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RETURNS AND SPILLOVER CONNECTEDNESS OF SI-NBFCS WITH MAJOR INDIAN EQUITY INDICES: A QUANTILE COVAR BASED APPROACH

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Abstract
The role of Non-Banking Finance Companies (NBFCs) in systemic spill over came under spotlight in the aftermath of the global financial crisis (GFC). Its phenomenal growth as an alternative to conventional banking has further led to exponential interconnectedness with the other financial system participants. The study employs applicable risk methodologies such as quantile regression in the TENET framework and network analysis in the TVP-VAR framework to estimate the value at risk of systemically significant Indian capital market indices in the event of a tail risk in the NBFC sector index. This coupled with the granular analysis leads us to three significant findings: One, NIFTY EX BANK representing NBFC sector exhibits a lambda of 0.5 and greater across quantiles. Second, granular analysis reveals that in the Banking sector space NIFTY PVT BANK exhibits higher connectedness than NIFTY PSU BANK as depicted by average and total connectedness lambda over years. Third, NBFC sector commands highest HUB score based on the PAGERANK algorithm in the financial system network. The study concludes with evidence that global economic shocks have no significant impact on the ranks of Systemic Risk Emitter and Recipient as also corroborated in RBI FSR 2022 that capital adequacy of Indian Banks provides sufficient cushion in stress test scenarios.
Keywords: *Systemic risk, NBFC, Shadow banking, VaR, CoVaR, Quantile Regression, TVP-VAR*
JEL Classification: C23, G12, G23

I. Introduction

In the modern World, Non-Banking Finance Companies (NBFCs), which account for over 20% of the credit given by the financial sector, are a crucial pillar of the Indian economy. The reach and last-mile advantage of NBFCs have enabled them to provide formal financial services to India's underbanked and unserved sectors. With the knowledge gained during the pandemic, NBFCs now have a superior awareness of local dynamics, collection methods, and personalized services, enabling them to capitalize on digital business. As a result, the sector's footprint has significantly increased. In March 2022, the aggregate credit extended by NBFC stood at ₹28.5 trillion. The loans to industry constituted the most significant segment, followed by personal loans and those to services. By acting as an additional conduit of credit intermediation complementary to banks, NBFCs have become an integral part of the financial system. Its rapid growth has recently brought it under the spotlight due to implications for financial stability.

The Reserve Bank of India, in its latest Financial Stability Report (FSR) dated June 30, 2022, emphasized the need to realign the regulatory framework of NBFC due to its evolving risk profile and systemic significance. The sector has seen a phenomenal growth of more than 10% YoY (FSB, 2020), albeit with a higher risk appetite. Loans & advances constitute a major portion of the assets, while borrowings from SCBs constitute the biggest source of funding (refer to Figure 1)

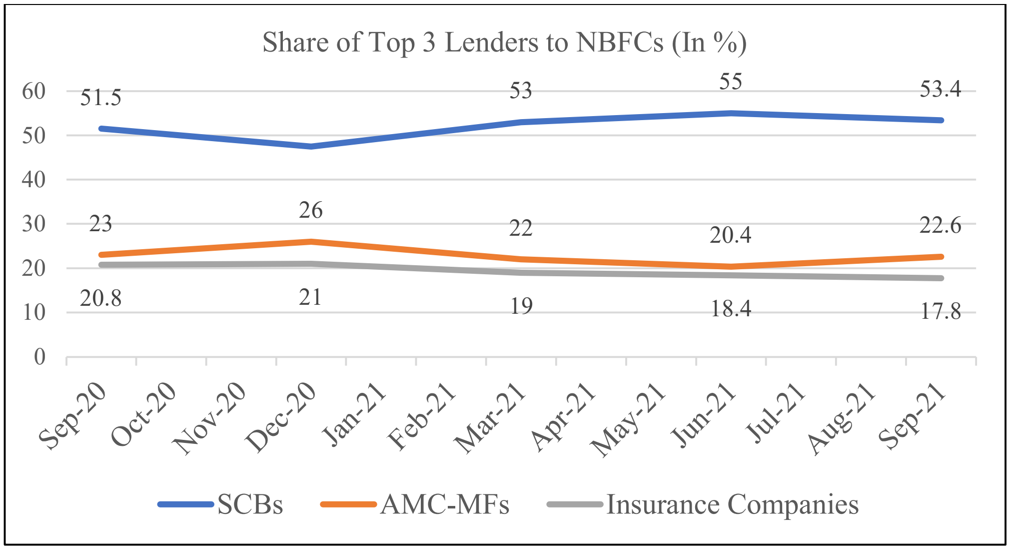

Figure 1: Depicts the share of the top 3 lender groups to NBFCs
Source: RBI (2022)

With total payables of 12.06 lakh crores as of the end of September 2021, NBFCs were the largest borrowers of funds from the financial system. NBFCs are entangled in a web of interconnections with banks, capital markets, and other financial organizations as the greatest borrowers from the financial system (refer to Figure 2). Given the significant portion of the money, they absorb at the system level, any NBFC or HFC failure can produce solvency losses. These can spread through financial contagion and cause the financial system to lose a significant amount of money, up to 2.26% of the bank's Tier 1 Capital (RBI, 2021).

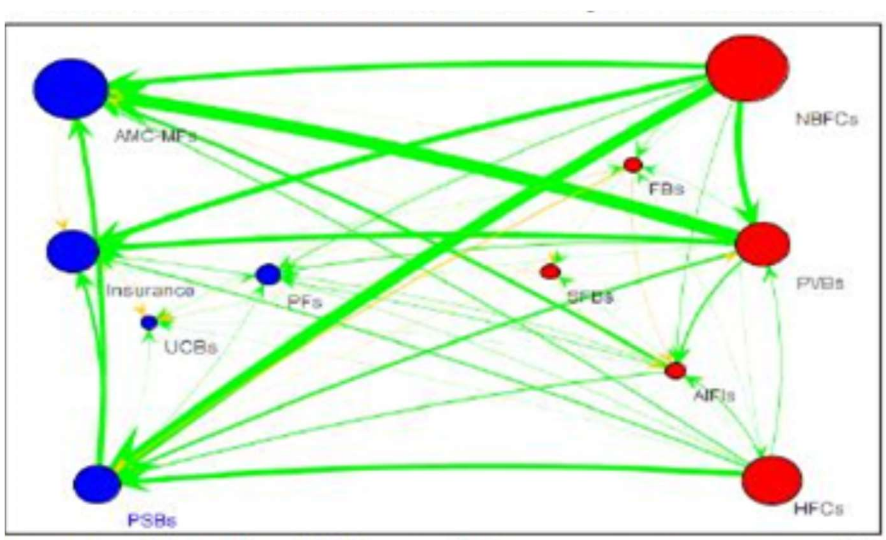

Figure 2: Interconnectedness of the Indian Financial System

Note: The greatest fund providers in the system were AMC-MFs (Asset Management Company-Mutual Fund), followed by insurance firms, while the top fund recipients were NBFCs, followed by HFCs, in terms of inter-sectoral exposures.
Red circles depict net payable institutions, while blue circles depict net receivable institutions.
Source: Financial Stability Report, RBI, dated June 30, 2022.

