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Examining Systemic Risk using Google PageRank Algorithm: An Application to Indian Non-Bank Financial Companies (NBFCs) Crisis

Anurag Chaturvedi
University School of Management & Entrepreneurship,
Delhi Technological University,
East Delhi Campus, Vivek Vihar, Phase-2, Delhi-110095, India.
Corresponding author: canurag17@gmail.com

Archana Singh
Delhi School of Management,
Delhi Technological University,
Shahbad Daulatpur, Main Bawana Road, Delhi-110042, India.
E-mail: archanasingh205@gmail.com

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Abstract
In the recent financial crises, attention has shifted towards "too-central-to-fail" to recognize the sources of systemic risk. The NBFC Crisis of 2018-19 adversely affected other financial institutions and the real economy of India. The NBFCs crisis highlighted the role of smaller institutions in perpetuating and amplifying the crisis. Thus, the present study models the interconnection of NBFCs with the rest of financial institutions using a complex Granger-causality network based on returns data. The PageRank algorithm identifies the central and important nodes and ranks financial institutions in pre-crisis and crisis periods. The financial institutions are also ranked based on the maximum percentage loss suffered during the crises. Using non-parametric rank-based regression, the PageRank ranking of financial institutions in the pre-crises period (explanatory variable) is regressed with the ranking of financial institutions based on maximum percentage loss suffered by them during the crises period (dependent variable) along with Leverage and Size as control variables. We found that PageRank from pre-crisis can significantly identify most financial institutions that suffered loss during NBFCs crises even in the presence of control variables.

Keywords- Complex financial network, Network centrality, Pagerank centrality, Systemic risk, Non-banking financial companies, Early warning signal, Too-central-to-fail.

1. Introduction

Over the past decade, the frequency and severity of crises have increased. The globalization and financial integration of economies have also ensured that crises from a particular region quickly spread to another part of the world. The Global Financial Crisis (GFC) of 2007-08 highlighted the role of "too-big-to-fail" institutions in exacerbating the crisis due to their size and operations. The identification of systemically important financial institutions (SIFIs) post GFC also relied on "too-big-to-fail" methodology. It does not consider the complex relationships between the financial institutions. Many smaller institutions amplified and propagated the shocks during the GFC through their complex credit intermediation and maturity transformation. Thus "too-connected-to-fail" and "too-central-to-fail" institutions pose a more significant risk to the financial system. "Too-big-to-fail" focuses on big financial institutions and thus mainly uses data from the nodes. "Too-connected-to-fail" focuses on financial institutions' relationships and thus prioritizes information from edges connected to big nodes. "Too-central-to-fail" focuses on information from both nodes and edges of all financial institutions in the network. It helps in discovering the intricate relationship which can become critical in distress. The "too-central-to-fail" approach explores the network centrality measures like eigenvector centrality, betweenness centrality, Katz centrality, and PageRank centrality.

Thus, recently "too-central-to-fail" has replaced the "too-big-to-fail" and "too-interconnected-to-fail" in identifying systemic nodes.

The earliest research of (Danielsson & De Vries, 2000; Hartmann et al., 2004; Lehar, 2005; Gray et al., 2007; Chan-Lau et al., 2009; Huang et al., 2009; Acharya et al., 2010; Adrian and Brunnermeier, 2011; Brownlees and Engle, 2012; Hautsch et al., 2015) based on historical data and often identifies “too-big-to-fail” institutions. They work best when systemic risk is well represented by historic data and does not consider the simultaneous losses experienced by newly connected parts due to rapid financial innovations. The modern financial system is a complex network of interconnected institutions at many levels. Therefore, the complex network-based systemic risk measures like like Billio et al.(2012) PCAS and Granger-causal network; Diebold and Yilmaz (2014) variance decomposition; Battiston et al. (2012) DebtRank and Härdle et al. (2016) TENET (Tail Event-driven NETwork) have gained importance as they can capture and simulate time-varying intricate relationships between financial institutions and based on “too-interconnected-to-fail” hypothesis. However, the theoretical literature is inconclusive whether dense interconnection makes financial networks more resilient to shocks or make it more fragile by amplifying a large negative shock (Allen and Gale, 2000; Freixas et al., 2000; Dasgupta, 2004; Brunnermeier and Pedersen, 2009; Acemoglu et al., 2015; and Minoiu et al., 2015). Thus, it is necessary to study the role of institutions in contributing to the systemic risk of the network from “too-central-to-fail” perspective.

Taking a cue from the study done in social networks, it was established that not all nodes in financial networks contribute effectively to the spread of contagion. Thus, studying the topological position of nodes becomes critical. Billio et al. (2012) used Eigenvector and Closeness centrality measures to study GFC systemic institutions. Thurner and Poledna (2013) proposed modified Katz centrality based on DebtRank to study systemic risk of the hypothetical network. Kuzubaş et al.(2014) calculated a centrality measure for the overnight money market to study the Turkish Banking Crisis of 2000. Wang and Huang (2021) used network centrality measures to study the tail dependence of the Chinese financial network from 2009 to 2018. Xu and Corbett (2020) calculated FIRank, a measure of interconnectedness based on the PageRank algorithm, for ranking countries on the financial interconnectedness with the global bank-lending network. Yun et al. (2019) used the PageRank algorithm to simulate the network. PageRank captures network topology better than balance sheet measures like CoVaR and MES. Thus, we propose to use PageRank centrality measure to study the critical nodes of systemic importance in the financial network.

