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Measuring Systemic Risk in Vietnam's Banking System

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Abstract

In the context of globalization and increasing economic integration, systemic risk in the banking sector has emerged as a critical threat to the stability of modern economies, particularly in emerging markets like Vietnam. This study focuses on applying the CoVaR (Conditional Value-at-Risk) index to measure systemic risk in Vietnam's commercial banking system, a method chosen for its ability to capture spillover effects and market volatility during periods of financial instability. Utilizing daily stock price data from 18 listed commercial banks between 2015 and 2024, the research provides new empirical evidence on their systemic risk contributions. The findings reveal distinct phases of systemic risk, with a notable increase during the 2022 period, and identify specific institutions with higher contributions to systemic risk. From a theoretical perspective, this study contributes to the academic literature by providing empirical evidence on systemic risk using CoVaR in an emerging market context. From a practical standpoint, it offers evidence-based policy recommendations to enhance systemic risk monitoring and mitigation, particularly for identifying systemically important institutions, thereby supporting targeted supervision and the establishment of appropriate capital and liquidity requirements. These findings aim to bridge the gap between theory and practice in systemic risk management in Vietnam and provide a foundation for regulators to develop more effective control measures.

Keywords: systemic risk, banking system, Vietnam, CoVaR, emerging markets, financial risk management

1. Introduction

In the contemporary landscape of globalization and intensifying economic integration, financial systems constitute the fundamental infrastructure of modern economies. The banking sector, functioning as the principal financial intermediary, not only facilitates capital allocation but also serves as a critical nexus for risk concentration and dissemination throughout the economic framework. However, the escalating complexity and interconnectivity of financial institutions have precipitated the emergence of systemic risk – a potential catalyst for cascading failures capable of destabilizing the entire financial ecosystem with profound implications for the real economy. Extant literature emphasizes that the failure of a single systemically significant financial institution can compromise the stability of the broader financial architecture, and that ensuring the robustness of individual entities is necessary but insufficient to guarantee systemic resilience (Benoit et al., 2017; Meuleman et al., 2020). The global financial crisis of 2008-2009 vividly illustrated these devastating ramifications, accentuating the imperative for sophisticated systemic risk measurement and surveillance mechanisms (Acharya et al., 2017; Adrian & Brunnermeier, 2016).

Vietnam's rapid economic transformation over the past three decades has driven substantial banking sector expansion, transitioning it from a mono-banking system to a diversified ecosystem of credit institutions. This expansion, coupled with the proliferation of increasingly sophisticated financial instruments, has intensified intra-system interconnections, thereby amplifying exposure to systemic risk. Market perturbations observed during 2011-2012 and the subsequent restructuring of underperforming institutions underscore Vietnam's susceptibility. While recent assessments from international financial institutions acknowledge improvements in asset quality and capitalization (World Bank, 2022; International Monetary Fund, 2023), they also caution about latent vulnerabilities and emphasize the necessity for enhanced systemic risk oversight in emerging economies like Vietnam. Given Vietnam's continued economic integration and the banking sector's pivotal role, a robust understanding and measurement of systemic risk are crucial for maintaining financial stability and informing prudential policy, especially in light of recent global and domestic economic uncertainties.

Notwithstanding preliminary investigations into systemic risk within Vietnam's banking sector, specific knowledge gaps persist. While some studies have explored banking risks in Vietnam, few have specifically applied dynamic systemic risk measures like CoVaR to a recent and extended dataset covering periods of significant economic volatility (e.g., the COVID-19 pandemic and subsequent recovery). Furthermore, a detailed classification of banks based on their systemic risk contribution using such measures remains limited.

To address these identified research gaps, this study, entitled "Measuring Systemic Risk in Vietnam's Banking System," aims to measure systemic risk within Vietnam's commercial banking ecosystem by applying the Conditional Value-at-Risk (CoVaR) methodology. After reviewing existing methodologies, this study adopts the CoVaR approach due to its capacity to quantify the spillover effects from an individual bank's risk to the entire financial system and its compatibility with data from the Vietnamese stock market. From a theoretical perspective, this research contributes to the extant literature by providing empirical evidence on systemic risk using CoVaR in an emerging market financial system. From a practical standpoint, it provides a rigorous assessment of systemic risk within Vietnam's banking sector, identifies key contributory institutions, and proposes evidence-based policy recommendations for effective risk monitoring and mitigation, establishing a foundation for targeted regulatory oversight and future prudential frameworks.

This investigation offers significant contributions. First, it provides new empirical evidence on systemic risk in Vietnam's commercial banks using the CoVaR index with data spanning from 2015 to 2024, capturing market volatility and ensuring responsive analysis during financial instability. Second, it evaluates systemic risk levels and classifies institutions by their risk contribution, offering insights for regulators. Identifying systemically important institutions enables targeted supervision and appropriate capital and liquidity requirements. The study also aims to bridge the gap between theory and practice in Vietnam's systemic risk management, creating a foundation for improved regulatory frameworks.

The manuscript is structured into five distinct sections. Following this introduction, Section 2 provides a comprehensive review of systemic risk conceptualizations and measurement methodologies, with a justification for the CoVaR approach. Section 3 delineates the CoVaR model and data employed. Section 4 presents an analytical assessment of the current systemic risk landscape within Vietnam's banking system. Based on these empirical analyses, Section 5 articulates policy recommendations for enhancing systemic risk management.