The discussion on systemic risk (SR) via NBFCs acquired global prominence in the aftermath of the 2008 global financial crisis (GFC). The IL&FS debacle of 2018 and the DHFL crisis represent the most recent instances of crises led by shadow banking within the Indian economy. An array of studies have emphasised how shadow banking contributes to the opaqueness of financial intermediation and amplifies systemic risk (Adrian & Brunnermeier, 2016; Bhattacharjee & Pati, 2022; Pozsar, 2010). Investors who perceive trouble will withhold investment returns during periods of market volatility, creating a run-like scenario that adds to the complexity of asset liquidation (Acharya & Viswanathan, 2011; Imbierowicz & Rauch, 2014). Numerous studies have examined aspects of risk measurement, variables that contribute to risk, and the influence exerted (Acharya et al., 2016; Betz et al., 2016; Bostandzic & Weiss, 2018; Giglio et al., 2016)). Using the demise of IL&FS as an example, Ram Mohan (2018) identified the issue of illiquidity resulting from an asset-liability mismatch as the most significant factor contributing to the collapse. Chandrashekhar (2020) attributed the collapse of NBFCs to a lack of due diligence, inadequate financial management, and overall organisational environment. Mall (2018) developed a risk assessment model for evaluating credit exposure risk and predicting the likelihood of default using the receiver operator index. Mohanty et al. (2022) highlighted the growth and development interdependence between banking and the shadow banking sector. The study concluded that a strengthened regulatory framework is required to complement NBFCs' greater growth prospects. With the growing interdependence, the contagion spread from bank channel to NBFCs have received adequate research attention (Verma et al., 2019; Bhattacharjee & Pati, 2022). Shadow banking's function in risk transmission to other systemically important (SI) or too-big-to-fail institutions has been largely neglected in Indian research to date. A novel study by lysandri and Singh (2022) modelled the interconnectedness and systemic risk from shadow banks using Granger-causal network measures on a restricted sample of 52 financial institutions over a four-year period (2016-2019). The study found that the shadow bank complex network is denser during times of crisis than in times of peace.

The catalyst role of global economic shocks and the sector level contagion spread via shadow banking channel remains largely unanswered. To address this important research gap, our study investigates the transmission of volatility from SI-ND NBFCs to select Indian indices representing systematically important sectors. This further complemented with the granular analysis of 54 SI financial institutions in context of the recent most global economic shocks - COVID-19 and the Russia-Ukraine Conflict helps us answer whether the rate of transmission increased during such outbreaks. In comparison to the traditional early warning models, a CoVaR measure is the most suitable bilateral downside risk metric for assessing the predicted loss of a financial system conditional on an individual institution's VaR (Acharya et al., 2017; Zhang et al., 2020; Wu et al., 2021). We utilize the CoVaR metric in a novel way to evaluate the projected shortfall or tail risk of a specific sector conditional on the network-level risk triggered by the tail event, which encompasses all industries in the sector. Our research is by far the first to investigate sector-level contagion effects via shadow banking channel, and makes a substantial contribution to the existing literature by encompassing a larger data set of more than one lakh observations (weekly data for 45 variables over 2015-2022). Essentially, the study addresses the following research issues:

- Are NBFCs the driving force behind systemic risk?
- Does a shadow bank's failure significantly impact the major participants of the economic system?
- Does the magnitude and pace of spillover vary during different global economic shocks?

The study's following sections are organized as follows: The review of recent and previous literature on the subject is discussed in Section 2 of this article. The paper's data and methodology are presented in Section 3. Results and discussions are shown in Section 4. Section 5 concludes the study with some limitations and policy implications.

II. Review of Literature

The emphasis on SR has become more extensive with the passage of time. The pre-GFC era, 2008, centred on spillovers and their extensive ramifications. In the aftermath of the crisis, however, attention has turned to disruptions in the operations of the financial system and the spread of the contagion. Multiple studies have examined the motivations of banks in establishing and expanding shadow banking as well as its consequences (Lysandrou & Nestvetailova, 2015; Pozsar et al., 2013). One such study concluded that shadow banking contributed to the exacerbation of the financial crisis (Kirchner, 2020). Conventional banking operations were limited to the buy-and-hold approach, which introduced credit risk. In order to mitigate credit risk and facilitate the development of securitization, financial institutions began utilising market-based intermediaries to carry out off-balance sheet operations. By allowing the transfer of balance sheet operations from the regulated to the unregulated sectors of the industry, the origin-to-distribute banking model supplanted the origin-to-hold model (Pozsar et al., 2010; Constancio, 2012). Numerous participants emerged as a result of the interconnected activities of banks and non-banks; these included finance, insurance, leasing companies, money market institutions, credit hedgers, conduits, and special purpose vehicles (SPV) (Swati et al., 2012). The exponential growth of shadow banking can therefore be ascribed to the evolving characteristics of the financial industry (Bhattacharjee & Pati, 2022). One of the key functions of financial intermediaries is to facilitate investor decision-making, economic growth, and stability through the alignment of banking and non-banking activities (Passarella, 2014). However, it should be noted that their lax regulations pose an exorbitant level of risk and have the capacity to cause significant disruptions to the entire financial system (Liang & Reichert, 2012). Numerous post-GFC studies have reached the consensus that SBs emerged as a significant source of systemic risk during the financial crisis, thereby impeding the functionality of financial system and compromising its resilience to future shocks (De Bandt and Hartmann, 2000; Colombo et al., 2020). Credit intermediaries operate beyond the purview of conventional banking systems, engage in opaque forms of intermediation, and are subject to insufficient regulation (Bernanke et al., 2011; Sharma, 2014; Claessens & Ratnovski, 2014). Financial institutions are considered systemically important if their failure to meet obligations causes a system-wide failure and SBs fall into this category. Their failure has a catastrophic effect on the economy, as evidenced by the Global Financial Crisis of 2007 and Infrastructure Leasing & Financial Services Limited (IL&FS) in India, due to their immense scale and interdependence with the rest of the financial system.. As determined by the apex regulator, the Reserve Bank of India, NBFCs with assets exceeding 500 Crore are systemically significant. The SBs work with narrow margin which severely constrains its capacity to absorb internal risks. With the insufficient capital generated to sustain the risk internally, the company must turn to external sources. The absence of central funding and deposit insurance further adds on to their risk-taking inability, which leaves the final investors at an inflated degree of risk (Fein, 2013). In contemporary research, the measurement of varied aspects of risk, including SR, as well as the factors that contributing to risks, their impact, and numerous other nuances of their operations, are examined. The multidimensional character of SR & its measurement has made it a significant area of interest for researchers (Acharya et al., 2017; Betz et al., 2016; Giglio et al., 2016; Thiemann et al., 2021). The prompt identification of systemic hazards can provide regulators with initial signals to implement preventive measures.

