INTERCONNECTEDNESS AND SYSTEMIC RISK OF INDIAN SHADOW BANKS - DETECTION MEASURES AND EFFECT ANALYSIS

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By

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DECLARATION

I hereby declare that all the work presented in the thesis entitled **“Interconnectedness and Systemic Risk of Indian Shadow Banks- Detection Measures and Effect Analysis”** in fulfillment of the requirement for the award of the degree of Doctor of Philosophy at Delhi School of Management, Delhi Technological University, Delhi is an authentic record of my own work carried out under the guidance of **Dr. Archana Singh,** Associate Professor, Delhi School of Management, Delhi Technological University, Delhi.

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ABSTRACT

The Indian Non-Banking Financial Companies (NBFC, also Indian shadow banks) crisis of 2018-19 is a systemic event that affected the entire financial in India. The crisis started in FY 2018-19 when Infrastructure Leasing & Financial Services (IL&FS), one of the largest shadow banks in India, defaulted on its debt obligations. This led to a loss of confidence in the shadow banking sector and made it difficult for other shadow banks to raise funds. The crisis had a significant impact on the Indian economy. It led to a slowdown in economic growth, a decline in investment, and a rise in unemployment. The crisis also had a negative impact on the Indian financial system, as it eroded confidence in the shadow bank sector and made it difficult for banks to lend to shadow banks. The shadow banks play an important role in the Indian financial system and economy by providing financial services to individuals, small and medium-sized enterprises (SMEs), and other businesses that are not served by traditional banks. They offer a wide range of products and services, including loans, investments, and insurance. They account for over one-fifth of total assets held by the Indian financial system. They are the largest credit provider to the micro, small and medium enterprises. They help in financing of important infrastructure projects like roads, bridges, energy power plants, dams and real estate. They contribute to over five percent of GDP of India. They help in creating millions of jobs directly and indirectly. Thus the present study models the interconnectedness and systemic risk of the shadow banks and its effect on the Indian financial system and the economy.

The study models the financial interconnectedness and systemic risk of shadow banks using Granger-causal network-based measures and takes the Indian shadow bank crisis of 2018–2019 as a systemic event. The study employs pairwise linear Granger-causality tests on return series adjusted for heteroskedasticity and autocorrelation on a rolling window of weekly returns data of 52 financial institutions from 2016 to 2019 to construct network-based measures and calculate network centrality. The empirical result demonstrated that the shadow bank complex network during the crisis is denser, more interconnected, and more correlated than the tranquil period. The network centrality established the systemic risk transmitter and receiver roles of institutions. The financial institutions that are more central and hold prestigious positions due to their incoming links will suffer maximum loss. The shadow bank network also showed

small-world phenomena similar to social networks. The Granger-causal network-based measure ranking of financial institutions in the pre-crisis period (explanatory variable) is rank-regressed with the ranking of financial institutions based on maximum percentage loss suffered by them during the crises period (dependent variable). The network-based measures have out-of-sample predictive properties and can predict the systemic risk of financial institutions. Supervisors and financial regulators can use the proposed measures to monitor the development of systemic risk and swiftly identify and isolate contagious financial institutions in the event of a crisis. Also, it is helpful to policymakers and researchers of an emerging economy where bilateral exposures' data between financial institutions are often not present in the public domain, plus there is a gap or delay in financial reporting.

The out-of-sample predictive property of network-based measures is compared with firm level variables: size, leverage, short-term funding, non-interest income, non-performing asset. The shadow bank leverage and non-performing asset is not a significant predictor but size, non-interest income and short-term-funding are significantly related to the maximum loss an institution faced during the crisis. However, network-based measures’ out-of-sample is more statistically significant, supporting the importance of “too-central-to-fail” and “too-connected-to-fail” over “too-big-to-fail” approach in identifying systemically important financial institution rather than relying on approach.

To study the impact of shadow banking on the financial market distress, we modeled the rollover risk caused by over reliance on short term debt to fund the complex operations of the shadow bank. The rollover risk of the Indian shadow banks caused the increase in the default risk and market volatility of the institutions. However, rollover risk is non-significant in predicting the systemic risk of the institutions

The study also examined the impact of Indian shadow bank on the real economy of India. The shadow bank incremental credit growth has surpassed commercial banks in the last decade. The real GDP is negatively affected by the shadow bank crisis. The sectors like consumer durable, MSME, automobiles, commercial housing and large industries have witnessed the degrowth during the shadow bank crisis. Despite a lower share in credit supply than banks, shadow banking negatively affects the real output productivity due to its specialized lending and securitization services.

LIST OF PUBLICATIONS AND CONFERENCES

Published Papers

- Research paper titled "**Examining the interconnectedness and early warning signals of systemic risks of shadow banks: an application to the Indian shadow bank crisis**" Kybernetes ISSN: 0368-492X (SSCI IF- 2.35). Published Article publication date: 21 April 2022. https://doi.org/10.1108/K-12-2021-1280

- Research paper titled **"Examining Systemic Risk using Google PageRank Algorithm: An Application to Indian Non-Bank Financial Companies (NBFCs) Crisis."** International Journal of Mathematical, Engineering and Management Sciences. ISSN: 2455-7749 (IF 1.6). Vol. 7(4):575-588 Year: 2022. 10.33889/IJMEMS.2022.7.4.037

Accepted Paper

- Research paper titled "**Product Market Competition, Debt Rollover Risk and Financial Default Risk: Evidence from Indian Corporates**" accepted in Managerial Finance, ISSN: 0307-4358 (SSCI IF-1.90)

- Research paper titled "**An empirical study of the effect of Rollover Risk on Default Risk of Indian Firms**" accepted in Empirical Economics Letters (ISSN: 1688-8997)

Conferences

- Presented poster titled "Examining the interconnectedness and early warning signals of systemic risks of Indian Shadow Banks." at PAN-IIM World Management Conference 2019, organized by IIM Rohtak on 13/12/2019.

- Presented paper titled "Examining Systemic Risk using Google PageRank Algorithm: An Application to Indian Non-Bank Financial Companies (NBFCs) Crisis." At 5th International Conference on Mathematical Techniques in Engineering Applications, organized by Graphic Era Deemed to be University, Dehradun, from 3/12/2021 to 4/12/2021.

- Presented paper titled "An empirical study of the effect of Rollover Risk on Default Risk of Indian Firms." At International Conference on Behavioural Finance organized by IIIT Allahabad from 18/6/2022 to 19/6/2022.

- Presented paper titled "The Impact of Interaction Between Industry Competition and Rollover Risk on Corporate Financial Default Risk." at 4th SEBI-NISM Research Conference on "Indian Securities Markets-The Next Agenda" organized by NISM-Mumbai from 2/03/2023 to 3/03/2023

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

AIFI	All India Financial Institution
AUM	Asset Under Management
BC	Bank Credit
BCBS	Basel Committee on Banking Supervision
CAGR	Compound Annual Growth Rate
CDS	Credit Default Swaps
CRAR	Capital to Risk-Weighted Assets Ratio
DCI	Dynamic Causality Index
ES	Expected Shortfall
FSB	Financial Stability Board
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GFC	Global Financial Crisis
HFC	Housing Finance Companies
Idiovol	Idiosyncratic Volatility
ILFS	Infrastructure Leasing & Financial Services
LASSO	Least Absolute Shrinkage and Selection Operator regression
LDMF	Liquid Debt Mutual Funds
MBFC-MFI	NBFC-Micro-Finance Institution
MES	Marginal Expected Shortfall
MF	Mutual Funds
MSME	Micro, Small and Medium Enterprises
NABARD	National Bank for Agriculture and Rural Development
NBFC	Non-Banking Financial Company
NBFC-D	NBFC-Deposit Taking

NBFC-IFC	NBFC-Infrastructure Financing Company
NBFC-ND	NBFC-Non-Deposit Taking
NBFC-ND-SI	NBFC-ND-Systemically Important
NBFI	Non Banking Financial Institution
NHB	National Housing Bank
NII	Non Interest Income
NPA	Non Performing Assets
OLS	Ordinary Least Square
PD	Primary Dealer
RBI	Reserve Bank of India
ROA	Return on Asset
RR	Rollover Risk
SARFAESI	Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest Act
SB	Shadow Banking
SIFI	Systemically important financial institution
STF	Short Term Funding
TENET	Tail Event driven Network risk
VaR	Value-at-Risk
VAR	Vector Autoregressive

CHAPTER 1
INTRODUCTION

1.1 Introduction

After the Global Financial Crisis (GFC) of 2007-08, Shadow banking and its systemic importance in financial systems and macroeconomic implications have made it an interesting area of investigation for scholars, regulators and business professionals. Many researchers have blamed Shadow Banking as the main culprit for causing and amplifying the Global Financial Crisis (Gorton and Metrick, 2010; Ashcraft and Adrian, 2012; Ban and Gabor, 2016). These shadow entities borrow short-term in liquid markets to fund long-term, risky and illiquid assets, making them vulnerable to fire sales in case of credit event (Geithner, 2008). Unlike commercial banks that receive government guarantees, liabilities for shadow banks are not insured. In financial distress, the government generally protects commercial banks while no such recourse is available to the shadow banks. Researchers have highlighted the key role of Shadow Banks as liquidity providers to traditional banks, which mitigated some of the damage caused by liquidity shocks during the Global Financial Crisis (Wallison 2012; Culp and Neves 2017). The Shadow Banking system also helps in diversifying the portfolios of the commercial banks and also absorbs some of the risks related to loan origination. Thus, Shadow Banks and its systemic risk has largely been a debatable topic in finance literature to this date.

With the development of new financial products and structure, the complexity of Shadow Bank operations and its risks is also expanding with financial innovation. In many jurisdictions, Shadow Banks enjoys light-touch regulations and often does not report every activity to regulators, making it difficult to estimate their size and operations. This makes a clarion call by some researchers to tame this wild horse on par with banks. Some researchers even issue dire warnings that if Shadow Banking is regulated differently or left unregulated, it will trigger the next GFC (Moosa, 2018). Others argue that Shadow Bank operates in areas that are traditionally not served by banks and help in financialization and economic development (Wallison, 2012; Acharya et al., 2013). Whether the proponents and distractors agree or not, the AUM of

Shadow Banking is growing and accounts for 31% of total global financial assets, with most growth coming from emerging economies like Argentina, Chile, Indonesia, India, China, and Saudi Arabia (FSB, 2019). This has spurred the need to model the fragilities exerted by Shadow Banking on the financial system and real economy.

Financial institutions like banks, insurance and pension funds, etc. can be exposed to systemic risk of Shadow Banks via its intricate web of direct and indirect interconnections. These linkages are formed due to Shadow Banks activities like credit intermediation (Adrian and Ashcraft, 2016), liquidity transformation (Duca, 2016), imperfect credit risk transfers like securitization (Diamond and Dybvig, 1983), leverage, bilateral exposure to common portfolios, fire sale of assets (Pozsar *et al.*, 2012), etc. (Billio *et al.*, 2012; Fong, Sze and Ho, 2021; Jin, 2021) showed empirically that beyond the threshold, interconnectedness can lead to contagion causing financial distress. In India also Shadow Banking is consistently growing and is now the third largest and accounts for 9% of the financial sector's total assets (FSB, 2019). They are also the biggest recipient of funds. Also, the Indian Shadow Banking crisis of 2018 and the consequent financial meltdown and economic slowdown have renewed attention to understand the externalities imposed by Shadow Banking on the financial and real sectors.

The remaining part of the chapter provides a premise for the study and helps in understanding the rationale behind conduct of the study. It has the following sections

- Shadow Banking
- Systemic Risk
- Shadow Banking in Emerging Economies
- Indian Shadow Banks
- Regulatory Landscape of Indian Shadow Banks
- Structure of Indian Shadow Banks
- Rationale for Research
- Broad Objectives of the Study
- Scope of the Study
- Brief overview of Methodology adopted
- Outline of the thesis

1.2 Shadow Banking

The term Shadow Banking was coined by Paul Allen McCulley, an American economist and former director of PIMCO. The term “shadow bank” used to refer to the US non-banking financial institutions that are engaged in maturity transformations. Maturity transformation is a practice followed by a financial institution whereby they borrow short term to finance long-term loans. However, the formal definition is given by the Financial Stability Board (2012) which defined it as “credit intermediation involving entities and activities (fully or partially) outside the regular banking system”. Thus, shadow banking involves three activities: Credit intermediation- defined as any type of lending activity where the saver does not lend directly to the borrower and at least one intermediary is involved; Liquidity transformation- investing in illiquid assets while acquiring funding through more liquid assets; Maturity transformation-defined as use of short-term liability to fund long term assets.

In the past couple of years because of competition, growing innovation, changes in the regulatory framework in the financial sector, even existing banks have shifted their part of the activities outside the regulatory framework in the form of subsidiaries registered as non-banking entities or shadow banks. This has contributed to the growth of the shadow banks. As a result, shadow banks have spread to areas where the scope of regulatory arbitrage is higher. Also, market demand for the innovative financial instruments that can reduce risks and yet yield higher returns has sustained the growth of these shadow banks.

There are some key differences between the shadow banks and the commercial banks. Shadow banks, like regular banking entities, perform intermediation activities, however, in many ways they are different from traditional banking. First, shadow banks, unlike commercial banks, cannot create money. Second, in many jurisdictions, unlike commercial banks, the functions of shadow banks are not so tightly regulated. Third, shadow banks, unlike commercial banks which raise funds mostly through public deposits, raise funds mostly through commercial papers, debentures, bonds, or other structured products. Fourthly, shadow banks, unlike commercial banks that receive Government guarantees, the liabilities of shadow banks. Fifth, in times of financial distress, the government generally protects commercial banks while no such recourse is available to the shadow banks.

Claessens and Ratnovski (2014) identified that most of the definition focuses on a functional approach that treats shadow banking as a collection of specific intermediation services. However, it does not specify researchers and policymakers about the essential characteristics of shadow banking. Therefore, it is unclear where to look for shadow banking activities and risks that may arise in the future. Also, depending on the jurisdiction, the Shadow Banking definition differs (like in Europe, leading insurance companies, "Wealth Management Products" offered by banks in China and lending by Bank affiliated finance companies in India are called Shadow Banks).

Traditional banking transforms risks on a single balance sheet using the laws of large numbers, monitoring, and capital cushions to convert risky assets into safe assets like bank deposits. Shadow Banking distributes risks across the financial system using methods akin to capital markets. However, shadow banking differs from capital markets activities like trading stocks and bonds as it needs backstops to operate. Though most undesirable risks can be distributed and diversified away, some residual risks are often rare and systemic ones (tail risks) usually remain. As shadow banking operates on a large scale - low margins and information that can be easily measured - they cannot generate risk absorption capacity internally. Claessens and Ratnovski (2014) have described the reliance on Backstops (either privately by using the franchise value of existing financial institutions or publicly by using explicit or implicit government guarantees) as a "Litmus Test" to distinguish between shadow banks from other types of financial institutions.

1.3 Systemic Risk

Interest in systemic risk intensified after the Global Financial Crises of 2007-09. The bankruptcy of Lehman Brothers (2008), followed by the Eurozone sovereign debt crisis, has exposed the financial system's vulnerability. These events undermined investors' confidence in the existing financial system, causing a chain of panicked reactions that is felt worldwide. Summer (2003) states that there is no universal definition of systemic risk. (DeBandt and Hartmann, 2000) define a systemic crisis as a systemic event that affects a large number of financial institutions and markets in a strong sense. Thus, it severely impairs the proper functioning of the financial system. The systemic risk is more than just the failure of a bank due to the depositor run. One of the major causes of systemic events is the "contagion" effect, which means the propagation of shocks from one institution, market, or system to another (De Bandt and Hartmann, 2000). A more appropriate definition of systemic risk is "*any circumstances that cause instability or loss of public confidence in the entire financial system"* (Billio et al., 2012). The European Central Bank (2009) defines it as a risk of financial instability "so widespread that it impairs the functioning of a financial system to a point where economic growth and welfare suffer materially." Mishkin (1999) defined the financial crisis as "occurring when shocks to the financial system interfere with the information flows so that the financial system can no longer do its job of channeling funds to those with productive investment opportunities."

Systemic risk is measured as the probability of arising from a systemic crisis. A systemic crisis generally has three critical mechanisms: first, there is an initial shock; second, there is an amplification and propagation mechanism; and third, there is a disruption in the financial sector as a whole. Therefore, the systemic risk can be reduced by reducing the probability of a shock, dumping the amplification mechanism, or isolating the financial system's crucial parts. The initial shocks can be idiosyncratic, like a single bank may fail due to its bad management and fraud, or they can be systematic, like when a recession hits all the banks simultaneously. Mishkin (1999) identified that there are four causes of initial shock: first, a combined deterioration in the balance sheets of financial institutions; second, a rise in interest rates; third, an increase in uncertainty; and fourth, a deterioration in the balance sheets of the non-financial institutions. The study identified two different amplification and propagation mechanisms: first, contagion within financial system and procyclical connection between the financial sector and the real economy**.** Reinhart and Rogoff (2009) explained the financial crisis that has unfolded over the past eight decades and thus is a new reference standard in this field. In general, systemic risk can also be characterized by the four "L"s of the financial crisis - leverage, liquidity, losses, and linkages.

Though no particular definition can correctly define systemic risk (Bisias et al., 2012). Systemic risk is multifactorial; thus, no single risk metric can capture or explain all systemic risk events. Even a single consensus measure of systemic risk is neither possible nor desirable. Thus, a wide variety of perspectives and a continuous process of monitoring financial system and re-calibrating the systemic risk measures will provide a robust framework for managing financial system stability. Borio & Drehmann (2009) observed that there is as yet no single consensus explanation for the behavior of the financial system during crises. Because they are such infrequent events in the most developed financial centers, identifying stable and reliable patterns across the events is virtually impossible in one lifetime. Thus one must be practical in choosing the economic concepts to be measured, deciding the frequency and observation interval, and the level of granularity and accuracy for the systemic risk. The summary measures involve different choices in filtering, transforming, and aggregating the raw inputs.

The Journal of Economic Literature (JEL) classification system provides a basis for the systemic risk measurement taxonomy. Due to the size and complexity of the financial system concerning legal and institutional constraints, market practices, participants' characteristics, and exogenous factors, the JEL groupings do not provide sufficient resolution within the narrow subdomain of the systemic risk measurement (Bisias et al., 2012).

1.4 Shadow Banking in Emerging Economies

Shadow banking in emerging economies **(**Ghosh, 2011) involves many credit intermediation steps that mainly involve financing, leasing, factoring companies, investment and equity funds, insurance companies, pawnshops, and underground entities. Often these credit intermediation steps are lighter and simpler than those of shadow banks in advanced economies. In emerging economies like India and China (Sherpa D. 2013), the increase in shadow banking can be attributed to financial liberalization and deregulation, making them more interconnected and systemically important. As per FSB (2019) report showed, overall, shadow bank assets have grown to 31% of total global financial assets, with most growth coming from emerging economies like Argentina, Chile, Indonesia, India, China, and Saudi Arabia [Fig. 1.1].

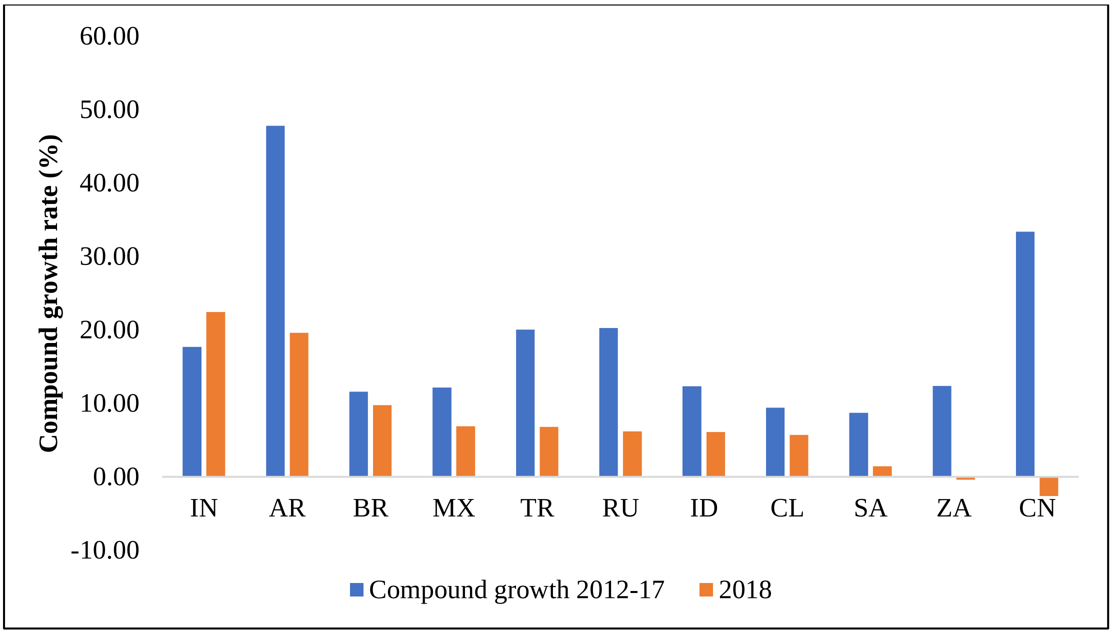


Fig. 1.1: Shadow Bank's Asset Annual Growth Rate

In India and China, finance companies (non-bank finance companies) mainly led this growth. These shadow banks depend on bank loans and investments by Insurance Companies and Pension Companies in their securities. This bilateral exposure of assets and liabilities between balance sheets led to direct financial linkages between shadow banks and the rest of the financial institutions [Fig. 1.2].

Fig. 1.2: Shadow Bank's Asset as % of Total Asset end-2018

They are also indirectly linked via portfolio overlap and co-movement of their debt and equity securities. Shadow banks in emerging economies rely heavily on direct lending from banks and often act as a substitute for bank lending in those areas which are underserved by the traditional banking system(Acharya et al. 2013). Most of these shadow banks access liquidity through asset-backed money market commercial papers whose major buyers are commercial banks. Besides being providers of funds, these banks also invest in their financial products and systems. They also have indirect linkages in the form of joint holdings of assets and derivative positions. These banks provide explicit or implicit support to shadow banks for credit/maturity transformation. Thus, their primary source of financing is banks [Fig. 1.3].

