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Beyond VaR: Unravelling the Nuances of CVaR and Its Role in Evaluating Financial Institution Risks Metrics

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ABSTRACT

The study investigates the application of CVaR and VaR approaches in risk assessment, demonstrating a discrepancy in accuracy between confidence levels. It highlights how crucial the choice of confidence level affects the accuracy of risk assessment. The study also demonstrates how adding the Generalised Breach Indicator and CVaR improves the accuracy of risk assessment in financial institutions. The study looks at risk assessment tools for different types of financial institutions, like public, private, and NBFC banks. It emphasizes how these tools are adaptable to different industry characteristics and have practical implications. It also offers customized risk management solutions, emphasizing how flexible these methodologies are. The study highlights the practical usefulness of VaR and CVaR techniques in enhancing the accuracy of risk assessment for financial institutions, while also offering insightful information about them. Bootstrap test, Kruskal Wallis Test, and GBI were used for the study. Sophisticated risk management frameworks are essential for maintaining stability and sustainability across multiple industries as the financial landscape changes.

Key Words: VaR, CVaR, NBFC, Public sector bank, Private Sector bank, GBI.

1. Introduction

Effective risk management is essential to the stability and long-term viability of conventional banks as well as non-banking financial companies (NBFCs) in the ever-changing financial sector. Robust risk assessment procedures are crucial, as demonstrated by the unprecedented events of the past, including the global financial crisis of 2008 and the recent economic issues resulting from the COVID-19 epidemic and in addition to this the increase in the domain of Shadow Banks in the year 2020.VaR and Conditional VaR, two commonly used risk metrics, are used in this study's thorough comparative examination of Indian NBFCs and traditional banks to explore the field of risk measurement. NBFCs stand out from traditional banks due to their distinctive qualities, which include their multiple funding sources, specialized lending procedures, and diverse business structures. In light of this, it is critical to recognize and measure the inherent risks in both entities. The purpose of this study is to illuminate the complex risk profiles of Indian NBFCs and traditional banks, offering useful information to stakeholders, practitioners, and regulators.

Recently, there have been major reforms in the Indian banking system with the goal of improving performance, efficiency, and economic growth (Priyajit, 2023) (Thapliyal, 2018). Both public and private sector banks have expanded as a result of these reforms, advancing the nation's overall development (Pandey, 2022). Because of the intense competition among Indian banks, retaining talent has become a crucial concern, prompting studies on efficient retention tactics for the banking industry (Habeeb, 2022). More than half of the assets in the financial sector are accounted for by the Indian banking system, which is vital to the nation's social and economic development (Mehrotra, 2022). The market now has competition, greater transparency, and structural improvements as a result of the reforms. In general, India's banking industry is essential to the country's economic stability, inclusive growth, and the nation's overall development.

The study seeks to uncover important risk variables, identify commonalities in the risk profiles of NBFCs and traditional banks, and draw conclusions for risk management techniques. In the context of the Indian financial landscape, this study adds to the body of knowledge by providing a thorough comparative analysis that closes the gap between theory and real application. To manage possible losses, ensure acceptable limits, allocate resources, and comply with regulations, risk measurement, monitoring, capital allocation, and regulatory compliance are essential processes. VaR, which is computed daily, is a key risk statistic for banks under the Basel Accords. Extreme risk above VaR is measured by Conditional Value at Risk, or CVaR. Measurement of relative industry risk is crucial to risk management (Allen & Powell, 2007). It is challenging to compare Value at Risk and CVaR models since they only quantify the realization of a single data-generating process; therefore, more research is necessary to identify significant statistical discrepancies(Zikovic, 2012). As we begin this investigation into uncertainty, the results should help financial institutions manage the complex web of risks in a constantly shifting environment through strategic decision-making, regulatory frameworks, and risk mitigation techniques.

1.1 Non-Financial Banking Corporation

Non-Banking Financial Companies (NBFCs), which provide a broad range of financial services to both consumers and corporations, are essential middlemen in the Indian financial system. They are governed by the Reserve Bank of India (RBI) and serve underprivileged populations. Asset Finance Companies (AFCs), Loan Companies, Investment Companies, Infrastructure Finance Companies, and Systemically Important Core Investment Companies (CICs) are the several categories under which NBFCs fall. By reaching out to disadvantaged and unbanked communities through creative products and flexible lending procedures, they play a critical role in fostering financial inclusion. Market, credit, and liquidity risks are among the difficulties that NBFCs must overcome, underscoring the significance of effective risk management procedures. The goal of the NBFC-Microfinance Institution (MFI) segment is to offer economically disadvantaged groups microfinance services.