The study's objective is to apply the PageRank algorithm approach in examining the systemic risk of financial institutions by taking the NBFC crisis of 2018-19 as a systemic event. Reserve Bank of India (RBI), the central bank of India, defines NBFC “as a registered company under Company Act, 1956 and engaged in the business of loans and advances, acquisition of shares/ stocks/ bonds/ debentures/ securities issued by Government or local authority or other marketable securities like leasing, hire-purchase, insurance business, chit funds”[1]. Unlike banks, they are subjected to light touch regulations by RBI. Often Banks use NBFCs for regulatory arbitrage, and most NBFCs are either subsidiaries or have ownership of Banks. NBFCs do not have federal support or deposit insurance like banks in a crisis. NBFC crises started in June 2018 when one of the subsidiaries of Infrastructure Leasing and Financial Services (IL&FS), classified as "Systemically Important Non-Deposit taking NBFC" (NBFC-ND-SI), defaulted on its debt papers. This contagious effect quickly spread to other NBFCs, and by the end of the third week of September 2018, the top 15 NBFCs are estimated to have lost over Rs 75000cr in market capitalization[2]. In Oct 2018, the benchmark index NIFTY and SENSEX hit their six-month low[3]. It was called India's Lehman moment, comparing events preceding the Global Financial Crisis. The crises prevailed over 2019, and many NBFCs like Reliance Home Finance, Reliance Commercial Finance, etc., were declared bankrupt or shut down their business. As the crises intensified, Mutual Funds started dumping the Commercial Papers (CPs) of stressed NBFCs creating liquidity shock and further intensifying crises. This development has led to a concern about the systemic risk possessed by NBFCs which are smaller institutions than Banks.

We adopted the Granger-causal relationships of Billio et al. (2012) to construct the complex network of financial institutions. Mensah and Premaratne (2017), Zhang and Broadstock (2018), and Lai and Hu (2020) have also used Granger-causal network to study the interconnectedness and systemic risk of the financial institutions. We calculated the PageRank centrality score using Page et al. (1999) and Yun et al. (2019) methodology for the financial institutions. Taking the NBFC crisis of 2018-19 as a systemic event, we compared topological structures of pre-crisis and crisis periods. To explore the predictive property, we regressed the PageRank of financial institutions in the pre-crisis period on the maximum percentage loss of the institutions during the crisis period by controlling the firm's level factors. (Fong et al., 2020; Jin, 2020) extended complex networks to non-bank financial institutions. However, this study is the first to extended the applicability of the "too-central-to-fail" concept in modeling the systemic crisis limited to the non-bank financial institutions. The study is also the first to model the Indian NBFC crisis using the PageRank algorithm. The study uses real-time market data, which is publicly available, making it a dynamic and responsive measure. It also does not depend on balance sheet data which generally comes with a lag. Thus, regulators can use the proposed PageRank measure as an alarm or early warning signal to detect systemic risk in the network.

In the remaining paper, Section 2 develops empirical framework and hypothesis; Section 3 defines data, Section 4 empirical analysis of developed indicators on the Indian NBFC crisis; Section 5 discusses the usefulness of study and policy recommendation, and Section 6 presents the critical conclusion derived from the study.

2. Empirical Framework

2.1 Granger-Causal Complex Network

The pairwise Granger-causality test (Billio et al.2012) measures the dynamic propagation of shocks to the financial system. The rolling window (sub-periods) of 52 weeks performs the Granger-causality tests and builds the network parameters.

Let r_t^i and r_t^j be the two stationary log return time series of financial institutions assumed to have zero mean. If r_t^j contain information that helps in predicting r_t^i beyond the information that is contained in lagged values of r_t^i alone then r_t^j is said to be "granger-cause" r_t^i.

$$r_{t+1}^i = a^i {r_t}^i + b^{ij} r_t^j + e_{t+1}^j$$
$$r_{t+1}^j = a^j {r_t}^j + b^{ji} r_t^i + e_{t+1}^i \quad (1)$$

where, e_{t+1}^j, e_{t+1}^i are uncorrelated residual series assumed to be white noise and a^i, b^{ij}, a^j, b^{ji} are coefficients of the model. Then r_t^j Granger-causes r_t^i if b^{ij} is different from zero. BIC (Bayesian Information Criteria) is used to determine the number of lags in the model.