2. Literature review

2.1. Systemic risk definition

Systemic risk represents the potential for widespread financial system disruption due to interconnections that amplify individual shocks throughout the entire system. The scholarly literature has extensively examined this phenomenon, developing sophisticated frameworks for its analysis and management. Quantification of systemic risk has advanced through methodologies that reconstruct economic and financial networks using advanced statistical techniques (Cimini et al., 2015; Chen et al., 2020; Ye & Douady, 2018), with the copula method emerging as particularly valuable for capturing multidimensional risk dynamics across various scales (Hochrainer-Stigler et al., 2018). Interconnectivity within financial systems serves as the primary mechanism through which distress propagates, creating spillover effects and cascading failures (Dastkhan & Gharneh, 2016; Xuemin et al., 2014), giving rise to the "too interconnected to fail" paradigm that emphasizes the need for robust regulatory frameworks (Hüser, 2015). Regulatory challenges necessitate approaches that transcend micro-level analysis to incorporate macroeconomic indicators and stress scenarios (Serguieva, 2014), with recent innovations proposing mechanisms such as systemic risk transaction taxes to attenuate high-risk behaviors in interconnected markets (Poledna & Thurner, 2016; Verschuur et al., 2022). The development of sophisticated indicators, particularly the Conditional Value-at-Risk (CoVaR) methodology, has provided critical insights into risk characteristics under diverse conditions (Adrian & Brunnermeier, 2011). This comprehensive body of research underscores that effective management of systemic risk requires an integrated approach combining advanced analytical techniques with proactive regulatory interventions to address the complex interplay of interconnected risks and their broader macroeconomic implications.

2.2. Systemic risk measures

Literature Review: Advances in Systemic Risk Measurement Methodologies

Systemic risk measurement plays a pivotal role in identifying vulnerabilities within interconnected financial networks. Sophisticated methodologies have been developed to quantify the potential cascading effects when individual institutions experience distress. Among these methodologies, the Conditional Value-at-Risk (CoVaR) has emerged as a prominent measure, effectively capturing system-wide risk conditional on the failure of specific entities. Similarly, the Systemic Expected Shortfall (SES) provides complementary insights by incorporating the interconnectedness dimension of financial institutions (Hoffmann et al., 2018; Ellis et al., 2022).

Theoretical frameworks have substantially enhanced the precision of systemic risk assessment techniques. Biagini et al. (2018) introduced a methodological approach utilizing multivariate acceptance sets to aggregate individual risk exposures into comprehensive system-wide risk metrics. This framework, which quantifies the minimum capital buffer required to insulate the system against collective distress, builds upon established principles in mathematical finance and operational risk management, representing a significant advancement in risk quantification methodology (Dhaene et al., 2019). These theoretical innovations establish a robust foundation for both ongoing academic inquiry and practical implementation in systemic risk evaluation.

Empirical investigations complement theoretical developments by contextualizing systemic risk measures within real-world financial environments. Ahmad et al. (2021) implemented a copula-based estimation approach to evaluate systemic risk utilizing balance sheet data from U.S. Bank Holding Companies. This methodology offers distinct advantages over conventional market price data approaches, providing more stable risk representations during periods of market volatility and establishing a globally applicable framework that accounts for institutional interdependencies. This methodological diversification underscores the importance of multifaceted approaches in achieving comprehensive risk assessments.

Regulatory frameworks significantly influence the dynamics of systemic risk. Research conducted by Yalla et al. (2018) demonstrates how regulatory pronouncements can either attenuate or amplify systemic vulnerabilities, contingent upon their design and implementation parameters. Furthermore, Brøgger and Cokayne (2018) elucidate the consequences of regulatory cliffs—discrete regulatory threshold changes—that potentially induce synchronized behavior among financial entities, thereby magnifying systemic risk exposure. These findings emphasize the necessity for adaptive regulatory oversight to effectively address evolving financial system vulnerabilities.

Advanced computational methodologies, particularly those incorporating deep learning techniques, are expanding the boundaries of traditional systemic risk measurement. Feng et al. (2022) investigate the application of artificial intelligence frameworks to enable dynamic risk assessments that reflect the rapidly evolving nature of contemporary financial markets. These technological advancements hold considerable promise for enhancing predictive accuracy and strengthening institutional resilience against unforeseen financial shocks.

The equity dimension of systemic risk measurement constitutes another critical area of investigation. Biagini et al. (2020) demonstrate that systemic risk assessments may exhibit inherent biases, potentially imposing disproportionate regulatory burdens on smaller financial institutions. This consideration is particularly relevant for regulatory authorities, who must ensure equitable treatment across the financial ecosystem to prevent unintended consequences arising from risk management policies.

Among these measures, CoVaR, developed by Adrian and Brunnermeier (2016), offers distinct advantages for this study. Specifically, it quantifies the contribution of an individual institution to overall systemic risk conditional on the institution being in distress, captures spillover effects, and is well-suited for analysis using available market data in Vietnam. Unlike simpler measures like individual VaR, CoVaR directly addresses interconnectedness. While other advanced methods like SES or network models provide valuable insights, CoVaR was selected for its established methodology, interpretability, and data compatibility for the Vietnamese banking sector within the scope of this research.

3. Research Methodology

3.1. Research Design

This study employs a desk research approach combined with quantitative analysis to systematize the theoretical foundations and methodologies for measuring systemic risk through the Conditional Value-at-Risk (CoVaR) index, a method proposed by Adrian and Brunnermeier (2016). CoVaR has been selected due to its capacity to quantify the spillover effects from an individual bank's risk to the entire financial system, and its compatibility with data from the Vietnamese stock market.

3.2. Data and Collection Sources

Data Source: Daily stock price data of commercial banks listed on the HOSE and HNX exchanges during the period from 2015 to 2024 were collected from Vietstock—a reputable financial data provider in Vietnam.