By offering lending facilities to companies, non-banking financial organisations (NBFCs) contribute significantly to the financial sector, creating jobs and fostering economic growth (Lam, 2023). High credit risk, inadequate industrial growth, and competition from conventional banks are some of the difficulties that NBFCs must overcome, though (Yang, 2022). For NBFCs to remain solvent and profitable, credit risk management and non-performing asset control are essential (Philipp, 2022). The total factor productivity (TFP) of non-financial companies (non-FEs) is greatly impacted negatively by their shadow banking business (SBB) Yang, 2022). European banks are required to comply with non-financial reporting regulations; yet, the standard of non-financial reporting is subpar (Belen, 2020).

To improve client satisfaction and operational effectiveness, NBFCs have embraced technology innovations. Indian banks are having difficulty managing Non-Performance Assets (NPA) and increasing capital, which is causing them to lend less on major projects. They obtained their funding from foreign loans, mutual funds, and banks; nonetheless, regulators disapprove of evergreening since it obscures facts and hazards (Manda& Rani, 2019). The regulatory focus on corporate governance and transparency has intensified, necessitating strict adherence to norms by NBFCs. A designation of Systemically Important NBFCs (SI-NBFCs) has been given to some NBFCs, signifying their importance to the financial system. One-fifth of India's credit is managed by non-banking finance companies (NBFCs), although they encountered difficulties following IL&FS's September 2018 failure. NBFC giants such as Shriram Transport Finance, Dewan Housing Finance, and India Bulls Housing Finance all took a hit (Malankar& Jape, 2021). The credit intensity of NBFCs is shown by the NBFC credit to GDP ratio in India, which was at 13.7% in 2021 and indicated the NBFCs' share of the country's GDP. Since last year, this ratio has steadily climbed from about 12%. While the GDP's direct contribution from NBFCs is not disclosed, it is an important measure of their economic importance.

Shadow Banks: Financial companies known as "shadow banks" offer services that are comparable to those of ordinary banks but operate outside of the established banking system. According to the report, Indian banks see lending to NBFCs as a way to offset direct lending in rural regions, but this view is limited by government assistance(Acharya, 2013). Since their establishment in the 1970s, shadow banks—which first appeared in India—have expanded rapidly in emerging nations. The IL&FS Group's collapse in 2018 halted investment, upset the credit cycle and had an impact on GDP growth(Sivaramkrishna, 2019). But they don't have the same regulatory supervision or protections when they do it. Money market funds, hedge funds, non-bank financial institutions, and other financial intermediaries are examples of entities that fall under the category of shadow banks.

Shadow banks are not covered by government rules or insurance when they face financial difficulties. Because many of these entities do not report to regulators, estimating their size and operations is difficult(Chaturvedi, 2023). The COVID-19 pandemic of 2020 caused a great deal of disruption to the global financial markets, mostly because of the effect shadow banks had on the stock market. Because shadow banks mainly rely on short-term borrowing, there were problems with liquidity as a result of heightened market uncertainty. As a result, money was abruptly removed from several financial markets, including those that shadow banks supplied. The rise of global shadow banking (SB) underscores its significance in the financial system and calls for an evaluation of its efficacy in conjunction with banking institutions(Bhattacharjee, 2021). This increased market volatility and placed pressure on asset values. Due to the economic impact of the epidemic, investors became extremely nervous, which resulted in a sell-off of all asset classes, including stocks. The financial system as a whole was impacted by the higher borrowing costs' detrimental effects on the stability and profitability of companies and financial institutions. Because shadow banks were not subject to regulatory scrutiny, they were more vulnerable to dangers, and the linked nature of the financial system raised concerns about the potential for a contagion effect.

1.2 Public Sector Banks

Government-owned financial institutions known as public sector banks (PSBs) are essential to the economic growth of India since they offer a wide range of consumer financial products and banking services. These banks offer crucial banking services and support efforts for financial inclusion and literacy through their vast network of branches and ATMs. They also carry out government programs that support social development, financial inclusion, and poverty reduction. Public sector banks are required to meet social and economic goals, including lending targets for priority sectors. The strategy of nationalizing banks has, according to empirical evidence, improved capital productivity, savings, investment, and GDP, although it hasn't entirely met its objectives(Ketkar, 1993). Customers view them as solid and secure because of the government's support. They function inside the Reserve Bank of India's (RBI) regulatory framework, which guarantees adherence to risk management procedures and prudential standards. Significant structural changes have occurred in the Indian banking sector since liberalization, which has resulted in financial problems such as growing non-performing assets (NPAs), a weak capital position, an increase in fraud, and a sluggish pace of financial inclusion(Meghani, 2020).

The Indian public sector banks and the stock market have been examined. Examining the variables that affect profitability in Indian public sector banks, it was discovered that variables including inflation, bank asset size, cost to income, net non-performing assets, and credit deposit ratio all have an adverse effect on profitability metrics. However, profitability is positively impacted by credit risk and economic growth (Dogra, 2022). The report also noted a number of operational and financial problems that public sector banks face, such as difficulties with financial inclusion, money laundering instances, non-performing assets, and inadequate capital positions (Chalam, 2023). Furthermore, it was discovered that public sector banks' first responses to pandemic-related events were non-reactive but significantly sensitive to specific interventions, such as financial measures implemented by the Reserve Bank of India (Meghani, 2020). Studies have also been conducted on the volatility of the stock prices of banking sector companies, especially during India's demonetization era (Mahnoor, 2022).