2.2 Control for Heteroskedasticity and Return Autocorrelations

As equation (1) is a regression equation with Ordinary Least Square (OLS) estimates, so error term $\epsilon_t$may have conditional heteroskedasticity and serial correlations. It results in inconsistent OLS estimates. Financial assets return shows volatility clustering phenomena leading to persistence in amplitudes of price changes. Thus, a baseline Generalized Auto-Regressive Conditional Heteroskedasticity GARCH (1,1) model is used for our log-returns of financial institutions. Let r_t^i be log-return series of institution i and $a_t^i = r_t^i - \mu_i$ be the innovation of institution i at time t. Then a_t^i and σ_{it}^2 is conditional on the financial system information and $\mu_i, \omega_i, \alpha_i$, β_i are the coefficients of the model.

$$a_t^i = \sigma_{it}\epsilon_t^i \ , \epsilon_t \sim WN(0,1),\ \sigma_{\mathrm{it}}^2 = \omega_i + \alpha_i a_{t-1}^2 + \ \beta_i\sigma_{\mathrm{it}-1}^2 \tag{2}$$

To control the heteroskedasticity and return autocorrelation among the institutions, the Granger-causality test in equation (1) is performed on $\tilde{r}_t^i$=$r_t^i/\hat{\sigma}_{it}$ where $\hat{\sigma}_{it}$ is estimated using the GARCH(1,1) model as defined in (2)

Granger causality helps in modeling time-varying and complex relationships among financial institutions. An adjacency matrix of the network of N financial institutions is defined as

$$(j \rightarrow \ i\ ) = \begin{cases} 1, & if\ j\ Granger\ causes\ i \\ 0, & otherwise \end{cases} \tag{3}$$

and define $(j \rightarrow j)$ =0.

2.3 PageRank Centrality

PageRank algorithm (Page et al., 1999) ranks the financial institution based on relative importance. The incoming link to a node is seen as a vote of support, and thus, that node becomes a democracy where other nodes vote for importance by linking to them. Yun et al. (2019) used PageRank to measure the centrality of financial institutions from a "too-central-to-fail" perspective. Based on the same method, we calculate the effect matrix whose entity (e_{ijt}) uses F-values of the granger causality network to account for the wider variations. We define the effect weight of each financial institution as $E_{ijt} = \frac{e_{ijt}}{\sum_i e_{ijt}}$ where e_{ijt} and E_{ijt} denotes the extent of the effect and effect weight respectively by financial institution i on financial institution j at time t. To obtain the PageRank

$$PageRank_{it} = \frac{1-\alpha}{N} + \ \alpha \sum E_{ijt} PageRank_{jt} \tag{4}$$

where, $PageRank_{it}$ is the rank of the firm i at time t, α is the damping factor and is generally set to 0.85, and N is the total number of financial institutions in the system. PageRank is always the positive value and a higher PageRank indicates that the institution has a higher contribution to the systemic risk.

2.4 Hypothesis Formulation

Based on the PageRank centrality measure, the financial institutions are ranked in descending order. For detecting stressed financial institutions during the crises, the variable maximum percentage loss(Max%Loss) is defined as the difference between the market capitalization of the institution(Asset Under Management (AUM) in case of Mutual Funds) at the beginning of the crisis(i.e.,the start of June 2018) and the minimum market capitalization during the entire shadow bank crisis period (June 2018 to Dec 2019) divided by the market capitalization or fund size at the beginning of the crisis period.

The financial institutions are ranked based on Max%Loss, where rank 1 means that the financial institution has suffered maximum loss during financial crises.

Hypothesis Testing: The Kendall τ(1938) statistic detects the relationship between the rankings based on PageRank centrality and Max%Loss. Kendall τ(1938) is a non-parametric test to measure the ordinal association between two measured quantities. $\boldsymbol{\tau}$lies between -1 & 1. The $\boldsymbol{\tau}$ is also corrected for the ties between rankings. Kendall$\boldsymbol{\tau}$ is even less sensitive to outliers and has superior statistical power to Pearson's coefficient which is important for systemic events.
The purpose of the present study is to identify and quantify financial crisis periods and to determine the predictive power of PageRank centrality measure in predicting which institutions will suffer maximum loss in out-of-sample tests. Thus, the following hypothesis is formed:

$$H_\alpha : \ PageRank\ score\ is\ significant\ determinant\ of\ Max\%Loss.$$

2.5 Multivariate Regression

We used the following out-of-sample rank-regression to study the predictive power of the PageRank centrality measure.

$$Max\%Loss_{i,crisis} = \alpha + \beta_1 PageRank_{i,pre-crisis} + \beta_2 Size_{i,pre-crisis} + \beta_3 Leverage_{i,pre-crisis} + \varepsilon \quad (5)$$

Here i represents the financial institution. The dependent variable is Max%Loss, an institution that suffered during the crisis. The primary explanatory variable is the *PageRank* score of the institution measured in the pre-crisis period. We controlled the firm-specific factors that can affect the institutions' systemic risk by using the Size and Leverage of the institutions in the pre-crisis period. *Size* is defined as the natural logarithm of total assets, $\ln(Total\ Assets)$, and *Leverage* as the ratio of debt to equity $Debt/Equity$. We expect a positive and significant β_1 even in the presence of control variables *Size* and *Leverage*.