The assessment of SR gauges the contribution and systemic significance of financial institutions. Various methodologies evolved for quantifying SR, the probability of contagion, bank runs, financial crises, and liquidity problems throughout the past decade (Tian et al., 2016; Acharya et al., 2016; Benoit et al., 2017). Initial methods for systemic risk assessment utilised a structural approach based on contingent claims analysis of financial institutions' assets (Lehar, 2005; Gapen et al., 2008). Huang et al. (2009) used reduced form-measures of systemic risk to estimate expected credit losses above a given proportion of the financial sector's total liabilities. Using Credit Default Swap (CDS) in a multivariate context, Goodhart & Segoviano (2009) examined the contribution of each individual firm to the overall financial system distress. De Jonghe (2010) conducted a novel study that employed the TENET framework and presented tail betas for European financial firms. Billio et al. (2012) established a measure of systemic risk based on auto covariances in Granger Causality framework. For the longest time, tools such as Value-at-Risk (VaR) at the institution level were used to assess the risk of the financial system (Allen & Saunders, 2002). In their seminal work, Adrian and Brunnermeier (2016) proposed Conditional Covariance (CoVaR), which utilized quantile regression to quantify the VaR of the financial sector assuming that a SI bank has experienced a VaR loss. Brownlees and Engle (2017) developed SRISK measure to quantify the predicted shortfall of a financial firm in the event of a sustained market slump. Acharya et al. (2016) addressed the gap between theoretical models and the practical demands of regulators by formalising and developing an ex-ante measure of the systemic risk, Marginal Expected Shortfall (MES), based on losses in the tail of the aggregate sector's loss distribution. According to existing literature, the SRISK and CoVaR measures are the most important indicators for measuring systemic risk (Zhang et al., 2020; Benoit et al., 2017; Grundke & Tuchscherer, 2019). The CoVaR metric developed by Adrian and Brunnermeier permits the creation of time-varying estimates of each financial institution's systemic risk contribution (Arsov et al., 2013; Lopez-Espinosa et al., 2015). A CoVaR measure is a bilateral downside risk metric suitable for assessing the predicted loss of a financial system condition on an individual institution's VaR. This measure is the most suitable for assessing systemic risk spillovers because it consistently adds predictive power to conventional early warning models (Acharya et al., 2017; Zhang et al., 2020; Wu et al., 2021). Therefore, we use this measure to assess the systemic risk of specific sectors represented by the representative index conditional on the tail risk event in the Indian shadow banking sector, also known as NBFC, represented by the specific index.

III. Data and Methodology

A financial system's central institutions, the banks, are directly responsible for system-level risk and shock transmission. The stability of the NBFC sector gets severely threatened by the risk resulting from frequent exposures to asset price shocks. The study uses weekly closing price data for significant NBFCs with asset sizes of 500 CR or more, classified as ND-SI NBFCs, from 2010–11 to the present. The data is compiled from the CMIE Prowess database and the BSE and NSE websites. Select indices representing different sectors: BANK NIFTY, NIFTY FINANCE, NIFTY 200 TRI, NIFTY PSU Bank, NIFTY PVT Bank, and NIFTY Financial Ex-Bank is included in our dataset for system-level analysis. The analysis is carried out in stages that represent worldwide systemic shocks. Weekly returns are calculated as natural log values of closing price series, defined as $R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$. Apart from the return series, macro variables (weekly market returns, market volatility, credit spread, and liquidity spread (consistent with Zhang et al., 2020)) reflecting economic situations along with four micro variables (size, turnover ratio, P/E, and P/BV ratio) depicting the fundamental strength of the company are taken. To capture the global economic uncertainty (EPU), we take Global EPU Index data from the Economic Political Uncertainty Index developed of Baker et al. (2016), based on the global news extraction and its linkages with the uncertainty worldwide.

A measure of systemic risk

The analysis is carried out following the TENET framework proposed by Hardle et al. (2016), consistent with the non-linear dependency between interacting financial assets in a bi-variate setting, especially in periods of economic uncertainty (Chao et al., 2014). We extend the systemic risk analysis framework suggested by Zhang et al., 2020 while measuring the economic interconnectedness between financial institutions in the Chinese Stock Market. There are three steps in the analysis.:

1. Estimation of VaR

VaR is outlined as the maximum value loss at a specific level of confidence over a particular time horizon. In order to specify the capital requirements for financial institutions, the BASEL II accord incorporated VaR as a measure of market risk. It is given as the τ-quantile of the return distribution such that:

$$P(X_{i,t} \leq VaR_{i,t}^{\tau}) = \tau \tag{1}$$

$$R_{i,t} = \alpha_i + \gamma M_{t-1} + \epsilon_{i,t} \tag{2}$$

$$\widehat{VaR}_{i,t,\tau} = \widehat{\alpha}_i + \widehat{\gamma}_i M_{t-1} \tag{3}$$

M_{t-1} represents the macroeconomic variables and γ_i depicts parameters from equation (2).

2. Measuring CoVaR

When an institution, j experiences financial distress in comparison to its median state, CoVaR gauges the value of the financial institution i that is at risk. As a result, CoVaR illustrates the systemic tail risk connectivity between industries. By taking into consideration non-linear dependencies between variables and employing the single index quantile regression technique for systemic risk contribution (Zhang et al., 2020) resulting from the change in the relevant industry, the risk connectedness analysis is carried out:

$$P\left(X^j \leq CoVaR_q^{\frac{j}{t}} \mid X^i = VaR_q^i\right) = q\% \tag{4}$$

$$\widehat{CoVaR}_{j|\,Z_{j,i,t}}^{net} = g\left(\hat{\beta}_{j|\,Z_j}^{T} Z_{j,t}\right) \tag{5}$$

$\widehat{CoVaR}_{j|\,Z_{j,i,t}}^{net}$ represents the risk at the network level triggered by the tail event, inclusive of all the relevant industries on sector j; the non-linearity is accounted for by partial derivative function g.

3. Network Topology measured by the Outdegree

Network methodology to gauge system connectedness and dependency (Diebold & Yilmaz, 2014) has become an integral part of the financial literature on systemic volatility and connectedness. Taking a lesson from the research conducted on social networks, it has been determined that not all nodes in financial networks successfully contribute to the spread of contagion. Consequently, it becomes crucial to examine the topological position of nodes. Billio et al. (2012) examined GFC systemic institutions using Eigenvector and Closeness centrality indicators. Kuzubaş et al. (2014) calculated a centrality metric for the overnight money market in order to examine the 2000 Turkish Banking Crisis. Wang et al. (2022) examined the tail reliance of the Chinese financial network from 2009 to 2018 using network centrality indicators. Xu and Corbett (2020) derived FIRank, a measure of interconnectedness based on the PageRank algorithm, in order to rank countries according to their financial interconnectedness with the global bank-lending network. Yun et al. (2019) simulated the network using the PageRank algorithm. PageRank captures network topology more accurately than balance sheet metrics such as CoVaR or MES (Chaturvedi et al., 2002). We utilize node strength measured by the Outdegree of influence exerted on the network as the measure of risk spillover. The out strength as a measure of risk contagion also reflects on the impacted sectors' ability to absorb the contagion spread. The node's size measures the out-degree of influence while edges depict the direction of influence. The study utilizes frequency connectedness technique under TVP-VAR framework of network methodology to conduct granular analysis of the systemic risk exerted by select 37 NBFC players (on basis of years of existence and market capitalization) on the financial sector network. The formulae give outdegree:

$$OS_i = \sum_{j=1}^{n} \left| \widehat{D}^{s}_{j|t} \right|$$

IV. Results and Findings

Table 1: Descriptive Statistics

Panel A: Summary Statistics of Select Indices

Codes	Index	Codes	Index
NIFTY 200	*NIFTY 200 stock Index*	**NIFTY FIN 25/50**	*NIFTY Financial Sevices 25/50 Index*
NIFTY 50	*NIFTY 50 stock Index*	**NIFTY FIN EX BANK**	*NIFTY Financial Services EX Bank Index*
NIFTY BANK	*NIFTY Banking Index*	**NIFTY FIN**	*NIFTY Financial Services Index*