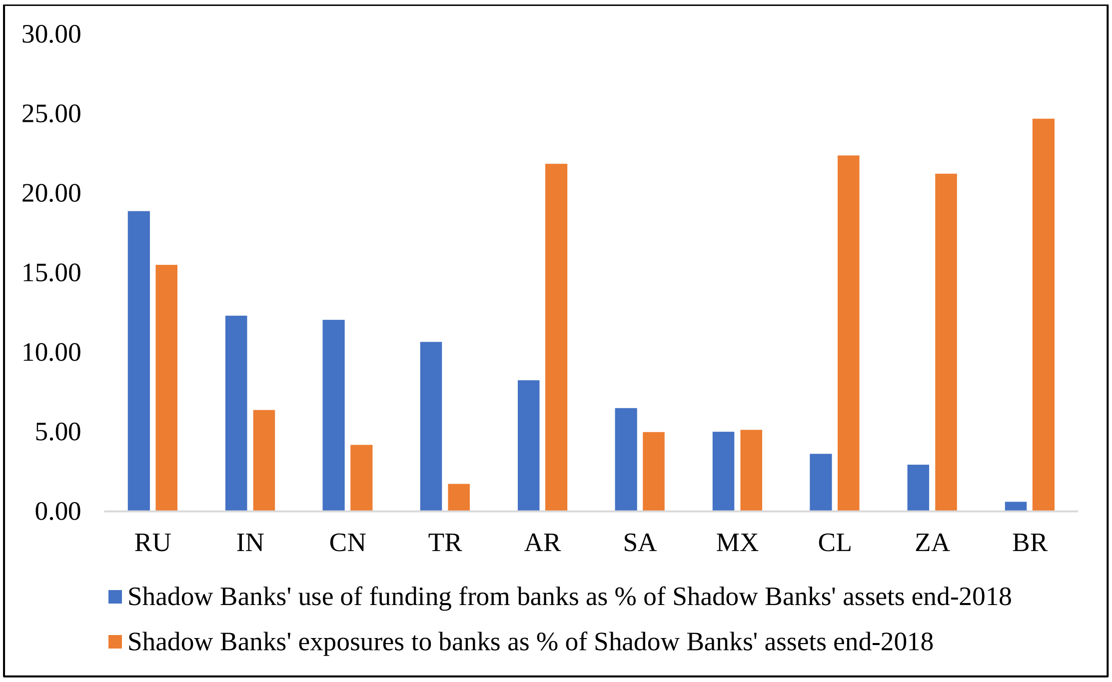
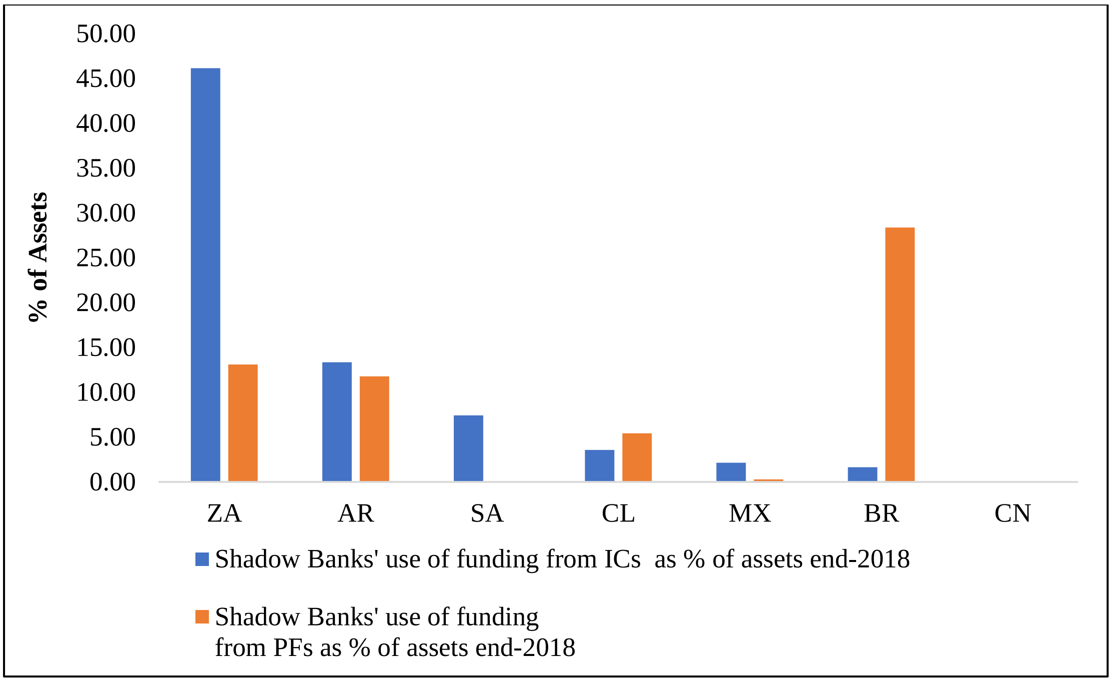


Fig. 1.3: Interconnectedness of Shadow Banks with Banks

In comparison to banks, insurance and pension funds provide lesser funding to shadow banks. In many emerging economies, regulations define the credit rating threshold for commercial papers below which insurance and pension funds cannot invest. This makes insurance and pension products' contribution to the funding of shadow banks even more insignificant [Fig. 1.4].



Countries: RU: RUSSIA, IN: INDIA, CN: CHINA, TR: TURKEY, AR: ARGENTINA, ZA: SOUTH AFRICA, MX: MEXICO, CL: CHILE, BR: BRAZIL, SA: SAUDI ARABIA, AR: ARGENTINA, ID: INDONESIA

Fig. 1.4: Interconnectedness of Shadow Banks with Insurance Co. and Pension Funds

1.5 Indian Shadow Banks

In India, shadow banks are mainly registered Non-Banking Financial Companies (NBFCs) (Gandhi 2014a). Vijaya Bhaskar (2014) defined NBFCs as companies engaged in making loans/advances, acquiring securities, hiring-purchase finance, insurance business, and chit fund. Unlike many other countries, NBFCs are distinctively different in India as the Reserve Bank of India (RBI), the central bank, regulates them. The RBI regulates them on the same level as the banking system to prevent any regulatory arbitrage. Over the past several decades, NBFCs have gained traction among the small-scale and retail sectors, especially in underserved areas and unbanked sectors. This is due to their wider reach and better customer knowledge. The NBFC’s contribution to the economy has grown from 8.4% in 2006 to above 14% in March 2015[1]. Their share in the total financial assets is about 9 percent of the financial sector’s total assets- the third-largest segment after the Scheduled Commercial Bank (64 percent) and insurance companies (14 percent) and mutual funds based on their linkages with the financial sector. They are also the biggest recipients of funds surpassing banks which signifies their systemic importance. NBFCs are further categorized based on the nature of deposit mobilization: NBFCs-D (deposit-taking) and NBFCs-ND (non-deposit taking). NBFCs-ND is further subdivided into NBFCs- Systematically Important Non-Deposit taking NBFC (NBFC-ND-SI) and other Non-Deposit taking NBFCs (NBFC-ND) based on their asset size. NBFCs with asset sizes greater than Rs 5 billion are categorized as NBFC-ND-SI. This classification helped ensure greater regulatory and supervisory control over NBFC-ND-SI, which due to their larger size, poses a greater systemic risk than NBFC-ND.

1.6 Structure of the Indian Shadow Banks

NBFCs are majorly regulated by RBI. NBFI is regulated by other regulators. The RBI regulates and supervises three categories of NBFIs namely (i) All-India Financial Institutions (AIFIs), (ii) Primary Dealers (PDs) and (iii) NBFCs. NBFCs are further categorized based on the nature of deposit mobilization: NBFCs-D (deposit-taking) and NBFCs-ND (non-deposit taking). NBFCs-ND were further subdivided into two categories of NBFCs- Systematically Important Non-Deposit taking NBFC (NBFC-ND-SI) and other Non-Deposit taking NBFCs (NBFC-ND) based on their asset size. NBFCs with asset sizes greater than Rs 1 billion are categorized as NBFC-ND-SI. This threshold was further raised to Rs 5 billion in 2014. This classification helped in ensuring greater regulatory and supervisory control over NBFC-ND-SI which due to their larger size poses a greater systemic risk as compared to NBFC-ND. The number of NBFC-ND-SI increased till 2014. However, after 2014 their number declined because of an increase in threshold asset size for defining NBFC-ND-SI.

NBFCs are classified into 12 categories based on their activities. Traditionally the core area of NBFCs has been lending and investment. However, with the growth of NBFCs, they have specialized and diversified their products and services as per the need of a particular industry or customer type. In 2006, the “equipment leasing” and “hire-purchase” were merged and categorized as Asset Finance Company (AFCs)[3]. In 2010, a separate category “Infrastructure Finance Companies (NBFC-IFC)” is defined to finance long term infrastructure projects and prevent the arising of asset-liability mismatch while funding such projects. NBFC-IFCs were envisioned to take over the loans provided for infrastructure projects under the Public-Private Partnership (PPP) route. Subsequently, in 2015 they were allowed to take over long term infrastructure loans/investment in non-PPP projects as well. In 2011, the RBI notified the “NBFC-Factor” to give teeth to the Factoring Act, 2011. In 2012, the RBI was set up “Microfinance Institutions (NBFC-MFI)” to serve the underserved segments of the society more effectively. The NBFC-MFI was to strengthen lending and recovery practices in the segment by developing ways to price credit and launching multiple borrowing options to lower over-borrowing.

Even after sub-classifying NBFCs into various categories, NBFC-Lending remains the largest category in terms of asset size, with a share of 36.2 percent in terms of total asset size as of end-March 2017. The second-largest on the list are the NBFC-IFCs with a share of 31.5% (March 2017) which shows the increased thrust of infrastructure spending over the last decade after the Global Financial Crisis. Asset Finance Company (AFCs) is in third spot with 13.7% of total assets. They are followed by investment companies. Though NBFC-MFI accounts for only 3% of total assets, their share in terms of asset size has steadily grown since their inception.

1.7 India’s Shadow Bank Crisis

The Indian Shadow Bank crisis started in June 2018 when one of the subsidiaries of Infrastructure Leasing and Financial Services (IL&FS) defaulted on its debt papers. By September 2018, the IL&FS and its subsidiaries defaulted on a series of repayments. It caused panic among the banks, fund houses, and corporates IL&FS was regarded as a “too big to fail” institution and classified as “Systemically Important Non-Deposit taking NBFC” (NBFC-ND-SI). The bank lending to IL&FS represented 16% of total lending to the NBFC sector, and as many as 34 debt and hybrid schemes under 13 AMCs have exposure to the stressed IL&FS papers.

The IL&FS defaults panicked the debt capital market which saw a sharp rise in Indian bonds’ credit risk premium. In particular, debt mutual funds became cautious of their credit risk and stopped rolling over CPs issued by various NBFCs, resulting in a sharp decline in rollover rates from more than 95% to less than 10%. This led to a freeze in a CP market, which is the prime source of liquidity for NBFCs. The MFs, also highly exposed to NBFCs, saw a mini-run from investors. Suddenly, in a short span, the entire supply of funds for thousands of NBFCs dried up.

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. The crises prevailed all over 2019, and many NBFCs like Reliance Home Finance, Reliance Commercial Finance, etc., were declared bankrupt or shut down their business.

The Indian credit market, which was already reeling under a slowdown in bank credit, the NBFCs crisis has further aggravated credit supply, resulting in a sharp decline in economic productivity (GDP from 6.1% in FY2019 to 4.2% in FY2020). This development has led to a concern about the systemic risk of NBFCs in the Indian Financial Sector.

The unfolding of the NBFC crisis and its impact on liquidity and continued economic slowdown have highlighted the importance of developing a framework to examine the financial linkages between Shadow Banks and the rest of the financial system. The crisis has also highlighted the importance of smaller institutions in forming a channel of contagion.

1.8 Regulatory Landscape in India

Below is the snapshot of the regulatory development in the Indian shadow banking (also the NBFCs):

- 1956: NBFCs are registered companies under Section 3 of Companies Act, 1956
- 1966: RBI introduced Chapter IIIB in RBI Act, 1934 to regulate deposit taking NBFCs(NBFC-D)
- 1999: RBI enacted prudential norms like banks for NBFC-D and raised the capital requirements from Rs 2 lakhs to Rs 200 Lakhs.
- 2006: RBI classified NBFC-ND (Non-Deposit) on the basis of asset size as NBFC-ND-SI (Systematically Important) (> Rs 100 crore) and not systematically

important NBFC-ND (<Rs 100 crore); where NBFC-ND-SI are subjected to tighter bank like prudential norms.

- 2009-2015: After GFC, G-20 meeting at Seoul, for "strengthening regulation and supervision of shadow banking" and constituted FSB to monitor and strengthen regulation of shadow banking and their systemic risk. RBI constituted some notable committees: 2009 Rajan Committee on Financial Sector Reforms; 2011 Usha Thorat Committee; 2013 Nachiket Mor Committee on financial inclusion and 2013 Financial Sector Legislative Reforms Commissions. Some of the recommendations adopted are : (i) NBFC-MFI category formed for NBFC operating in microfinance segment to curb the malpractices adopted by MFIs like charging high interest rates, evergreening of loans, multiple lending, etc., (ii) For governance, constitution of audit committee is made mandatory for assets worth than Rs 50 cr and deposits worth more than Rs 20 cr. For NBFC-D and NBFC-ND-SI, it is mandatory to constitute nomination and risk committee and should have "fit and proper criteria" for appointment to director posts and provide additional disclosure requirements. Also, prior permission from RBI will be required when any takeover or acquisition of control of NBFC or any change in shareholding resulting in acquisition/transfer of 26% or more of paid-up equity capital of NBFC. (iii) Finance Ministry allowed NBFCs with asset size greater than Rs 100 crore can use SARFAESI Act 2002 to recover loans above 50 lakhs. The loan threshold is lowered to Rs 20 Lakhs in 2021.
- 2016: Earlier all NBFC-D, NBFC-ND-SI, NBFC-MFI and NBFC-IFC have to maintain CRAR of 15% in the Tier 1 and Tier 2 capital. With long-standing demand of NBFC to have risk weights similar to banks, NBFCs demanded the freedom to choose differential risk weights on assets. This will help in lowering the CRAR requirements and will free up additional capital for operational use. Keeping this in mind RBI has partially heeded to industry request by reviewing the risk weights of domestic sovereign debts. Now onwards all loans given or guaranteed by the central government will carry a risk weight of zero as opposed to earlier. Similarly, all direct loans/credit/overdrafts given to the state government or investment in the state government securities will have zero weight. However, loans guaranteed by the state

government, which has not defaulted will attract a risk weight of 20% and if it has defaulted for more than 90 days will attract 100% weight.

- 2017: NBFCs that are part of group companies or are floated by a group of promoters should not be viewed on a standalone basis but in aggregate for regulatory and supervisory purposes. The committee made it necessary to combine the total assets of all the NBFCs in the group (including NBFC-D) to categorize NBFC as NBFC-ND or NBFC-ND-SI or NBFC-D. If the combined asset totals above Rs 500 cr then each NBFC has to comply with NBFC-ND-SI.
- 2018: Indian Shadow Banking (NBFC) Crisis
- 2019: After the crisis, RBI introduced Liquidity Risk Management system which is made compulsory for all NBFCs having asset size above Rs 100cr. The Board of NBFCs have to draw a framework to ensure sufficient liquidity that can provide cushion against a range of stress events. Regulation of HFC moved to RBI while supervision of HFC still remain with NHB, a subsidiary of RBI.
- 2020: Regarding co-origination of loans by banks and NBFCs, RBI made it mandatory to retain 20 percent of the individual loan on its book.
- 2021: Scale Based Regulations for NBFCs is adopted. Under this framework regulatory structure of NBFCs will comprise of four layers based on their size, activity and perceived riskiness. The four layers are NBFC-Base Layer (NBFC-BL), NBFC-Middle Layer (NBFC-ML), NBFC-Upper Layer (NBFC-UL) and NBFC-Top Layer (NBFC-TL). The revised framework will come into effect from Oct 1, 2022.

1.9 Rationale of the Research

The following points highlight the importance of exploring systemic risk of Shadow Banks in the context of emerging countries like India

- A significant amount of academic literature has focused on the systemic risk of Shadow Banks of US and European Union (Nath and Chowdhury, 2021) and therefore may not be applicable to shadow banks in Indian context which are structurally different.

- Since shadow banking institutions differ in structure and operations, therefore literature on systemic risk of shadow banks focuses only on specialized institutions falling under shadow banks. Like Allen *et al.* (2019) entrusted loans of shadow banks; Zhu *et al.* (2019) off-balance-sheet shadow banking activity of Chinese commercial banks; and López Avilés *et al.* (2021) Chilean mutual funds. Thus, we need a measure of systemic risk that provides an overall risk profile of the shadow banks and does not get affected by the type of institutions.
- As per FSB (2019) report, shadow banks are the biggest recipients of funds, even surpassing commercial banks in 2018. In India, they also constitute about 9% of total funds received by financial institutions. Their major suppliers of funds are commercial banks and mutual funds. Therefore, any credit event in shadow banks can spill over to commercial banks and mutual funds, which in turn can affect the entire financial system of the economy. Thus, it is necessary to model the linkages and develop a measure for early detection of risk in shadow banking to avoid the spread of contagion.
- In the past decade in India, credit supply by commercial banks has slowed down as they are saddled with high NPAs and regulatory costs due to higher capital requirements under BASEL III regulations. Meanwhile, at the same time, shadow banks (NBFCs) lending picked up and they started capturing the market share of commercial banks. Their credit supply to the real economy increased grew at CAGR of 11.4% from FY 2013 to FY 2017 and whooping 23.4% from FY 2017 to FY 2019. Thus, any risk to shadow banks can hamper the productivity of the real economy.
- India's shadow banking caters to specialized lending in sensitive sectors like infrastructure, automobiles, consumer credits, automobiles, and financial markets, and performs co-lending with banks to meet PSL targets. These small ticket loans are the bedrock of the Indian economy. Any risk to Shadow banks could translate into a slowdown in core demand, industry output and employment, and could disproportionately affect the most vulnerable sections.
- India's shadow banking crisis showed the importance of small institutions in amplifying the crisis. This necessitated the need to develop a measure of systemic

risk for shadow banks that can take into account the different structures and operations of shadow institutions as well as their linkages with the rest of the financial system.

1.10 Objectives of the Study

The aim of the study is to explore the interconnectedness and systemic risk of the Indian shadow banks; and to develop measures for early detection of systemic risk; and to study its impact on financial markets and the real economy.

1. **Develop a Model for Early Warning Signals of Systemic Risk to the Indian Shadow Bank:** Though financial interconnectedness helps in diversifying the risk, it also amplifies the propagation of risk during financial distress. The default of IL&FS debt papers and subsequent drying of liquidity in the NBFC space has created a domino effect impacting all the financial intermediaries: Banks, Insurers, Pension Funds, Mutual Funds, etc. The NBFCs depend on Banks' short-term loans for their working capital and also fund their short-term liquidity through Commercial Papers whose major investors are Liquid & Money Market Mutual Funds, Banks, Insurers, and Pension Funds. In the event of financial distress, this complex web of interconnectedness is identified as one of the major causes of system-wide losses. To capture interconnection, we simulate the linkages using a network-based approach where nodes are the financial institutions, and edges are represented using the Granger-causality measure. Thus, by simulating their linkages through network approach and calculating measures like dynamic granger causality, out-connections, in-connections, centrality measures which helps in predicting the buildup and flow of systemic risk among institutions and sectors. These graph theory measures based on Granger-casualty tests are unconditional, dynamic, direct, and based on returns. Whether these measures have prediction capability and can be used as early warning indicators by regulators is to be explored.

2. **Examining the Impact of Firm Level Relationships on the Measure of Interconnectedness of Systemic Risk of Indian Shadow Bank:** The literature suggests that systemic risk is influenced by bank size, leverage, bank-capital, and

ownership structureless. Thus, it is interesting to find out whether the measure of the interconnectedness of systemic risks has any significant relationship with the structure of NBFC, shortfall in capital, threshold liquidity in the system, maturity structure of debt, funding structure, asset structure, income strategy, organizational complexities. Thus, it will help to identify whether firm-level variables can influence the systemic risk of the system. We can help in framing timely control of financial contagion with appropriate regulatory and supervisory controls.

3. **Study the Impact of Systemic Risk of Shadow Banks on Financial Market Distress:** Mutual funds are the major buyers of the commercial papers of the NBFCs. Other banks also have investments in the NBFCs. As NBFCs represent different sectors due to their specialization they are also preferred among the retail investors. Generally, NBFCs rollover the CPs to the next period if they are unable to pay for the maturing debt. The rollover of short-term debt comes with repricing risks caused by an increase in interest rates or as compensation to investors. In the event of a shock, more NBFC's short-term debt will go for rollover, leading to rollover and repricing risk. At the same time, Mutual Funds will also face increased redemption pressure from their investors, leading them to run risks. This run risk will create a liquidity crunch for Mutual Funds and they will fire-sale the short-term debt papers held by them. All these risks are due to interconnectedness and increased concentration of debt papers of stressed NBFCs. A hit in the valuation of NBFCs will also lead to stock market distress. Thus, it will be interesting to look for the factors affecting the overall liquidity in the financial system and its consequent effect on the systemic risk of the NBFCs.

4. **To assess the Spillover Effect of Systemic Risk of Shadow Banks on the Real Economy:** Shadow banks generally specialize in some form of assets like housing, automobiles, SMEs, etc. They also have common exposures among themselves. In the event of negative externalities, there is an abrupt slowdown in credit flow to these real sectors directly or indirectly via retail credit. Fire sales of the assets held by these shadow banks have also induced a further slowdown in these real sectors. Thus, by taking a combined measure of interconnection and leverage one can check the feedback mechanism which exists between the shadow banks and the real economy.

1.11 Scope of the Study

The scope of the study covers the description of the boundary within which the research is conducted. The specific research questions that will be addressed are a) the modeling of interconnectedness of the shadow banks with the rest of the financial system b) the development of the interconnectedness variable which can help in predicting of systemic risk of the financial system c) to understand the channel of contagion for spillover of shadow bank crisis to the rest of the financial system d) to analyze and compare the pre and post effect of shadow bank crisis on the real economy. For the study, we chose the Indian Non-Banking Financial Companies as the shadow banks. The Indian shadow bank crisis happened in the year 2018-19. To analyze the first two questions, we took a sample of shadow banks, commercial banks, mutual funds and Housing Finance Companies which has continuous data from 2010 to 2020. For the third objective, we chose all the shadow banks and commercial banks from 2010 to 2020. For the fourth objective, we have done an observational study to compare the effect of the shadow bank crisis on different real economic variables.

1.12 Brief Overview of Methodology Adopted

The study uses empirical research and econometrics to understand the interconnectedness of the shadow banks with the rest of the financial system. To analyze the interconnectedness among the financial institutions, it uses the Granger causality tool on GARCH adjusted returns of the financial system to develop a network of financial institutions and calculate centrality scores. To find the predictive power of interconnectedness measures with other firm level variables, we used linear regression. To find the spillover effect of the crisis on the rest of the financial system, we conducted a panel-based regression on the dataset from 2010 to 2020. To analyze the spillover effect on the real economy, we performed observational studies based through patterns which appeared in time series of economic variables pre and post crisis.

1.13 Outline of the Thesis

- Chapter 1: Introduction
- Chapter 2: Literature Review
- Chapter 3: Research Methodology
- Chapter 4: Interconnectedness as a Measure of Systemic Risk between Shadow Banks and Rest of Indian Financial System
- Chapter 5: Examining the Impact of Firm-level Relationships on the Systemic Risk of the Indian Shadow Banks
- Chapter 6: Effect of Systemic Risk of Indian Shadow Banks on the Financial Market Distress: A Panel based Study
- Chapter 7: Effect of 2018-19 Shadow Banking Crisis on the Real Economy of India: An Observational Study
- Chapter 8: Conclusion, Future Scope and Social Impact
- References
- Appendices

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Shadow banking is important for the financial system because it provides an alternative source of credit for businesses and individuals. Shadow banks are not subject to the same regulations as traditional banks, which allows them to take on more risk and offer higher yields. It can be beneficial for businesses and individuals who are unable to obtain credit from traditional banks. Thus, increasing the credit availability for the business and the households. Shadow Banks led in financial innovation by developing new financial products which can create more liquidity and depth in the financial system. Shadow Banks have low cost of operations than traditional banks, making them more efficient. However, shadow banking also poses some risks to the financial system. Shadow banks are not as well-regulated as traditional banks, which means that they are more likely to fail. If a shadow bank fails, it could have a ripple effect throughout the financial system, leading to a wider crisis. The risky operations of the shadow banks can artificially drive up the demand and price of the assets. Shadow banks are often opaque, which makes it difficult to assess their risks. This can make it difficult for regulators to monitor them and for investors to make informed decisions. Overall, shadow banking is a complex and multifaceted issue. It has both benefits and risks, and it is important to carefully consider both sides before making a judgment. Further, there are very few academic research on the systemic risk of the Shadow Banks. To delve deeper into the interconnectedness and systemic risk of the shadow bank, literature review is conducted to understand the topic in detail. The literature review is arranged in the following themes:

- Shadow Banking and Systemic Risk
- Measurement of Systemic Risk
- Understanding Interconnectedness as source of systemic risk
- Systemic risk and firm level relationship
- Shadow Banking and the financial market distress

- Shadow Banking and the Real Economy
- Studies from India covering Indian Shadow Banks
- Research Gap

2.2 Shadow Banking and Systemic Risk

(Huang, 2018; Acharya et al., 2013; Gorton and Metrick, 2010; Pozsar et al., 2010) banks pursue regulatory arbitrage through shadow banking, making it procyclical and increasing endogenous risk. (Diamond and Dybvig, 1983; Pozsar et al., 2012; Adrian and Ashcraft, 2016; Duca, 2015) shadow banks are intrinsically fragile as they would transform risk and maturities without any explicit public source of liquidity or insurance. Istiak (2019) states that shadow bank leverage has become an important economic indicator due to its influence on key economic variables. Ferrante (2018) showed that shadow banks make the system more fragile by financing lower-quality loans and their exposure to bank runs. Fève, Moura, and Pierrard (2019) concluded that shadow banking is a powerful amplification mechanism during a financial crisis and also reduces the effectiveness of macroprudential policies targeting the banks.

