time regulatory responses

AUTHOR CONTRIBUTIONS

Conceptualization: Soufiane Benbachir, Mohamed Beraich.
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Visualization: Soufiane Benbachir, Mohamed Beraich.
Writing – original draft: Soufiane Benbachir.
Writing – reviewing & editing: Soufiane Benbachir.

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