	Min.	Max.	Mean	Median	Std. Dev.	Skewness	Kurtosis	JB
Weekly Returns								
NIFTY 200	-0.2021	-0.0016	-0.0389	-0.0342	0.0274	-2.5305	12.8884	0.0000
NIFTY 50	-0.2045	-0.0017	-0.0389	-0.0339	0.0276	-2.5886	13.1592	0.0000
NIFTY BANK	-0.2883	-0.0028	-0.0556	-0.0475	0.0411	-2.8516	14.2829	0.0000
NIFTY FIN 25/50	-0.2624	-0.0053	-0.0515	-0.0407	0.0378	-2.8675	14.2825	0.0000
NIFTY FIN EX BANK	-0.2716	-0.0036	-0.0539	-0.0430	0.0393	-2.5891	12.2675	0.0000
NIFTY FIN	-0.2672	-0.0040	-0.0519	-0.0438	0.0382	-2.8748	14.3044	0.0000
Value at Risk (VaR)								
NIFTY 200	-0.1287	0.1175	0.0019	0.0040	0.0235	-0.5040	7.5491	0.0000
NIFTY 50	-0.1296	0.1197	0.0019	0.0036	0.0235	-0.4314	7.7845	0.0000

NIFTY BANK	-0.2140	0.1540	0.0020	0.0037	0.0338	-0.3808	9.4369	0.0000
NIFTY FIN 25/50	-0.2090	0.1279	0.0021	0.0045	0.0313	-0.5223	9.2697	0.0000
NIFTY FIN EX BANK	-0.2135	0.1364	0.0021	0.0052	0.0327	-0.6992	8.3392	0.0000
NIFTY FIN	-0.2036	0.1363	0.0022	0.0025	0.0317	-0.3814	9.3417	0.0000

Panel B: Summary Statistics of select NBFCs

Company Name	Codes	Mean	Median	Std. Dev.	Skewness	Kurtosis	JB
Aditya Birla Capital Ltd.	ABCL	-0.0037	-0.0059	0.0625	0.1220	5.4115	0.0000
Arman Financial Services Ltd.	Arman Fin	0.0052	-0.0021	0.0679	-0.1805	6.9423	0.0000
Bajaj Finance Ltd.	Bajaj Fin	0.0072	0.0077	0.0535	-0.3046	6.3104	0.0000
Bajaj Holdings & Invst. Ltd.	Bajaj Hold	0.0031	0.0018	0.0417	-0.5915	9.2057	0.0000
Capital First Ltd. [Merged]	Capital First	0.0021	0.0008	0.0492	0.0552	2.9666	0.9440*
Cholamandalam Financial Holdings Ltd.	Cholamandalam	0.0048	0.0031	0.0586	-0.3727	9.0403	0.0000
Cholamandalam Investment & Finance Co. Ltd.	Chola Inv & Fin	0.0024	0.0012	0.0418	-0.5455	7.8477	0.0000
Cox & Kings Financial Service Ltd.	Cox & kings Fin	-0.0516	0.0000	0.1460	0.3631	3.6983	0.1233*
Creditaccess Grameen Ltd.	Creditaccess	0.0044	0.0038	0.0777	-1.0418	9.9583	0.0000
Edelweiss Financial Services Ltd.	Edelweiss Fin	-0.0002	0.0000	0.0777	-0.4844	7.3907	0.0000

Equitas Holdings Ltd.	Equitas	-0.0013	0.0007	0.0649	-0.4496	9.0394	0.0000
I D F C Ltd.	IDFC	-0.0027	-0.0021	0.0732	-4.1128	49.9584	0.0000
Indian Railway Finance Corpn. Ltd.	IRFC	-0.0068	-0.0076	0.0648	0.0057	6.8879	0.0000
Indostar Capital Finance Ltd.	Indostar	-0.0029	-0.0043	0.0287	0.9010	4.8560	0.0000
L & T Finance Holdings Ltd.	L&T Fin	0.0003	0.0018	0.0579	-0.3818	6.8796	0.0000
Mahindra & Mahindra Financial Services Ltd.	M&M Fin	-0.0002	0.0009	0.0621	-0.7726	6.7684	0.0000
Manappuram Finance Ltd.	Manappuram Fin	0.0024	0.0062	0.0610	-0.3820	6.4988	0.0000
Mcdowell Holdings Ltd.	McDowell Hold	0.0017	-0.0099	0.0854	0.9662	5.2414	0.0000
Motilal Oswal Financial Services Ltd.	Motilal Oswal	0.0028	-0.0002	0.0568	0.4765	3.9930	0.0000
Muthoot Capital Services Ltd.	Muthoot Cap	0.0007	-0.0016	0.0673	0.5038	8.3276	0.0000
Muthoot Finance Ltd.	Muthoot Fin	0.0042	0.0004	0.0504	0.4124	6.0803	0.0000
Nahar Capital & Financial Services Ltd.	Nahar Cap	0.0039	-0.0009	0.0669	0.2002	7.3064	0.0000
P N B Gilts Ltd.	PNB Gilt	0.0027	-0.0030	0.0845	1.1002	16.5995	0.0000
P T C India Ltd.	PTC	0.0019	-0.0013	0.0553	1.9088	13.7624	0.0000
Paisalo Digital Ltd.	Paisalo	0.0022	0.0000	0.0837	0.6130	8.0493	0.0000

Poonawalla Fincorp Ltd.	Poonawalla	-0.0009	0.0027	0.0491	-0.2203	4.0340	0.0000
Power Finance Corpn. Ltd.	Power Fin	-0.0004	-0.0004	0.0510	-0.0780	4.5274	0.0000
Reliance Capital Ltd.	Reliance Cap	-0.0095	-0.0064	0.0952	0.0641	4.7285	0.0000
S I L Investments Ltd.	SIL Inv	-0.0004	-0.0015	0.0525	0.5135	10.3303	0.0000
S R E I Infrastructure Finance Ltd.	SREI Infra	0.0005	-0.0005	0.0677	-0.4892	7.7026	0.0000
Shriram City Union Finance Ltd.	Shriram City	0.0034	-0.0005	0.0710	0.7299	6.3818	0.0000
Shriram Transport Finance Co. Ltd.	Shriram Trans	-0.0045	-0.0131	0.0793	0.3249	4.9210	0.0000
Spandana Sphoorty Financial Ltd.	Spandana	-0.0064	-0.0085	0.0915	0.8419	7.2074	0.0000
Summit Securities Ltd.	Summit	0.0020	-0.0002	0.0622	0.1570	5.8272	0.0000
Sundaram Finance Ltd.	Sundaram	0.0009	-0.0011	0.0415	0.2164	5.9331	0.0000
T C I Finance Ltd.	TCI Fin	0.0022	-0.0007	0.0377	0.3381	5.3583	0.0000
Tata Investment Corpn. Ltd.	Tata Inv	-0.0057	-0.0155	0.0777	1.0871	5.5421	0.0000
Vardhman Holdings Ltd.	Vardhman	0.0034	-0.0014	0.0623	1.5331	10.3148	0.0000

Source: The authors

Note: The table provides summary statistics for all variables. The natural log of weekly returns (In percentages) is used for all representative indices and individual NBFCs within the scope of the study. The Jarque-Bera, JB test (1987) illustrates the results of the goodness-of-fit test with the joint null hypothesis of the third and fourth moment being zero. All values except those highlighted with * indicate rejection of joint null of JB test at 95% level.