(Fong et al., 2021; Jin, 2021) analyzed interconnections and cross-contagion effects of shadow banks in between economies and financial sectors. (Jiang and Fang, 2022) attributed credit, maturity and liquidity mismatches via cross-use of funds for the cross-contagion of shadow banks' risks and financial sectors. (Holod et al., 2020; and Fève, Moura, and Pierrard, 2019) Analyzed the procyclical effect of shadow banking on commercial banks' macro-prudential policies and risk-taking ability. (Zhou, 2019; Klimenko and Moreno-Bromberg, 2016) find that credit risk transmission of shadow banks on commercial banks is positively correlated with the scale of their interbank business Istiak (2019) showed that shadow bank leverage had become an important economic indicator due to its capacity to influence fundamental economic variables. Ferrante (2018) showed that shadow banks make the system more fragile by financing lower-quality loans and their exposure to bank runs. Conlon et al. (2020) pointed out that shadow banking causes fragmentation and opacity in the capital market, making it difficult for investors to understand information and causing market panic and financial distress.

2.3 Measurement of Systemic Risk

It is difficult to find a systemic risk measure that is both practical and justifies a general equilibrium model (Saunders and Allen, 2002). The gap is so vast that the value-at-risk (VaR), an institution-level risk measure, has been widely used to regulate the financial system's risk. Lehar (2005) estimated the dynamics and correlations between bank asset portfolios. The risk of the regulator's portfolio comprising the entire banking system is measured using the standard tools regulators require the banks to use for their internal risk management. The individual liabilities the regulator has to each bank are modeled as contingent claims on the bank's assets.

Gray, Merton and Bodie (2007) used contingent claim analysis (CCA) through a risk-adjusted balance sheet to show the sensitivity of the firm's assets and liabilities to the external "shocks." This approach is suited to quantifying the effects of asset-liability mismatches within and across institutions. Risk-adjusted balance sheets help in simulations and stress testing of the potential impact of policies that help manage systemic risk. Gray and Jobst (2010) proposed using contingent claims analysis (CCA) to measure systemic risk from market-implied expected losses, with immediate practical applications to the analysis of implicit government contingent liabilities, i.e., guarantees. Besides, the framework also helps quantify the individual contributions of financial institutions to overall contingent liabilities in the event of systemic distress.

Acharya et al. (2017) Systemic Expected Shortfall (SES) measures the contribution of financial institutions to systemic risk, that is, its propensity to be undercapitalized when the system as a whole is undercapitalized. Huang, Zhou and Zhu (2009) measured the systemic risk by the insurance price against financial distress. The hypothetical insurance premium is based on expected credit loss above a given share of the financial sector's total liabilities, estimated by the stock return correlations across these firms and the CDS spreads. A conceptually closely related model is the distressed insurance premium (DIP) of Huang, Zhou, and Zhu (2009), which measures the conditional expected shortfall (CoES) of an institution, conditional on systemic distress. The DIP represents a hypothetical insurance premium against systemic distress, defined as total losses exceeding a threshold level of 15% of total bank liabilities. Adrian and Brunnermeier (2016) proposed that change in CoVaR is defined as the change in value at risk of the financial system conditional on the institution's distress. The CoVaR can be significantly predicted by leverage, size, maturity mismatch, and asset price boom. The forward-looking measure of CoVaR helps predict the buildup of systemic risk but does not causally predict which institutions are responsible for it.

Brunnermeier et al. (2020) find that non-interest income positively relates to the total systemic risk for a large sample of US Banks. Primarily trading and venture capital income are significantly related to systemic risk. Girardi and Ergün (2013) modified CoVaR by including scenarios where institutions are most at their VaR. Engle (2011) stated that both long-run and short-run risks could be separated, and long-run risks are one of the major causes of financial crises. Brownlees and Engle (2012) proposed the SRISK index, a function of the degree of Leverage, Size, and Marginal Expected Shortfall. MES is characterized by time-varying volatility and correlation at the tail. SRISK measures the capital shortage of firms when the overall market is declining. SRISK provides an early warning signal of distress in the real economy.

Kritzman et al. (2011) provided an absorption ratio that measures the fraction of total variance of a set of asset returns that a fixed number of eigenvectors can explain. Zheng et al. (2012) state that the increase in principal components shows cross-correlation among stocks and stock indices associated with financial crises. Li et al. (2017) used a support vector machine built using principal components to explain complex nonlinear characteristics of systemic banking risk. Avanzini and Jara (2015) used data reduction techniques as the principal component to assess SIFI in Chile.

Diebold and Yilmaz (2014) analyzed cross-market volatility spillovers using a generalized vector autoregressive framework in US markets which showed that as crises intensified during GFC, the volatility spilled over from the stock market to other markets. Bekaert and Hoerova (2014) used the VIX index and derived conditional variance of stock returns and equity variance premium. The results showed that variance premium predicts stock returns, and conditional variance predicts economic activity and financial instability. Diebold and Yılmaz (2014) use network topology theory to measure interconnectedness with variance decomposition of VAR as weights of directed networks. Barunķk and Křehlķk (2018) measured connectedness using the spectral representation of variance decompositions. The study stated that when the connectedness is created at lower frequencies, it suggests that shocks are persistent and are being transmitted for more extended periods.

Battiston et al. (2012) used the DebtRank measure to determine a systemically important node in the graph. The study suggested that too-central-to-fail is an even bigger issue than too-big-to-fail**.** Roukny et al. (2013) analyzed the interplay of network topology, banks' capital ratios, market illiquidity, and random vs. targeted shock and found that topology matters substantially when the market is illiquid**.** Cimini et al. (2015) presented an innovative method to reconstruct a system based on limited information using knowledge of intrinsic node-specific properties and linkages of a limited subset of nodes. This provides a valuable tool to gain insights into a privacy-protected financial system. Das (2016) proposed a new systemic risk score that depends on the individual risk and the interconnectedness across institutions, irrespective of how the interconnectedness is measured. The regulator can use the systemic risk score to tax the individual entity, as the risk score is easily decomposable into risk contribution from an individual entity. Tianyun, Zihui, and Jieyi (2014) use TENET(Tail Event-driven NETwork)to identify that small firms are systemically crucial due to their high level of incoming(outgoing) connectedness. Härdle, Wang and Yu (2016) proposed the TENET (Tail event-driven NETwork) measure, which combined the dynamics of the tail event and network dynamics in one context. Demirer et al. (2018) used LASSO to shrink, select & estimate the high dimensional network of global banks. The study found that most systemic events are mostly cross-country as opposed to within-country links.

2.3.1 Interconnectedness as the Source of Systemic Risk

As there is no universal definition of systemic risk, it also implies that risk of such events have been multifactorial and unable to be captured by single metric. The literature review on systemic risk identified four L's: leverage, liquidity, losses and linkages. The systemic risk measure based on leverage, liquidity and losses can work well when systemic losses can be represented by historical data. However, during period of rapid financial innovations, parts of financial institutions which has never experienced any simultaneous losses, becomes well connected to other parts which increases their systemic risk. Thus we have chosen “Linkages” over other L’s. It is well known fact that likelihood of a financial institution facing crisis is related to the degree of correlation among the holdings of the financial institutions and their sensitivity to changes in market prices and economic conditions. How much concentrated the risk is ? During the Indian shadow bank crisis, the other L’s may not have work as shadow banks have faced simultaneous losses for the first time, their credit ratings were of investable grade before the crisis, their exposure to banks, insurance and mutual funds were increasing due to their increased lending, they are not subjected to asset classification norms of RBI before the crisis, their bilateral dealings or contracts were mostly opaque. Thus, we used linkages as tool to capture the systemic risk.

Financial networks may get distressed via direct and indirect interconnections between financial institutions. These interconnections are prominent in the financial sector rather than other industries as they arise through the intricate web of financial contracts. Interconnections help pool the liquidity needs of institutions where a party with excess liquidity provides surplus funds to institutions that need it. It also leads to efficient risk-sharing by reducing loss arising from idiosyncratic shocks. However, this contractual relation also means that if one institution fails, its networks will also bear losses. Many authors have studied the role of interconnections in creating financial fragility in the system**.** Dasgupta (2004) showed that interbank deposit networks lead to contagion if creditor bank fails. De Bandt et al. (2012) proposed a hypothesis leading to financial fragility based on complex interbank networks, maturity transformation, and financial contracts’ information content. Allen and Gale (2000) argued that incomplete networks during liquidity shock lead to financial fragility by disproportionately hitting some institutions, causing bankruptcy and bank runs. Kyle and Xiong (2001) analyzed financial institutions’ lending behavior and argued that the wealth effect and risk aversion might cause contagion if investors lend to the same borrowers. Other prominent studies analyzing network issues are (Freixas et al. 2000) systemic risk in the interbank system, (Gheorghiu, 2017) maturity transformation, (Battiston et al. 2012) short-term lending, (Allen et al. 2012) rollover risk, (Bluhm, 2018) balance sheet interconnections to measure endogenous systemic risk. Allen et al. (2010) showed that there exists no relation between welfare and level of financial interconnectedness.

The complexity of shadow banking operations makes it highly interconnected with the rest of the financial system. The direct interdependencies arise from the contractual relationship of shadow banks in the form of bank lending, money market operations, credit intermediation, and securitization activities. The indirect interdependencies arise from the cross-holding of portfolios, regulatory or insurance reasons. The financial linkages help shadow banks share risk efficiently in case of idiosyncratic shocks. (Culp and Neves, 2017; Barth *et al.*, 2015; Zhou and Tewari, 2019; Landau, 2019) shows that interconnections of traditional banks with shadow banks prevent banks from experiencing liquidity crises and diversifying their risk exposure. However, studies like (Allen and Gale, 2000 and Dasgupta, 2004) focus on the contagion effect of interconnections. The cause of contagion in shadow banking resulting in spillover effect to the financial system is attributed to excessive reliance on short-term debt, opaque activities (Conlon, Cotter and Molyneux, 2020; Ferrante, 2018), credit intermediation without explicit public insurance (Adrian and Ashcraft, 2016; Duca, 2016; Diamond and Dybvig, 1983; Pozsar *et al.*, 2012), high leverage (Istiak, 2019), and regulatory arbitrage (Huang, 2018; Acharya, Schnabl and Suarez, 2013; Gorton and Metrick, 2010). (Billio *et al.*, 2012; Fong, Sze and Ho, 2021; Jin, 2021) showed empirically that beyond a threshold, interconnectedness can lead to contagion causing financial distress. *Thus, there is need to find the threshold above which interconnectedness can lead to contagion causing financial distress.*

2.4 Systemic Risk of Shadow Banks and Firm-Level Relationship

The operations and features of shadow banks can directly contribute to their interconnectedness and systemic risk. Here we discuss the firm-level characteristics that can be potential determinants of their interconnectedness.

2.4.1 Systemic Risk and Leverage

Their leverage position can primarily influence the risk-taking ability of shadow banks. As leverage is a double-edged sword, excessive leverage can increase risk-taking and lead to default. While leverage helps increase return on equity, financial institutions' excessive leverage can lead to financial crises. As per Merton's (1976) default model, it triggers bankruptcy whenever the value of assets falls below the leverage. It occurs whenever there is excessive leverage or negative shock to the asset value of shadow banks (Moore and Zhou, 2012). Therefore, a high leverage position may lead to a disconnected position within the financial system. Billio et al. (2012) state that leverage affects a magnifying glass. It expands small profit opportunities into larger ones and amplifies small losses into larger ones. When the financial crisis hit, the value of such collateral decreased, leading to the forced liquidation of more prominent positions over a short period. Such fire sales intensify the systemic event, and financial institutions become even more interconnected. Bank borrowing lending relationship become the primary channel to spread an idiosyncratic shock to the entire system. Interbank lending positions, network positions and connectivity of the network are crucial parameters to determine the financial stability (Kuzubas, Saltoglu, and Sever, 2016). The seminal work of (Adrian and Shin, 2010 ; Danielsson et al., 2012) showed the importance of leverage in giving rise to increase volatility in market price of assets, leading to higher risk. The empirical work of (Thurner, 2011; Brunnermeier and Sannikov, 2011; Ramadan, 2012) demonstrate the positive correlation effect between high leverage positions and more systemic risk in the financial system. (Cincinelli, Pellini, and Urga, 2021) revealed a direct relationship between leverage and systemic risk measures of (Adrian and Brunnermier, 2016) dCoVaR; MES (Acharya et al. (2017)), SRISK (Brownlees and Engle (2012)). (Roukny, Battiston, and Stiglitz; 2018) modeled the effect of leverage on the interconnectedness of the financial system and found that leverage both in the interbank market and the external asset increases the interconnectedness and systemic risk of the system. *Thus, Leverage of the financial institution is positively related to the systemic risk of the financial system.*

2.4.2 Systemic Risk and Size

There is an unclear view on the relationship between the effect of size on the institutions' systemic risk. The size of the financial institution played a key role in

Global Financial Crisis of 2008-09. Since then, size has become a critical factor in understanding the systemic importance of the financial institution by exposing the reality of ‘too-big-to-fail’ (TBTF) financial institutions (Pais and Stork, 2013). The seminal work of (Laeven, Ratnovski and Tong, 2016) has showed that large financial institutions increase the overall systemic risk of the financial institutions. This stem from the “moral hazard” affecting large financial institution, that in the event of the insolvency these banks will be bailed out by the regulator or the government (Jorion, 2009). The managers of large financial institution have a higher advantage to become highly levered in expectation of higher returns (Balasubramnian and Cyree, 2011). A large financial institution generally has less liquid capital, relies more on unstable funds, has more market-based activities, and is more organizationally complex than small financial institutions. It may be suggested that a large financial institution can be inherently less stable than a smaller one. Also, their systemic risk increases when they have unstable funding and poor asset quality. Large financial institutions get a comparative advantage over smaller institutions while accessing capital at lower funding cost even with higher systemic risk. (Penas and Unal, 2004) find that the market power of large financial institutions and their ability to bargain with the regulator negatively impacts their shareholder returns during the crisis. Also, the mergers and acquisitions in financial institutions do not offer diversification benefits during the period of crisis (Carow et al., 2003; Banal-Estanol and Ottaviani, 2007). *Thus, size of the financial institution is significantly positively related to the systemic risk of the financial system.*

On the other hand, the empirical work of (Hughes et al., 1999; Upper and Worms, 2004; Iyer and Peydro, 2011) proved the beneficial role of size effect on the financial institution’s stability. (Hughes et al., 1999) find that the consolidation in the financial system reduces the individual insolvency risk. (Upper and Worms, 2004) shows that the transmission of risk in the interbank market is greater among the small financial institutions. (Iyer and Peydro , 2011) find that the contagion in the Indian financial institution due to failure of a large bank is larger for the smaller financial institutions as compared to larger one. *Thus, size of the financial institution is significantly negatively related to the systemic risk of the financial system.*

2.4.3 Systemic Risk and Short-term Funding

The type of funds a financial institution relies on is vital in determining its stability. Excessive reliance on short-term funding creates asset-liability mismatch and liquidity risk (Goodhart, 1988). The banks relying on short-term funds face banks run by panicked investors during a market downturn. The reliance on wholesale funding correlates with the financial institution's downside tail risk (Acharya et al., 2013) like that of Northern Rock's funds in September 2007. Similarly, a run-on financial institution's wholesale funding triggers a funding shock that can erode investor confidence. It can cause investors to freeze the rollover of short-term funds creating liquidity pressure on other financial institutions. Thus, the shock specific to a financial institution can spill over, resulting in bank runs at other institutions with high retail deposits. The long-term wholesale funding does not suffer from maturity mismatch problems are regarded as a stable form of funding. Thus, financial institutions with higher proportions of wholesale funding will have high idiosyncratic and systemic risks over the other financial institutions (Laeven, Ratnovski and Tong, 2016). Shadow banks often find it easier to access low-cost, short-term funding from the market to fund its long-term assets. This approach lowers its overall cost of funds. However, this precipitates asset-liability mismatch without any safeguard mechanism or threshold. It will critically affect the shadow bank ability to meet its liquidity position in terms of timely repayment of short-term obligations. When bad news arrives in the form of crisis, financial institution finds it difficult to access short-term funds, as the market expects them to become insolvent (Pierret, 2015). (Pierret, 2015; Fernandez and Martin, 2014) finds that the higher use of short-term debt in funding the capital required to purchase long-term assets leads to more systemic risk during the crisis for the financial institution. *Thus, short-term funding is significantly positively related to systemic risk.*

2.4.4 Systemic Risk and Non-Performing Asset

Financial institutions try to maximize their income by reducing the risk. In this process, they construct portfolios with similar risk profiles, and their risk management styles are similar. Thus, a deterioration in asset quality in one bank can send a shock to other banks. It can lead to a fire-sale of such assets, which leads to low-value realization and lower profitability. Thus, a financial institution with higher non-performing assets in its portfolio can have higher systemic risk. Non-Performing Assets of financial institutions leads to a decline in profitability, leads to more write-offs in their portfolio, and leads to a higher provision for the financial institutions. (Beltrame, Previtali, and Sclip, 2018) found a direct association between leverage and declining asset quality in increasing the systematic risk of the banks. (Festiae and Repina, 2009) periods of booms with soft loan constraints lead to higher non-performing loans during the slowdown of economic activities and higher systemic risk of the financial institutions. (Bayazitova and Shivdasani, 2012) that banks with lower asset quality in a crisis period get more equity infusions which can lead to lower systemic risk. Also, the more specialized an institution, the higher its rate of return and more downside risk (Kamp et al., 2007; Gorton and Winton, 1998). While a non-specialized financial institution may not be exposed to the general sector, its idiosyncratic risk is much higher than a well-diversified institution. *Thus, a non-performing asset is significantly positively related to systemic risk.*

2.4.5 Systemic Risk and Non-Interest Income

Interest income is regarded as a more stable source of income than non-interest income. In the aftermath of GFC 2008-09, it was seen that banks with a higher share of interest-bearing income than non-interest income contributed less to the systemic risk and were less affected during GFC (Acharya et al., 2013). Generally, the more a financial institution has interest income, the well-diversified its portfolio and more exposure to a general shock to the system. The specialized bank with more non-interest-bearing activities generally gets lured by exotic operations to increase their bottom line and is more exposed to standard shock or idiosyncratic risk. It makes their downside risk relatively high in case of a specific event. Also, non-interest-bearing income is more volatile and thus can evaporate quickly during a market crisis. Loosening of the regulation and competition led to the diversification of functions of financial institutions into non-interest income-generating activities. It has led to an accumulation of risky assets on institutions' balance sheets at the cost of profitability. These activities include investment banking, trading, securitization, venture capital, commissions, brokerage, and fiduciary services from non-hedging derivatives (Brunnermeier et al., 2020).

However, such diversification leads to more asset correlation among the financial institutions leading to more interconnectedness during a systemic event (Wagner, 2010). Tasca et al. (2014) argued that higher asset correlation and commonalities among the financial institutions led to a herding effect during the financial crisis. Also, the non-interest income activities of financial institutions can lead to high tail betas and thereby lower the financial system's stability. *Therefore, we conjecture that non-interest-bearing activities positively correlate with systemic risk.*

2.5 Shadow Banking and Financial Market Distress

The studies on shadow banking impact on the financial stability are mixed and inconclusive. Some authors have directly ascribed GFC to shadow banks (Ban and Gabor, 2016; Acharya, Khandwala, and Oncu, 2013) while some authors (Wallison, 2012; Culp and Neves, 2017) have attributed the shadow banking activities like securitization as way to manage liquidity and avert future financial crises. Today, it is of consensus that for a stable financial system we need a stable shadow banking (Wullweber, 2020). Shadow Banking increases the financial layering thereby increasing financial fragility (Bouguelli, 2020). As most shadow banking are present as off-balance-sheet financing of commercial banks, this creates limited risk sharing which does not address financial fragility created by such activities (Huang, 2018). Also, Shadow Banks creates an alternative channel for funding of commercial banks, this adds to the financial fragility of the system (Bouguelli, 2020). While loan origination of shadow banking helps in increase in loanable funds for banks and thus diversify some of the risk of commercial banks.

The studies of shadow banking and its impact on financial market distress is even scarer in the emerging market. Most of the studies focus on the China. The growth of shadow banking in China has resulted into a lowering of default risk of Chinese commercial banks (Bashir, 2023). However, the study of (Ding, Fung, and Jia, 2020) in Chinese banking space, shows that shadow banking is positively related to the credit risk and negatively related to the profitability of the Chinese banks. Gabrieli et al. (2018) found that shadow banking in China also positively correlate with enhanced savings and diversifying the financial sector.

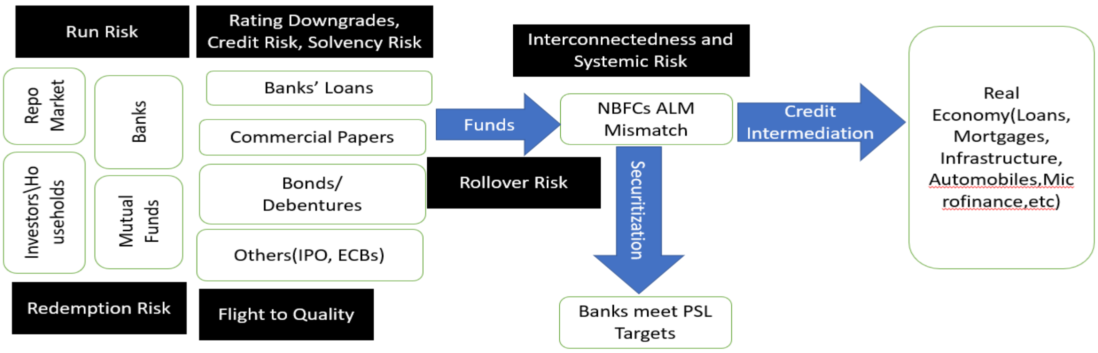


Fig. 2.1: Shadow Bank and the Financial Market Integration

2.5.1 Shadow Bank Rollover Risk

Rollover risk is a type of risk associated with shadow banking. It occurs when a financial institution or other entity borrows short-term funds to finance long-term investments. This type of risk is especially prevalent in the shadow banking system, which is made up of non-bank financial institutions such as hedge funds, money market funds, and other investment vehicles. When a financial institution borrows short-term funds to finance long-term investments, it is taking on rollover risk. Rollover risk is the risk that a financial institution will not be able to roll over its short-term debt when it comes due. This can occur when investors are unwilling to purchase the debt, or when the financial institution does not have access to the necessary funds. As the institution must continually roll over the short-term debt in order to keep the long-term investments funded. If the institution is unable to do so, it may be forced to liquidate its investments, resulting in losses. Shadow banks are particularly vulnerable to rollover risk because they are not subject to the same regulations as traditional banks and may not have access to the same sources of funding. (Zhang, 2014) Shadow Banking increases chance of rollover risk in the financial system via maturity transformation and liquidity transformation. (Adrian and Ashcraft, 2016) Shadow Banks suffers from rollover risk as they fund illiquid long-term asset from short-term credits. (Sunderam, 2015) notes that Shadow Banking transfers the rollover risk to investors using Asset Backed Commercial Paper (ABCP).

2.5.2 Shadow Banking Rollover Risk and Liquidity

Shadow banks depend on liquidity to refinance their short-term debt needs (rollover risk). The liquidity crises occur when the shadow bank either could not take funding or there is market freeze. Funding liquidity helps in attracting the new investors by issuing new instruments whereas market liquidity helps in selling assets or to use collateralized assets. Reduced market liquidity or funding liquidity causes financial distress. Markets froze in several phases during systemic event. In the first phase, when the negative information of delinquencies and bad debts becomes apparent, the market liquidity and funding liquidity began evaporating for structured instruments floated by shadow banks. This correlates with the increase in defaults of mortgaged bank loans. In the second phase, the bad economic condition and market freeze, the interest rate goes up intensifying liquidity crises. In the third phase, as more market participants start selling their distressed assets, this led to fire sale and flight to quality problem, resulting in increase in haircut and depressing of balance sheets of shadow banks. (Morris and Shin, 2004 and Acharya et al., 2010) established that a firm's debt maturity in the short term increases the firm's default risk through rollover channels during market liquidity disruptions.

2.5.3 Shadow Banking Rollover Risk and Redemption Risk in Liquid Mutual Funds

(He and Xiong, 2012; Anshuman and Sharma, 2020; Mählmann, T. and Sukonnik, G., 2022) that anticipating defaults investors in the commercial papers of shadow banks resorted to excessive redemptions in liquid debt mutual funds which in turn exacerbated the rollover risk of the shadow banks. Liquid mutual funds are a type of mutual fund that invests in highly liquid assets such as cash, money market instruments, and short-term government bonds. These funds are designed to provide investors with a low-risk, low-volatility investment option that can be quickly and easily converted into cash. Liquid mutual funds typically offer higher yields than money market accounts and other cash equivalents, but with slightly higher risk. Liquid mutual funds invest in shadow banks by buying their Commercial Papers or Certificate of Deposits. NBFCs account for around 20% of Liquid Debt Mutual Funds investments as of 2022. The major investor in LDMFs in India are the corporate sectors who tend to invest in funds of shorter durations. This is heavily in contrast to the US, where major investors of LDMFs are retail investors who invest to seek out a safe investment for their retirement. The fund flow to these LDMFs are guided by the strong operating performance of the corporates who typically invest more of their cash flow into the financial instruments during the good economy.