3. Data and Empirical Results

The study employs the Private Banks (PB), Public Sector Banks (PSB), Non-Banking Financial Companies (NBFC), Housing Finance Companies (HFC), and Liquid Debt Mutual Funds (LDMF). HFCs are also NBFCs whose primary business is to provide financing to housing. HFCs were modeled separately as they suffered maximum distress during the NBFC crisis. NBFCs depend on bank borrowings and Commercial Papers to meet working capital for operations. LDMFs are a major buyer of NBFCs' Commercial Papers along with banks. The short-term fund is used to lend for long-term infrastructure, housing, construction, etc., causing asset-liability mismatch (ALM) issues.

The study uses weekly return data for PBs, PSBs, NBFCs, HFCs, and Net Asset Value (NAV) return data for LDMFs. The period selected is from January 2017- January 2020. S&P BSE Finance Index is used to draw a sample of PB, PSB, HFC & NBFCs. Association of Mutual Funds of India (AMFI) report is used to select LDMFs. The weekly return series data is taken from CMIE Prowess, and NAV return data from ACE MF.

Table 1. Composition of financial institutions.

Constituents	# Number	% of representation of total Market Capitalization for Banks, HFCs, and NBFCs, and Asset Under Management (AUM) for LDMFs as of March 2020
Private Banks (PB)	8	85
Public Sector Banks (PSB)	10	89
Housing Finance Companies (HFC)	5	99
Non-Banking Finance Company (NBFC)	21	69
Liquid Debt Mutual Funds (LDMF)	8	74

Table 2 shows the summary statistics of weekly logarithmic returns of financial institutions. Dickey and Fuller (1981) and Phillips and Perron (1988) tests check series stationarity. The stationarity is a necessary condition for applying pairwise Granger-causality tests. All the financial institutions time series are covariance stationary. The negative mean return and negative skewness imply loss to the investors. Kurtosis greater than three means log return distribution is more peaked and fatter tailed than the standard distributions. It implies that there is more chance of observing extreme or abnormal returns. Thus, the institutions with a negative mean return, negative skewness, and large kurtosis are crucial for our analysis.

Table 2. Summary statistics of financial institutions.

Financial Institutions	Abbreviation	Mean(%)	Std_Dev(%)	Min(%)	Max(%)	Skewness	Kurtosis
Axis Bank Ltd.	AXIS	0.334292	3.70687	-13.996	12.72232	-0.11101	1.45042
City Union Bank Ltd.	CUB	0.471559	3.396569	-9.33992	9.942288	0.010289	0.503474
H D F C Bank Ltd.	HDFCB	0.481075	2.034737	-5.18879	6.090392	0.212894	0.495926
I C I C I Bank Ltd.	ICICI	0.54173	3.802105	-8.77222	15.52305	0.56947	1.634147
Indusind Bank Ltd.	INDUS	0.230609	4.031364	-15.7273	18.27098	0.158926	3.310951
Kotak Mahindra Bank Ltd.	KOTAK	0.534872	2.618217	-8.15476	10.36817	0.19658	1.376781
Federal Bank Ltd.	FED	0.212609	4.201613	-10.9183	15.28349	0.236453	0.772422
Yes Bank Ltd.	YES	-0.9896	9.194739	-35.5217	26.08091	-0.66113	2.221234
Bank Of Baroda	BOB	-0.2638	5.645859	-18.7244	25.68177	0.689325	3.243198
Bank Of India	BOI	-0.26256	6.55626	-18.1873	29.5352	0.807366	2.655518
Canara Bank	CAN	-0.12967	5.975111	-20.9416	28.93743	0.581479	3.554909
Central Bank Of India	CBI	-0.96251	7.132521	-25.6834	31.6876	0.397422	4.420071
Indian Bank	INDB	-0.45014	6.624989	-19.5819	20.44384	0.21244	0.865743
Indian Overseas Bank	IOB	-0.51134	4.455384	-10.4094	15.64055	0.670257	1.355178
Punjab National Bank	PNB	-0.38755	6.517907	-22.2267	41.73586	1.163536	10.45713
State Bank Of India	SBI	0.182267	4.461946	-11.7805	24.79216	1.07117	5.627177
Uco Bank	UCO	-0.4425	5.747935	-10.883	35.93031	1.982775	9.266191
Union Bank Of India	UNION	-0.5128	6.645952	-17.3674	33.3118	0.788049	3.588716
Can Fin Homes Ltd.	CANFIN	0.137797	5.027593	-20.8047	15.03889	0.049389	1.573127
Dewan Housing Finance Corpn. Ltd.	DHFL	-1.69372	11.18042	-63.1482	24.15523	-2.29752	8.92448
G I C Housing Finance Ltd.	GICH	-0.29614	5.686067	-21.432	20.97907	-0.01383	1.959854
Housing Development Finance Corpn. Ltd.	HDFC	0.439927	2.777253	-7.11769	10.45762	0.339777	1.061961
L I C Housing Finance Ltd.	LICH	-0.13259	3.95153	-12.2675	13.19275	-0.01456	0.499158
Bajaj Finserv Ltd.	BAJ_FIN	0.804814	3.833633	-11.0913	10.97736	-0.08996	0.427177
I I F L Finance Ltd.	IIFL	-0.36727	8.90523	-80.5081	18.6136	-4.52792	39.37111
J M Financial Ltd.	JMFIN	0.194178	5.458024	-18.5688	16.88881	-0.00852	0.544158
Religare Enterprises Ltd	REL	-1.11492	10.39327	-27.3293	43.54213	0.545469	2.280063
IFCI Ltd.	IFCI	-0.85108	6.335381	-23.8156	25.21311	0.225625	2.737318
Power Finance Corpn. Ltd.	PFC	-0.00504	4.83824	-13.9083	16.82958	0.092799	0.529145
R E C Ltd.	REC	0.096642	5.057822	-19.1621	18.93926	-0.03719	1.665538
Tourism Finance Corpn. Of India Ltd.	TFCI	0.141956	6.052502	-24.2699	21.83576	-0.14111	4.973959
Bajaj Finance Ltd.	BAJ_FIN	1.041482	4.017809	-11.6054	14.39224	0.170782	1.192955
Bajaj Holdings & Invst. Ltd.	BAJ_HL	0.412572	3.126099	-13.4939	11.0087	-0.02793	2.890414