The present study employs the natural log of weekly returns for all variables. As these are weekly returns, it is not surprising that the return values are close to zero. Mean and median returns are similar for NIFTY200 and NIFTY50. The return series of all indices under the study exhibit negative skewness and leptokurtic distribution with fait tails, typical characteristic of financial asset returns with higher probability of extreme outlier values when compared to a normal distribution. VaR of representative indices are also mentioned in Table 1. As illustrated, VaR values are positive for all variables, notably all variables under the study have similar mean VaR values. The joint null hypothesis of 3rd and 4th moment being zeros is rejected for all variables, representing non-zero higher moments and dispersion in the return distributions.

Quantile Regression Estimates

The aforementioned CoVaR coefficients of representative indices represent the quantile regression estimates of variables under the study taking VaR of NIFTY FIN EX BANK as the explanatory variable. The CoVaR of representative indices are calculated conditional on the tail risk event in the NBFC sector. For all the variables under the study, the coefficient of NIFTY FIN EX BANK is statistically significant even at 1% level of significance as p-value is lesser than 0.01. The coefficient of greater than 0.9 in NIFTY BANK, NIFTY FIN 25/50 and NIFTY FIN signifies the strong linkage with tail risk events in the shadow banking sector, further implying that a 1% increase in median value of tail risk in NBFC sector leads to increase in 0.9% (and more) in CoVaR of NIFTY BANK, NIFTY FIN 25/50 and NIFTY FIN. Panel B of the table depicts CoVaR coefficients of the representative indices with credits spread as the explanatory variable. The coefficients of credit spread as an explanatory variable though statistically significant for NIFTY 200, NIFTY50 and NIFTY BANK, are insignificant in magnitude, underling the effect of varying credit spread on the conditional VaR of representative indices. This makes for an interesting observation as Credit Spread determines interest rate risk of the financial services sector. It is clear from the results shared in the Table 2, that Credit Spread offers less explanatory power in CoVaR of variables under the study. The quantile process estimates per every 10th quartile for all variables under the study are shown in Figure 1. It is noteworthy that NIFTY EX BANK representing the NBFC sector stocks commands statistically significant explanatory power till the 0.6 quantile across all variables under the study.

Table 2: Quantile Regression Estimates at (0.05,0.25,0.5,0.75,0.95) quantiles

Quantiles	0.05	0.25	0.5	0.75	0.95	Adj. R^2	S.E.
NIFTY 200							
NIFTY EX BANK	0.7029	0.6900	0.6560	0.5994	0.5184	0.6079	0.0063
	0.0201	0.0106	0.0273	0.0219	0.0269		
Credit Spread	-0.0032	-0.0022	-0.0018	(-0.0012)*	(-0.0006)*		

	0.0100	0.0005	0.0008	0.0008	0.0008		
NIFTY 50							
NIFTY EX BANK	0.6858	0.6966	0.6720	0.5949	0.4698		
	0.0215	0.0108	0.0250	0.0456	0.0365	0.5833	0.0072
Credit Spread	-0.0025	-0.0020	-0.0018	(-0.0007)*	(-0.0003)*		
	0.0013	0.0007	0.0006	0.0008	0.0012		
NIFTY BANK							
NIFTY EX BANK	0.9345	0.9580	0.9584	0.7938	0.5561		
	0.0259	0.0205	0.0282	0.0893	0.0427	0.4597	0.0132
Credit Spread	0.0050	0.0055	0.0069	0.0017	0.0023		
	0.0015	0.0014	0.0015	0.0017	0.0028		
NIFTY FIN 25/50							
NIFTY EX BANK	0.9312	0.9530	0.9501	0.8731	0.7141		
	0.0145	0.0105	0.0125	0.0684	0.0248	0.6938	0.0074
Credit Spread	(0.0003)*	(0.0018)*	0.0024	0.0021	(0.0009)*		
	0.0010	0.0007	0.0008	0.0007	0.0019		
NIFTY FIN							
NIFTY EX BANK	0.9185	0.9158	0.9357	0.8362	0.5632		
	0.0405	0.0156	0.0194	0.0944	0.0365	0.5366	0.0112
Credit Spread	(0.0021)*	0.0039	0.0039	(0.0003)*	(0.0025)*		
	0.0017	0.0011	0.0013	0.0010	0.0016		

Source: The Authors

Note: Estimated quantile tau value = 0.05, 0.25, 0.5, 0.75 & 0.95; Test quantiles = 0.9; Test statistic compares all coefficients. All values are significant at 95% level except those highlighted with *