2.5.4 Shadow Banking Rollover Risk and Flight-to-Quality

Flight to quality is an investment strategy in which investors move their money from riskier investments to safer investments. This is typically done when the market is experiencing a downturn or when there is a general feeling of uncertainty. Investors may move their money from stocks to bonds, from corporate bonds to government bonds, or from stocks to cash. The goal is to protect their capital from losses and to preserve the value of their investments. (Rinaldi, 2011; Acharya et al., 2013; Valenzuela, 2016) showed that risk averse investor fears that during distress there won't be much liquidity in case they need it. Thus, they move their capital to the safest possible asset. Leading to fire sale in illiquid market and flight to quality phenomena in liquid market. This also led to the market freeze of rollover of short-term debt.

2.5.5 Shadow Banking Rollover Risk and Default Risk

Shadow Banking asset structure plays an important role in determining systemic risk and financial market distress in case of crisis. Shadow banks usually borrow short-term to fund long-term assets. It causes asset-liability mismatch, where the duration of income received from those assets exceeds the duration of payment on these short-term funds. To extend the duration of payment on these maturing short-term bonds, shadow banks replace these bonds with longer-maturity bonds by promising a higher yield to the investors. It can lead to rollover risk or refinancing risk. While rolling over, the firm is exposed to liquidity risks and interest rate risks. If the interest rate increases, it will result in higher interest rate expenditures causing higher refinancing costs. If the borrower's credit profile changes or the credit market tightens, it can cause liquidity risk, negatively affecting the primary channel that firms need to rollover their debt. Since shadow banks' assets are inherently opaque (Flannery, Kwan, and Nimalendran, 2010), it is hard to ascertain the fundamental value of shadow banks' assets. The only certain information which investors have is whether a shadow bank will be solvent or insolvent if any negative signal is received by the market. Rollover is almost certain if a good signal is realized, but not after a bad signal where investors could not even recover their opportunity cost. It forces the shadow bank into early liquidation if the maturing debt could not be rolled over (Allen, Babus, and Carletti, 2012). He and Xiong (2012) showed that deterioration in debt market liquidity leads to an increase in not only the liquidity premium of corporate bonds but also credit risk. Further study of Gopalan et al. (2014), Wang et al. (2017), and Wang and Chiu (2019) tested empirically the hypothesis of He and Xiong (2012), that higher use of short-term debt increases default probability.

2.6 Shadow Banking and Real Economy

Feve, Moura, and Pierrard (2022) showed that accounting for the collapse of shadow banks is vital as there has been muted growth in GDP, investment and inflation after GFC for many years. The increasing importance of shadow banking in the economy is because of regulatory arbitrage, where shadow banks take on various functions of commercial banks with far lesser capital (Meeks, Nelson, and Alessandri, 2017). The main functions replicated by shadow banks are credit and maturity transformation of traditional banks through the securitization process that results in increased leverage of the whole system, contributing to the financial crisis. Adrian and Shin (2008) linked the securitization process by shadow banks to create financial instability. Gertler and Kiyotaki (2015) showed that when banks are subject to idiosyncratic shocks, the interbank lending market helps in the cross-sectional sharing of risks. In the absence of a well-functioning interbank market, the asset prices of two ends of interbank markets are not equal. It makes shadow banks, a marginal supplier of credit, become more levered than average, resulting in amplification of shocks. It happens because the investors' demand for good collaterals drives banks to increase securitization when faced with idiosyncratic risks resulting in more levered shadow banks (Gennaioli, Shleifer, and Vishny, 2015).

2.6.1 Shadow Banking crisis and Bank Credit

den Haan and Sterk (2011) found an astonishing pattern between commercial bank credit and shadow bank credit; periods of contraction in bank credit coincided with periods of expansion of shadow bank credit. They further postulated that in the period post-1984 in the USA, financial assets of commercial banks were positively correlated with GDP while outside financial assets were negatively correlated with GDP. Nelson, Pinter, and Theodoridis (2015) showed that the financial assets of banks and shadow banks are oppositely correlated with monetary tightening. Loutskina and Strahan (2009) proved the fact through commercial bank data. *Thus, we can say that periods of contraction in shadow bank credit coincides with expansion of commercial bank credit.*

2.6.2 Shadow Banking Crisis and GDP

Greenwood and Scharfstein (2013) state that the growth in US GDP mirrors the growth in the financial services industry. This expansion is primarily fueled by growth in non-bank credit intermediation (shadow banking). Feve, Moura, and Pierrard (2022) showed that the collapse of shadow banking is responsible for slower recovery after the Global Financial Crisis. Le et al. (2021) used a DSGE model to show that the frequency of growth slowdown in China is mainly driven by real sector shocks caused by shadow bank shocks and less affected by the financial sector shocks. Diallo and Al-Mansour (2017) predicted that the negative externality of the insurance sector on financial stability gets amplified through shadow banking channels. *Thus, we can say that periods of contraction in shadow bank credit coincides with periods of contraction in real GDP.*

2.6.3 Shadow Banking Crisis and Leverage Cycle

In an economy, there exist two types of financial intermediaries. Commercial banks, the primary agent, provide loans to non-financial firms. They generally retain some loans on the balance sheet, and the rest sell to shadow banks. These shadow banks raise the secondary claims by forming a pool of loans they acquire in the form of Asset-Backed Securities (ABS). Banks are incentivized to also participate in the securitization process, as tradable loans in the form of securitized assets are much more profitable than the opaque and idiosyncratic loans they retain on the balance sheet. Thus, shadow banking can be thought of as a manufacturer of collateral by taking raw material loans from commercial banks and transforming Asset-Backed Securities (ABS) (Hölmstrom and Tirole (2011, Epilogue). Also, increased securitization increases the real economic output by increasing the amount of pledgeable assets; however, it does not reduce the bank's exposure to the risk. The securitization, which was thought of as a way to reduce leverage from the balance sheet, is in the way helps "leverage up" the system where intermediaries buy one another securities (Adrian and Shin, 2010). The leverage of shadow banks is high when balance sheets are large, and credit intermediation is expanding. This procyclical nature of leverage is a hallmark of shadow banking (Adrian and Shin, 2010; Adrian and Boyarchenko, 2012). It leads to inflated asset prices and decreased risk premium, which leads to busts. Since market volatility is countercyclical, this led to decreased funding to the intermediaries. Meeks, Nelson, and Alessandri (2017) showed that securitization exacerbated the amplitudes of leverage cycles of the shadow bank entities. *Thus, we can say that growth in shadow banking assets increases the leverage of the financial system.*

2.6.4 Shadow Banking Crisis and Household Credit

The procyclical nature of shadow bank leverage also affects the real asset-output relationship. Geanakoplos (2010) found a positive correlation between the housing prices (output) and AAA securities prices (asset) and leverage. The rise in asset prices leads to an increase in consumer expenditure through the wealth effect. Also, the Tobin Q Theory of Investment supports the increase in investment expenditure because of the increase in asset prices. It led to an increase in aggregate demand and the economy's real output. As the value of the asset increases, the financial institutions need more capital and collateral requirements to fund the credit. The household becomes a creditor to these institutions and supplies capital through deposits or investments into securities. However, when the negative total factor productivity (TFP) shock hits the household, it shrinks both the borrower's and lender's wealth (Ghiaie, 2020). This reduction in wealth is shown as a reduction in capital returns, housing values, wages, etc. The shrinkage in lenders' wealth results in rollover risk for the deposits of banks and short-term securities of shadow banks. It puts pressure on the financing ability of these intermediaries and pushes them into distress. Further, the falling wealth of borrowers reduces the demand for credits, tightens collateral requirements, and shrinks financial institutions' assets. On the other hand, a negative TFP also affects the liability side of the financial institution's balance sheet. The highly levered institutions cannot absorb more leverage due to the deterioration of assets, resulting in deleveraging operations and an obligation to reduce capital investments and credit supply. It results in a vicious circle of falling capital and real output. The shadow bank crisis in India was primarily evident in real estate market, where the real estate financing shadow bank adversely affected house prices. *Thus, we can say that contraction in the shadow banking activity decreases the availability of household credit and coincides with fall in the real output of the economy.*

2.6.5 Shadow Banking Crisis and Monetary Policy Transmission

The generally proposed theories of monetary transmission predict that a high-interest rate reduces deposit creation (Drechsler, Savov, and Schnabl, 2017). However, a high-interest rates increase shadow bank deposits (Xiao, 2020). Given the competition between banks and shadow banks in attracting depositors, shadow banks are more likely to pass the interest rate hikes than commercial banks quickly. It attracts yield-sensitive depositors whenever central banks raise the interest rates. In the USA, shadow bank deposits comprise more than 30% of total deposits. Thus, the rising share of shadow bank deposits makes them an important channel for monetary policy transmission. As shadow bank deposits are uninsured by federal deposit insurance and not guaranteed, they can significantly affect financial stability. Thus, the money supply expands during the monetary policy tightening through shadow banking channels. It is against the conventional wisdom that monetary tightening reduces money creation in the commercial bank sector. After the GFC, it is clear that the financial intermediaries' balance sheet, through the capital market, represents monetary policy transmission better than the federal funds rate (Adrian and Shin, 2010). This is also corroborated by the study of Serletis and Xu (2019). They hypothesize that the complementarity/ substitutability relationship between shadow banking and commercial banking is a significant factor affecting monetary policy transmission. They proved that money supply aggregate through the balance sheet of financial institutions is a better measure of monetary policy than the interest rates.

As banks could not catch up with the market interest rates, these led to the development of money market mutual funds (MMMFs) (Duca, 2016). These MMMFs are shadow banks that offer a liquid way of investing in short-term money market instruments. Most of these investment goes into Commercial Papers (CPs), thereby reducing the cost of borrowings through CPs. MMMFs reduced the cost of CPs relative to bank loans (Duca, 2016). It led to increased funding in the shadow banks, as they are significant suppliers of CPs. During expansionary monetary policy, most funds are invested in shadow banks through CPs, which offer better rates during falling interest rates. *Thus, expansionary monetary policies fuel shadow banking.* It calls for reforming MMMFs to make them more resilient to liquidity and financial shocks (McCabe et al., 2013; Rosengren, 2014).

2.7 Research on Indian Shadow Banks

Acharya and Kulkarni (2012) showed that the public sector bank with high systemic risk ex-ante and low Tier 1 capital received greater capital support from the government and hence outperformed private sector banks. Ghosh (2011) developed a bank fragility index and classified banks as high, moderate, and low stable. Mishra, Mohan, and Singh (2012) constructed Systemic Liquidity Index (SLI) for measuring systemic liquidity from the Indian perspective by taking various rates across financial markets like call, and repo for the banking sector, commercial paper, and certificate of deposit for corporates implied deposit rate of the forex market and expectation of liquidity conditions using steepness of overnight index swap curve. Thus SLI captures funding liquidity conditions across the market. Singh (2013) identified twin deficits, i.e., high prices of tangible assets and fragile financial interdependence between banks and governments, which causes systemic risk. The paper presented five mitigating factors, i.e., financial repression in banks, regular bailouts, unanticipated jumps in the inflation rate, misplaced confidence, and good growth, which have helped India to avoid financial crises. The author argues that good growth is not a reliable hedge and is more camouflage than a solution. Verma et al. (2019) the paper adopted the Tail Event driven

NETwork (TENET) approach to assess systemic risk in Indian Banks. Using TENET paper identified systemically important Indian banks and banking networks. Stiglitz, JE (2013) argued that the current monetary policy is determined mainly by the banking system (or financial markets). The liquidity trap may not be caused by a high elasticity of demand for money as in Keynesian economics; it may be due to the low responsiveness of bank lending even when the central bank provides enough liquidity. The author attributed this to GFC in the US and Europe.

Karmakar and Bandyopadhyay (2017) used market illiquidity as measured by the daily stock market price of the top 100 firms in India as per their market capitalization from July 2007 to March 2016 and compared the result with the Financial Stability Report published by RBI. The results showed the relationship between the spread and risk associated with the financial system. Prabu (2013) studied all the FMIs (Financial Market Intermediaries) qualitatively in India and gave recommendations for improving the reporting of corporate bond and debt derivatives and commodity markets. Datey and Tiwari (2014) studied the Basel III parameters like Capital Ratio Targets, RWA requirements, and Liquidity standards and compared them with Basel II norms. Bhat et al. (2016) modeled the sequence of defaults in the dynamical system using the Eisenberg-Noe model for systemic risk without empirical testing on the datasets. Gupta and Jayadev (2016) study the banks' business strategic choices (focus, diversification, and differentiation) on systemic risk using panel data for 29 quarters. Banks' systemic risk is reduced if they focus less on corporate segments.

Eichengreen and Gupta (2013) studied the deposit flight experience of Indian Banks during the GFC. The Indian depositors shifted their savings to government-owned banks, most of which went to the State Bank of India. However, factors of recapitalization of public banks cannot explain this reallocation of deposits to SBI. This heavy shift to SBI is somewhat attributed to implicit guarantees of liabilities of SBI by the government. Board and Gandhi (2014) highlight in RBI reports the danger posed by shadow banks in India. First, the growing size and interconnectedness of NBFCs raise the systemic risk. Second, as NBFCs work in different areas and their operations are complex, their danger is altogether different. Third, many incorporated and unincorporated companies doing financial activities are unregulated by RBI. Fourth, many financial entities sprung up now and then, endangering customer interests. Chakrabarty (2014) has explained the experience of RBI in implementing macroprudential policy. The paper argued that the macroprudential policy is best suited to improve the financial system's resilience to shocks. Also, in the emerging economy, the policy should be such that it does not stifle growth. The countercyclical policy like countercyclical capital buffer (CCB) as used by RBI will not be calibrated only on credit-to-GDP as suggested by BIS but will also take other reference points and indicators from time to time, as high credit growth by itself is not a matter of concern for emerging markets. Anshuman and Sharma (2020) developed Health Score to estimate the financial fragility of retail Indian shadow banks and evaluated that it could predict these firms' rollover risk.

2.8 Research Gap

- In India, there are very few studies that have analyzed the systemic risks of shadow banks. Many studies like Ghosh (2011) bank fragility index, Mishra, Mohan, and Singh (2012) systemic liquidity index, Verma et al. (2019) TENET(Tail Event-driven NETwork), etc only focuses on the commercial banks. Some major studies like Acharya, Khandwala, & Oncu(2013) identified factors of systemically important NBFCs and Anshuman and Sharma (2020) developed Health Score metric for the NBFCs during the recent shadow bank crisis. Thus, the present study aims to further add and extend the literature of systemic risk of Indian shadow banks.
- Shadow banks have unique operations and perform specialized financial services. The literatures on systemic risk of shadow banks like Pellegrini, Meoli and Urga (2017) UK Money Market Funds (MMFs); Zhu *et al.* (2019) off-balance-sheet shadow banking activity of Chinese commercial banks; Allen *et al.* (2019) entrusted loans of shadow banks; and López Avilés *et al.* (2021) Chilean mutual funds cover only a specific type of shadow institution and thus cannot be generalized. Thus, we need a measure which can measure systemic risk of shadow banks without getting affected by the type of the institution.

- Shadow banks are highly interconnected with commercial banks, insurance, pension and mutual funds in the financial network. The existing studies of Acharya et al. (2013) and Anshuman and Sharma (2020) only used shadow banks and commercial banks to construct the metric. The present study aims to extend it to include the debt mutual funds, pension funds, and insurance companies also into the analysis.
- There is need to identify a better measure of systemic risk which does not depend on the bilateral trading data between the institution. These data are confidential and mostly available to the regulators to perform stress testing in the financial network. Thus, a systemic risk measure based on publicly available information like accounting data can help researchers and policymakers to constantly monitor the systemic risk of the financial system. Studies like Lehar (2005) regulator's portfolio, Gray, Merton and Bodie (2007) contingent claim analysis (CCA), Huang, Zhou and Zhu (2009) Distress Insurance Premium (DIP) Acharya, Pedersen, et al. (2017) Systemic Expected Shortfall (SES), Adrian and Brunnermeier (2016) CoVaR, International Monetary Fund (2009) Co-Risk, etc. measure the degree of correlation among the holdings of the financial institution and their sensitivity to changes in market prices and economic conditions. However, "contagion" effect of systemic risk is better measured and simulated by the granger causal networks than SES, CoVaR, DIP, etc. (Billio et al., 2013) as first, the above measures work best when systemic losses are well represented by historical data, but due to rapid financial innovations the newly connected part may not have experienced a simultaneous loss though it has contributed to systemic risk; second, measures based on probability relies on the increase in market volatility but during the period of growth and prosperity volatility is lower than the period of distress. This means lower estimates of systemic risk and so these metrics are not suitable as Early Warning Indicator; Third, over the last decade, the correlations between different participants of the financial system tend to become much higher during and after the crises and not before. Thus, the measures based on extreme losses like SES and CoVaR will have small values during the non-crisis period; Fourth, the measure through granger causal networks measures correlation unconditionally and directly, and can detect the new linkages

between the part of the financial system that does not have simultaneous losses; Fifth, the Granger-causality is based on time series which is not the case with conditional loss measures, hence it can capture lead-lag relation which is important. Diebold and Yılmaz (2014) argued that the Granger causal networks have certain shortcomings. First, it treats the network as directional but exclusively pairwise and unweighted; Second, it tests zero vs non-zero coefficients with arbitrary significance levels; Third, it does not track the information in the magnitude of the non-zero coefficients. However, the granger causal network is useful as it does not have any underlying assumption which is present in variance decomposition and impulse response analyses. Thus, the present study aims to simulate the systemic risk of shadow bank network using the interconnectedness measures based on Granger causal network.

- The measures based on accounting often do not help in gauging systemic risk measure as accounting data is often published with lag. Also, accounting data is based on book value concept and represents the historical costs with adjustments. Thus, they are not suitable for measuring real time systemic risk in shadow bank network. Then, there are measures based on market-based information like stock return and stock volatility. In particular, Office of Financial Research (2017) reported the volatility paradox, which is the possibility that the low volatility leads investors to behave in such a way that makes the financial system more prone to crisis. The report analyzed that low volatility leads to increased leverage, reduced hedging, and risk management models. The report cited that volatility is not a good early warning signal of financial stress. The measures based on VaR or realized volatility as a key input often led investors to take more risk. Thus, present study takes risk adjusted return series to solve for the return autocorrelation and volatility clustering problem present in the financial data return series.
- Most of the recent research like Wang and Huang (2021), Xu and Corbett (2020), and Yun et al. (2019) explored the centrality features of financial network in exploring the systemic risk receiver and systemic risk transmitter nodes. The present study also tries to extend the interconnectedness-based measures with

centrality-based measures to identify the different roles of systemic nodes present in the Indian shadow bank network using closeness centrality, eigenvector centrality, PageRank centrality and Clustering coefficient.

- The shadow bank network causes financial market distress through rollover channels. Anshuman and Sharma (2020) and RBI report (2020) both talked about the significance of rollover risk of short-term debt of shadow banks in amplifying the crisis and its spillover to entire financial network. The present study determines the significance of rollover risk in amplifying the default risk, market distress and the systemic loss suffered by the institutions, in the presence of control variables.
- The shadow banking strongly correlates with real output productivity. The contraction in shadow banking activity during the crisis also spill over to the real economy with fall in credit supply and real output. The present study also supplemented the existing literature by conducting observational study to understand the effect of shadow banking crisis on the real economic variables.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

Systemic risk based related research has used a variety of empirical framework like standard measures based on VaR (Value-at-Risk) and ES (Expected Shortfall); contingent claim analysis; conditional measures like SES, CoVaR, SRISK index, etc; principal component analysis; network or graph theory to simulate and measure systemic risk of the financial system. As discussed in the Research Gap section, most of these measures work best when systemic losses are well represented by historical data. However, during rapid financial innovations in the pre-crisis period, the newly connected part may not have experienced a simultaneous loss though it has contributed to systemic risk. Also, the above measures based on probability relies on market volatility and can suffer from volatility paradox phenomena and thus not suitable for Early Warning Indicators. Also, Indian shadow bank crisis showed the importance of small institutions in amplifying the crisis. This necessitated the need to develop a measure of systemic risk for shadow banks that can take into account the different structures and operations of shadow institutions as well as their linkages with the rest of the financial system. On further analysis of the recent systemic events, one finds that the correlations between different participants of the financial system tend to become much higher during and after the crises and not before. Thus, the measures based on extreme losses like SES and CoVaR will have small values during the non-crisis period. So, we have adopted and extended the methodology of granger causal based network measures (Billio et al., 2013) to construct the early warning indicator to detect the systemic risk in the Indian shadow bank network. The granger causal network-based measures have advantage as it can measure correlation unconditionally and directly. It can also detect the new linkages between the part of the financial system that does not have simultaneous losses. Also, the Granger-causality is based on time series which is not the case with conditional loss measures, hence it can capture lead-lag relations. We also supplemented it with centrality-based measures of Wang and Huang (2021), Xu and Corbett (2020), and Yun et al. (2019) to understand the systemic risk receiver and transmitter profiles of the nodes in the shadow bank network. Further, we have also compared the performance of network-based measures with the firm level-based variables as a predictor of systemic risk. Also, during the recent systemic events, the shadow bank crisis spillover to entire financial network through rollover channels of short-term debt. The shadow banks' rollover risk has been a major issue in amplifying the crisis. The present study also used panel data methodology to examine the role of rollover risk in predicting the default risk, market distress and systemic losses of the institutions. Further, we used the observational study to asses the spillover effect of Indian shadow banking crisis on the real economic variables. To understand the detailed research methodology of the present study, the chapter is arranged in the following:

- Research Questions of the study
- Objectives of the study
- Empirical framework of the Objective 1
- Empirical framework of the Objective 2
- Empirical framework of the Objective 3
- Empirical framework of the Objective 4

3.2 Research Questions

The study proposes to answer the following Research Questions:

- How are Indian Shadow Banks interconnected to the rest of the Indian Financial System?
- Do financial linkages serve as ex-ante early warning signals to predict the buildup of systemic risk in Indian Shadow Banks?
- Does there exist any significant relationship between the systemic risk and structure of Shadow Banks, size, leverage, maturity structure of debt, stressed assets, operations of the shadow banks, etc.?
- How does shadow bank slowdown cause overall market distress?

- How does liquidity risk in shadow banks spread to other financial institutions like banks and mutual funds?
- What is the impact of the shadow bank crisis affect economic indicators like GDP growth, IIP, automobile sales, MSME, real estate, infrastructure, etc.?

3.3 Research Objectives

- To develop a model for early warning signals of systemic risk of Indian Shadow Bank
- To examine the impact of firm level relationship on the Systemic Risk of Indian Shadow Bank
- To study the impact of systemic risk of shadow banks on financial market distress.
- To assess the spillover effect of systemic risk of Shadow Banks on the real economy.

3.4 Empirical Framework for Objective 1

To develop a Model for Early Warning Signals of Systemic Risk of Indian Shadow Bank

The pairwise Granger-causality test (Billio et al.2012) is used to model the interconnectedness (a source of systemic risk) of the shadow banks.

3.4.1 Data

The study uses stock returns series of Banks and Shadow Banks and the LDMFs. The return series is adjusted for conditional heteroscedasticity and serial autocorrelations using Generalized Auto-Regressive Conditional Heteroskedasticity GARCH (1,1) model.

3.4.2 Sample

The study used S&P BSE Finance Index constituents to select Banks, HFCs & NBFCs, and AMFI report to select the LDMFs.

Table 3.1: Composition of the Sample for Objective 1

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
Shadow Bank - Housing Finance Companies (HFC)	5	99
Shadow Bank - Non-Banking Finance Company (NBFC)	21	69
Liquid Debt Mutual Funds (LDMF)	8	74

3.4.3 Time Period

To explore the out-of-sample predictive performance of the Granger-causality network-based measure for the recent shadow-bank crisis, which began in June 2018 we divided the entire period into a tranquil period, pre-crisis period, and crisis period. Tranquil Period is from Nov 2016-Nov 2017, Pre-Crisis Period from June 2017-May 2018, Crisis Period is from Aug 2018-July 2019. Thus, overall time period taken is from 2016 to 2020.