Data Scope: The study utilizes data from 18 commercial banks with continuous listing periods and complete stock price data throughout the research timeframe. The selection of these 18 banks was based on the following criteria: (i) a minimum listing period of 5 years to ensure data continuity and sufficient time series length for quantitative analysis; (ii) complete trading data without interruptions during the 2015-2024 period; (iii) significant representation in terms of total assets and market capitalization within the banking system, encompassing state-owned banks, private banks, and foreign-invested institutions. The limitation to 18 banks aims to ensure the quality and representativeness of the research sample, while adequately reflecting the structure and interconnectedness of Vietnam's current commercial banking system.

3.3. CoVaR Modeling

The CoVaR (Conditional Value at Risk) model developed by Adrian and Brunnermeier (2016) is an important tool for measuring financial systemic risk that applies a "bottom-up" approach to assess the vulnerability of the entire financial system when a specific institution falls into distress, unlike traditional VaR which only measures individual institutional risk; it quantifies risk contagion through the financial network, with its extension ΔCoVaR calculating the difference between

CoVaR in distressed and normal states to represent each financial institution's marginal contribution to overall systemic risk, effectively capturing both "herd behavior" phenomena and the horizontal linkages between institutions as well as vertical linkages of risk accumulation over time, thereby overcoming limitations of traditional risk measurement methods.

Quantitatively, CoVaR measures the VaR of the financial system in the context where the volatility of a specific FI is at the q-th percentile, as the stock price of that institution declines sharply to its risk-bearing value. The mathematical formulation is expressed as:

$$Pr(X^m \leq CoVaR_q^{m|X^i} | X^i) = q$$

Where X^m represents the volatility of the system index, and X^i denotes the volatility of the stock price of bank i. If the risk event for bank i is defined as $X^i = \mathrm{VaR}_q^i$, then CoVaR is determined as:

$$Pr(X^m \leq CoVaR_q^{m|X^i=VaR_q^i} | X^i = VaR_q^i) = q$$

To evaluate the change in market conditions due to the impact of a specific institution, the contribution of bank i to SR is calculated as the difference:

$$\Delta CoVaR_q^{m|i} = CoVaR_q^{m|X^i=VaR_q^i} - CoVaR_q^{m|X^i=Median}$$

A higher value of $\Delta\mathrm{CoVaR}_q^{m|i}$ indicates a greater impact of risk volatility at bank i on the system.

Steps for calculating CoVaR:

Step 1: Individual VaR Estimation

Quantile Regression at the 5% level is applied to determine the VaR for each bank, where the dependent variable is the daily logarithmic return R_(i,t)=ln(P_(i,t)/P_(i,t-1)) and the independent variable is the market return R_(m,t).

Regression equation:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$$

Where the VaR of bank i at the 5% level is $\hat{R}_{i,t}^{5\%}$

Step 2: Systemic CoVaR Calculation

The condition where bank i reaches its VaR threshold (R_(i,t)≤R̂_(i,t)^(5%)) is identified, followed by estimating the system's VaR under this condition using quantile regression:

CoVaR_(system|i)=α_(system|i)+β_(system|i) R̂_(i,t)^(5%)

$$CoVaR\ (system|i) = \alpha(system|i) + \beta(system|i)\hat{R}_{i,t}^{5\%}$$

3.4. Python Implementation

Analytical Tools*:*

Primary libraries: Pandas (for data aggregation), Statsmodels (for quantile regression), Arch (for testing stationarity of return series).

Automated Process*:*

Development of a pipeline for importing data from Vietstock in CSV/Excel format.

Automated calculation of returns, individual VaR, and CoVaR for each bank.

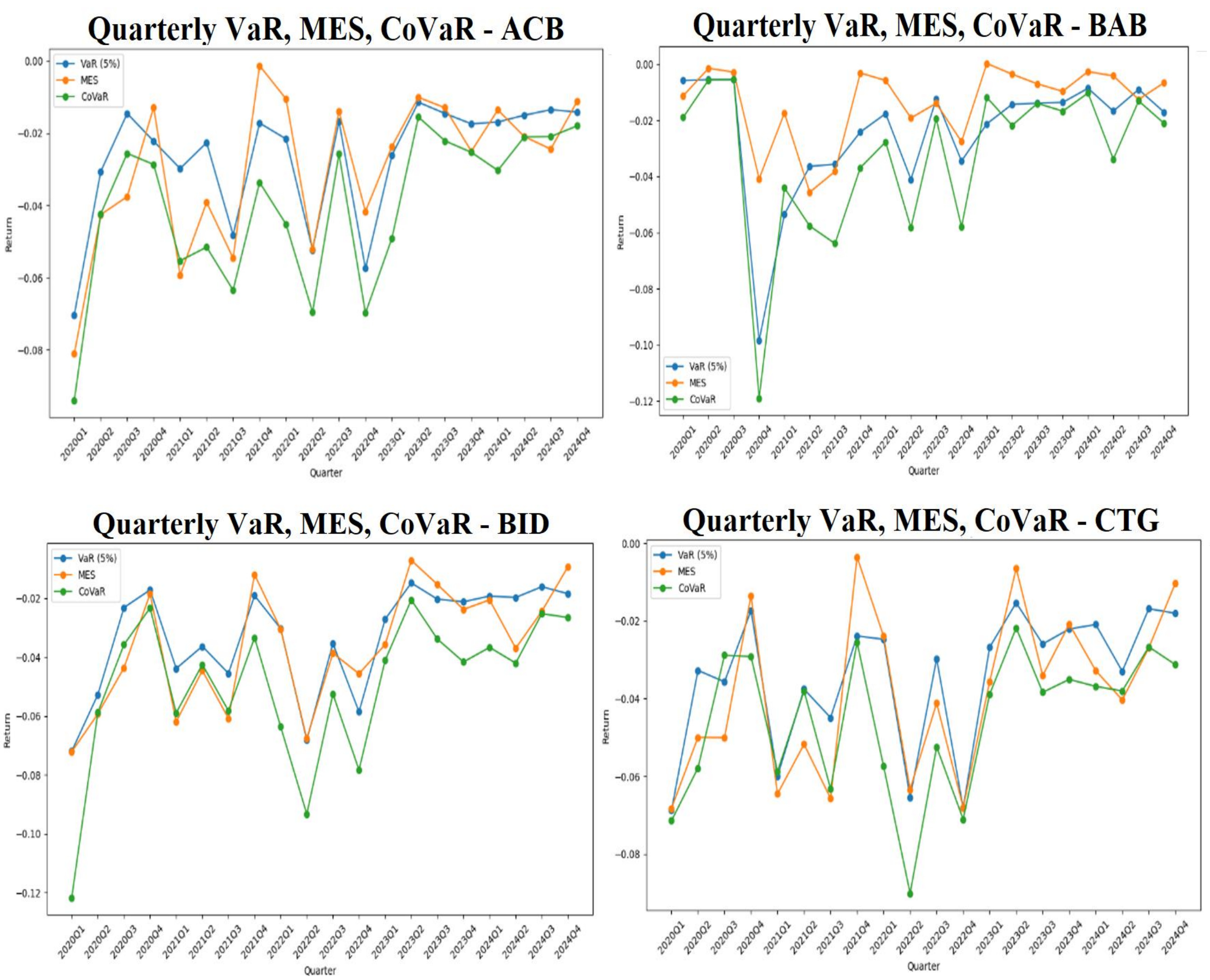
Generation of dynamic reports in the form of heatmaps (using Seaborn) to visualize risk contribution levels over time.