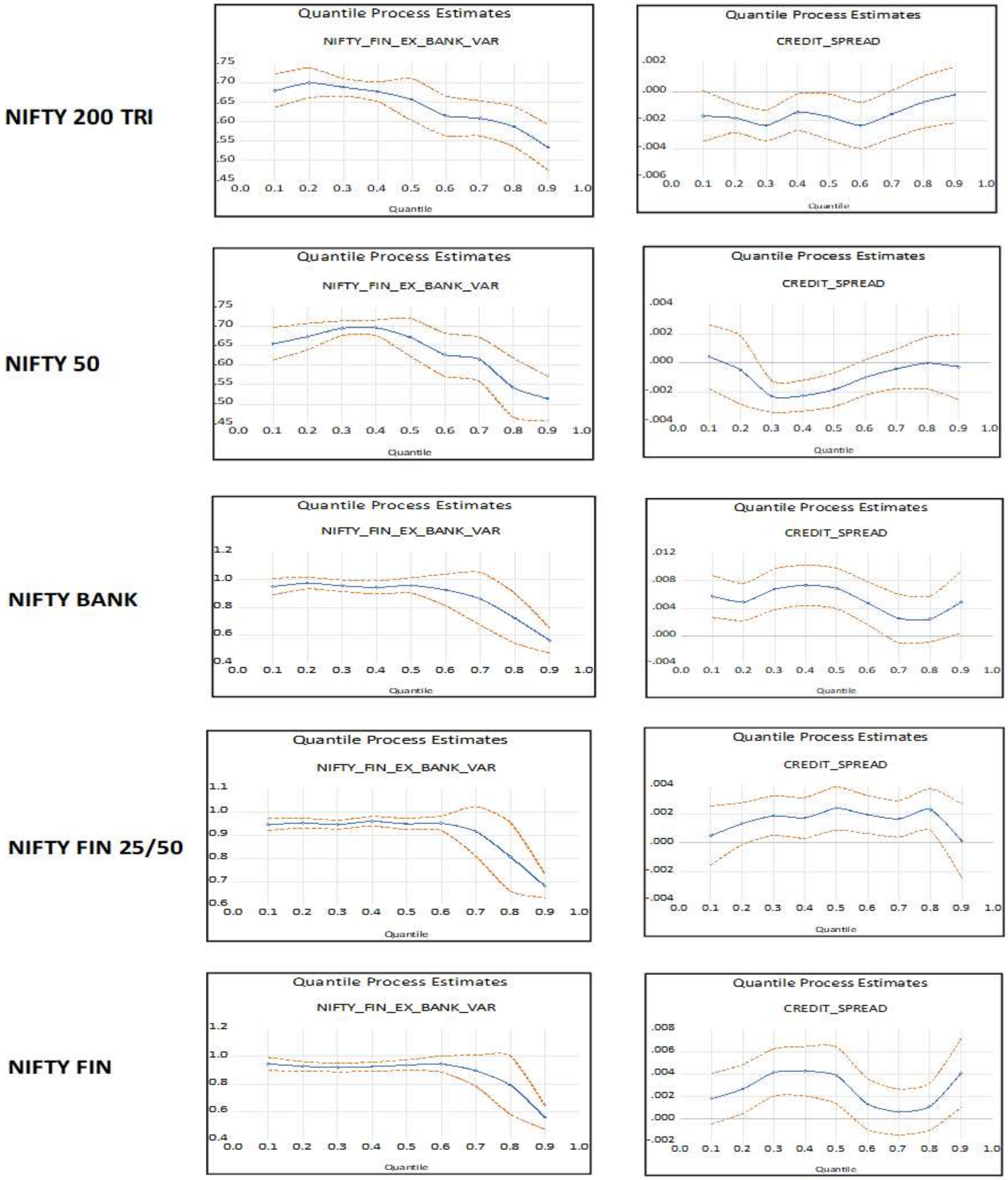

Figure 3: Quantile process estimates

Note: The figure shows quantile process estimates per 10th quantile for variable under the study with NIFTY EX BANK and Credit Spread as independent variable.

Accuracy Test Results

Quantile Regression unlike the ordinary least squares technique is likely to establish to a large extent comprehensive relationship among variables and it is robust in modelling outliers (Boako et al., 2016). Table 3 presents results of Wald Test for quantile coefficients of NIFTY FIN EX

BANK reported in Table 1 above. According to Wald Test the Chi square statistic value of slope equality test is statistically significant at even 1% level of significance since p-value < 0.01 for all variables under the study. This further implies that slope equality is different across quantile levels. The p-value rejects null of slope equality, signifying that relationship between explanatory variable and the dependant variable varies across quantile intervals, confirming the model fit (Bera et al, 2014).

Table 3: Goodness of Fit

Quantile Slope Equality Test			
	Chi-Sq. Statistic	**Chi-Sq. d.f.**	**Prob.**
NIFTY50	63.5498	16	0
NIFTY Bank	106.8909	16	0
NIFTY FIN 25/50	79.5514	16	0
NIFTY FIN	131.3293	16	0
NIFTY 200	70.2331	16	0
H0: β_0 is zero			
Symmetric Quantiles Test			
	Chi-Sq. Statistic	**Chi-Sq. d.f.**	**Prob.**
NIFTY50	19.95034	12	0.048
NIFTY Bank	14.7587*	12	0.0549
NIFTY FIN 25/50	55.0553	12	0
NIFTY FIN	36.6031	12	0.0003
NIFTY 200	34.2336	12	0.0006
H_0: Quantile distribution is symmetric			

Source: The Authors'

Note: All values are significant at 95% level except those highlighted with *

The results of the test for symmetry between quantiles are also presented in Table 3. The test's null hypothesis is that the distribution is symmetrical. The test statistic is statistically significant at the 5% significance level, rejecting the null hypothesis of symmetry between quantiles and confirming the heterogeneous impact of explanatory variables on the likelihood of tail risk events in various sectors, conditional on the tail risk events in the NBFC sector.

Granular Analysis

The graph (figure 4 (a), (b) and (c)) below represents a comparative view of the variation in the interconnectedness of private sector (PVT) and public sector banks (PSU) with tail risk events in NBFC sector. Average value of median quantile coefficient (lambda) represents the measure of connectedness. The coefficients at 0.1 quantile are calculated for individual PSU Banks included in NIFTY PSU BANK Index and NIFTY PVT BANK and, an average of the lambda values over the years are taken as representative of varying connectedness conditional on the tail risk events in NBFC sector. The average connectedness values for PSU demonstrate an upward trend beginning in 2015, as the average lambda grows quickly, followed by a sudden decline in 2018, which may be attributable to the IL&FS debacle. Since the outbreak of the crisis, banks have been reluctant to lend to the sector, putting them in a bind. The connectivity rises again in 2021, which may be correlated with the post-COVID recovery era in the NBFC sector. Since 2019, however, the average connectedness for PVT has been on the rise, which may be attributable to confidence-building measures such as recapitalization, improved credit market conditions, and regulatory tailwinds such as RBI's 2019 large exposure guidelines, which increased the exposure limit to a single NBFC from 20% to 25% of the upper layer in exceptional circumstances. The recommendations were published to provide priority sector lending a boost, with an emphasis on improved disclosures by NBFCs regarding their exposure to the real estate market, the capital market, and intra-group entities. It is evident from the preceding graph that private sector banks (PVT) have, on average, more interconnectivity with tail risk events in the NBFC industry than public sector banks (PSU). NBFCs fund the majority of their operations via a combination of market borrowings and bank loans; the banks' share of aggregate NBFC borrowings has increased to 35.1%, per the RBI September 2023 bulletin. Due to their substantial reliance on bank loans, they constitute the most substantial net borrowers, thus forging a complex link with the broader financial system. This interconnection is illustrated by the NIFTY EX BANK's consistent Total Connectedness lambda value of 0.5 or greater with the banking industry at large (refer to Figure 4(c)).