3.4.4 Granger Causality Test

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^jbe the two stationary log return time series of financial institutions assumed to have zero mean. If r_t^jcontain 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 "granger-cause."

$$r_t^i.r_{t+1}^j = a^j r_t{}^j + b^{ji} r_t^i + e_{t+1}^i \tag{1.1}$$

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-causesr_t^i if b^{ij} is different from zero. BIC (Bayesian Information Criteria) is used to determine the number of lags in the model.

3.4.5 Control for Heteroskedasticity and Return Autocorrelations

As equation (1) is a regression equation with 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 (Cont, 2007). Thus, a baseline Generalized Auto-Regressive Conditional Heteroskedasticity GARCH (1,1) model is used for our log-returns of financial institutions. Let r_t^ibe log-return series of institution i and $a_t^i = r_t^i - \mu_i$ be the innovation of institution i at time t.

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

is conditional on the system information and $\mu_i, \omega_i,\ \alpha_i\ ,\ \beta_i$ are the coefficients of the model.

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)

3.4.6 Calculating Graph-based Connectedness Measures

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

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

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

Based on the adjacency matrix, the following network-based measures of connectedness are defined:

3.4.7 Dynamic Causality Index (DCI)

The fraction of statistically significant Granger-causal connections to the total $N(N-1)$ pairs of connections between N financial institutions.

$$\mathrm{DCI} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i}^{N} j \rightarrow i \tag{4}$$

Granger causal connections can happen due to chance. Thus, a threshold K is defined using the *Monte Carlo simulation* procedure, which is above the normal sampling variation happening due to chance. Monte Carlo simulation tests the causal relationships among randomly generated series representing 52 financial institutions and notes the percentage of significant connections. The entire exercise is repeated a thousand times, and trial results are plotted. The 95^{th} percentile of distribution represents the threshold K above which we can reject the causal relationship happening due to chance. Thus, the period in which DCI exceeds the threshold K, the risk of the financial network experiencing any systemic event becomes high.

3.4.8 Calculating Graph-based Interconnectedness Measures

Considering each financial institution as a node in the adjacency matrix, #Out indicates the count of financial institutions significantly Granger-cause by institution j and #In indicates the count of financial institutions significantly Granger-cause institution j. The sum of these two measures is #In+Out. The following simple connections are defined, where S represents system:

$$\begin{aligned}
&\#\mathrm{Out}: (j \rightarrow S)|DCI \geq K = \frac{1}{N-1} \sum_{i \neq j}^{N} (j \rightarrow i)|DCI \geq K, \\
&\#\mathrm{In}: (S \rightarrow j)|DCI \geq K = \frac{1}{N-1} \sum_{i \neq j}^{N} (i \rightarrow j)|DCI \geq K, \\
&\#\ \mathrm{In} + \mathrm{Out}: (j \leftrightarrow S)|DCI \geq K = (\#In + \#Out)/2
\end{aligned} \tag{5}$$

3.4.9 Sector Conditional Connections

It is the same as the number of connections except that it is conditioned on different types of financial institutions. Given M(in the study, it is three: Banks, Shadow Banks & LDMFs) be types of financial institutions indexed as $\alpha, \beta = 1, .., M$. Let O be defined as number of financial institutions coming from different sectors except the one under consideration.

#Out-to-Other :

$\big((j|\alpha) \rightarrow \sum_{\beta\neq\alpha}(S|\beta)\big)|DCI \geq K = \frac{1}{O}\sum_{\beta\neq\alpha}\sum_{i\neq j}((j|\alpha) \rightarrow (i\,|\beta))|DCI \geq K$

#In-from-Other :

$$\Big((S|\beta) \rightarrow \sum_{\beta\neq\alpha}(j|\alpha)\Big)\,|DCI \geq K = \frac{1}{O}\sum_{\beta\neq\alpha}\sum_{i\neq j}((i|\beta) \rightarrow (\,j|\alpha))|DCI \geq K \qquad (6)$$

#In+Out-Other :

$\big((j|\alpha) \leftrightarrow \sum_{\beta\neq\alpha}(S|\beta)\big)|DCI \geq K$=($\#Out - to - Other\ +\ \#In - from - Other)/2,$

#Out-to-Other is the count of other types of financial institutions significantly Granger-caused by institution j, #In-from-Other is the count of other types of financial institutions significantly Granger-caused institution j and #In + Out is the sum of the two.

3.4.10 Calculating Graph-based Centrality Measures

3.4.10.1 Closeness Centrality

Closeness Centrality of a financial institution is defined by the inverse of the average length of the shortest paths to **(Closeness-Out)** all other institutions in the network.

$$Closeness = \frac{1}{sum(distance(i,j), i\neq j)} \qquad (7)$$

If there is no directed path between two financial institutions, then the total number of financial institutions (N) is used in the above formula instead of the path length.

3.4.10.2 Eigenvector Centrality

The eigenvector centrality represents the prestige of a financial institution by giving relative scores to them based on how they are connected to the rest of the network. If an institution has high eigenvector centrality, it is connected to institutions connected to many others (and so on). Let A be adjacency matrix as defined: $[A]_{ji} = (j \rightarrow i)$

The eigenvector centrality is eigenvector v of adjacency matrix having eigenvalue 1, i.e., $Av = v$

Thus, eigenvector centrality of institution j can be written as a total of eigenvector centralities of financial institutions Granger-caused by:

$$v_j = \sum_{i=1}^{N} [A]_{ji}\, v_i \tag{8}$$

3.4.10.3 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:

$$E_{ijt} = \frac{e_{ijt}}{\sum_i e_{ijt}} \tag{9}$$

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:

$$PageRank_{it} = \frac{1-\alpha}{N} + \alpha \sum E_{ijt} PageRank_{jt} \tag{10}$$

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.

3.4.10.5 Directed Clustering Coefficient

The clustering coefficient measures the probability that the neighbors of a node are neighbors themselves. The higher the value, the easier it is to form a clique. In a binary directed network, clustering coefficients can be defined using a variety of ways (Tabak et al., 2014). The clustering coefficient can be defined for node i as the ratio between all possible triangles formed by node i and the number of all possible triangles that could be formed. Let A be adjacency matrix, d_i^{in}be in-degree, d_i^{out} be out-degree, $d_i^{tot} =$

$d_i^{in} + d_i^{out}$ be the total degree of node i, $d^{\leftrightarrow} = \sum_{j \neq i} a_{ij} a_{ji} = A_{ii}^2$. The clustering coefficient for a node i in the binary directed network is defined as the ratio between all possible triangles formed by node i and the number of all possible triangles that can be formed.

$$C_i^D(A) = \frac{(A+A^T)_{ii}^3}{2[d_i^{tot}(d_i^{tot}-1)-2d^{\leftrightarrow}]} \qquad (11)$$

3.4.11 Hypothesis

The purpose of the present study is to identify and quantify financial crisis periods and to determine the predictive power of graph-based connected measures in predicting which institutions will suffer maximum loss in out-of-sample tests. Based on these measures of connectedness and centrality based measures, 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 (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 and so on.

Thus, the following hypothesis is formed:

$H_{1,1}$: $\#Out\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,2}$: $\#In\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,3}$: $\#In + Out\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,4}$: $\#Out - to - Other\ \ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,5}$: $\#In - from - Other\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,6}$: $\#In + Out - Other\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,7}$: $Closeness\ centrality\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,8}$: $Eigenvector\ centrality\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,9}$: $PageRank\ centrality\ is\ significantly\ positively\ related\ to\ Max\%Loss$

$H_{1,10}$: $Directed\ Clustering\ Coefficient\ is\ significantly\ positively\ related\ to\ Max\%Loss$

3.4.12 Hypothesis Testing

The Kendall τ(1938) statistic detects the relationship between the rankings based on connectedness and Max%Loss.Kendall τ(1938) is a non-parametric test to measure the ordinal association between two measured quantities. Let (r_{i1},r_{j1}), … …, (r_{iN},r_{jN}) be ranking of Nfinancial institutions based on connectedness measure and Max%Loss (r_i, corresponds to ranking based on connectedness and r_j corresponds to ranking based on Max%Loss). Any pair of observations (r_{ix},r_{jx}) and (r_{iy},r_{jy}) where $x < y$, are said to be concordant if the sort order of (r_{ix},r_{iy}) and (r_{jx},r_{jy}) agrees: i.e., if either both $r_{ix} > r_{jx}$ and $r_{iy} > r_{jy}$ holds or both $r_{ix} < r_{jx}$ and $r_{iy} < r_{jy}$, otherwise, they are said to be discordant

Thus **Kendall $\boldsymbol{\tau}$ coefficient**

$$\tau = [(numberofconcordantpairs) - (numberofdiscordantpairs)]/N(N-1)/2 \qquad (12)$$

The value of $\boldsymbol{\tau}$lies between -1 & 1. The $\boldsymbol{\tau}$ is also corrected for the ties between rankings. Since it is a non-parametric test, it does not have any underlying assumptions on the distribution of dependent or independent variables. Also, data ranking helps deal with outliers that are of significant use when dealing with systemic events. Kendall $\boldsymbol{\tau}$ is even less sensitive to outliers and has superior statistical power to Pearson's coefficient.

3.5 Empirical Framework for Objective 2

The impact of firm level forces on the measure of interconnectedness of systemic risk is analyzed using variables (Moore and Zhou, 2012) Leverage, (Ibragimov et al., 2011; Laeven, Ratnovski & Tong, 2016) Size, (Acharya et al., 2010) Short-Term Funding, (Kamp et al., 2007; Gorton and Winton, 1998) Distressed Assets, (Acharya et al., 2009) Non-Interest Income.

3.5.1 Sample and Time Period

The study used S&P BSE Finance Index constituents to select Banks, HFCs & NBFCs. LDMF are omitted as firm level variable are not applicable to them. To explore the out-of-sample predictive performance of the firm level variable we have taken Pre-Crisis

Period as June 2017-May 2018 and out of sample crisis period taken is June 2018-Dec 2019.

3.5.2 Variables

(i) Leverage of the Financial Institution

Leverage ratio is used for measuring leverage to evaluate solvency of the company and capital structure. A highly levered firm can be risky during declining profit but can also amplify the shareholder returns during the beneficial times

$$Debt - to - Equity\ \ Ratio = \frac{Total\ Debt}{Total\ Equity} \tag{13}$$

(ii) Size of the Financial Institution

Size of financial institution is the natural log of the total asset on the balance sheet.

$$Size\ of\ the\ financial\ institution\ = Ln(Total\ Asset) \tag{14}$$

(iii) Short-Term Funding of the Financial Institution

Short Term Funding of the capital usually refers to the short-term debt used by the financial institution to support the capital. Short-term debt of financial institutions mainly composed of repurchase agreements (repos), uninsured deposits, short-term borrowings and federal funds received to support the liquidity.

$$Short\_Term\ Funding\ \ = \frac{Short\_Term\_Funding}{Total\ Asset} \tag{15}$$

(iv) Distressed Assets of the Financial Institution

Net Non-Performing Asset is the metric financial institutions use to measure the non-performing assets after deducting the provisions made for bad and doubtful debts from the gross non-performing asset.

$$Non - performing\ Asset\ = \frac{Net\ Non\ Performing\ Asset}{Net\ Advance} \tag{16}$$

(v) Non-Interest-Income of the Financial Institution

$$Non - Interest\ Income\ = \frac{Non\ Interest\ Income}{Working\ Funds} \tag{17}$$

Working funds are calculated as the average of total assets (excluding accumulated losses, if any) as reported to the Reserve Bank of India in Form X under Section 27 of the Banking Regulation Act, 1949, during the 12 months of the financial year.

3.5.3 Hypothesis

- $H_{2,1}: Leverage\ is\ significantly\ positively\ related\ to\ Max\%Loss$
- $H_{22}: Size\ is\ significantly\ positively\ related\ to\ Max\%Loss$

OR

- $H_{2,2}: Size\ is\ significantly\ negatively\ related\ to\ Max\%Loss$
- $H_{2,3}: Short - Term\ Funding\ is\ significantly\ positively\ related\ to\ Max\%Loss$
- $H_{2,4}: Non\ performing\ asset\ is\ significantly\ positively\ related\ to\ Max\%Loss$
- $H_{2,5}: Non - interest - income\ is\ significantly\ positively\ related\ to\ Max\%Loss$

3.5.4 Hypothesis Testing

The institutions are ranked on these firm level variables (independent variables) calculated in the pre-crisis time period in the descending order. Similarly financial institutions are ranked on the Max%Loss (dependent variable) from the crisis period. In order to test the out-of-sample prediction property of firm level variables, we performed Kendall τ rank regression.

3.6 Empirical Framework for Objective 3

To study the Impact of Systemic Risk of Shadow Banks on Financial Market Distress

Shadow Banking asset structure plays an important role in determining systemic risk and financial market distress in case of crisis. Shadow banks usually borrow short-term to fund long-term assets. It causes asset-liability mismatch, where the duration of income received from those assets exceeds the duration of payment on these short-term funds. To extend the duration of payment on these maturing short-term bonds, shadow banks replace these bonds with longer-maturity bonds by promising a higher yield to the investors. It can lead to rollover risk or refinancing risk. While rolling over, the firm is exposed to liquidity risks and interest rate risks. If the interest rate increases, it will result in higher interest rate expenditures causing higher refinancing costs. If the borrower's credit profile changes or the credit market tightens, it can cause liquidity risk, negatively affecting the primary channel that firms need to rollover their debt. Since shadow banks' assets are inherently opaque (Flannery, Kwan, and Nimalendran, 2010), it is hard to ascertain the fundamental value of shadow banks' assets. The only certain information which investors have is whether a shadow bank will be solvent or insolvent if any negative signal is received by the market. Rollover is almost certain if a good signal is realized, but not after a bad signal where investors could not even recover their opportunity cost. It forces the shadow bank into early liquidation if the maturing debt could not be rolled over (Allen, Babus, and Carletti, 2012).

The theoretical literature regarding rollover risk dates to Diamond & Dybvig (1983), who examined the interaction of short-term debt and refinance risk by showing that an absolute negative shock can increase the probability of short-term debt holders determining not to refinance debt and increases the chances of default. Diamond (1991) and Titman (1992) show that when there is a tight credit market or a weakening of a firm's fundamentals, it is difficult to rollover or refinance the maturing short-term debt. He and Xiong (2012) used the structural model with mixed debt maturities and an illiquid bond market. Firms face rollover losses by issuing new bonds to replace maturing bonds whenever debt market liquidity deteriorates. Then firm's shareholders must absorb rollover losses to avoid the default. This inherent conflict of interest between debtholders and shareholders would let shareholders choose a comparatively high firm value as a default threshold. Morris and Shin (2009) analyzed rollover risk using bank run literature through coordinated failure in short-term creditors. He and Xiong (2012) examined a dynamic model of panic runs of creditors triggered by fear of a firm's future rollover risk. Acharya et al. (2008) found a robust positive correlation between cash and credit spreads. The high credit risk firms save cash as a precautionary motive. Using instrument variables like growth options and private managerial costs of financial distress, they find that the cash holdings "exogenous" component negatively correlates with credit spreads. Carey et al. (1998) showed that bank-dependent firms are more likely to have trouble finding long-term debt financing because bank debts have shorter average maturities than publicly traded debt. Barclay and Smith (1995) find that a firm's debt maturity correlates positively with credit risk for rated firms but negatively for unrated firms.

The literature on rollover risk gained significant prominence after the Global Financial Crisis. There are many empirical studies on rollover risk which directly attributes rollover risk to financial market distress. Almeida et al. (2009) used rollover risk and firm investment to study the Global Financial Crisis of 2008. Acharya et al. (2010) show that debt capacity will diminish with high rollover frequency. Lemmon and Zender (2010) empirically examined that unrated firms suffer high borrowing costs, lower debt-servicing capacity, and lower value of collateral assets during financial crises. They have a higher propensity to be affected by rollover risk. Forte and Peña (2011) investigated refinancing risk and proved that debt refinancing leads to systematic rating downgrades and increases default risk unless minimum value growth occurs. However, the results are asymmetric. For lower firm value growth, downgrades are particular and more significant in absolute number, but higher growth rates generate upgrades. Gopalan et al. (2014) find that rollover risk becomes prominent for firms having unsatisfactory and speculative-grade ratings during declining profitability and economic recession. Chen et al. (2018) found that a more considerable drop in debt maturity led to significant increases in credit spreads for firms with high leverage and systematic risk during the Global Financial Crisis. Wang et al. (2017) empirically tested that rollover risk increases the expected default probabilities of a company. Therefore, if creditors recognize the effect of rollover risk on a borrower's creditworthiness, they would demand a higher risk premium to compensate for the increased credit risk. Valenzuela (2016) analyzed corporate bond spreads of international bonds and found that corporate bond spreads are directly affected by the illiquidity of the debt market via rollover risk. The above studies focus on the role of short-term debt in exacerbating rollover risk during tightening market liquidity. This theoretical literature and empirical findings establish that a firm's debt maturity in the short term increases the firm's default risk through rollover channels during market liquidity disruptions.

3.6.1 Hypothesis

$H_{3,1}$: $Higher\ rollover\ risk\ is\ positively\ related\ to\ higher\ market\ risk$

$H_{3,2}$: $Higher\ rollover\ risk\ is\ positively\ related\ to\ higher\ default\ risk$

$H_{3,3}$: $Higher\ exposure\ to\ rollover\ risk\ is\ positively\ related\ to\ higher\ systemic\ risk$

3.6.2 Variables

3.6.2.1 Dependent Variable

(i) Default Risk Variable

To calculate the Rollover risk for a large sample of firms, we need a structural model where default risk is linked with the firm's capital structure and microeconomic model and is flexible enough to be applicable across the market.

Merton (1974) helps to understand how the firm will service its financial obligations vis-à-vis weighing the probability of credit default. It models stock equity as a European call option on the market value of the firm's total assets, with the exercise price equal to the nominal value of the firm's total debt. The answer lies in the limited liability of equity holders, where they will choose to default in case the value of the total asset is less than the outstanding debt. The shareholders will have a positive payoff if the firm's total asset value is greater than the total outstanding debt. The shareholders will have zero value when total asset value touches the total value of outstanding debt and firm defaults. The market value of the firm's assets is the sum of its debt and equity market values. We can observe the firm's equity market value through stock price but not the firm's debt market value. Merton(1974) uses Black-Scholes(1973) Options pricing model to calculate the implied market value of a firm's asset and its implied volatility using a set of observable variables. The assumptions of Black-Scholes(1973) model are log-normal stock price distributions, no dividend payout, a frictionless fully liquid financial market with no transaction costs, no brokerage and commissions, no-arbitrage or no opportunity for making riskless profits, lending and borrowing rates are same, risk free interest rate is constant, and no restrictions on short-sales. The market value of firm's assets is assumed to follow a Geometric Brownian Motion. Thus, the following stochastic process explains the firm's assets market value V_A:

$$dV_A = \mu V_A dt + \sigma_A V_A dz \quad (18)$$

where, $dV_A$the change in asset value, μ the drift rate and σ_A the volatility of a firm's asset value, and dz standard Wiener process.

The capital structure represents the single class of equity and debt. The F represents the book value of the debt due at time T, then using the Black-Scholes formula the market value of equity V_E and the market value of assets V_A are linked by :

$$V_E = V_A N(d_1) - e^{-rT} F N(d_2) \quad (19)$$

where, r is the risk-free interest rate, $N(d_1)$ and $N(d_2)$ are the standard cumulative normal of d_1 and d_2 given as:

$$d_1 = \frac{\ln\left(\frac{V_A}{F}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \quad (20)$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \quad (21)$$

The equity volatility (σ_E) and asset volatility (σ_A) are related using Ito's lemma:

$$\sigma_E = \frac{\partial V_E}{\partial V_A} \cdot \frac{V_A}{V_E} \cdot \sigma_A \quad (22)$$

From the Black-Scholes options pricing formula, $\frac{\partial V_E}{\partial V_A} = N(d_1)$. Thus, the above expression can be rewritten as:

$$\sigma_E = N(d_1) \cdot \frac{V_A}{V_E} \cdot \sigma_A \quad (23)$$

(6) V_E ,σ_E , F, T, r are already known. The non-linear equations 1 and 2 is solved simultaneously by minimizing the sum of the squared errors to calculate V_A and σ_A :

$$e^2 = e_1^2 + e_2^2 \quad (24)$$

where

$$e_1 = V_E - V_A N(d_1) - e^{-rT} F N(d_2) \quad (25)$$

and

$$e_2 = \sigma_E - N(d_1)\,.\frac{V_A}{V_E}.\sigma_A \tag{26}$$

Distance to default (DtD) is calculated using values of V_A and σ_A :

$$DtD = \frac{V_A - F}{V_A \sigma_A} \tag{27}$$

$DtD$is continuous and represents the time-series dimension of the default risk. It uses publicly available balance sheet information and stock. Credit Ratings provide the relative probability of default over discrete time levels. Also, credit ratings provide ordinal rankings and depend on the business cycle; thus, the link between short-term probabilities of default and the ratings of firms may change with time. Also, DtD measures the probability of a firm defaulting shortly, rather than the past, which is the spirit of the rollover risk.

(ii) Measure of Stock Volatility

The stock return volatility ($StockVol$) is determined using the annualized standard deviation of daily log returns over a year. (Bennett et al., 2015; Campbell & Taksler, 2003) have used the $StockVol$ as a measure of the firm's distress. $StockVol$ is a forward-looking measure of the market risk. Financial market volatility is mainly reflected in the deviation of the expected future value of assets. The possibility, that is, volatility, represents the uncertainty of the future price of an asset. This uncertainty is usually characterized by variance or standard deviation. There are currently two main explanations in the academic world for the relationship between these two: The leverage effect and the volatility feedback hypothesis. Leverage often means that unfavorable news appears, stock price falls, leading to an increase in the leverage factor, and thus the degree of stock volatility increases. Conversely, the degree of volatility weakens; volatility feedback can be simply described as unpredictable stock volatility that will inevitably lead to higher risk in the future. Thus, we have used stock market volatility as measure of financial market distress.

(iii) Measure of Systemic Risk

For measuring systemic risk, we are using the maximum percentage loss (Max%Loss) for a financial institution, which is the Rupee amount of the maximum cumulative decline in market capitalization or fund size for each financial institution for the above periods.

3.6.2.2 Independent Variable

(i) Rollover Risk (RR)

Rollover risk is the amount of short-term debt maturing in a year scaled by the firm's total asset (Almeida et al., 2012; Gopalan et al., 2014). (Almeida et al.,2012; Gopalan et al., 2014) used the proportion of long-term debt that matures every year as a measure of rollover risk. Long-term debt payable during the year mainly captures rollover risk because the current credit profile and risk characteristics influence the short-term debt profile, causing endogeneity problems. The long-term debt matures near the time and depends on the firm's previous long-term debt maturity decisions but is less correlated with the firm's current risk characteristics or credit quality.

(RR) is used as a rollover risk variable which denotes the amount of a firm's long-term debt at the end of year $t-1$ due for maturity(repayment) in year t divided by total assets.

3.6.2.3 Control Variables

The control variables are adopted from Gopalan et al. (2014) to account for relevant firms related factors that can impact the default risk of firms in the empirical model: (1) $Size$, computed using the logarithm of total assets; (2) $Cash$, the ratio of cash holdings to total assets; (3) $Idiovol$, computed using the standard deviation of excess equity returns; (4) Tax, the ratio of tax expenditures to the book value of total assets; (5) P/B, the ratio of the market value of total equity to the book value of total equity ; (6) $Non\ Performing\ Asset$, the ratio of non-performing loan to total asset; (7) $Leverage$, the ratio of total debt to total assets; and (8) $Profitability$, the ratio of operating income to sales; (9) $IntCov$, interest coverage.

Table 3.2: List of Control Variables for Objective 3

	DtD	$StockVo$	Max% Loss	Explanation
Explanatory Variable				
RR	−	+	+	The larger the rollover risk greater the stock volatility
Control Variable				
$Cash$	+	−	−	Cash is used to pay debt obligations
P/B	+	−	−	A Higher P/B ratio means better investor return
$Idiovol$	−	+	+	Higher the financial institution's idiosyncratic volatility greater the stock volatility
$Size$	+	−	−	Larger firms are more diversified than smaller firms and thus have low operating risk.
ROA	+	−	−	A higher return on asset of the financial institutions, more will be stable capital volatility provided by the investor.
$Profitability$	+	−	−	Profitable firms are less likely to default and have lower stock volatility
$Non-Performing$ $Asset$	−	+	+	Financial Institution with high NPA will have more chances of bank run due to poor asset quality.
$Leverage$	−	+	+	Firms with high leverage have greater chances of becoming insolvent and bankrupt
$IntCov$	+	−	−	The Interest Coverage ratio measures the debt servicing capacity of the firm. The higher the ratio less likely the firm will default.
$Bank\ Credit\ (BC)$	+	−	−	The higher the bank credit provided to the financial institution lesser will be the rollover risk

3.6.3 Sample and Time Period

All listed Banks and NBFCs companies from 2016 to 2020.