Private Sector Banks

Private sector banks are autonomous financial institutions with a profit-generating objective that is owned by private individuals, companies, or a combination of the two. They serve both individual and business clients, and they are an important part of India's banking and financial industry. In the stock market, private-sector banks—like HDFC, ICICI, and Kotak Mahindra—are supposedly outperforming public-sector banks(Balaji& Kumar, 2017). Banks in the private sector are renowned for their customer-centric strategies, emphasizing individualized care and customized financial products. Their focus is on the market, and they make technological investments to enhance risk management and optimize operations. It has been observed that private sector banks in India are fiercely competing with their counterparts in terms of efficiency and financial performance (Singh, 2018). The CAMEL model, which contrasts the total financial performance of the biggest banks in the nation, has been used to assess the performance of private sector banks (Kanagarathinam, 2016). According to the report, private sector banks are promoting inclusive growth and aiding in the nation's financial development (Mayur, 2018). Furthermore, the research suggests that there is an adverse correlation between Indian stock markets and banks (Dixit, 2016). It is noteworthy, therefore, that the offered abstracts do not specifically address the nature of the link between private sector banks and the stock market. They minimize risks by implementing strong risk management procedures and concentrating on maximizing shareholder profits. They follow prudential guidelines and are governed by regulatory oversight under the Reserve Bank of India's regulatory framework. To establish confidence and credibility in the financial markets, private sector banks usually follow strict guidelines for corporate governance, emphasizing accountability to shareholders, transparency, and moral behaviour.

Over 75% of domestic output and investment are driven by the private sector, which makes a substantial contribution to India's economy. Since the 1980s, it has greatly increased its employment and GDP share. India has increased private sector investment by allocating 5.5%

of its GDP to infrastructure development. To draw in foreign direct investment, the government has concentrated on loosening regulations on private manufacturing and labour markets. The 6.7% GDP growth in India is anticipated to come primarily from capital accumulation. The private sector also significantly influences India's external sector performance.

1.3 Value at risk model

The financial environment in which Non-Banking Financial Companies (NBFCs) operate is dynamic and frequently complex. They take part in a range of financial activities, including investing, lending, and wealth management, and they run the danger of experiencing credit, liquidity, and market risks in addition to other uncertainties. For NBFCs, VaR is an essential risk management tool that aids in evaluating and limiting possible losses in their portfolios.

VaR is a statistical metric used in financial risk management to calculate the greatest loss that a financial asset portfolio could experience in a typical market. With a 95% confidence level indicating a 5% possibility of the portfolio losing more than $1 million, it is expressed as a particular monetary sum or percentage of the portfolio's value.

Three models are used to calculate VaR in asset pricing & to know the potential losses: parametric VaR, historical VaR, and Monte Carlo VaR. The Normal VaR Measure, Stressed VaR Measure, and Incremental Risk Charge (IRC) for positions with particular risks are among the essential parameters for VaR models that are mandated by the IMA circular dated April 7, 2010(Swamy, 2016). To represent non-normality and time-varying volatility, historical simulation makes use of past price changes. VaR, or PVaR, was computed using the variance-covariance approach (parametric VaR) to assess downside risk for all regimes and times(Das, 2020). The parametric model assumes that asset returns follow a particular distribution for simplicity and computing efficiency. Monte Carlo simulation VaR is a flexible tool for modeling complicated portfolios and non-linear interactions through the generation of alternative future possibilities for asset prices by random sampling. That needs assumptions about the distribution of asset returns, though, and is computationally demanding. For liquid markets with returns that are regularly distributed, these models work well.

Formula to Calculate VaR is:

$$VaR = \mu + Z \times \sigma$$

Where **VaR** denotes Value at risk, μ indicates mean or average returns of portfolio investment or individual stocks on a specified time horizon, and **Z** refers to the Z-score corresponding to the desired confidence level such as 90%, 95% & 99% depending upon the individual investor risk tolerance and investment behaviour. ***σ refers*** to the standard deviation for individual assets.

1.4 Conditional Value at Risk

VaRis a risk measure that is expanded upon by CVaR also referred to as ES. Although VaR offers a maximum potential loss estimate at a particular confidence level, CVaR goes one step further by estimating the average or expected loss above the VaR threshold, subject to the threshold being crossed. Beyond VaR, ES computes the anticipated value of losses that happen over the VaR boundary. Risk-averse agents behave differently from risk-neutral ones, according to a study that uses the CVaR risk measure to investigate the structural characteristics of social learning(Krishnamurthy, 2016). In essence, it is the conditional mean of the distribution's tail losses. An insightful assessment of portfolio risk above and beyond the VaR threshold is offered by CVaR, a cogent risk metric. The accuracy of the result is contingent upon the fulfillment of specific return distribution assumptions and the sub-additivity property. All portfolios, though, might not find it suited.