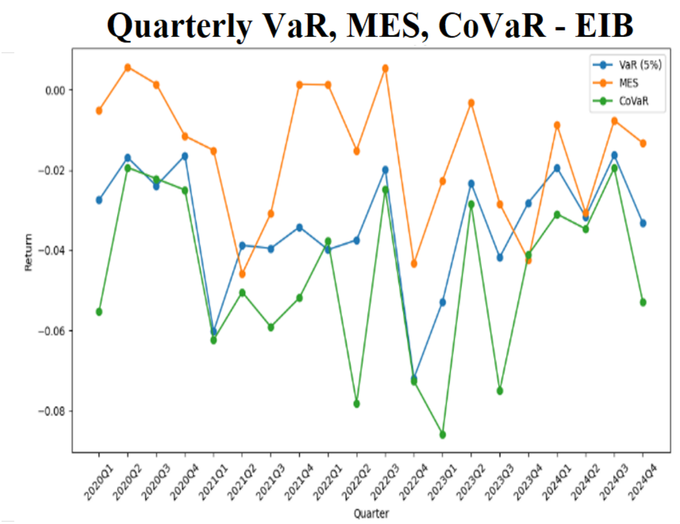
4. Results of systemic risk measurement

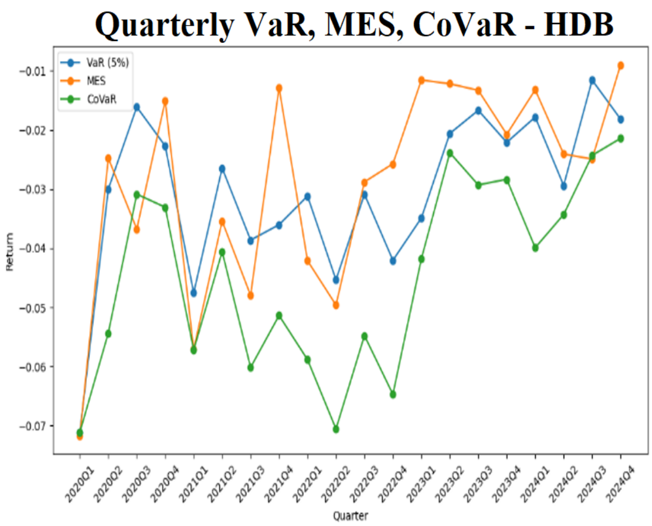
4.1. CoVaR Index Volatility at Commercial Banks

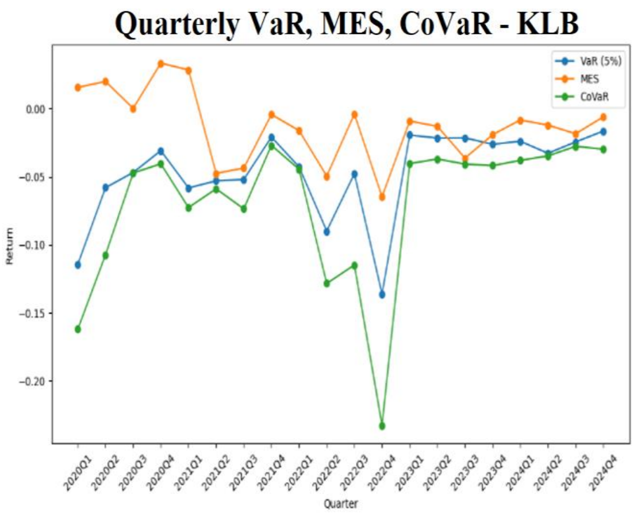
Graph 1 displays the quarterly estimated values of CoVaR, MES, and VaR (5%) for each bank during the 2020-2024 period, illustrating the level of contribution each bank made to systemic risk during the corresponding research timeframe.