3.6.4 Methodology

Panel data regression with fixed effects is performed with rollover risk as independent variable and Distance-to-Default, StockVol and Max%Loss as dependent variable and controlled for the firm-level variables. The firm fixed effect and year fixed effects are used.

3.7 Empirical Framework for Objective 4

To assess the Spillover Effect of Systemic Risk of Shadow Banks on the Real Economy

The recent financial crises have clearly highlighted the role of shadow bank institutions as an important financial intermediary providing credit intermediation and liquidity transformation services. The connection between the financial system and macroeconomic variables also runs through the liabilities of the financial institutions (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014). The ups and downs of the events around financial crisis is closely related to the rise and fall of the shadow banking sector, whose liabilities are an important source of liquidity in the financial system. The shadow banks issue safe liquid liabilities against the risky illiquid assets by using securitization process. The issuance of equity against the tranching of illiquid assets in securitization process is somewhat costless subject to collateral constraints. This led shadow banks to lever up the collateral value of their assets, during the tranquil phase. Though this expands the liquidity but also led to fragility of liquidity, a phenomenon of boom in shadow banking. Over time, it creates economic boom at the cost of economic fragility. It gradually led to rise in uncertainty where households demand crash-proof, fully-collateralized liquid securities. Financial intermediaries started the process of delivering. It led to shut down in shadow banking. The system wide liquidity start falling and discount rates start increasing. The asset prices fall amplified by collateral runs and haircuts, give rise to flight-to-quality effect in safe assets driving up their prices. It also stifles the investment and economic growth. The shadow banking slowdown further exacerbates the slower recovery process once the uncertainty subsidies.

3.7.1 Variables

To understand the effect of shadow banking activity on the real economy we have taken real economic variables like flow of incremental commercial credit, Gross NPA, Non-Food Credit to GDP ratio, sectoral wise deployment of credit, Credit deployment to Real Estate, Credit deployment to India Industrial Sector, Credit Deployment to India Automotive sector and compared with the bank.

3.7.1.1 Incremental Commercial Credit

Commercial credit is defined as the line of credit available to business to pay for a large variety of financial obligations including credit line to pay for inventory, capital expenses, working capital needs to meet day to day operational expenditures, etc. It is often extended as revolving line of credit which business can use anytime. Based on the credit profile of the company, the bank approves a maximum amount of credit, which works like a credit card. The interest charged would be on the amount drawn until it is paid back. This revolving line of credit is either secured or unsecured. Secured commercial credit is backed by a collateral. Unsecured credit is riskier for the lender as there is no collateral attached to it and generally have higher interest rates. The commercial credit can also be used to fund any new business opportunity which typically fall out of the normal business operations. The other type of commercial credit is one which business directly get through bond market or money market through their debt papers.

3.7.1.2 Gross Non-Performing Asset

A non-performing asset (NPA) refers to the classification of the loans or advances that are either considered defaulted or is in arrears. NPA is the sign of distressed assets in the financial institution. NPAs can be classified as a substandard asset, doubtful asset, or loss asset depending on the length of time overdue since the borrower has missed the repayment and the probability of default or non-repayment. RBI classifies a loan account as NPA when the interest or the installment of the principal is overdue for more than 90 days.

$$Gross\ NPA\ \% = \frac{Gross\ NPA}{Total\ Advance}\ X\ 100 \tag{28}$$

3.7.1.3 Non-Food Credit

The Gross Bank Credit of the financial institutions is composed of Food Credit and Non-Food Credit. The food credit indicates the lending made by banks to the Food Corporation of India (FCI) mainly for procuring foodgrains. It is a small share of the total bank credit. The major portion of the bank credit is the non-food credit which comprises credit to various sectors of the economy (Agriculture, Industry, and Services) and also in the form of personal loans. The data on bank credit is collected on a monthly basis by the RBI.

$$Non - Food\ Credit\ \% = \frac{Non\text{−}Food\ Credit}{GDP}\ X\ 100 \tag{29}$$

3.7.1.4 Sectoral deployment of Credit

Reserve Bank of India (RBI) classifies the non-food credit into the following heads: Agriculture, Micro and Small Industries, Medium Industries, Large Industries, Commercial Real Estate, Retail Trade, Consumer Durables and Housing Loans.

$$Growth\ of\ Sectoral\ Credit\ Y - o - Y$$

3.7.1.5 Credit Deployment to Housing Sector

Housing finance companies (HFCs) are specialized lending institutions which, along with SCBs, are the main purveyor of housing credit. The Finance (No.2) Act, 2019 (23 of 2019) amended the NHB Act, 1987 transferring regulation of HFCs to the Reserve Bank, effective August 9, 2019. HFCs are henceforth treated as a category of NBFCs for regulation purposes.

$$HFC\ Credit\ to\ SCB\ Credit\ Ratio = \frac{HFC\ Credit\ to\ Housing\ Sector}{SCB\ Credit\ to\ Housing\ Sector} \tag{30}$$

3.7.1.6 Credit Deployment to Industrial Sector

We analyzed the effect of shadow bank slowdown during the crisis on the industrial sector using Industrial Gross Value Added at Constant Prices, Index of Industrial Production, and NBFC Credit to Industrial Sector Y-o-Y growth.

3.7.1.7 Credit Deployment to Automobile Sector

We analyzed the effect of shadow bank slowdown during the crisis on the automobile sector, which is a major employment generation sector in India, using Passenger Vehicle Sales Growth Y-o-Y, Commercial Vehicle Sales Growth Y-o-Y, and NBFC Vehicle Loans Growth Y-o-Y.

3.7.2 Hypothesis

$H_{4,1}: Incremental\ Credit\ of\ commercial\ banks\ is\ negatively\ related\ to\ Incremental\ Credit\ \ of\ NBFSc$

$H_{4,2}: Gross\ NPA\%\ in\ commercial\ banks\ is\ negatively\ related\ to\ Gross\ NPA\%\ in\ NBFCs$

$H_{4,3}: Non\ Food\ Credit\ \%\ of\ shadow\ banks\ is\ positively\ related\ to\ GDP$

$H_{4,4}$: $NBFC\ Credit\ to\ Industrial\ Sector\ growth\ \ is\ \ positively\ related\ to\ Industrial\ GVA\ and\ IIP$

$H_{4,5}$: Growth in $NBFC\ Credit\ to\ Automobile\ Sector\ \ is\ \ positively\ related\ to\ Growth\ in\ Vehicle\ Sales$

3.7.3 Sample and Time Period

The real economic variables for the shadow banks and commercial banks are taken from the Database of Indian Economy and RBI reports from the period 2016-2020.

3.8 Conclusion

The research methodology chapter defines the key hypothesis to test the research objectives to measure interconnectedness and systemic risk of the Indian shadow banks. The research methodology chapter also defines the key variables that are used to test the hypothesis. The chapter provides the empirical research framework for the objectives which are tested in the following chapters. We used the graph-based interconnectedness and centrality measures and non-parametric test to test the objective 1 and objective 2 in the following chapter 4 and chapter 5 respectively. The objective 3 is tested using panel dataset in the chapter 6. The objective 4 is tested using the observational study in the chapter 7. Thus, the research methodology chapter provides a very exhaustive framework for testing the different set of research objectives undertaken to study the systemic risk of Indian shadow banks.

CHAPTER 4

INTERCONNECTEDNESS AS A MEASURE OF SYSTEMIC RISK BETWEEN SHADOW BANKS AND REST OF INDIAN FINANCIAL SYSTEM

4.1 Introduction

This section empirically investigates the results of proposed empirical framework for the objective 1, which is to develop a model for early warning signals of systemic risk of Indian Shadow Banks. Interconnectedness can increase the systemic risk of the shadow banks, by increasing the probability of shock from one financial institution to spread quickly to entire financial network. We used the Granger-causality-based network model as proposed in section 4 of research methodology. The rolling window (sub-periods) of 52 weeks is used to perform the Granger-causality tests and build the network-based parameters and centrality measures. The heteroskedasticity is filtered out by using a GARCH (1,1) model.

Table 4.1 shows the descriptive statistics of financial institutions' individual weekly logarithmic returns. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to check the institutions' stationarity of the weekly logarithmic return series. The null hypothesis that the return series has unit root is rejected for all the financial institutions. Thus, return series are stationary, which is necessary for applying pairwise Granger causality tests. If the weekly log return series distribution is negative, more observations are negative, implying more negative returns or losses to the investors. The kurtosis greater than three means that the log return distribution is more peaked and fatter tailed than the normal 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 4.1: Descriptive Statistics of Financial Institutions

Financial Institutions	Abbreviation	Mean(%)	Std_Dev(%)	Min(%)	Max(%)	Skew	Kurtosis
Axis Bank Ltd.	AXIS	0.365	4.412	-16.411	13.401	0.009	0.629
City Union Bank Ltd.	CUB	0.478	3.520	-12.213	15.359	0.347	1.651
H D F C Bank Ltd.	HDFCB	0.426	2.407	-8.280	9.468	-0.129	0.860
I C I C I Bank Ltd.	ICICI	0.351	4.265	-11.038	17.660	0.496	1.439
Indusind Bank Ltd.	INDUS	0.458	4.012	-15.727	18.271	0.196	1.981
Kotak Mahindra Bank Ltd.	KOTAK	0.488	3.150	-10.665	10.368	0.008	0.475
Federal Bank Ltd.	FED	0.238	4.467	-12.989	16.289	0.224	0.754
Yes Bank Ltd.	YES	-0.003	7.150	-35.522	26.081	-0.661	3.872
Bank of Baroda	BOB	-0.066	5.593	-18.724	25.682	0.217	1.805
Bank of India	BOI	-0.317	6.200	-18.187	29.535	0.397	1.809
Canara Bank	CAN	-0.112	6.009	-20.942	28.937	0.448	2.905
Central Bank Of India	CBI	-0.308	6.226	-25.683	31.688	0.017	4.263
Indian Bank	INDB	-0.140	6.584	-31.115	26.112	0.354	2.556
Indian Overseas Bank	IOB	-0.452	4.829	-20.514	17.025	0.195	1.646
Punjab National Bank	PNB	-0.210	6.125	-25.139	41.736	0.499	5.723
State Bank of India	SBI	0.166	4.636	-12.553	24.792	0.549	2.356
Uco Bank	UCO	-0.272	5.817	-20.355	35.930	0.683	4.018
Union Bank of India	UNION	-0.271	6.809	-20.011	33.312	0.428	1.933
Can Fin Homes Ltd.	CANFIN	0.764	5.414	-20.805	35.626	0.753	4.786
Dewan Housing Finance Corpn. Ltd.	DHFL	-0.412	8.602	-63.148	25.955	-1.953	12.017
G I C Housing Finance Ltd.	GICH	0.202	5.339	-21.432	23.418	0.266	2.242
Housing Development Finance Corpn. Ltd.	HDFC	0.317	3.183	-8.881	10.458	0.059	0.270
L I C Housing Finance Ltd.	LICH	0.164	4.236	-14.320	13.193	-0.156	0.503
Bajaj Finserv Ltd.	BAJ_FIN	0.741	4.139	-11.512	18.740	0.401	1.129
IIFL Finance Ltd.	IIFL	0.288	7.363	-80.508	28.421	-2.930	33.847
JM Financial Ltd.	JMFIN	0.486	6.455	-19.027	35.347	0.651	2.536
Religare Enterprises Ltd.	REL	-0.531	6.946	-27.329	43.542	0.570	7.063
IFCI Ltd.	IFCI	-0.281	6.406	-23.816	33.331	0.504	3.144
Power Finance Corpn. Ltd.	PFC	0.130	5.573	-21.322	24.674	0.077	1.744
REC Ltd.	REC	0.148	5.236	-19.356	18.939	-0.061	1.048
Tourism Finance Corpn. of India Ltd.	TFCI	0.276	6.103	-24.270	30.319	0.502	5.131
Bajaj Finance Ltd.	BAJ_FIN	1.020	4.379	-14.616	16.014	-0.003	1.106

Financial Institutions	Abbreviation	Mean(%)	Std_Dev(%)	Min(%)	Max(%)	Skew	Kurtosis
Bajaj Holdings & Invst. Ltd.	BAJ_HL	0.389	3.199	-13.625	13.634	-0.065	2.770
Cholamandalam Investment & Finance Co. Ltd.	CHOLA	0.621	4.505	-17.827	21.523	0.587	2.400
Edelweiss Financial Services Ltd.	EDEL	0.365	6.832	-29.431	34.087	0.294	2.839
L & T Finance Holdings Ltd.	L&TF	0.243	5.152	-15.526	26.440	0.658	2.704
Magma Fincorp Ltd.	MAG	0.017	6.160	-24.440	25.988	0.300	2.246
Mahindra & Mahindra Financial Services Ltd.	M&MF	0.242	5.226	-20.114	21.596	0.041	2.395
Manappuram Finance Ltd.	MANA	0.322	7.232	-37.310	29.963	0.026	3.551
Motilal Oswal Financial Services Ltd.	MOTOS	0.570	5.745	-14.320	26.695	0.660	1.530
Muthoot Finance Ltd.	MUTH	0.383	5.590	-23.500	24.067	0.183	2.176
Shriram City Union Finance Ltd.	SH_CIT	0.251	4.003	-16.062	17.580	0.295	2.510
Shriram Transport Finance Co. Ltd.	SH_TR	0.210	5.001	-20.505	18.769	-0.043	1.215
Tata Investment Corpn. Ltd.	TICL	0.148	3.236	-10.163	15.778	0.722	2.802
Axis Liquid Fund-Reg(G)	AXIS_M	0.149	0.027	-0.016	0.262	-0.411	5.269
Baroda Liquid Fund(G)	BAR_MF	0.149	0.031	-0.032	0.330	0.053	6.638
HDFC Liquid Fund(G)	HDFC_MF	0.147	0.030	0.000	0.262	0.093	3.452
ICICI Pru Liquid Fund(G)	ICICI_MF	0.149	0.029	0.000	0.264	0.034	3.187
L&T Liquid Fund(G)	L&T_MF	0.148	0.030	-0.078	0.257	-0.835	8.687
BNP Paribas Liquid Fund(G)	BNP_MF	0.148	0.029	0.000	0.264	0.175	3.689
Aditya Birla SL Liquid Fund(G)	ABSL_MF	0.149	0.031	-0.031	0.267	-0.032	4.732

Table 4.2 presents the summary statistics period-wise and group-wise for the weekly logarithmic returns of financial institutions using a rolling window (sub-periods) of 52 weeks. Table 3 reported year wise annualized mean, annualized standard deviation, maximum, minimum, median, kurtosis, and skewness for the groups of financial institutions. The period 2016 & 2017 were relatively more stable than 2018 & 2019. The period 2018 and 2019 encompass the crisis period where Public Sector Banks (PSBs), Housing Finance Companies (HFCs), and Non-Banking Financial Companies(NBFCs) groups suffered significant erosion of their market capitalization (negative annualized mean return and minimum mean return values) and greater volatility (large standard deviations of annualized mean returns).

Table 4.2: Summary Statistics Period-wise and Group-wise of Financial Institutions

Groups	Mean(%)	SD(%)	Min(%)	Max(%)	Median(%)	Skew.	Kurt.
				2016			
PB	16	30	-12	18	0	0.22	1.1
PSB	2	47	-25	26	0	0.18	1.52
HFC	16	35	-19	14	0	-0.38	1.5
NBFC	23	42	-20	30	0	0.18	2.09
LDMF	7	0	0	0	0	3.48	17.72
				2017			
PB	37	24	-15	16	1	0.23	4.44
PSB	18	43	-18	42	0	1.96	9.8
HFC	43	30	-9	21	0	0.8	2.07
NBFC	48	37	-27	22	1	-0.07	3.6
LDMF	6	0	0	0	0	-0.34	5.4
				2018			
PB	0	34	-36	18	0	-1.25	9.63
PSB	-43	45	-26	20	-1	-0.28	1.42
HFC	-39	47	-56	23	0	-2.86	22.25
NBFC	-24	39	-25	24	-1	0.01	2.6
LDMF	7	0	0	0	0	2.06	10.26
				2019			
PB	-1	40	-30	26	0	-0.75	7.45
PSB	-33	43	-20	36	-1	0.88	4.23
HFC	-55	58	-63	24	0	-2.61	15.76
NBFC	-18	47	-81	26	0	-1.4	24.13
LDMF	6	0	0	0	0	0.53	1.72

4.2 Analysis of Pairwise Granger-Causality Relationships

Table 4.3 presents the descriptive statistic of the number of interconnections formed by significant Granger-causality relationships among the weekly returns of private banks, public sector banks, housing finance companies, non-banking financial companies, and liquid debt mutual funds. The total number of possible connections among N institutions is N*(N-1). In this study, there are 52 institutions which results in 2652 total possible connections. For two types of institutions as i and j,

$$Number\ of\ connections\ as\ \%\ of\ total\ possible\ connections = \frac{No.of\ significant\ Granger\ Relationships\ between\ i\ and\ j}{i*j\ or\ i*(i-1)} \tag{1}$$

The number of connections increased from 4% in 2016 to 15% in 2018 & 2019, clearly showing that 2018 and 2019 are crisis periods. Also, the institutions which suffered maximum losses are highly interconnected. In the shadow bank crisis period (2018-2019), the Public Sector Banks significantly affected the Housing Finance Companies and Non-Banking Financial Companies but both the institutions do not reciprocate with the same effect to banks. As shadow banks depend on banks for financing, any restriction in rollover of debt by banks severely affects the returns of the shadow institutions. Though, both shadow institutions significantly affect the Private Banks without getting much affected by them.

Table 4.3: Analysis of Pairwise Granger-Causality Relationships

	No. of connections as % of all possible connections					No. of connections				
	To					To				
	PB (%)	PSB (%)	HFC (%)	NBFC (%)	LDMF (%)	PB	PSB	HFC	NBFC	LDMF
FROM					**2016**					
All			6					168		
PB	0	0	3	4	0	0	0	1	6	0
PSB	16	7	18	6	0	13	6	9	13	0
HFC	13	2	10	5	15	5	1	2	5	6
NBFC	5	3	10	6	1	8	6	11	24	2
LDMF	22	0	18	4	39	14	0	7	7	22
FROM					**2017**					
All			4					117		
PB	4	5	0	2	8	2	4	0	3	5
PSB	9	13	6	5	3	7	12	3	11	2
HFC	5	4	5	3	3	2	2	1	3	1
NBFC	4	3	5	3	1	6	7	5	14	1
LDMF	9	1	5	5	16	6	1	2	8	9
FROM					**2018**					
All			15					398		
PB	4	3	10	3	5	2	2	4	5	3
PSB	23	30	28	30	19	18	27	14	63	15
HFC	15	4	15	10	13	6	2	3	10	5
NBFC	15	14	14	20	11	25	29	15	84	19
LDMF	5	10	5	4	48	3	8	2	7	27
FROM					**2019**					
All			15					408		
PB	4	3	5	5	2	2	2	2	9	1
PSB	26	38	30	36	15	21	34	15	76	12
HFC	13	10	20	11	5	5	5	4	12	2
NBFC	17	15	17	23	7	28	32	18	98	12
LDMF	3	5	3	4	9	2	4	1	6	5

4.3 Analysis for Dynamic Causality Index

Dynamic Causality Index (DCI), as shown in Fig. 4.1, is compared against the threshold of 0.06 or 6%, which is the 95th percentile of the distribution obtained under the null hypothesis of no causal relationships performed using Monte-Carlo simulation as shown in Fig. 4.2. The Monte Carlo simulation is used to check whether Granger-causal relations among the financial institutions (Banks, shadow bank-NBFCs, shadow bank-HFCs, and LDMFs) are due to chance. Based on the assumption of independence among financial institutions, we randomly simulated 52-time series, which represented the financial institutions' return in our sample, and tested Granger-causality at a 5% level among all the causal relationships (a total of 2652 possible causal relationships) and noted the number of significant connections. This exercise is repeated 500 times, and the resulting distribution is shown in Fig. 4.2. The distribution is centered at 0.052 period and represents the fraction of significant connections to the total possible connections assuming the null hypothesis of no statistical relations among institutions (i.e., connections due to chance). The area between 0.044 to 0.06 captures 95% of the simulations. So, if we observe more than 0.06 or 6% of significant relationships in our actual data, it is unlikely to result from Type 1 error.

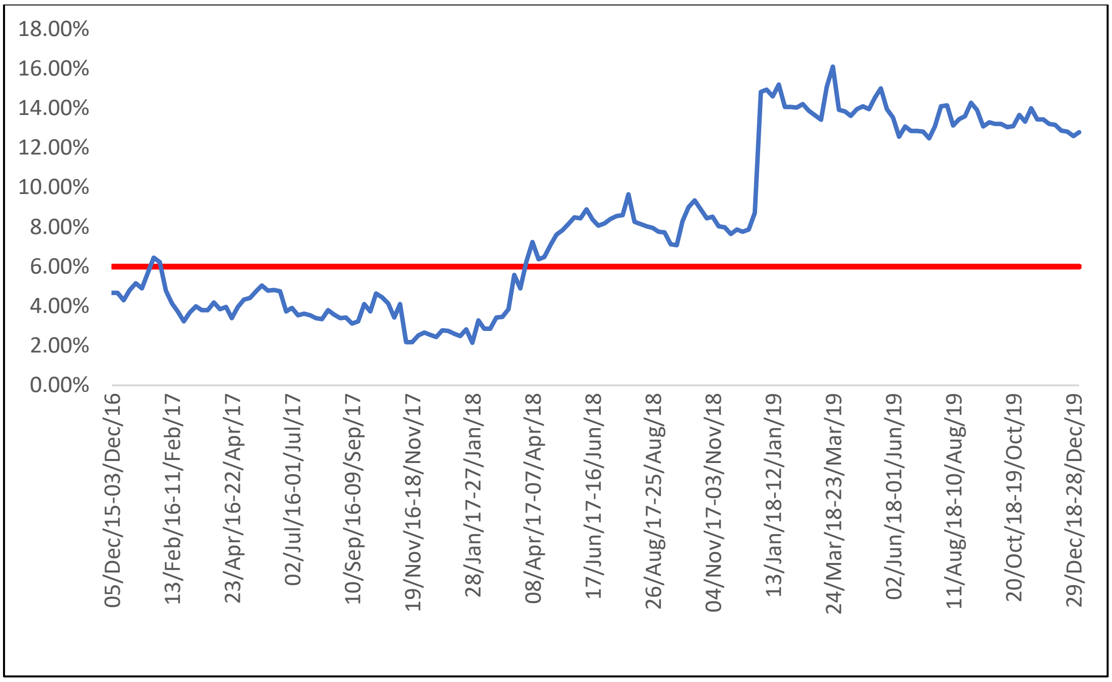


Fig. 4.1: Dynamic Causality Index

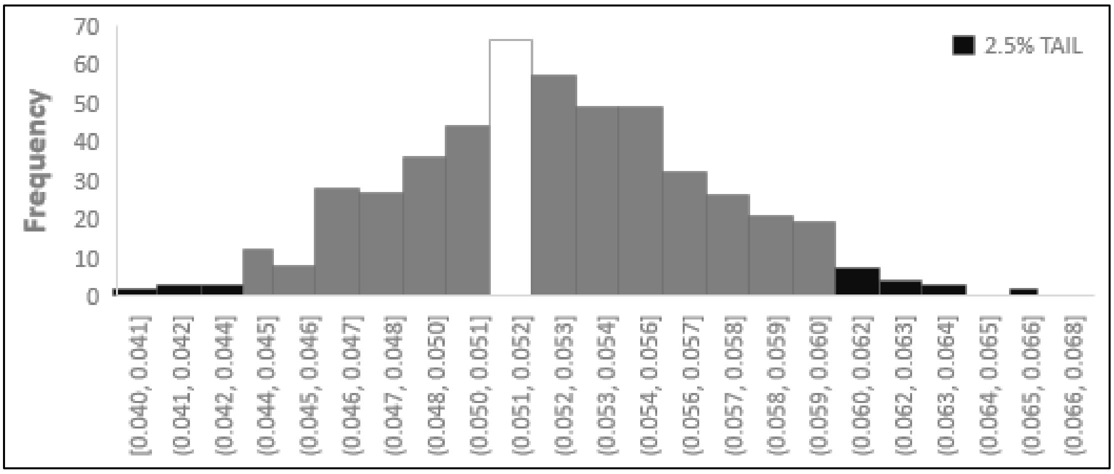
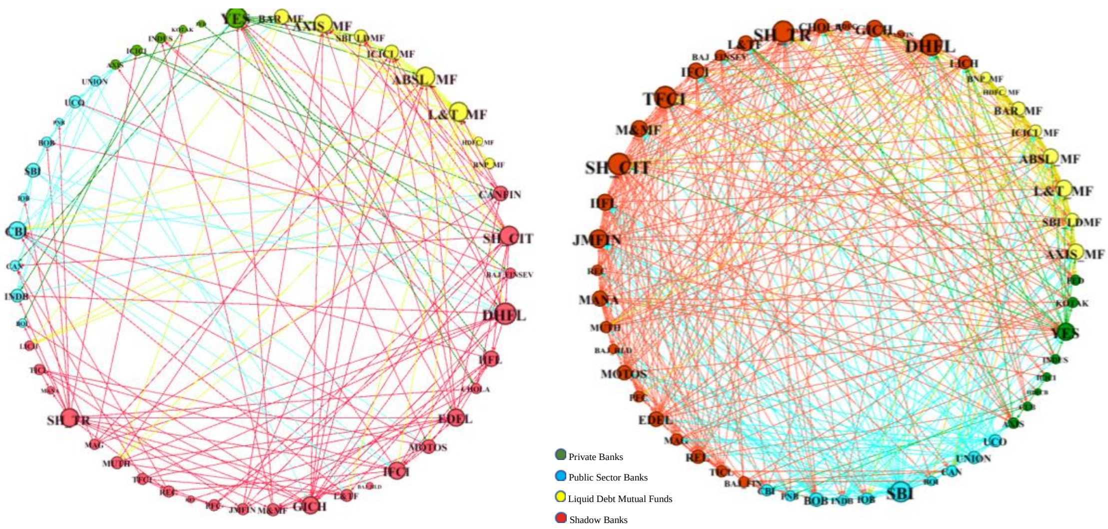


Fig. 4.2: Histogram of simulated Granger-causal relationships between financial institutions assuming independence among institutions

We can clearly distinguish between tranquil and distress periods based on the Dynamic Causality Index (DCI). From December 2016 to March 2018, DCI fluctuated from 2%-6% and only very briefly crossed the threshold 6%. Thus, this marks the stable period or tranquil period. From March 2018- January 2019, DCI rises steadily and crosses the threshold to increase to as high as 14%. Thus, the period marks the onset of the crisis period. The DCI remained elevated from January 2019- December 2019 and ranged from 12% to 16%, marking the full development of the crisis. The DCI index peaked during the shadow bank crisis in March 2019 period. Based on the DCI index, three periods are identified to make effective comparisons and find network-based measures' predictive properties. The three periods chosen represent the tranquil period from Nov 2016- Nov 2017, the pre-crisis period from June 2017-May 2018, crisis period from Aug 2018-July 2019.