CVaR formula $= \dfrac{1}{1-c}\displaystyle\int_{-1}^{VaR} xp(x)\,dx$

Where p(x)The probability density of receiving a return with value "x" is equal to dx.
c is the distribution's cut-off point at which the analyst establishes the VaR breakpoint.
VaR is the predetermined VaR level.
The Indian stock market has been the subject of research on the CVaR model. Risk has been measured using a variety of techniques, such as parametric and non-parametric models. When returns are non-normally distributed, it has been discovered that VaR models predicated on the assumption of normalcy underestimate risk (Jitender, 2021). It has been discovered that there is risk transfer from dramatic price swings in crude oil futures to the stock market when the EVT-VaR method is applied to quantify tail risk in widely traded Indian commodities futures returns (Agnihotri, 2022). Explicit formulas for VaR and CVaR have been examined, and the Laplace distribution has been used as an alternative to the normal distribution for obtaining better scalar estimates of risk (Malik, 2022). Numerical simulations have been done to bolster the results of using the GARCH model for risk management in the stock market (Bony, 2020). Simulation studies (Long, 2020) have verified the superiority of employing the extreme value distribution in risk management.

2. Literature Review

The examination of extreme value prediction methodologies within the ASEAN stock markets reveals a compelling exploration into the juxtaposition of quantum econometrics and conventional econometrics, particularly in forecasting VaR and ESusing risk management analysis (Chaiboonsri, 2021). While Basel III prompted a significant reassessment of risk measurement practices, particularly in transitioning from VaR to CVaR, the lack of quantitative analysis by the BCB hindered a comprehensive understanding of potential improvements, underscoring methodological challenges such as selecting appropriate multiplication factors and confidence levels (Rossignolo, 2017). In the context of the Indian stock market's inherent volatility, the adoption of Extreme Value Theory (EVT) emerges as a robust approach for estimating tail-related risk indicators like VaR and CVaR, particularly through a conditional approach due to the stochastic nature of return series (Karmakar, 2013). Building upon the Basel Committee's framework, empirical investigations reveal that while intra-day data does not significantly enhance VaR and CVaR forecasts, GARCH models based on inter-day information exhibit superior predictive accuracy, especially for multi-day forecasts across various asset classes (Degiannakis, 2017). The Indian stock market has been the subject of research on VaR and CVaR. Research has demonstrated that range-based volatility estimates, which are incorporated into GARCH models like RGARCH and RTARCH, yield more accurate VaR forecasts than traditional models that just rely on closing prices (Padmakumari, 2023). Tail risk in actively traded Indian commodity futures returns has been measured using the EVT-VaR method. The results show that stock market volatility is impacted by shocks to crude oil futures but not by those to zinc or natural gas futures (Agnihotri, 2022). It has been discovered that non-parametric models—like historical simulation—better reflect the risk associated with returns that are not regularly distributed in the Indian equities market (Jitender, 2021). For financial market risk management, a deep learning and particle swarm optimisation algorithm-based CVaR prediction model has been suggested (Wu, 2022). In the Indian stock market, mutual information-based stock networks have been used to assess the VaR of a portfolio of stocks. It has been found that there are non-linear correlations between stock returns (Sharma, 2021).

3. Research Gap

There is a study deficit in understanding the severity of risk over an extended time horizon, specifically three years, despite the growing importance of risk management in the banking industry and the widespread usage of CVaR and (VAR) models. While daily VaR calculations have been the subject of earlier research, little has been done to thoroughly assess how well CVaR and VAR models capture and quantify the dynamic nature of risk exposure in the banking industry over a long period. Through a three-year investigation of various financial institutions and the introduction of the Generalised Breach indicator, this research seeks to fill in the gaps in the comparative analysis of risk occurrences in the banking sector.

4. Objectives of the Study

- To explore the distinctions of VaR and CVaR methodology contribute to the observed differences in the risk estimates.
- To analyze the impact of varying confidence levels on VaR and CVaR accuracy and evaluate their resilience across diverse markets, offering actionable insights for risk management.
- To assess financial institution risks, employ CVaR, enhance accuracy with the Generalised Breach Indicator, and explore their relationship for insights.

5. Hypothesis

1. H_0: The distinctions in VaR and CVaR methodology do not contribute to the observed differences in the risk estimates.
   H_1: The distinctions in VaR and CVaR methodology significantly contribute to the observed differences in the risk estimates.
2. H_0: There is no significant difference in the precision of VaR and CVaR estimations across various confidence levels.
   H_1: There is a significant difference in the precision of VaR and CVaR estimations across various confidence levels.
3. H_0: The use of CVaR and the Generalised Breach Indicator does not significantly contribute to the accurate assessment of financial institution risks.
   H_1: The utilization of CVaR and the Generalised Breach Indicator significantly enhances the accuracy in evaluating financial institution risks and provides valuable insights.