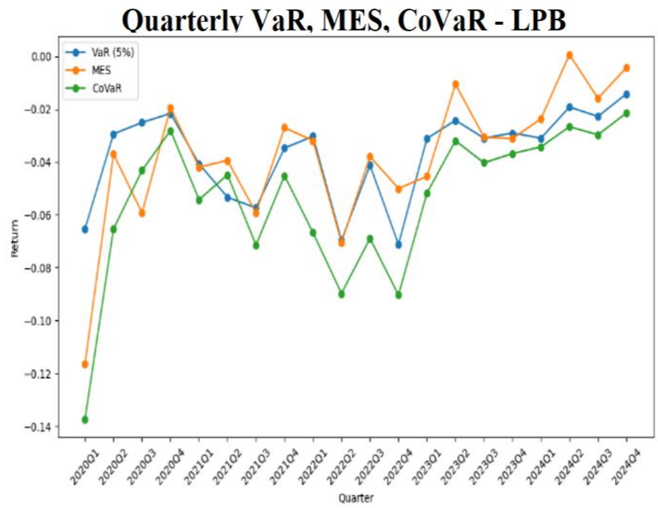
Graph 1. CoVaR, MES, VaR (5%) values of Vietnamese Commercial Banks by quarter during the 2020-2024 period

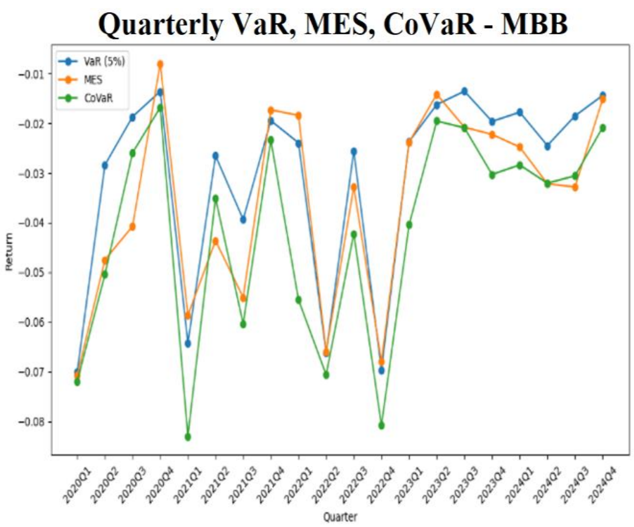


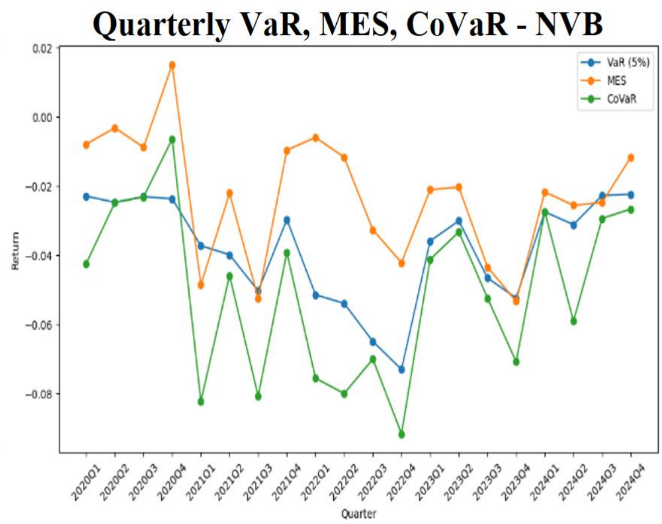

Quarterly VaR, MES, CoVaR - EIB
VaR (5%)
MES
CoVaR
Return
Quarter

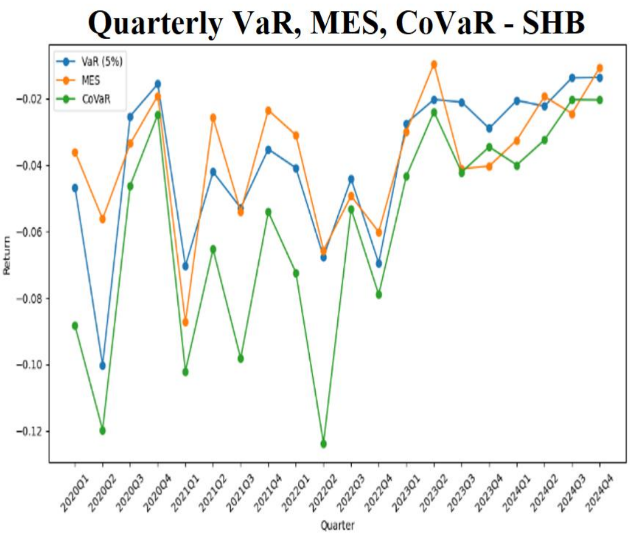

Quarterly VaR, MES, CoVaR - HDB
VaR (5%)
MES
CoVaR
Return
Quarter

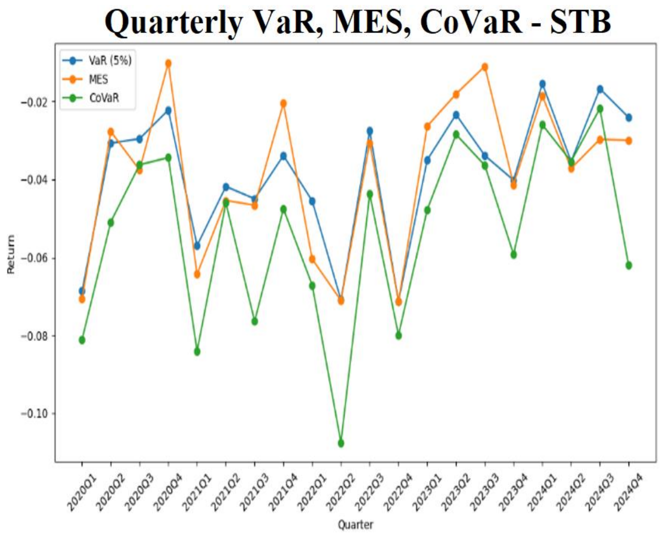

Quarterly VaR, MES, CoVaR - KLB
VaR (5%)
MES
CoVaR
Return
Quarter

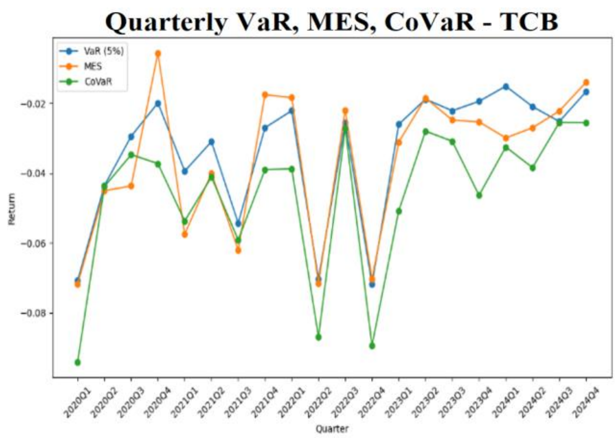

Quarterly VaR, MES, CoVaR - LPB
VaR (5%)
MES
CoVaR
Return
Quarter

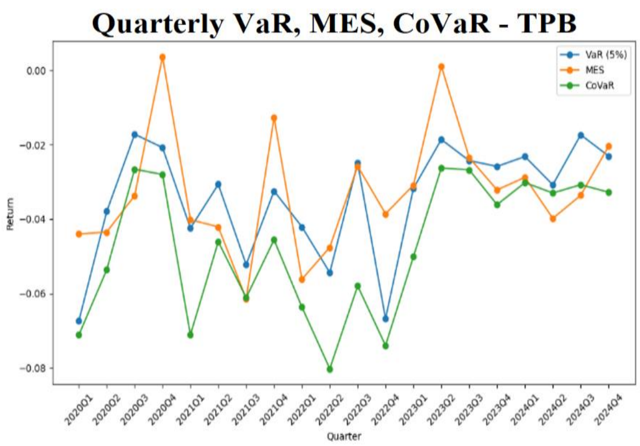

Quarterly VaR, MES, CoVaR - MBB
VaR (5%)
MES
CoVaR
Return
Quarter

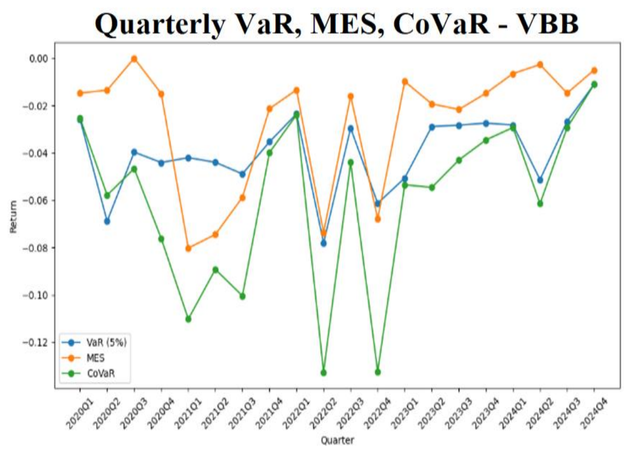

Quarterly VaR, MES, CoVaR - NVB
VaR (5%)
MES
CoVaR
Return
Quarter

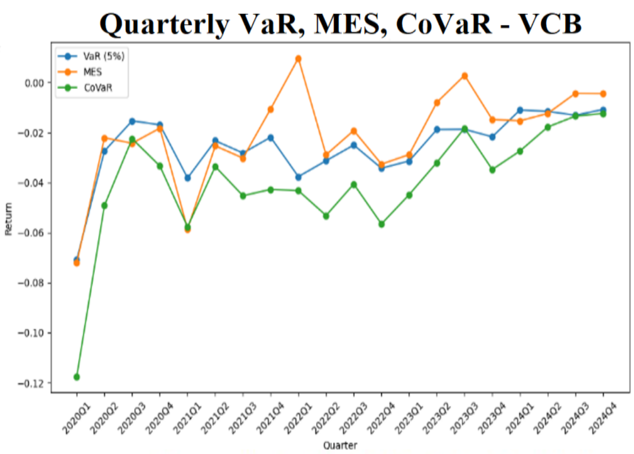

Quarterly VaR, MES, CoVaR - SHB
VaR (5%)
MES
CoVaR
Return
Quarter

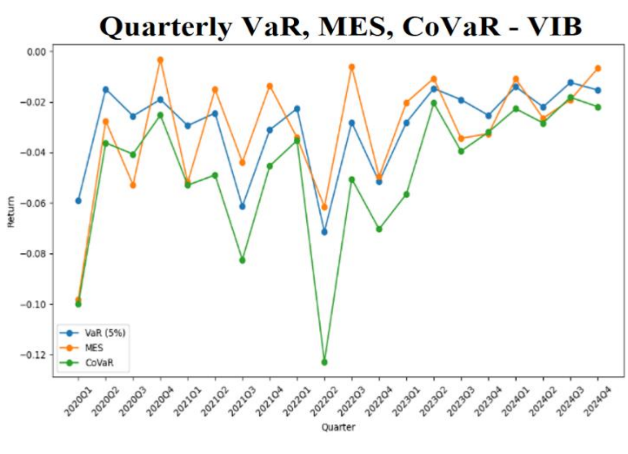