Table 2. *Continued*.

Cholamandalam Investment & Finance Co. Ltd.	CHOLA	0.305698	4.138868	-8.91946	10.54501	0.301148	-0.31483
Edelweiss Financial Services Ltd.	EDEL	0.122921	7.995963	-29.4308	23.13902	-0.18346	1.396137
L & T Finance Holdings Ltd.	L&TF	0.214884	5.450814	-15.5262	22.03432	0.224353	1.473308
Magma Fincorp Ltd.	MAG	-0.34237	6.491625	-24.4396	24.24678	0.081554	2.100321
Mahindra & Mahindra Financial Services Ltd.	M&MF	0.170572	4.903248	-19.7095	21.59613	0.235862	2.768684
Manappuram Finance Ltd.	MANA	0.674046	5.201224	-18.0184	14.07662	-0.04754	0.673289
Motilal Oswal Financial Services Ltd.	MOTOS	0.30579	5.649899	-13.0923	19.22658	0.440702	0.394769
Muthoot Finance Ltd.	MUTH	0.652315	4.031772	-12.552	13.17436	0.134566	0.08237
Shriram City Union Finance Ltd.	SH_CIT	-0.15036	3.924391	-10.0771	15.48557	0.287507	1.616644
Shriram Transport Finance Co. Ltd.	SH_TR	0.194179	5.139068	-15.5961	18.76867	0.222944	1.06192
Tata Investment Corpn. Ltd.	TICL	0.233727	3.481101	-10.1634	15.77827	0.969773	3.321327
Axis Liquid Fund- Reg(G)	AXIS_M	0.127874	0.018069	0	0.205384	-1.56439	17.49282
Baroda Liquid Fund(G)	BAR_MF	0.127583	0.01892	0	0.197111	-1.46409	13.06267
HDFC Liquid Fund(G)	HDFC_M	0.124672	0.018655	0	0.177808	-1.78485	11.73002
ICICI Pru Liquid Fund(G)	SBI_M	0.125309	0.018249	0	0.219017	-0.87274	18.3344
ICICI Pru Liquid Fund(G)	ICICI_M	0.126709	0.01856	0	0.222609	-1.12925	16.72627
L&T Liquid Fund(G)	L&T_MF	0.126896	0.018636	0	0.187435	-1.79365	12.95456
BNP Paribas Liquid Fund(G)	BNP_MF	0.127038	0.017928	0	0.180221	-2.07157	14.76169
Aditya Birla SL Liquid Fund(G)	ABSL_M	0.12766	0.018222	0	0.208723	-1.60752	16.1296