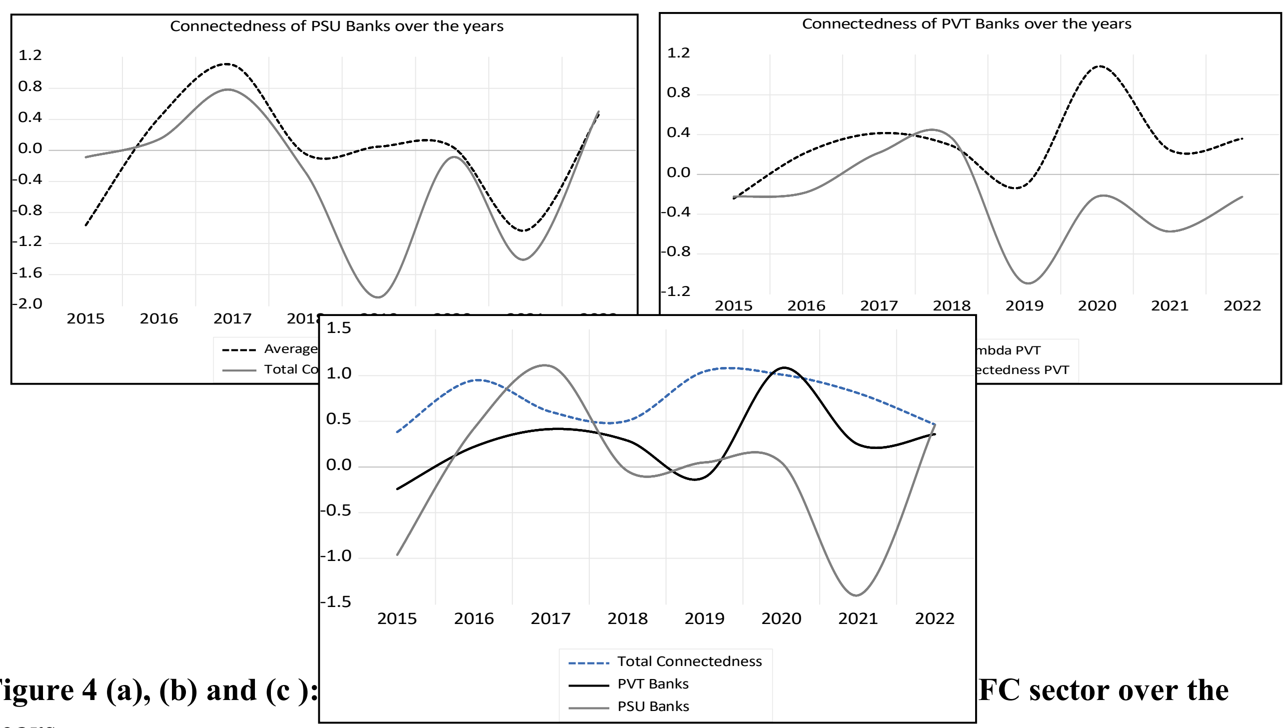

Figure 4 (a), (b) and (c): FC sector over the years

Note: Figure 4(a) depicts the connectedness of PSU Banks with the NBFC sector measured by Average lambda (λ) values of CoVaR estimation of PSU Banks included in NIFTY PSU Bank Index and NIFTY FIN EX BANK at 10% quantile. Y-axis shows the connectedness index values ranging between -1.5 to 2.5 . Figure 4 (b) depicts the average and total connectedness (measured by λ) over the years with NIFTY EX BANK at 10% quantile. Figure 4(c) presents a comparative view of total connectedness lambda of NIFTY EX BANK with BANK as a whole and average connectedness with PSU and PVT Banks.

Hyper-Link Induced Topic Search (HITS) Score for interconnectedness

To explore further, the study also calculates and plots HITS scores for all variables under the study. HITS algorithm (Kleinberg, 1999); also known as Hubs and Authorities, is a link-based analysis algorithm that rates webpages relevant for a particular search. Hubs in the model serve as large directories and considered high in quality if it links to many high-quality nodes. Authority measures the value of content of the page and considered high-quality if many high-quality nodes link to it. As depicted in the graph below, NIFTY Ex Bank ranks highest followed by broader index NIFTY 200 TRI in the order of directional spill over and the authority it commands in the network. While Capital First ranks highest on the ranking as a hub as it links to many high-quality nodes.

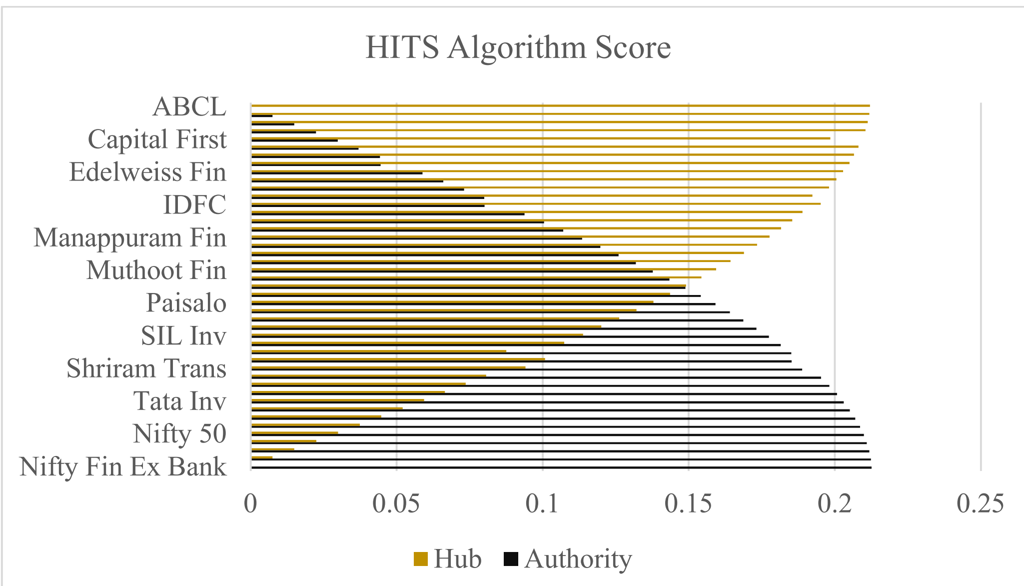

Figure 5: HITS Algorithm score of individual NBFCs and representative indices

Note: The figure shows the connectedness of top entities ranked in the order of HITS and PageRank Scores. HITS algorithm utilizes a recursive relationship between webpages. Authorities are pages having important content. Hubs are pages that act as resource list, guiding users to authorities. PageRank algorithm is utilized by Google search to rank webpages in their search engine results with higher scores indicating higher relevance.

Directional Connectedness (Systemic Risk Emitter and Receivers)

Table 4 and 5 shows the overall directional connectivity of the top 10 Systemic Risk Emitter (SRE) and Systemic Risk Receiver (SRR) Banks and NBFCS with rank 1 assigned to the top most SRE and SRR respectively in the order of magnitude of out-degree and the in-degree of influence exerted in the network. Global economic shocks serve as the break points in three distinct phases (Panel A to C) that evaluate the change in degree of connection. The collapse of IL&FS and Dewan Housing Finance Corporation Ltd. (DHFL) and the spread of systemic risk to other NBFC and banking sector participants define Phase I spanning from 2015-19. Phase II heralds the start of the COVID pandemic, an economic shock to the world's financial markets with ramifications across numerous industries. Phase III starts with the progressive opening up of economy and a gradual easing of COVID restraints. During this era, however, another geopolitical catastrophe occurred: the Russian invasion of Ukraine, which dealt a severe hit to global supply chain and manufacturing capability. Bajaj Holdings appears to have emitted the most shocks during phases I and II, followed by Edelweiss, IDFC, L&T Fin and M&M. Phase I depicts the turbulent phases of NBFCs' deteriorating health. Possible explanations include unfavourable loan market conditions and credit squeezing caused by the demonetization at the end of 2016. The results back with study by Acharya et al (2013), Verma et al. (2019) and Ahmad et al. (2019) that revealed that banks held a sizable portion of NBFC liabilities. With the multiplication in number of NBFC players post 2015, ABCL appears as the top systemic risk emitting NBFCs to overall financial services sector. This further implies that a tail-risk event ABCL may emit relatively larger degree of shocks to all other entities. ABCL is followed by Arman Fin, Bajaj Fin and Bajaj Hold. Amongst Banks Axis Bank appears as the top most SRE Bank followed by PSU Banks. It is noteworthy that among top 10 risk emitting institutions, NBFCs appear as the top risk emitters in Panel C, this underlines the need for scale-based regulations of NBFCs as noted by RBI, FSR 2022.