Quarterly VaR, MES, CoVaR - STB
VaR (5%)
MES
CoVaR
Return
Quarter

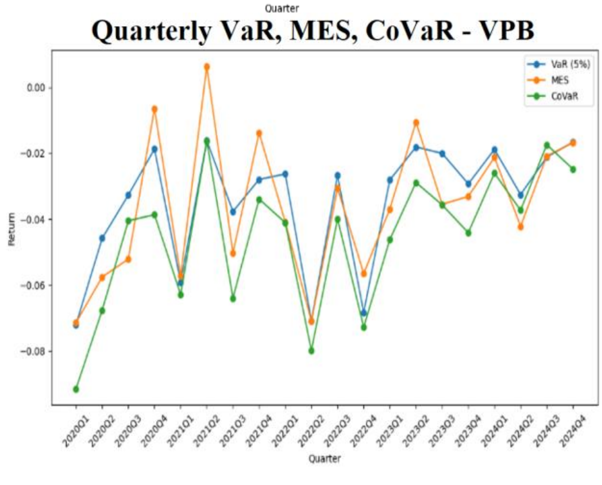

Quarterly VaR, MES, CoVaR - TCB
VaR (5%)
MES
CoVaR
Return
Quarter


Quarterly VaR, MES, CoVaR - TPB
VaR (5%)
MES
CoVaR
Return
Quarter


Quarterly VaR, MES, CoVaR - VBB
VaR (5%)
MES
CoVaR
Return
Quarter

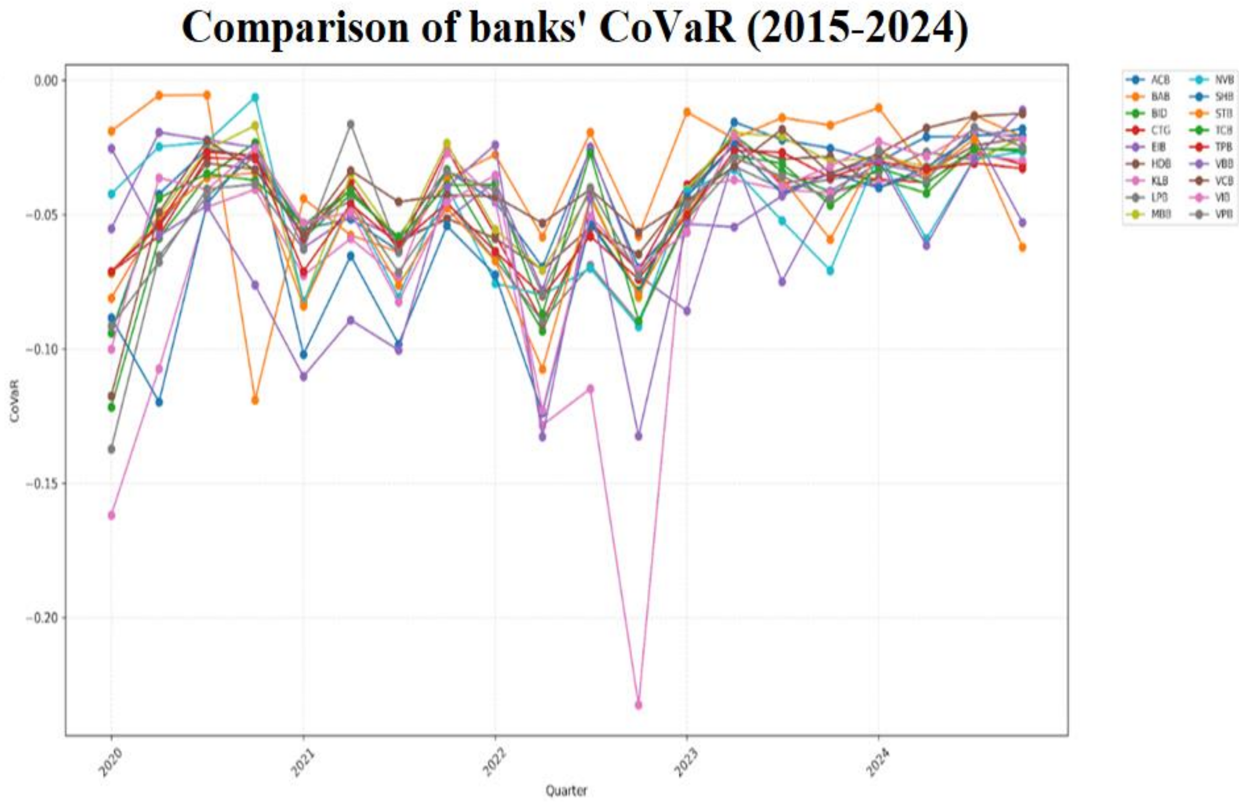

Quarterly VaR, MES, CoVaR - VCB
VaR (5%)
MES
CoVaR
Return
Quarter


Quarterly VaR, MES, CoVaR - VIB
VaR (5%)
MES
CoVaR
Return
Quarter


Quarterly VaR, MES, CoVaR - VPB
VaR (5%)
MES
CoVaR
Return
Quarter

Our CoVaR, MES, and VaR (5%) analysis of Vietnamese commercial banks during 2020-2024 reveals significant heterogeneity in risk profiles across institutions. The period exhibited three distinct risk phases: the pandemic outbreak (2020-2021) when risk indicators surged despite government interventions; the recovery with persistent challenges (2022-2023) when measures stabilized but remained elevated; and the stabilization phase (2024) showing further risk moderation. During the pandemic, VaR increased sharply reflecting uncertainty, MES escalated particularly for larger banks, and CoVaR rose markedly indicating intensified risk interdependence. As economic recovery commenced amid inflationary pressures and supply chain disruptions, risk measures gradually improved while maintaining higher interconnectedness than pre-pandemic periods. By 2024, improving conditions led to further risk indicator moderation, suggesting decreased contagion potential and enhanced financial health. Our analysis demonstrates MES and CoVaR's superiority over VaR in measuring systemic risk, particularly during economic upheaval, with their pronounced pandemic-era increases highlighting systemic vulnerability amplification. These findings underscore the importance of integrating these advanced metrics into macroprudential frameworks for timely risk detection and mitigation in Vietnam's banking system