The tranquil period (Fig. 4.3a) and crisis period (Fig. 4.3b) are shown using a graph where financial institutions are arranged as nodes and edges representing significant granger causal connections. The node size represents the number of connections, i.e., a larger node connects to more networks. Here, the green node is a private bank, the blue node is a Public Sector bank, the red node is Shadow Bank, and the yellow node is Liquid Debt Mutual Fund. As the complex granger causal network is a directed network, the edges are colored the same as the source node. So, if a shadow bank institution granger causes a private bank institution, the edge color will be red. The granger causal network represents both the correlation and co-movement of the return series of financial institutions. Comparing the graph between the tranquil and crisis period, the graph of the crisis period is denser, and institutions have higher interconnectedness. During the tranquil period, these interconnections represent the credit intermediation, mutual exposures, and liquidity provided by banks and liquid mutual funds to the shadow banks. Thus, financial institutions have specific correlations and co-movement, which intensified during the crisis.

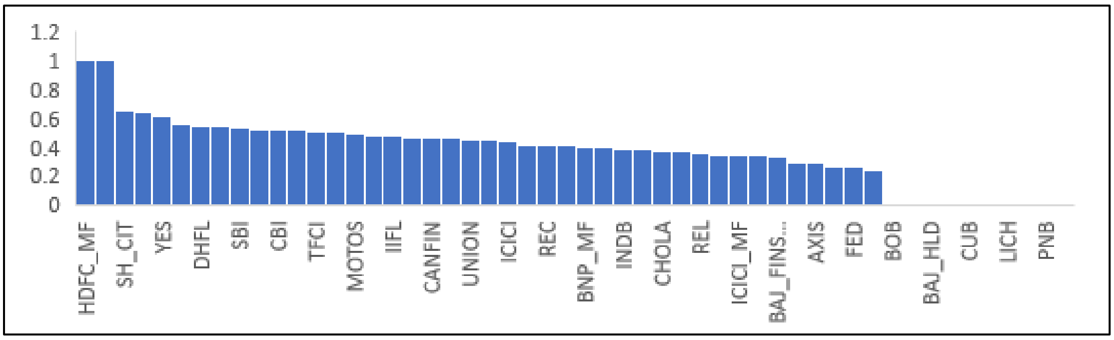


(a) (b)

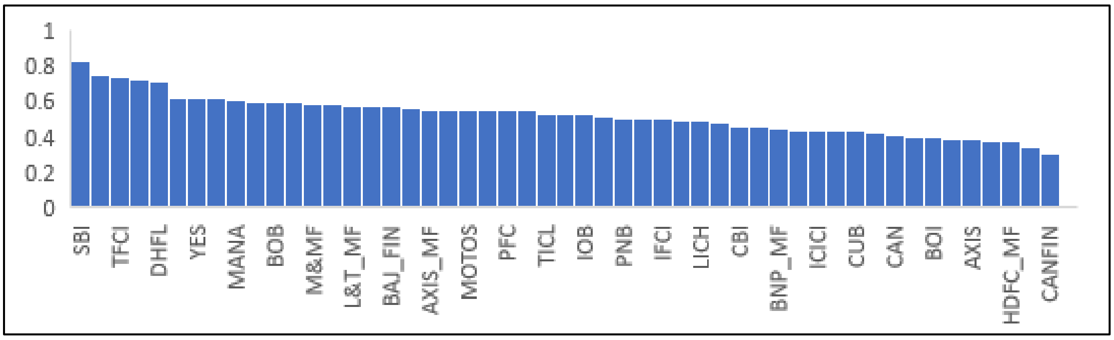
Fig. 4.3: Complex Granger-causality Shadow bank network comparison for (a) the tranquil period (b) the crisis period. The edges have color same as the source node

As the shadow bank crisis intensified, when one after the other shadow banks could not honor their short-term commitments, leading to downgrades and deterioration in funding. There is high uncertainty over the financial health of other shadow banks and their exposures to each other. Thus, suddenly most shadow banks could not access liquidity leading to defaults. As shadow banks defaulted, this created further pressure on lenders' balance sheets. To avoid the risk of losses, both banks and liquid mutual funds started deleveraging and revaluating their portfolios, leading to fire sales of distressed assets that caused more volatility and co-movements among financial institutions. Thus, a denser network during a crisis period represents a substantial probability of risk spillover as financial institutions are highly interconnected. In both tranquil and crisis periods, certain institutions like YES, SH_TR, DHFL, SBI, TFCI, etc., are primary source nodes and act as a powerful transmitter of risks. Some of these institutions suffer a higher loss of market capitalization during the shadow bank crisis. Acting on these nodes during the tranquil (stable period) and tracking their interlacing with other financial institutions can significantly minimize the risk spillover to entire financial institutions.

Fig. 4.4(a) and Fig. 4.4(b) show the institutions' closeness centrality in both the tranquil and crisis periods. The higher closeness centrality represents its closeness to the center of the network and its higher importance in risk spillover in the financial network. The crisis period has many institutions with closeness centrality greater than zero than the tranquil period. A zero-closeness centrality means an institution is one-way connected with the financial network or unconnected. Also, the closeness centrality of institutions is generally high during the crisis period. The individual closeness centrality score does not matter and cannot be compared. Ranking institutions in terms of closeness centrality help in recognizing most central nodes in the networks. Institutions like SBI, SH_CIT, DHFL, SH_TR, and YES are common in the top ten institutions in both the tranquil and crisis period. The shadow banks DHFL, SH_CIT, SH_TR, and private bank YES suffered a severe loss in market capitalization during the crisis period. The shorter transmission path of risk from these institutions led to a faster spread of contagion, triggering a series of defaults.



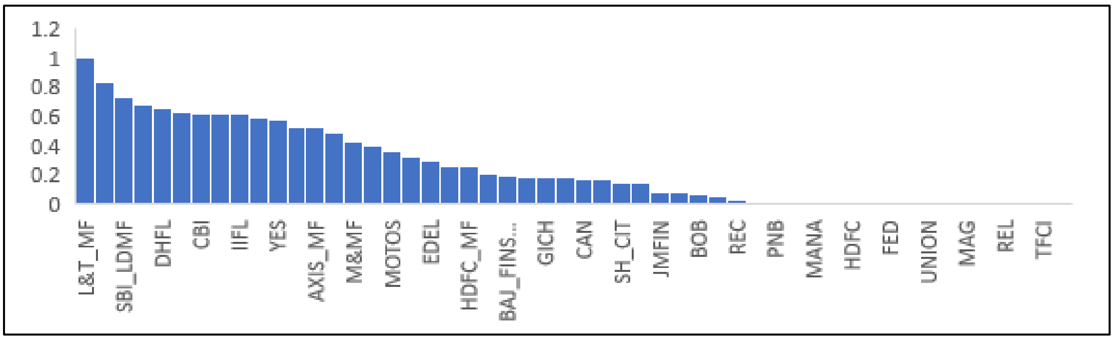
(a)



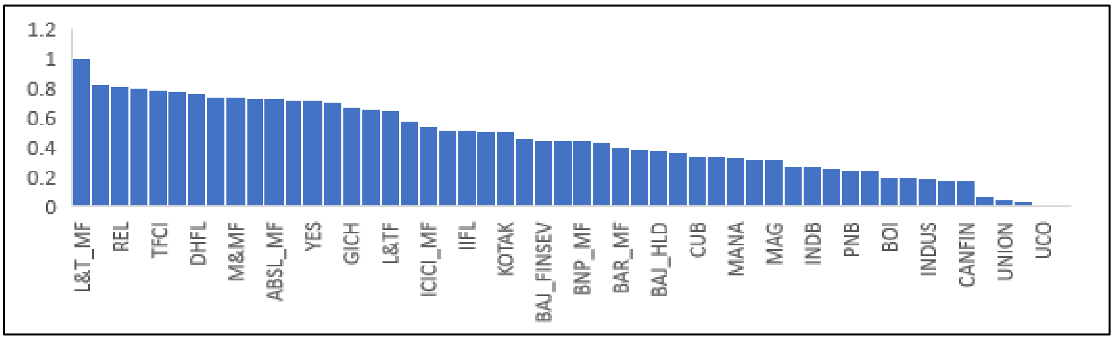
(b)

Fig. 4.4: Closeness Centrality for (a) Tranquil Period (b) Distress Period

Fig. 4.5(a) and 4.5(b) show the institutions' eigenvector centrality in the tranquil and crisis periods, respectively. The eigenvector centrality score of the institution in the financial network represents the importance of nodes as receivers of risk spillovers. If an institution has high eigenvector centrality, it may be connected to institutions with higher incoming links or have higher incoming links with other institutions. Thus, it represents the systemic vulnerability ranking of financial institutions. The crisis period has many institutions whose eigenvector centrality is greater than zero than the tranquil period. Also, eigenvector centrality scores of institutions are higher during the crisis period. There are three institutions L&T_MF, SBI_LDMF, and DHFL, common in both tranquil and crisis periods. In the crisis period, there are seven shadow banks REL, JMFIN, TFCI, SH_CIT, DHFL, M&MF, CHOLA, in the top ten financial institutions revealing their systemic vulnerability.



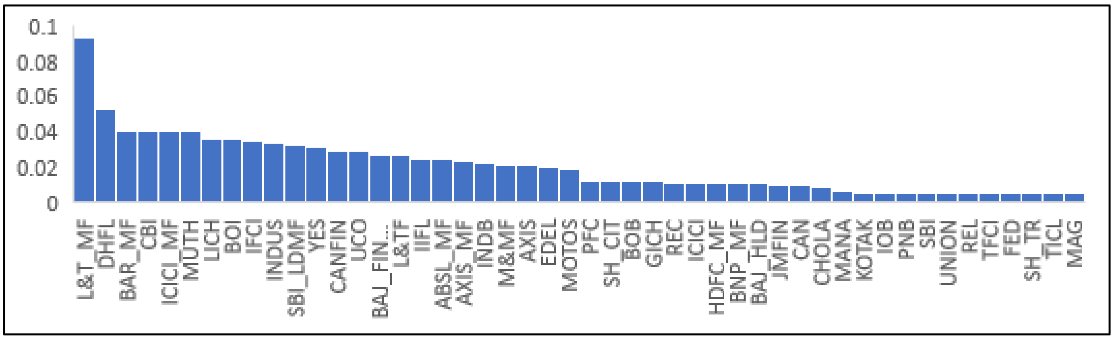
(a)



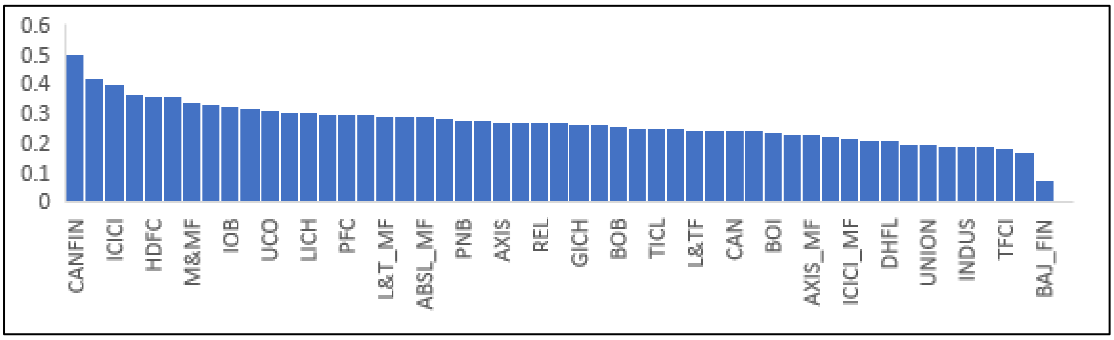
(b)

Fig. 4.5: Eigenvector Centrality Measure Comparison for (a) Tranquil Period (b) Distress Period

Fig. 4.6(a) and Fig. 4.6(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 coming 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.



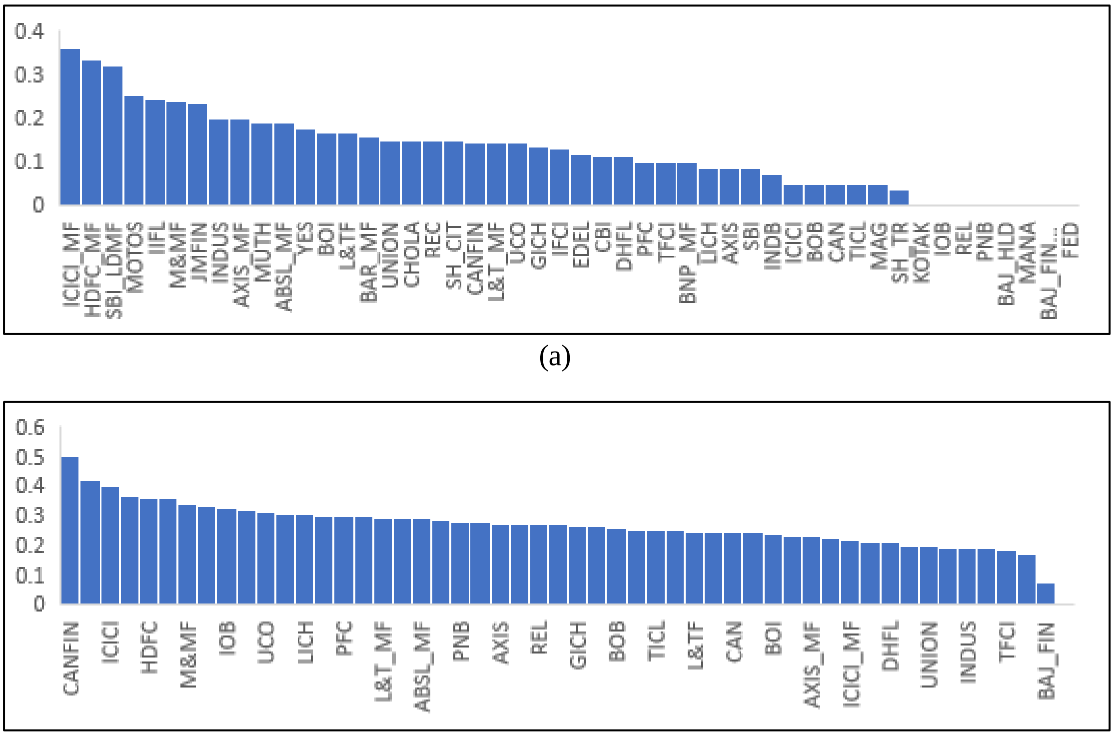
(a)



(b)

Fig. 4.6: PageRank Centrality for (a) Tranquil Period (b) Distress Period

Fig. 4.7(a) and Fig. 4.7(b) show the Clustering coefficients of the institutions in both the tranquil and crisis periods, respectively. The clustering coefficient score of an institution measure how each institution is "embedded" in the financial network. Clustering coefficient scores are generally high in the crisis period than tranquil period. Interestingly, most institutions with high clustering coefficients do not suffer a loss during the crisis period. It can be due to institutions forming cliques within the network where institutions that suffered loss are in a clique compared to other institutions. Thus, shadow bank network has small-world phenomena like social networks. Most institutions are not the neighbors of one another, but the neighbor of any given institution is likely to be neighbors.



(a)

(b)

Fig. 4.7: Clustering Coefficient for (a) Tranquil Period (b) Distress Period

4.4 Hypothesis Testing and Results

Billio et al. (2012), Lai and Hu (2021) demonstrated that Granger-causality network-based measures possess early warning signal properties to predict systemic crises. To this end, the present study explores the out-of-sample predictive performance of Granger-causality network-based measure for the recent shadow-bank crisis, which began in June 2018. The financial institutions are ranked from 1 to 52 based on these ten Granger-causal networks-based measures for the pre-crisis period June 2017-May 2018. The entire shadow bank crisis period from June 2018 to Dec 2019 is chosen as an out-of-sample period. For predicting the out-of-sample characteristic, the financial institutions are ranked from 1 to 52 based on the maximum percentage financial loss (Max%Loss) suffered by each financial institution in the shadow bank crisis period from June 2018 to Dec 2019. The financial institution with the highest measure value is ranked one, and the lowest is 52. The Max%Loss ranking is regressed on the Granger-causality network-based measures and coefficient, t-statistic, $Kendall\,\tau$, and its significance are reported.

Table 4.4 reported coefficient, t-statistic, and $Kendall\,\tau$ rank-correlation coefficient, and its significance for all network-based parameters. From the result, #In_Degree, #Out_Degree, #In+Out_Degree, Closeness_centrality, Eigenvector_centrality, & PageRank_centrality from the pre-crisis period can significantly determine the Max%Loss during the crisis period. Shadow Banks are smaller institutions as compared to banks. These shadow institutions are involved as both the transmitter and receivers of the contagion during shadow bank crises. It is conveyed by the statistically significant #In, #Out, #In+Out network-based parameters to determine institutions that suffered maximum during the crisis. Thus, the higher the interconnectedness greater is the ability to affect and get affected by the other. Herein, Closeness_centrality represents the systemic transmitter of risk. The significance of Closeness_centrality in determining Max%Loss shows that the financial institutions which are more central and closer to the center of the graph suffered most during the crisis. The ranking of institutions based on Closeness_centrality represents their systemic importance in the network. Eigenvector_centrality & PageRank_centrality represents the systemically vulnerable institutions and prime receiver of risk. The significance of Eigenvector_centrality & PageRank_centrality in determining Max%Loss show that financial institutions which are more prestigious or power-centered due to high incoming nodes suffered most during the crisis. The ranking of institutions based on Eigenvector_centrality & PageRank_centrality represents their systemic vulnerability in the network.

On the other hand, #In_from_other, #Out_to_other, #In+Out_other, and Clustering_coefficient do not significantly determine the Max%Loss variable in the crisis period. It shows that institutions that declined most during the shadow bank crisis do not significantly affect or get affected by institutions of other sectors. Also, the clustering coefficient shows a small world phenomenon where institutions in a particular clique get affected by each other.

Table 4.4: Out-of-Sample power of Granger-causal-network-based measures

	Coeff	t-statistic	Kendall τ
#In_Degree	0.5107	4.2	0.345***
#Out_Degree	0.4165	3.24	0.288***
#In+Out_Degree	0.4431	3.495	0.312***
#In_from_other	0.1545	1.106	0.122
#Out_to_Other	0.1897	1.366	0.124
#In+Out_Other	0.1807	1.299	0.13
Closeness_Centrality	0.3504	2.268	0.208**
Eigenvector_Centrality	0.4551	3.614	0.308***
Clustering Coefficient	0.2195	1.591	0.14
PageRank_Centrality	0.4226	3.297	0.288***

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

Regression Coefficient, t-statistic, Kendall τ rank-correlation coefficients and its significance for regression of Max%Loss from crisis period on Granger-causal-network-based measures from the pre-crisis period.

Table 4.5 shows the top ten institutions from Largest to Smallest based on Max%Loss from the entire crisis period June 2018 to Dec 2019 and the network-based parameters from the pre-crisis period from June 2017-May 2018. We compared the top ten institutions, common in the Max%Loss variable in the crisis period, and network-based measures of the pre-crisis period. There are five institutions of #In, #Out,#In+Out, & PageRank_centrality; four of Eigenvector_centrality, three institutions of #In_from_Other, #Out_to_Other, #In+Out_Other, and Closeness_centrality; and two institutions of Clustering coefficient.

Table 4.5: Comparison of top ten 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	**#In_Degree**	**#Out_Degree**	**#In+Out_Degree**	**#In_from_Other**	**#Out_to_Other**	**#In+Out_Other**	**Betweeness_Centrality**	**Closeness_Centrality**	**Eigenvector_Centrality**	**Clustering Coefficient**	**Page_Rank Centrality**
DHFL	IOB	SBI	SBI	YES	SBI	SBI	DHFL	KOTAK	GICH	BNP_MF	BAJ_FINSEV
IIFL	GICH	IIFL	GICH	GICH	BAR_MF	YES	SH_TR	BAJ_FIN	YES	IFCI	IOB
YES	YES	UNION	IIFL	DHFL	DHFL	GICH	YES	SBI	L&T_MF	BOI	REL
CBI	JMFIN	GICH	YES	IOB	GICH	DHFL	L&TF	IIFL	SH_CIT	FED	GICH
TFCI	EDEL	DHFL	IOB	INDB	L&T_MF	L&T_MF	IIFL	L&T_MF	TFCI	MUTH	YES
IFCI	REL	L&T_MF	DHFL	HDFC	YES	IOB	M&MF	BOB	IOB	TICL	TFCI
MAG	TFCI	BAR_MF	L&T_MF	LICH	CANFIN	INDB	L&T_MF	BAR_MF	IFCI	UNION	JMFIN
EDEL	DHFL	YES	JMFIN	L&T_MF	MUTH	HDFC	BAR_MF	SH_CIT	LICH	AXIS	DHFL
JMFIN	SH_CIT	JMFIN	UNION	SH_TR	INDB	BAR_MF	TFCI	DHFL	JMFIN	EDEL	EDEL
INDB	L&T_MF	TFCI	TFCI	EDEL	UCO	,	SH_CIT	TFCI	EDEL	L&TF	SH_CIT
MOTOS	LICH	SH_CIT	SH_CIT	SBI_LDMF	CHOLA	MUTH	IFCI	SBI_LDMF	SBI_LDMF	YES	SH_TR
L&TF	INDB	IFCI	IFCI	BOI	SH_CIT	LICH	AXIS_MF	GICH	AXIS_MF	L&T_MF	KOTAK

4.5 Conclusion

The Global Financial Crisis has established the role of shadow banking in amplifying crisis through its intricate and complex products and operations with other entities. Bilateral information of their trades is either confidential or not readily available as they are mostly unregulated. To this end, we constructed a complex shadow bank network based on granger-causality relations of financial institutions' stock return information, which is publicly available. The complex network's topological structures and centrality features are analyzed, taking the Indian shadow bank crisis as a systemic event. The network-based measures model interconnectedness and can predict the systemic risk of shadow bank networks. As crises are becoming frequent and the systemic role of smaller institutions like shadow banks in forming a channel of contagion is becoming prominent, we need an unconditional and dynamic measure to detect and predict systemic linkages and isolate them in the event of a crisis.