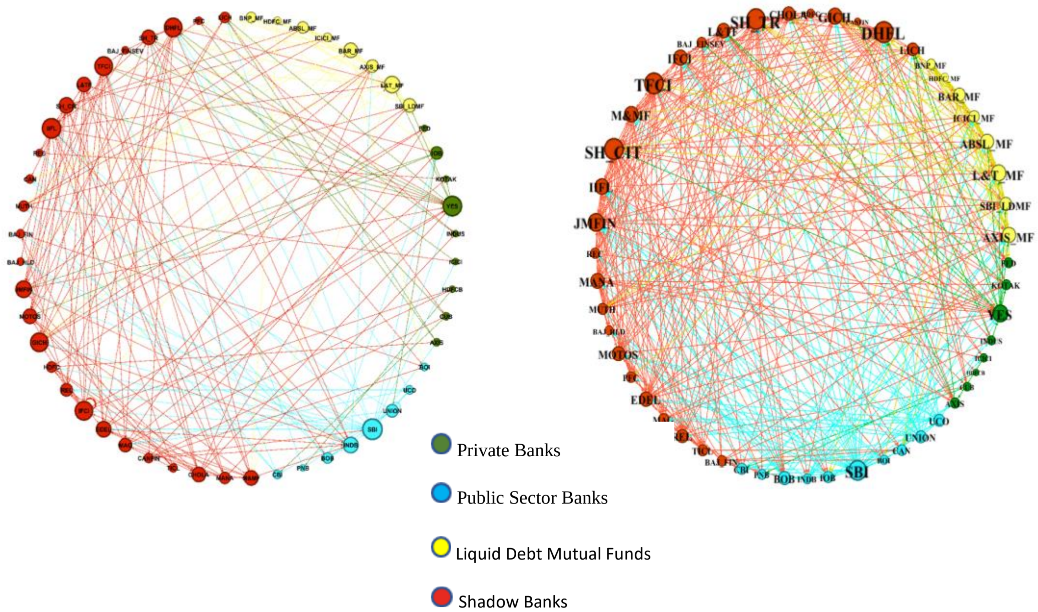
4. Empirical Analysis and Results

This section empirically investigates the use of PageRank centrality in measuring the institutions' systemic risk. We constructed the complex financial network using a rolling window (sub-periods) of 52 weeks. The pre-crisis period is selected from June 2017-May 2018, and the crisis period from Aug 2018- July 2019. We compared the topological graph and PageRank scores of pre-crisis and crisis periods. Then PageRank scores of the pre-crisis period are rank-regressed with Max%Loss during the crisis period.

4.1 Comparison of Topological Structures

The pre-crisis period (Figure 1a) and crisis period (Figure 1b) are compared using the complex network where nodes represent financial institutions and edges represent significant granger-causal connections. The node size represents its degree, i.e., a larger node connects to more networks. Here, the green node is a PB, the blue node is a PSB, the red node is NBFCs, and the yellow node is LDMFs. As it is a directed network, the edges assume color same as the source node. So, if the NBFC granger causes a PB, the edge color will be red. The complex graph of the crisis period is denser than the pre-crisis period. Also, financial institutions have higher interconnectedness during the crisis period.

During the pre-crisis period, the network has an optimal level of interconnectedness arising due to the financial institutions' common exposures and operational activities. The pre-crisis period represents a typical situation where NBFCs perform credit intermediation and risk transformation of the liquidity provided by the banks and liquid debt mutual funds. Also, the pre-crisis complex graph has higher risk absorbing and diversifying capabilities, making it shockproof to small distress events. During the crisis period, the interconnections among institutions got intensified. This reduced the diversification benefit, and any shock to the system gets amplified and spread like contagion. The denser network represents a high probability of risk spillover. In both pre-crisis and crisis periods, certain institutions have a higher degree and are highly interconnected with other institutions. However, not all of them suffered higher loss during the crisis period. Thus, visualizing complex graph help in picking the nodes that have high interlacing with other financial institutions. However, we need to identify central nodes which create greater externality in the system.

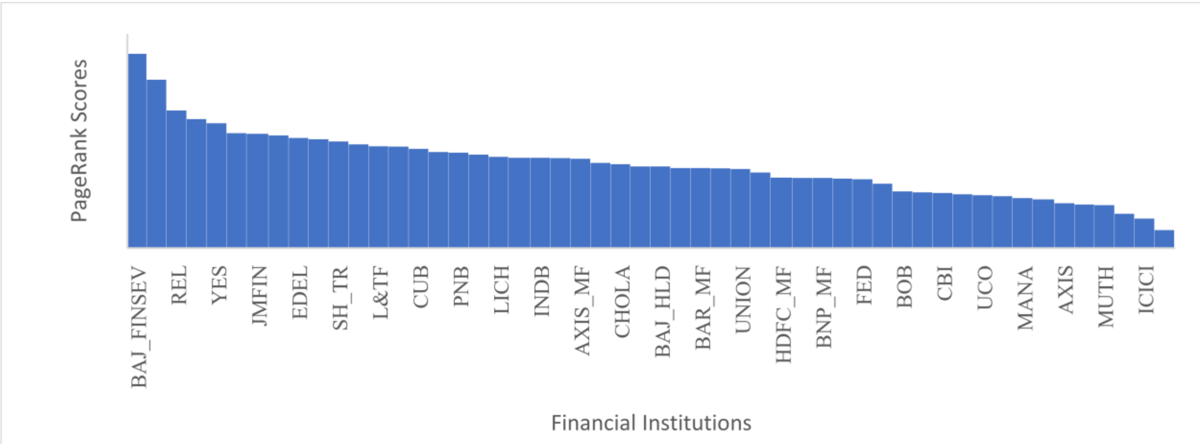


(a) (b)