Graph 2: Comparison of CoVaR for Vietnamese Commercial Banks



Overall, the CoVaR index of Vietnamese banks during the 2020–2024 period primarily fluctuated between -0.03 and -0.10, with some instances dropping below -0.15, particularly in 2022. At the start of 2020, most banks recorded negative CoVaR values, which aligns with the broader economic and banking sector trends in Vietnam amidst the financial instability caused by the COVID-19 pandemic. A relative recovery was observed in 2021, but in 2022, especially during Q2 and Q3, CoVaR sharply declined again, indicating an increase in systemic risk (SR). One of the banks with the lowest CoVaR during this period was KLB, reaching below -0.20, reflecting a significant contribution to SR during market shocks.

Banks such as BID, VCB, CTG, and MBB generally maintained CoVaR levels between -0.04 and -0.07. As large banks with strong financial capacity, they likely played a stabilizing role in the system during shocks. In contrast, KLB and SHB exhibited the most significant CoVaR fluctuations, with several quarters dropping below -0.15. This suggests higher SR, possibly due to riskier assetliability structures or weaker liquidity under stressed market conditions. Banks like ACB, TCB, TPB, and VIB showed moderate CoVaR fluctuations with relative stability during 2023–2024, indicating better adaptability to market volatility.

The 2020–2024 period witnessed substantial macroeconomic market fluctuations, including the prolonged impact of the COVID-19 pandemic, rising inflation, global monetary policy adjustments, and uneven economic recovery. These factors directly influenced the level of SR in the banking sector.

5. Recommendations

Based on the results of empirical research on systemic risk, the authors propose a number of recommendations to support management agencies in improving risk management capacity, limiting spillover effects and negative contributions to systemic risk in the entire industry.

First, control risks arising from non-credit activities.

5.1. Recommendations for the State Bank

First, it is necessary to strengthen the monitoring of systemic risks in a proactive and positive manner. The State Bank needs to develop an early warning framework based on big data, artificial intelligence (AI) and macro-econometric models to promptly detect signals of instability from the credit cycle, the level of systemic leverage, liquidity imbalances or the risk of risk transmission. Through stress-tests, important banks in the system can assess potential risks and quantify the level of loss that is likely to occur to the balance sheet and liquidity. This will be an important basis for the management agency to assess the appropriateness and effectiveness of the risk measurement measures being implemented, thereby making timely and more accurate decisions to adjust supervisory policies.

Second, it is necessary to expand the scope of supervision to high-risk non-credit activities. In the context of banks increasingly diversifying their business models, including insurance business, corporate bond investment, financial derivatives services, and complex financial products. The State Bank needs to develop a separate set of supervisory standards for each type of non-credit activity. At the same time, it is necessary to require full disclosure of information related to the level of risk, profit structure, and the bank's tolerance in adverse volatility scenarios.

Third, perfecting the legal framework for macroprudential supervision. The State Bank needs to be given more authority in applying macroprudential tools. In addition, the policy coordination mechanism between the State Bank, the Ministry of Finance, the Securities Commission, and other regulatory agencies needs to be institutionalized in the form of an inter-agency coordination process, in order to enhance information sharing and synchronous policy responses to systemic shocks.

Finally, improve organizational capacity, human resources and technology in financial system supervision. The State Bank needs to establish a specialized unit on financial stability, with the task of researching, monitoring and proposing timely policies when systemic risks arise. In addition, staff need to be trained in risk management, financial statistics, quantitative analysis and financial technology (fintech) to keep up with the trend of modernizing banking supervision in the world.

5.2. Recommendations for Commercial Banks

Commercial banks need to be cautious in expanding into non-core business areas, especially those with high risk levels and less related to the core competencies of the bank. Spreading out and unstrategic investment can lead to resource dispersion, increasing vulnerability to macro shocks and exacerbating systemic risk. Instead, banks should prioritize restructuring their portfolio of activities, focusing on upgrading the quality of financial products and services, promoting the application of digital technology in operations and interactions with customers, and expanding modern distribution channels. At the same time, develop value-added financial services, especially in the middle and high-end customer segments.

Second, control the level of financial leverage and enhance capital capacity. Commercial banks need to maintain a reasonable leverage ratio to ensure resilience to unexpected systemic shocks. At the same time, improving asset utilization efficiency and controlling operating costs will contribute to improving overall financial capacity, increasing capital safety and minimizing the risk of insolvency in volatile market conditions.

Third, strengthen credit risk control. Credit risk is still the largest component of overall banking risk and is the main transmission factor in financial crises. Therefore, banks need to improve the quality of credit appraisal processes, perfect internal credit rating systems in accordance with Basel II and III standards, strengthen post-disbursement monitoring and apply technology to detect early signs of deterioration in debt repayment capacity. In particular, it is necessary to have a policy to strictly control lending to high-risk sectors such as real estate, financial derivatives investment or industries with large fluctuations in cash flow.

Finally, build and complete a database system to measure and control systemic risks. A centralized, complete, timely and standardized database system is a prerequisite for effectively applying quantitative models such as CoVaR or SRISK in measuring systemic risks. Commercial banks need to proactively coordinate with the State Bank and relevant agencies in providing, comparing and standardizing data. In addition, it is necessary to improve the transparency, accuracy and ability to accurately reflect the financial status of periodic financial reports. Compliance with information disclosure standards according to international practices will also contribute to increasing the reliability of input data, thereby improving the quality of analysis and the effectiveness of macro-supervision.

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