6. Scope for the Study

The purpose of this research is to use VAR and ES models to do a thorough and in-depth analysis of the level of risk in the banking industry over three years. Public banks, private banks, and non-banking financial companies (NBFCs) are only a few of the financial institutions that will be included in the study. Through the use of historical market variable data, the study attempts to compute daily VaR and evaluate how well CVaR and VAR models capture and quantify the dynamic nature of risk exposure. By assessing the Generalised Breach indicator's suitability for use in risk assessment, the study will shed light on the risk management strategies used by the banking industry. It will offer useful ramifications for financial institutions and assist regulators, legislators, and industry professionals in making well-informed decisions.

7. Research Methodology

This study will use a systematic methodology to investigate the risk severity and comparative analysis between VaR and ES in the banking industry over three years (2019–2021). We'll gather historical data on important market indicators like interest rates and equity prices from the top five NBFCs as well as public and private banks. To improve the accuracy of risk assessment, a Generalised Breach indicator will be included for ES or CVaR. With a nuanced understanding of risk severity, this complete approach assesses the dynamic nature of risk exposure in chosen institutions. In addition, the public sector's stocks chosen were SBI, Bank of Baroda, PNB, Union Bank of India, and Indian Bank; the private sector's choices were HDFC, ICICI, Kotak Mahindra, India Bank, and Axis Bank. From NBFC Banks, the stocks chosen were Cholamandalam IFC, Shriram Finance, Muthoot Finance, L&T Finance Holding, and Sundaram Finance.

8. Data Collection

Secondary Data: For the study total 3 years daily, historical data was collected from the NSE website for the study from 2019 to 2021.

9. Limitation for the Study

- The study relying on past data to evaluate risk implies that market conditions in the future will resemble past trends.
- The banking industry may be impacted by unforeseen events such as market shocks, Geopolitical upheavals, or worldwide economic crises.
- The study depends solely on data from 2019 to 2021 and may not provide a complete explanation for these occurrences.
- To know the severity of the stocks, only one indicator was considered for the study.

10. Data Analysis & Interpretation

Objective 1: To explore the distinctions of VaR and CVaR methodology contribute to the observed differences in the risk estimates.

H_0: The distinctions in VaR and CVaR methodology do not contribute to the observed differences in the risk estimates.
H_1: The distinctions in VaR and CVaR methodology significantly contribute to the observed differences in the risk estimates.

Bootstrap Paired Sample T Test

Table: Comparative Analysis between VaR and CVaR

Bootstrap Specifications	
Sampling Method	Simple
Number of Samples	5000
Confidence Interval Level	95.0%
Confidence Interval Type	Percentile

Table 1: Paired Samples Statistics

Paired Samples Statistics							
			Statistic	Bootstrap			
				Bias	Std. Error	95% Confidence Interval	
						Lower	Upper
Pair 1	NBFC VaR90	Mean	-0.02808	0.00004	0.00232	-0.03249	-0.02368
		N	5				
		Std. Deviation	0.005712	-0.000804	0.001387	0.001297	0.006786
		Std. Error Mean	0.002555				
	NBFC ES90	Mean	-0.05184	0.00008	0.00527	-0.06113	-0.04041
		N	5				
		Std. Deviation	0.012983	-0.001902	0.003452	0.002955	0.016118
		Std. Error	0.005806				

		Mean					
Pair 2	NBFC VaR95	Mean	-0.04127	0.00007	0.00394	-0.04882	-0.03372
		N	5				
		Std. Deviation	0.009708	-0.001348	0.002296	0.002259	0.011291
		Std. Error Mean	0.004341				
	NBFC ES95	Mean	-0.07051	0.00011	0.00794	-0.08464	-0.05342
		N	5				
		Std. Deviation	0.019560	-0.002869	0.005227	0.005214	0.024713
		Std. Error Mean	0.008747				
Pair 3	NBFC VaR99	Mean	-0.09205	0.00010	0.01200	-0.11455	-0.06746
		N	5				
		Std. Deviation	0.029657	-0.004033	0.006881	0.013111	0.037147
		Std. Error Mean	0.013263				
	NBFC ES99	Mean	-0.12294	0.00021	0.01741	-0.15473	-0.08772
		N	5				
		Std. Deviation	0.042933	-0.006300	0.011519	0.013573	0.055415
		Std. Error Mean	.019200				
Pair 4	Public VaR90	Mean	-0.03392	-0.00001	0.00169	-0.03661	-0.03009
		N	5				
		Std. Deviation	0.004238	-0.000806	0.001601	0.000613	0.005653
		Std. Error Mean	0.001895				
	Public ES90	Mean	-0.05487	-0.00002	0.00221	-0.05884	-0.05036
		N	5				
		Std. Deviation	0.005501	-0.000904	0.001740	0.001265	0.007368
		Std. Error Mean	.002460				
Pair 5	Public VaR95	Mean	-0.04776	-0.00003	0.00201	-0.05162	-0.04403
		N	5				
		Std. Deviation	0.004991	-0.000695	0.001205	0.001948	0.006311
		Std. Error	0.002232				