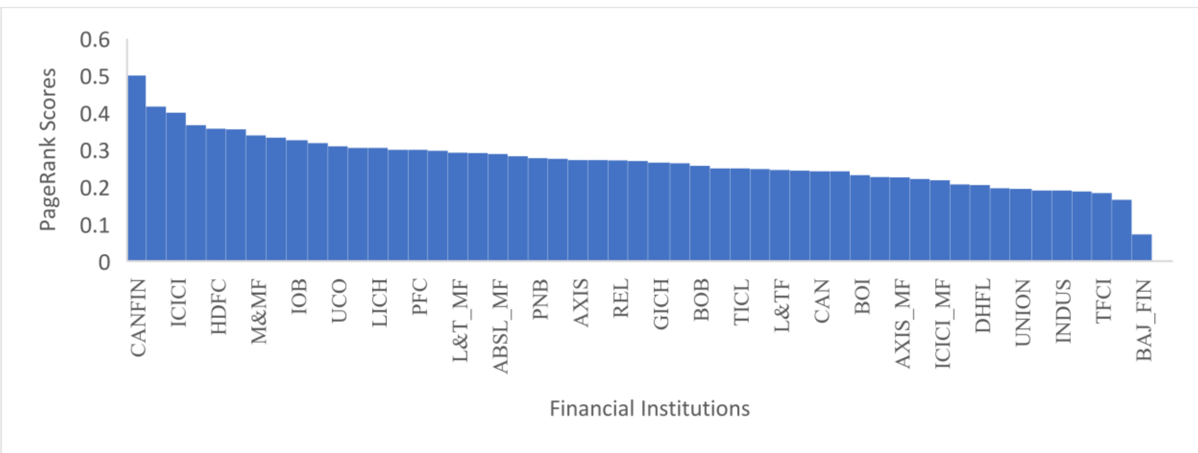
Figure 1. Complex Granger-causality NBFC network comparison for (a) the pre-crisis period (b) the crisis period. The edges have color same as the source node.

4.2 Comparison of PageRank Centrality Scores

Figure 2(a) and Figure 2(b) shows the PageRank centrality of the institutions in both the tranquil and crisis period, respectively. The PageRank centrality score of the institution in the financial network represents its ability to receive incoming links from high centrality neighbors. The algorithm dilutes the incoming centrality in proportion to the outgoing links from that high centrality neighbors. Unlike eigenvector centrality, in PageRank, the incoming connection from a parsimonious (low degree node) node is worthier than connections from a high degree centrality node. Thus, PageRank also represents systemic vulnerability and, in a true sense, captures the "too-central-to-fail" fallacy. PageRank scores are higher in the crisis period than the tranquil period. There are five shadow bank institutions, SH_CIT, TFCI, SH_TR, DHFL, and MANA, in the crisis period, in the top ten, and the rest are banks and mutual funds.



(a)



(b)

Figure 2. Page Rank Centrality for (a) Pre-crisis period (b) Crisis period.

4.3 Hypothesis Testing

The financial institutions are ranked from 1 to 52 based on PageRank score for the pre-crisis period June 2017-May 2018. The entire NBFC crisis period from June 2018 to Dec 2019 is chosen as an out-of-sample period. Then financial institutions are ranked from 1 to 52 based on the maximum percentage financial loss (Max%Loss) suffered by each financial institution in the NBFC crisis from June 2018 to Dec 2019. The financial institution with the highest measure value is ranked one, and the lowest is 52.

Using Max%Loss ranking in crisis period as dependent variable and PageRank of financial institutions in the pre-crisis period as an explanatory variable, we reported coefficient, t-statistic, $Kendall\ \tau$, and its significance in Table 3. Using the same methodology, we also reported the rank-regression test statistic for the control variable Size and Leverage.

Table 3. Out-of-Sample PageRank centrality on univariate rank regression.

	Coeff	t-statistic	Kendall τ
PageRank_Centrality	0.4226	3.297	0.288***
Size	-0.2258	-1.409	-0.127
Leverage	-0.1875	-1.295	-0.130

Note:*p<0.1; **p<0.05; ***p<0.01

4.4 Multivariate Regression Result

Table 4 reported the out-of-sample analysis of the PageRank measure. Using non-parametric multivariate rank-based regression. The PageRank centrality is statistically significant in predicting Max%Loss even after adding control variable Size and Leverage. The asset size and leverage have negative coefficients in all the regression and are not statistically significant in predicting the Max%Loss. That means the smaller institutions suffered more losses compared to bigger institutions. It may be because NBFCs are smaller institutions than private banks and public sector banks. Also, banks have a bigger capital buffer to sustain the financial distress. It also proves that measures based on "too-big-to-fail" and "too-interconnected-to-fail" that take size into account may not detect the systemic financial institutions during the crisis.

Table 4. Out-of-sample analysis. Parameter estimates of multivariate rank regression of Max%Loss as dependent variable and PageRank centrality as independent variable, size and leverage as control variables.

Dependent Variable **Max%Loss**	**1**	**2**	**3**
PageRank_Centrality	0.452***	0.419**	0.412**
	(0.005)	(0.010)	(0.011)
Size		-0.089	-0.137
		(0.572)	(0.399)
Debt			-0.150
			(0.336)
Constant	12.355	15.478	29.283
	(0.028)	(0.037)	(0.045)
Observations	52	52	52
Adjusted R2	0.160	0.169	0.187

Note:*p<0.1; **p<0.05; ***p<0.01

Table 5 presents the top twenty institutions from Largest to Smallest based on Max%Loss from the entire crisis period June 2018 to Dec 2019 and PageRank, Size and Leverage from the pre-crisis period June 2017-May 2018. There are twelve institutions of PageRank centrality score, three institutions based on Size of assets and seven institutions based on Leverage

Table 5. Comparison of top twenty financial institutions based on Max%Loss from crisis period and Granger-causal-network-based measures from the pre-crisis period.