Table 4: List of Top 10 SRE Banks and NBFCs

Top 10 SRE NBFCs at 5% Quantile						
Rank	Panel A		Panel B		Panel C	
	From To		**From To**		**From To**	
1	Bajaj Fin	43	Bajaj Fin	41	ABCL	53
2	Bajaj Hold	42	Bajaj Hold	40	Arman Fin	52
3	Chola Inv & Fin	37	Chola Inv & Fin	35	Bajaj Fin	50
4	Edelweiss Fin	36	Edelweiss Fin	34	Bajaj Hold	49
5	IDFC	32	IDFC	30	Cholamandalam	43
6	L&T Fin	26	L&T Fin	24	Chola Inv & Fin	42
7	M&M Fin	25	M&M Fin	23	Creditaccess	41
8	Manappuram Fin	24	Manappuram Fin	22	Edelweiss Fin	40
9	McDowell Hold	23	Motilal Oswal	21	IDFC	35
10	Motilal Oswal	22	Muthoot Fin	20	IRFC	32
Top 10 SRE Banks at 5% Quantile						
1	Axis	42	Axis	42	Axis	51
2	BoB	41	BoB	39	Bandhan	48
3	BoI	40	BoI	38	BoB	47

4	Canara	39	Canara	37	BoI	46
5	Central	38	Central	36	Canara	45
6	Federal	35	Federal	33	Central	44
7	HDFC	34	HDFC	32	Federal	39
8	ICICI	33	ICICI	31	HDFC	38
9	Indian	31	Indian	29	ICICI	37
10	IOB	30	IOB	28	IDFC First	36

Source: The Authors'

Note: The table provides the total connectedness of top 10 SREs over three distinct phases (Panel A to C). The ranks are decided on the magnitude of total direction connectedness measured by the out-degree of connectedness to other participants in financial system. "To All" signifies the extant of risk transmission (measured by edges) to all the sample NBFCs and Banks included in NSE NIFTY PSU and NIFTY PVT Bank indices under the study.

Table 5 depicts the top ten risk receivers across the three distinct phases described above. Amongst Banks, Yes Bank appears as the top most SRE across all the phases under the study. This is expected given the NPA crisis faced by the Bank due to its excessive exposure of 11.5% to IL&FS and DHFL which kick-started the NBFC crisis in India. This along with governance issues and excessive withdrawals which ultimately brought YES Bank under regulatory scanner in September 2019. It is noteworthy that PSU Banks Union Bank, Uco, PNB, SBI and PNB appear as top five risk receivers. The ranking as the top most risk receivers appear appropriate, as the findings align with the RBI report on Trends and Progress of Banking in India, 2020, which highlights that PSU Banks alone account for 64% of total lending to NBFCs, further reiterated in the RBI FSR 2021. The faster growth of bank funding in recent years reflects the growing interconnectedness of banks and NBFCs (Bhattacharjee and Pati, 2022). While NBFCs are under stringent regulatory monitoring, the interconnectedness of the financial system presents concerns because of asset-liability imbalances, inadequate corporate governance, and poor risk management. The borrowings in the form of term loans from banks constitute one-third of total borrowings in NBFC sector balance sheet. Despite a robust Capital to Risk Weighted Assets Ratio (CRAR) of 27.4% as on September'22, any tail event inducing liquidity, interest rate or credit risk might act as a solvency shock to their lenders dependent of exposure, and solvency losses can spread through contagion, as highlighted in RBI FSR, 2022.

Table 5: List of Top 10 SRR Banks and NBFCs

Top 10 SRR NBFCs at 5% Quantile						
Rank	Panel A		Panel B		Panel C	
1	Vardhman	43	Vardhman	41	Vardhman	52
2	Tata Inv	40	Tata Inv	38	Tata Inv	49
3	TCI Fin	39	TCI Fin	37	TCI Fin	48
4	Sundaram	38	Sundaram	36	Sundaram	47
5	Summit	37	Summit	35	Summit	46
6	Shriram City	35	Shriram	33	Spandana	44

7	SREI Infra	34	SIL Inv	32	Shriram City	43
8	SIL Inv	33	Reliance Cap	31	SIL Inv	42
9	Reliance Cap	32	Power Fin	28	Reliance Cap	41
10	Power Fin	29	Poonawalla	27	Power Fin	37
Top 10 SRR Banks at 5% Quantile						
1	Yes	44	Yes	42	Yes	53
2	Union Bank	42	Union Bank	40	Union Bank	51
3	Uco	41	Uco	39	Uco	50
4	SBI	36	SBI	34	SBI	45
5	PNB	31	PNB	30	RBL	40
6	PSB	30	PSB	29	PNB	39
7	Kotak	17	Kotak	17	PSB	38
8	J&K Bank	16	J&K Bank	16	Kotak	25
9	Indusind	15	Indusind	15	J&K Bank	24
10	IOB	14	IOB	14	Indusind	23

Source: The Authors'

Note: The table provides the total connectedness of the top 10 SRRs over three distinct phases. The ranks are decided on the magnitude of total direction connectedness measured by the in-degree of connectedness at 0.05 quantile from other participants in the financial system. "From All" signifies the extent of risk transmission (measured by the number of incoming edges) from all the sample NBFCs and select indices under the study.

V. Conclusion

This study aims to comprehend the role of NBFCs in systemic risk spillovers in the Indian financial system. It is well documented in academic literature that conventional banking has contributed to the growth of shadow banking. The rapid expansion of shadow banking has served as an immediate alternative to traditional banks in meeting the industry's financial needs, complementing the conventional banking system. Nonetheless, the complex, dynamic, and less transparent regulatory structure adds a degree of ambiguity to the entire NBFC space, highlighting its contribution to the fragility of the financial system. The findings of our study, which are based on the application of several risk methodologies, enable us to evaluate the risk and its spillover effect in detail. Using quantile regression within the TENET framework, the study determined the Value at Risk of significant financial system indices based on the tail event in the NIFTY EX BANK index, which represents the Indian NBFC sector. The VaR associated with tail events has a high explanatory power for the CoVaR of all broad and financial services sector indices examined. The relevant robustness tests lend credibility to the results. The granular analysis reveals that NIFTY EX BANK has consistently maintained a lambda (λ) of 0.5 or greater over the years, indicating a higher degree of interdependence with the NBFC sector. The HUB score of NIFTY EX BANK in the network further establishes the extent of the NBFC sector's influence, making it the most significant node for risk spill overs. At the end, the study identifies both Banking and NBFC entities that may play a pivotal role in the event of a tail event. In addition, the findings demonstrate that NBFCs and banks are collectively entangled in a network of interconnections and that banks must exercise caution due to their exposure to the parallel banking sector. Our findings align with the most recent scale-based regulations (SBR) introduced by the RBI in an effort to realign the regulatory framework for NBFCs in light of their evolving risk profiles. The SBR framework includes various aspects of NBFC regulation, including capital requirements, governance standards, prudential regulation, etc. The RBI FSR 2022 bolsters confidence in the Indian banking system, which continues to withstand shocks in the baseline scenario under the regulator's stress testing. The limitations of this study in terms of the number of quantiles and sample size examined, as well as the evolving role of new-age banks, provide opportunities for future research.

Declarations

Ethical Approval: The authors mentioned in the manuscript have agreed for authorship, read and approved the manuscript, and given consent for submission and subsequent publication of the manuscript. Well published secondary data from authorised source(s) is utilized under the study.

Competing interests: The authors declared no existing or potential conflict of interests with respect to the research, authorship and/ or publication of this paper.

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Availability of data and materials - The datasets relevant and utilized in study are available on request

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