		Mean					
	Public ES95	Mean	-0.06997	-0.00003	0.00309	-0.07575	-0.06389
		N	5				
		Std. Deviation	0.007666	-0.001126	0.002044	0.002521	0.010287
		Std. Error Mean	0.003428				
Pair 6	Public VaR99	Mean	-0.08464	-0.00005	0.00697	-0.09764	-0.07239
		N	5				
		Std. Deviation	0.017260	-0.002475	0.004440	0.007593	0.022111
		Std. Error Mean	0.007719				
	Public ES99	Mean	-0.10625	-0.00010	0.00567	-0.11711	-0.09479
		N	5				
		Std. Deviation	0.014121	-0.002052	0.003711	0.005109	0.018859
		Std. Error Mean	0.006315				
Pair 7	private VaR90	Mean	-0.02364	0.00002	0.00231	-0.02794	-0.01940
		N	5				
		Std. Deviation	0.005804	-0.000852	0.001481	0.002304	0.007680
		Std. Error Mean	0.002596				
	Private ES90	Mean	-0.04391	0.00007	0.00491	-0.05366	-0.03532
		N	5				
		Std. Deviation	0.012358	-0.001939	0.003515	0.003871	0.016364
		Std. Error Mean	0.005527				
Pair 8	Private VaR95	Mean	-0.03355	0.00004	0.00320	-0.04007	-0.02789
		N	5				
		Std. Deviation	0.008060	-0.001281	0.002336	0.002124	0.011003
		Std. Error Mean	0.003605				
	Private ES95	Mean	-0.05998	0.00010	0.00726	-0.07472	-0.04748
		N	5				
		Std. Deviation	0.018293	-0.002986	0.005526	0.005315	0.024204
		Std. Error	0.008181				

		Mean					
Pair 9	Private VaR99	Mean	-0.07832	0.00011	0.00723	-0.09248	-0.06499
		N	5				
		Std. Deviation	0.018179	-0.002777	0.004959	0.007758	0.023728
		Std. Error Mean	0.008130				
	Private ES99	Mean	-0.11448	0.00021	0.01394	-0.14383	-0.08925
		N	5				
		Std. Deviation	0.035130	-0.005587	0.010308	0.008380	0.045384
		Std. Error Mean	0.015710				
b. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples							

Table 2: Paired Samples Test

Paired Samples Test[a]									
		Paired Differences					**t**	**df**	**Sig. (2-tailed)**
		Mean	**Std. Deviation**	**Std. Error Mean**	**95% Confidence Interval of the Difference**				
					Lower	**Upper**			
Pair 1	NBFCVaR90 - NBFC ES90	0.0238	0.0076	0.0034	0.0143	0.0332	6.996	4	0.002
Pair 2	NBFCVaR95 - NBFC ES95	0.0292	0.0108	0.0048	0.0158	0.0427	6.035	4	0.004
Pair 3	NBFCVaR99 - NBFC ES99	0.0309	0.0151	0.0067	0.0122	0.0496	4.585	4	0.010
Pair 4	PublicVaR90 - Public ES90	0.0210	0.0033	0.0015	0.0168	0.0251	14.092	4	0.000
Pair 5	PublicVaR95 – Public ES95	0.0222	0.0030	0.0014	0.0184	0.0260	16.317	4	0.000
Pair 6	PublicVaR99 - Public ES99	0.0216	0.0099	0.0044	0.0093	0.0339	4.867	4	0.008
Pair 7	privateVaR90 - Private ES90	0.0203	0.0067	0.0030	0.0119	0.0286	6.718	4	0.003
Pair 8	PrivateVaR95 - Private ES95	0.0264	0.0104	0.0046	0.0136	0.0393	5.697	4	0.005
Pair 9	PrivateVaR99 - Private ES99	0.0362	0.0185	0.0083	0.0132	0.0592	4.363	4	0.012

a. No statistics are computed for one or more split files

Table 3: Bootstrap for Paired samples Test

Bootstrap for Paired Samples Test

		Mean	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
Pair 1	NBFC VaR90 – NBFC ES90	.023753	-.000028[b]	.003073[b]	.007[b]	.017293[b]	.029260[b]
Pair 2	NBFC VaR95 – NBFC ES95	.029239	-.000028[b]	.004379[b]	.009[b]	.020426[b]	.037299[b]
Pair 3	NBFC VaR99 – NBFC ES99	.030896	-.000095[b]	.006077[b]	.081[b]	.017465[b]	.041184[b]
Pair 4	Public VaR90 – Public ES90	.020952	.000006[b]	.001341[b]	.000[b]	.018153[b]	.023390[b]
Pair 5	Public VaR95 – Public ES95	.022214	.000001[b]	.001219[b]	.000[b]	.019840[b]	.024429[b]
Pair 6	Public VaR99 – Public ES99	.021609	.000043[b]	.003941[b]	.011[b]	.014801[b]	.029796[b]
Pair 7	Private VaR90 - PrivateES90	.020269	-.000041[b]	.002674[b]	.010[b]	.015830[b]	.025880[b]
Pair 8	PrivateVaR95 – Private ES95	.026431	-.000062[b]	.004113[b]	.010[b]	.019353[b]	.034995[b]
Pair 9	PrivateVaR99 - PrivateES99	.036166	-.000098[b]	.007346[b]	.088[b]	.023012[b]	.051935[b]
a. Unless otherwise noted, bootstrap results are based on 5000 bootstrap samples							
b. Based on 4995 samples							