Crisis Period	**Precrisis Period Institution Ranking (From Highest to Lowest) On Network Parameters**		
Max%Loss	**Size**	**Leverage**	**Page_Rank Centrality**
DHFL	SBI	SBI	BAJ_FINSEV
IIFL	HDFCB	REC	IOB
YES	ICICI	LICH	REL
CBI	PNB	BAJ_FIN	GICH
TFCI	BOB	CUB	YES
IFCI	AXIS	IFCI	TFCI
MAG	CAN	MAG	JMFIN
EDEL	BOI	EDEL	DHFL

Table 5. *Continued*.

JMFIN	UNION	REL	EDEL
INDB	HDFC	IIFL	SH_CIT
MOTOS	CBI	MUTH	SH_TR
L&TF	YES	FED	KOTAK
SH_CIT	PFC	CANFIN	L&TF
GICH	KOTAK	MANA	L&T_MF
M&MF	REC	UNION	CUB
SH_TR	INDB	IOB	M&MF
L&T_MF	IOB	JMFIN	PNB
CHOLA	INDUS	KOTAK	HDFCB
BAR_MF	UCO	CAN	LICH
REL	LICH	CHOLA	SBI_LDMF

5. Discussions

The study combined and extended the work of Billio et al. (2012) and Yun et al. (2019) to identify the systemic risk of institutions using the PageRank centrality approach. The PageRank centrality score can predict systemic institutions in line with the study of Xu and Corbett (2020) and Yun et al. (2019). The empirical results proved that asset size is not a significant predictor of systemic results and supports previous studies (Billio et al., 2012; Yun et al., 2019; and Wang and Huang, 2021). It also extended (Fong et al., 2020; Jin, 2020) in modeling the interconnectedness of non-bank financial companies or shadow banks using the complex network. After the NBFC crisis, the Reserve Bank of India (RBI) implemented a regulatory framework based on the systemic significance of shadow institutions. RBI classified systemic importance as a function of shadow lenders' size, activity, and risk profile[3,4] As shadow institutions operate in niche areas, there cannot be a one-size-fits-all regulatory framework, which can hamper their operational activities. Also shadow banks have smaller size as compared to banks. However, their activities of credit intermediation and maturity transformation make their role significant in financial network. Thus, a measure which is based on size or leverage will not reflect about the systemicity of the institutions.The PageRank score based on centrality measure can identify systemic risk of institutions based on their interconnectedness and position in financial network without getting affected by their size and leverage. Thus, it also supports (Billio et al., 2012; Lai and Hu, 2020; Mensah and Premaratne,2017; Zhang and Broadstock, 2018) for using Granger-causal network graphs in modeling complex financial relationships between the institutions. The PageRank centrality based on Granger-causal relationship serves as an unconditional, dynamic, and parsimonious way of generating an early-warning signal for measuring institutions' systemic risk.

6. Conclusion

The Global Financial Crisis has established that "too-central-to-fail" is a more significant concern for the systemic risk than "too-big-to-fail" and "too-connected-to-fail" institutions. As the frequency and severity of the crisis are increasing and the role of smaller institutions in spreading the crisis is becoming prominent, the too-central-to-fail approach proves a valuable measure in identifying critical nodes. To this end, we propose PageRank centrality measure on Granger-causal financial network to identify systemic institutions using the "too-central-to-fail" approach.

We used the Indian NBFCs crisis of 2018-19 as systemic event to test the applicability of PageRank centrality scores in identifying systemic institutions and testing the out-of-sample property of PageRank score in identifying institutions that may suffer most during the crisis. The complex network graph based on significant Granger-causal relationship between asset returns of the financial institutions has been studied for pre-crisis and crisis period. The topological structure of the crisis period is denser than the pre-crisis period indicating that institutions are more tightly coupled during the crisis period. Comparing

PageRank centrality measures, the financial institutions that hold prestigious positions due to their financial linkages have higher systemic vulnerability during the crisis. These critical positions give some financial institutions a dual role of risk transmitter and risk receptor, making them systemically important nodes. The rank-based regression shows that the PageRank centrality measure has out-of-sample properties in predicting market capitalization loss of institutions in the crisis period. The PageRank is a significant predictor of systemic institutions even after introducing the firm-level control variables. The high commonality in institution ranking on PageRank centrality measure from the pre-crisis period and market capitalization loss from the crisis period demonstrated its use as an alarm or early warning signal for detecting systemic risk. Regulators can swiftly isolate these critical nodes in the crisis and prevent the contagion from spreading to the entire financial network.

There are some critical limitations of this study and the scope of future research. First, it considers only the listed financial institutions. Secondly, it is susceptible to window size and frequency of the return, whether daily, weekly, or monthly and significance level of Granger-causality. Future research can explore the more extensive dataset using firm-related micro factors and economy-related macro factors along with the PageRank measure. The PageRank scores can also be compared with other centrality scores like Eigenvector centrality to test the "too-central-to-fail" hypothesis.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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