Interpretation:

A statistical technique called the Bootstrap test creates random samples from observed data to estimate a statistic's sampling distribution and evaluate its variability. For the study, the Bootstrap method to used to check whether the VaR and CVaR are both methodologies going in the same direction. Under Paired sample T-test, the VaR all the confidence levels such as 90%,95%, and 99% paired with ES all the confidence levels such as 90,95 and 99%. From this study, the p-value from the paired sample t-test is **significant** which is < 0.05 for all the 9 pairs, while coming to the bootstrap method(resampling process), the study finds that pair 3(VaR 99% & ES 99% under NBFC bank) and pair 9(VaR 99% &CVaR 99% under private banks) is **not significant** which is < 0.05, remaining pairs are **significant**, through this study conclude that, reject the null hypothesis and **Accept** the Alternative hypothesis which says the distinctions in VaR and CVaR methodology significantly contribute to the observed differences in the risk estimates.

Objective 2: To analyze the impact of varying confidence levels on VaR and CVaR accuracy and evaluate their resilience across diverse markets, offering actionable insights for risk management.

H_0: There is no significant difference in the precision of VaR andCVaR estimations across various confidence levels.
H_1: There is a significant difference in the precision of VaR and CVaR estimations across various confidence levels.

Table 4: Kruskal-Wallis Test

	VaR90	VaR95	VaR99	CVaR90	CVaR95	CVaR99	
median	-0.03013	-0.04459	-0.08201	-0.054	-0.0666	-0.1083	
rank sum	1193	979	366	809	557	191	
count	15	15	15	15	15	15	90
r^2/n	94883.27	63896.07	8930.4	43632.07	20683.27	2432.067	234457.1

H-stat	**70.52694**
H-ties	70.52694
df	5
p-value	0.000
alpha	0.05
sig	yes

Interpretation
To determine whether there are any noteworthy variations in the medians of three or more independent groups, one non-parametric statistical test to utilize is the Kruskal-Wallis test. The median for the group VaR 90%, 95% & 99% is -0.03, -0.044 and -0.082, and another group CVaR with the confidence level of 90%, 95% & 99% is -0.054, 0.066 & -0.108 respectively. The H statistics is 70.52 H-ties is also 70.52 the degree of difference is 5 and the p-value is < 0.05 which is **significant** where it says there is a significant difference in the precision of VaR and CVaR estimations across various confidence levels. With the help of the Median, we compare the VaR and CVaR and through this, the study Rejects the Null hypothesis and accepts the alternative hypothesis.
Objective 3: To assess financial institution risks, employ CVaR, enhance accuracy with the Generalised Breach Indicator, and explore their relationship for insights.
H_0: The use of CVaR and the Generalised Breach Indicator does not significantly contribute to the accurate assessment of financial institution risks.
H_1: The use of CVaR and the Generalised Breach Indicator does significantly contribute to the accurate assessment of financial institution risks.

Table 5: Generalised Breach Indicator

Sl No	NBFC Bank	Returns	Volatility	VaR	CVaR	GBI	Z-stat	P-Value
1	Cholamandalam IFC	-0.003%	3.34%	5.50%	-6.90%	16.533	-15.14	0.0000
2	Shriram finance	-0.107%	3.55%	-5.94%	-7.42%	17.977	-3.73	0.0002
3	Muthoot Finance	0.101%	2.73%	-4.38%	-5.52%	16.312	-16.88	0.0000

4	L&T finance holding	-0.139%	3.11%	-5.25%	-6.55%	20.971	19.9	0.0000
5	Sundaram Finance	0.007%	2.03%	-3.34%	-4.19%	16.069	18.8	0.0000
Sl no	**Public Bank**	**Returns**	**Volatility**	**VaR**	**CVaR**	**GBI**	**Z-stat**	**P-Value**
1	SBI	-0.045%	2.46%	-4.09%	-5.12%	22.545	32.33	0.0000
2	Bank of Baroda	-0.173%	2.95%	-5.02%	-6.26%	14.921	-27.86	0.0000
3	PNB	-0.226%	2.92%	-5.06%	-6.28%	22.565	32.49	0.0000
4	Union Bank of India	-0.247%	2.91%	-5.03%	-6.25%	21.288	22.41	0.0000
5	Indian Bank	-0.248%	3.21%	-5.54%	-6.88%	20.172	13.6	0.0000
Sl no	**Private Bank**	**Returns**	**Volatility**	**VaR**	**CVaR**	**GBI**	**Z-stat**	**P-Value**
1	HDFC	0.045%	1.78%	-2.88%	-3.62%	12.702	-45.39	0.0000
2	ICICI	0.042%	2.50%	-4.07%	-5.11%	16.226	-17.56	0.0000
3	Kotakmahindra	0.074%	2.08%	-3.35%	-4.22%	16.57	-14.84	0.0000
4	IndusInd Bank	-0.145%	3.62%	-6.09%	-7.61%	16.686	-13.93	0.0000
5	Axis Bank	-0.027%	2.78%	-4.61%	-5.77%	11.769	-52.75	0.0000

Interpretation:

A generalized breach indicator is a metric used to evaluate the magnitude and seriousness or severity of possible losses in a financial portfolio that could occur beyond a given level of confidence. A previous objective showed that there is a significant difference between VaR and CVaR, through this however VaR is a generally accepted model to check the potential losses whereas CVaR is used to find the losses beyond the threshold limit. This objective deals with whether the CVaR will find the severity of stock in the particular horizon.

From the above table, public sector GBI is more compared to the other two financial institutions heads such as private banks and NBFC, where the values range between 14 to 22.5, NBFC the GBI value range between 16 to 20, and private banks ranges from 11 to 16. Through this, the study finds that the public sector was facing severity in terms of risk in comparison with NBFC and Private banks. This study observed the pandemic time, where through this indicator public banks and NBFC faced a high severity situation in the market. While coming to the volatility, NBFC possesses a high volatility in the pandemic time. However, the p-value with the 95% confidence level is < 0.05 suggesting that we can **Reject null** and accept the alternative hypothesis which says the utilization of CVaR and the Generalised Breach Indicator significantly enhances the accuracy in evaluating financial institution risks and provides valuable insights.

11. Findings

- VaR is a statistical metric that assesses the possible loss of money over a given period with a given degree of confidence, so revealing the risk of a portfolio. CVaR, provides a more thorough understanding of potential tail risks in a financial portfolio by predicting the average size of losses that exceed the VaR threshold.
- The results of the study show that the paired sample t-tests for CVaR and VaR both yield significant results. The statistical significance suggests that the risk metrics are significantly different within the given period. This implies that there have been significant changes in the risk profile of the financial institution, highlighting the need for

dynamic risk management, the shadow bank sudden drop, and credit risk techniques to adjust to changing market circumstances and improve overall financial resilience, further with the study we find out that the distinctions in VaR and CVaR methodology significantly contribute to the observed differences in the risk estimates from the stock market.

- The research indicates a remarkable variation in the accuracy of VaR and CVaR approximations at varying degrees of confidence. These variations highlight how crucial it is to choose and understand confidence levels to conduct a precise and trustworthy risk assessment. This knowledge can help guide risk management choices by highlighting the necessity of a customized method for determining confidence levels by particular financial context requirements.
- The study emphasizes how crucial the Generalised Breach Indicator and CVaR are for determining the risks associated with financial institutions. CVaR examines the average magnitude of losses beyond VaR while the Generalised Breach Indicator gauges possible loss severity. This all-encompassing method improves risk assessments, offers a strong foundation for decision-making, and enables proactive risk management techniques to lessen negative effects.

12. Conclusion

To conclude, thorough research into risk estimation techniques—with a special emphasis on VaR and CVaR has produced important new information that greatly aids in the precise evaluation of financial institution risks. The differences between the VaR and CVaR approaches that have been identified are significant in determining the diverse risk estimations that are found at different confidence levels. The careful analysis of precision differences between VaR and CVaR estimates highlights how complex risk assessment is. These variations suggest that the selection of confidence levels has a significant impact on the precision and dependability of risk assessments. Effective risk management methods require a knowledge of these intricacies as financial institutions traverse more complex and dynamic markets.

In addition, the addition of CVaR and the application of the Generalised Breach Indicator are significant factors that improve the accuracy of risk assessment. By taking into account the mean number of losses that occur over the VaR cut-off, CVaR offers a more complete view of possible financial weaknesses. Concurrently, the risk assessment procedure gains further complexity from the Generalised Breach Indicator, which gauges the magnitude of possible losses.

The study uses risk management techniques on a range of financial organizations, such as public and private banks, NBFCs, and banks. It emphasizes the value of conducting a customized risk assessment for each type, taking into account their particular risk appetites and exposures. VaR, CVaR, and the Generalised Breach Indicator are useful tools for public banks to use, although private banks handle risks differently according to their business plans. The study emphasizes the significance of adopting methods like VaR, CVaR, and Generalised Breach Indicators to customize risk assessments for different financial organizations, including public and private banks, NBFCs, and banks.

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