The complex network graph of the crisis period is denser than the tranquil period indicating that institutions are more tightly coupled during the crisis period. Also, the Dynamic Causality Index, which measures total interconnectedness, remained elevated and sufficiently high during the crisis period. The increase in causality measure shows that both correlation and co-movement of institutions' returns increased during the crisis. The DCI crosses the threshold at the onset of the crisis, demonstrating its use as a systemic risk indicator. In the recent shadow bank crisis, the shadow institutions were much closer to the center of the network, thereby decreasing the path of spreading contagion and increasing their role as a transmitter of risk. Comparing centrality measures, the financial institutions are closer to the center of the network and have higher systemic vulnerability during the crisis. These core positions give some institutions a dual role as both transmitter and receptor of contagion, making them systemically important nodes. The shadow bank complex network also depicts small-world phenomena. The network has embedded nodes that divide graphs into small cliques where some cliques are more systemically vulnerable due to their connections. The rank-based regression shows out-of-sample properties of network-based measures in predicting financial institutions' loss of market capitalization in the crisis period. Overall, the more connected, more central, and more prestigious institutions suffered significant losses in their market capitalization during the shadow bank crisis. The commonality in institution ranking on network-based measures from the pre-crisis period and market capitalization loss from the crisis period demonstrated that the Granger-causal network-based measures could serve as an early warning tool when systemic risk increases.

Also, it is worth mentioning some critical limitations of this study and the scope of future research. First, the study considers only the listed financial institutions. Many shadow banks are smaller institutions and are not listed. Secondly, it is susceptible to window size and frequency of the return, whether daily, weekly or monthly. Thirdly, the choice of significance level for Granger-causality also affects the measure of connectedness (in the study, it is 5%). Future research can explore the more extensive dataset and role of leverage, liquidity, and size along with these connectedness measures.

CHAPTER 5

EXAMINING THE IMPACT OF FIRM-LEVEL RELATIONSHIPS ON THE SYSTEMIC RISK OF INDIAN SHADOW BANKS

5.1 Introduction

This section empirically investigates the results of proposed empirical framework for the objective 2, to examine the impact of firm level relationship on the Systemic Risk of Indian Shadow Bank. In this chapter we have used the firm level variables: leverage, size, short-term funding, distressed assets and non-interest income (as described in section 5 of research methodology) and compared their prediction results with the proposed interconnectedness and centrality-based variables of chapter 4. We have also used the evolving concepts of "too-big-to-fail"; "too-connected-to-fail" and "too-central-to-fail" to understand the Indian shadow banking crisis and sources of its 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 chapter aims to predict systemic risk of the shadow banks using the firm level variables and compare it with the interconnectedness based measures prediction capability. The financial institutions are ranked based on the maximum percentage loss suffered during the crises. Using non-parametric rank-based correlation, the firm-level variable based ranking of financial institutions in the pre-crises period (explanatory variable) is correlated with the ranking of financial institutions based on maximum percentage loss suffered by them during the crises period (dependent variable). We found that small firm size, use of short-term funding and non-interest from pre-crisis can significantly identify most financial institutions that suffered loss during NBFCs crises.

In the recent financial crises, attention has shifted towards identifying "Too-big-to-fail"; "Too-connected-to-fail" and "Too-central-to-fail" to recognize the sources of systemic risk. 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-connected-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., 2013; Adrian and Brunnermeier, 2016; 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.(2016) 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 that firm-level based variable based ranking and compare it with interconnecetedness based measures to study the critical nodes of systemic importance in the financial network.

5.2 Empirical Analysis

The study used S&P BSE Finance Index constituents to select Banks, HFCs & NBFCs. LDMF are omitted as firm level variable are not applicable to them. To explore the out-of-sample predictive performance of the firm level variable we have taken Pre-Crisis Period as June 2017-May 2018 and out of sample crisis period taken is June 2018-Dec 2019. In total our sample size consists of 43 financial institutions (Table 5.1) selected from the S&P BSE Finance Index and is same as the Objective 1.

Table 5.1: Composition of the Sample

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
Shadow Bank - Housing Finance Companies (HFC)	5	99
Shadow Bank - Non-Banking Finance Company (NBFC)	21	69

Table 5.2 presents the description of data for the empirical analysis. We have used the CMIE ProwessIQ database. For the Max%Loss suffered by the financial institution, we used the difference between the market capitalization of the institution 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. For the firm level variables, we have used the precrisis time period from the June 2017 to May 2018.

Table 5.3 presents the descriptive statistic of the variables. The Max%Loss is having negative mean and has high standard deviation, which implies that some of the financial institution disproportionately got affected by the crisis. The leverage ratio is also high during the precrisis period. The high mean and standard deviation of STF (short-term funding) implies that some of the financial institution has high dependence on the short-term funding than others. Also, some institutions have higher dependence on NII (non-interest income) as source of income. The high STF, NII and NPA values implies greater systemic vulnerability of these institutions.

The financial institutions are ranked based on firm-level variable from 1 to 43 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 43 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 43.

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 $Kendall\ \tau$, and its significance in Table 5.4. The Leverage and NPA is not significant factor for the out of sample prediction. The financial institution size is having negative and significant (at 1%) coefficient for rank-based correlation, 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" that take size into account may not detect the systemic financial institutions during the crisis. The short-term funding is another factor which is significant at 5% and positively correlated with ranking based on Max%Loss, which means that over reliance on the money market instruments like commercial papers, certificate of deposits and repos, may negatively affects the credit profile of the financial institutions due to rollover risk. The non-interest income positively identifies most of the institutions which suffered loss during the crisis period, which shows that the non-interest income activities of the financial institutions increases the earnings and cash flow volatility due to its unpredictable business operations. The Chapter 4 clearly identifies that interconnectedness and centrality based measures positively identifies most of the institutions which suffered during the shadow bank crisis. This shows that the "too-connected-to-fail" and "too-central-to-fail" hypothesis are at work during the shadow bank crisis.

Table 5.2: Description of the Data

Company_Code	Company Name	Max%Loss	Leverage Ratio	Size	STF (as %)	NPA (as %)	NII (as %)
AXIS	Axis Bank Ltd.	28.16	1.74	15.09	74.68	3.64	1.71
BAJ_FIN	Bajaj Finance Ltd.	57.07	3.19	14.16	47.02	0.45	32.1
BAJ_FINSEV	Bajaj Finserv Ltd.	20.67	6.16	10.49	14.80	1.47	41
BOB	Bank of Baroda	13.29	1.41	15.09	66.61	5.49	0.97
BOI	Bank of India	40.37	1.06	15.09	48.42	8.28	0.86
CANFIN	Can Fin Homes Ltd.	7.10	8.74	12.26	24.91	0.2	3.15
CAN	Canara Bank	-5.12	1.30	15.09	69.28	7.48	1.24
CBI	Central Bank of India	-62.29	0.31	15.09	35.32	21.48	18.15
CHOLA	Cholamandalam Investment & Finance Co. Ltd.	-17.90	6.75	13.39	29.32	1.83	21.61
CUB	City Union Bank Ltd.	11.97	0.38	13.12	74.18	1.7	1.44
DHFL	Dewan Housing Finance Corpn. Ltd.	-91.91	9.93	11.67	31.00	0.96	0.13
EDEL	Edelweiss Financial Services Ltd.	-52.17	0.04	10.51	16.75	0.45	37.31
FED	Federal Bank Ltd.	12.07	0.71	14.41	78.61	1.69	0.99
GICH	GIC Housing Finance Ltd.	-36.62	9.32	11.81	2.95	1.5	2.91
HDFCB	HDFC Bank Ltd.	12.05	0.85	15.09	87.77	0.4	1.68
HDFC	Housing Development Finance Corpn. Ltd.	18.17	5.04	15.09	10.20	0.8	3.4
ICICI	ICICI Bank Ltd.	47.32	1.44	15.09	54.16	5.43	2.24
IFCI	IFCI Ltd.	-58.14	3.00	12.44	29.75	17.69	12.94
IIFL	IIFL Finance Ltd.	-83.07	4.07	12.21	13.60	1.5	25.5
INDB	Indian Bank	-43.45	1.09	14.95	29.98	3.81	15.33

Company_Code	Company Name	Max%Loss	Leverage Ratio	Size	STF (as %)	NPA (as %)	NII (as %)
IOB	Indian Overseas Bank	30.03	0.39	14.77	86.31	15.33	1.52
INDUS	Indusind Bank Ltd.	-14.86	1.77	14.94	59.32	0.51	2.5
JMFIN	J M Financial Ltd.	-51.02	0.03	10.26	53.30	0.5	38.1
KOTAK	Kotak Mahindra Bank Ltd.	15.51	0.79	15.09	47.11	0.98	37.76
L&TF	L&T Finance Holdings Ltd.	-39.50	0.44	11.64	20.70	4.2	22.3
LICH	LIC Housing Finance Ltd.	8.88	10.56	14.61	6.64	0.43	0.84
M&MF	Mahindra & Mahindra Financial Services Ltd.	-35.54	5.27	13.56	53.63	6.6	22.46
MANA	Manappuram Finance Ltd.	9.07	3.38	12.39	16.79	2.85	23.91
MOTOS	Motilal Oswal Financial Services Ltd.	-41.55	0.54	11.09	80.00	0.1	27.21
MUTH	Muthoot Finance Ltd.	58.71	3.21	13.14	140.99	3.84	18.32
MAG	Poonawalla Fincorp Ltd.	-54.06	4.02	11.82	58.81	4.6	13.78
PFC	Power Finance Corpn. Ltd.	33.19	6.79	15.09	29.51	0.94	13.97
PNB	Punjab National Bank	39.13	0.87	15.09	72.70	11.24	1.16
REC	R E C Ltd.	19.67	8.19	15.09	36.68	3.79	14.21
REL	Religare Enterprises Ltd.	-15.20	0.22	10.14	96.00	0.57	44.99
SH_CIT	Shriram City Union Finance Ltd.	-38.52	3.24	12.80	22.33	3.08	12.44
SH_TR	Shriram Transport Finance Co. Ltd.	-33.57	5.26	14.03	20.34	3.98	6.03
SBI	State Bank of India	24.56	1.51	15.09	83.46	5.73	1.29
TICL	Tata Investment Corpn. Ltd.	-5.71	0.00	11.33	78.70	0	68.69
TFCI	Tourism Finance Corpn. of India Ltd.	-59.94	1.96	10.16	13.11	3.1	3.84
UCO	UCO Bank	64.30	0.93	14.67	46.64	13.1	0.47
UNION	Union Bank of India	14.34	1.71	15.09	63.30	8.42	1.02
YES	Yes Bank Ltd.	-73.23	5.24	14.76	41.04	0.64	2.2

It presents the data for the Max%Loss, suffered by each financial institution in the NBFC crisis from June 2018 to Dec 2019; and the firm level variables from the precrisis period from the June 2017 to May 2018 for the 43 financial institutions.

Table 5.3: Descriptive Statistic of the Variables

Variable	Obs.	Mean	Std.Dev.	Min	Max
Max%Loss	43	-7.6221	40.9951	-91.9125	64.3018
Leverage Ratio	43	3.0897	3.0061	0.0004	10.5612
Size	43	13.4607	1.7403	10.135	15.0912
STF (as %)	43	48.0637	29.62	2.95	140.9941
NPA (as %)	43	4.2041	4.9728	0	21.48
NII (as %)	43	14.0388	15.8904	0.13	68.69

Table 5.4: Out-of-Sample Power of Firm Level Variable Measures

	Kendall τ
Leverage Ratio	0.0122
Size	-0.4067***
STF (as %)	0.2182**
NPA (as %)	-0.1208
NII (as %)	0.1849*

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

Kendall τ rank-correlation coefficients and its significance for regression of Max%Loss from crisis period on firm level variable measure from the pre-crisis period. Max%Loss ranking is done in the descending order with institution having highest loss is ranked 1.

5.3 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-connected-to-fail and too-central-to-fail approach proves a valuable measure in identifying critical nodes. To this end, we propose interconnectedness and centrality measures based on Granger-causal financial network to identify systemic institutions.

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.

CHAPTER 6

EFFECT OF SYSTEMIC RISK OF INDIAN SHADOW BANKS ON THE FINANCIAL MARKET DISTRESS: A PANEL BASED STUDY

6.1 Introduction

Shadow banks often rely heavily on short-term funding to finance their activities. Excessive short-term debt in shadow banks can pose significant hazards to the stability of the financial system. Shadow banks are subjected to lesser regulatory and supervisory oversights than traditional banks. It allows them to take on higher level of leverage and engage in riskier activities. The shadow banks use relatively cheaper short-term debt to fund the long-term illiquid assets. This regulatory arbitrage can incentivize excessive borrowing and risk-taking, as shadow banks may exploit regulatory gaps to maximize profits. Even banks use regulatory arbitrage in setting up a shadow bank subsidiary and moving their riskier assets. The absence of adequate oversight and prudential regulations can contribute to the buildup of excessive short-term debt and increase the vulnerability of the financial system.

The excessive reliance on short term debt can lead to liquidity risk, asset liability maturity mismatch problem, contagion risk, systemic risk and market risk. Liquidity Risk: Shadow banks often rely heavily on short-term funding to finance their activities. This reliance on short-term borrowing can make them vulnerable to liquidity risks. If lenders lose confidence in a shadow bank's ability to repay its debts, they may refuse to roll over the short-term funding, leading to a liquidity crunch and potential insolvency. Contagion Risk: The interconnectedness of the financial system means that distress in one shadow bank can quickly spread to others, creating a domino effect. Excessive short-term debt in shadow banks can amplify the speed and magnitude of contagion, as the rapid withdrawal of funding from one institution can trigger a loss of confidence in others, potentially leading to a systemic crisis. Asset-Liability Maturity Mismatch: Shadow banks often engage in maturity transformation, where they borrow short-term to fund long-term or illiquid assets. This maturity mismatch can become problematic if the short-term debt is not rolled over or if the shadow bank cannot easily sell its illiquid assets to repay the debt. In times of financial stress or market disruptions, this imbalance can quickly erode the shadow bank's solvency. Systemic Risk: Excessive short-term debt in shadow banks can contribute to systemic risk, which is the risk of widespread disruption or collapse of the financial system. Shadow banks play a vital role in providing credit and liquidity to various sectors of the economy. If a significant number of shadow banks experience funding difficulties simultaneously, it can lead to a broader credit crunch, impacting businesses and households and potentially triggering an economic downturn.

This chapter empirically investigates the results of proposed empirical framework for the objective 3, which is to examine the systemic risk of Indian shadow banks on the financial market distress. We used the panel data regression with rollover risk as independent variable; and distance-to-default (a measure of default risk), stock volatility (a measure of market risk) and Max%Loss (a measure of systemic risk) as dependent variables; along with firm level control variables and adjusted for firm and year fixed effects.

6.2 Empirical Analysis

For the empirical study, all the listed commercial banks and non-banking financial companies (NBFCs) are taken from 2016-2020. Table 6.1 depicts the distribution of sample between commercial banks and NBFCs is shown. There is no survivorship bias as no listed commercial banks and NBFCs are omitted during the period.

Table 6.1: Composition of the Sample

Time Period	Commercial Bank	NBFC
2016	32	118
2017	34	127
2018	36	132
2019	38	139
2020	39	140

All the variables are winsorized at the 1st and the 99th percentiles (i.e., values below 1st percentile are set equal to the 1st percentile value, values above 99th percentile are set equal to the 99th percentile value) to reduce the impact of outliers on the results. CMIE Prowess-IQ database is used to download all the data. The final sample size consists of 835 firm-years observations of commercial banks and NBFCs.

Table 6.2 presents the descriptive statistics for the variables: the Rollover Risk (RR), Distance to Default (DtD), and other control variables. For DtD the mean value is positive (0.136), with a high standard deviation (0.115), indicating that it is likely that most of the firms in our sample have a high chance of default. For Rollover risk (RR), the mean is 0.0045, and the standard deviation of 0.0208, indicating there is wide variation in this measure of debt maturity across the financial institutions. $StockVol,$ which is a measure of market risk with a mean of 4.828 and standard deviation of 1.298, indicating that stock volatility of firms is high and thus most of them are under distress. $Profitability$ has a positive mean of 0.064, a very high standard deviation of 0.093, and a low positive maximum of 0.340 and minimum of -0.270, indicating that some financial institutions are unprofitable during the time period. The $Size,$ which is ln (Total_Asset) is having a mean of 10.647 and a standard deviation of 2.874, indicating that there is a very high variation in firm size. The $Leverage$ ratio, which is defined as total debt to total equity, for some firms is higher than 1, indicating the insolvent firms. $Ivol$ has a mean of 0.394 and a standard deviation of 0.137, indicating the inherent volatility of firms after removing the systematic volatility from the stocks. Interest Coverage ratio is the firms' debt servicing capacity has a mean of 21.74, a standard deviation of 124.717, indicating very high variations among firms with almost half of the firm sample year observations have negative interest coverage and thus being insolvent. NPA is having a mean of 0.08 and standard deviation of 0.02. Thus, many financial institutions are having NPA of 6% to 10% as there was stricter recognition and reporting of stressed assets by RBI. The other control variables like PB, $BC(Bank\ Credit)$, $StockRet$, $StockVol, Excess\_Ret, ROA, Cash$ descriptive statistic is presented in Table 6.2.

Table 6.2: Descriptive Analysis of the Variables

Variable	Obs	Mean	Std.Dev	Min	Max
DtD	835	0.136	0.115	0.000	0.566
RR	835	0.00455	0.020862	0	0.148528
PB	835	1.250903	2.100547	0.027128	16.43934
Ivol	835	0.394262	0.137529	0.161908	0.792656
Size	835	10.64768	2.873979	5.496596	15.09124
Leverage	835	1.509866	2.52252	0	13.91456
Profitability	835	0.064	0.093	-0.270	0.340
BC	835	0.070474	0.136669	0	0.538468
StockVol	835	4.828168	1.298264	2.205996	9.194396
StockRet	835	-42.284	16.44507	-71.7354	12.23882
Excess_Ret	835	-13.772	16.71849	-43.3759	35.9702
ROA	835	1.341763	7.765943	-24.588	27.33234
NPA	835	0.08	0.02	0.001	0.13
Cash	835	0.045	0.078	0.000	0.460
IntCov	835	21.740	124.717	-164.274	1114.194

Table 6.3 reports the Pearson's correlations for all the variables used in the empirical model for 835 firm sample year observations from 2016-2022. The correlation between DtD and RR is negative as the rollover risk increases the chances of default. $Cash$, Profitability, IntCov, PB, Size, BC, StockRet, BC has a positive correlation with DtD. It means that the financial institutions with higher cash, profitability, interests coverage ratio, price to book value, bigger asset size, stock return and higher bank credit is having less chance of default. Whereas $Idiovol$, NPA and $Leverage$ is having a negative correlation with DtD. It means that the financial institutions with higher share of stressed assets, use of higher leverage in funding asset purchase, and higher idiosyncratic volatility is having a high chance of default. A high value of DtD suggests lower chances of default. However, ROA has negative and non-significant correlation with DtD, which is against the expected sign.

Table 6.3: Pearson Correlation Coefficients matrix and their Significance for the variables used in the regression model

	DtD	Stockvol	LT	Cash	Leverage	Profitability	IntCov	PB	Idiovol	NPA	Size	BC	StockRet	RoA
DtD	1													
StockVol	-0.1337*	1												
RR	-0.0885*	0.0732*	1											
Cash	0.0940*	0.0164*	-0.0975*	1										
Leverage	-0.0953*	0.1148*	0.1676*	-0.0902*	1									
Profitability	0.0738*	-0.0204*	-0.0006	0.1204*	-0.0393*	1								
IntCov	0.1440*	-0.1017*	-0.0855*	0.1863*	-0.0756*	0.2863*	1							
PB	0.1774*	-0.0522*	-0.0251*	0.1442*	0.1569*	0.2505*	0.1989*	1						
Idiovol	-0.0591*	0.5225*	-0.0386*	-0.0190*	0.0381*	-0.1500*	-0.1147*	-0.0581*	1					
NPA	-0.0540*	0.1934*	0.2533*	-0.1098*	0.1628*	0.2019*	-0.0551*	0.0086	0.0479*	1				
Size	0.0437*	0.1176*	0.2511*	0.0721*	0.1654*	0.3713*	0.1397*	0.2003*	-0.1978*	0.2809*	1			
BC	0.0411*	-0.0573*	-0.0032	0.0496*	-0.0414*	0.1777*	0.1025*	0.1509*	-0.1214*	0.0439*	0.1880*	1		
StockRet	0.1680*	-0.1066*	-0.0985*	0.3336*	-0.1521*	0.6646*	0.4058*	0.3476*	-0.1767*	0.0140*	0.2734*	0.1667*	1	
RoA	-0.0846	0.3885**	0.0535	0.1601	0.1497	0.0032	-0.153	0.4258*	-0.0457	-0.1271	-0.2071	-0.081	-0.2201	1

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

The effect of rollover (refinancing) risk on the firm's default risk, market risk and systemic risk is empirically analyzed using panel data regression in Table 6.4. The dependent variable $DtD, StockVol, Max\%Loss$ represents firm $i's$ Distance-to-default, stock volatility and max percentage loss respectively during year t. The primary explanatory variable is RR, which denotes the firm's long-term debt repayment in year t, divided by the total assets. Thus, an increase in the value of RR implies that the rollover risk has increased over the year t

$$DtD_{i,t} = \alpha + \beta RR_{i,t} + \gamma X_{i,t} + Year\ FE + Firm\ FE + \epsilon_{i,t} \quad (31)$$

$$DtD_{i,t} = \alpha + \beta StockVol_{i,t} + \gamma X_{i,t} + Year\ FE + Firm\ FE + \epsilon_{i,t} \quad (32)$$

$$DtD_{i,t} = \alpha + \beta Max\%Loss_{i,t} + \gamma X_{i,t} + Year\ FE + Firm\ FE + \epsilon_{i,t} \quad (33)$$

$where\ X\ represents\ the\ control\ variables$

Table 6.4 presents the result of multiple linear regression. In Column (1), RR is regressed with DtD without the control variables. The estimated coefficient of RR is negative and is significant at a 1% significance level, which is accordant with hypothesis $H_{3,1}$. The coefficient of RR is -0.295, A 1% increase in the standard deviation of RR can lead to 4.53% decrease in the DtD, which means increase in default risk. The economic impact is calculated by multiplying the standard deviation of RR (0.0209 as computed in Table 6.2) with the estimated coefficient of RR (which is -0.295, as computed in Table 6.4) and then dividing by the mean of DtD (0.136). The calculation is (-0.295*0.0209)/ (0.136) = -0.0453 i.e. 4.53% .The impact of rollover(refinancing) risk is still economically significant on the distance-to-default of a firm, even in the presence of all control variables and accounted for firm fixed effects and year fixed effects. The influence of the control variable on the distance-to-default is mainly consistent with the expectation. $Leverage$, PB, $Size$,$IntCov$, $Profitability$, $Past\ Vol$, $Past\ Ret$ are statistically significant in affecting the DtD.

Table 6.4: Regression Results for impact of rollover risk on the default risk, Stock Volatility (measure of market distress), Max%Loss (a measure of systemic risk)

	DtD	StockVol	Max%Loss
RR	-0.295***	0.654***	0.322
	-0.0893	0.186	0.182
Cash	-0.0149	-0.279***	-0.777***
	-0.0416	-0.108	0.105
Leverage	-0.0124***	-0.271***	0.0128**
	-0.00195	0.02	0.013
Profitability	-0.144***	0.085***	-0.094
	-0.0551	0.005	0.05
IntCov	0.000144***	-0.001	-0.001
	-0.000034	0.001	0.001
PB	0.0118***	-0.057***	0.0113**
	-0.00124	-0.003	0.0013
Idiovol	-0.0196	1.140***	1.008**
	-0.014	0.041	0.037
NPA	0.0126	0.227***	0.432**
	-0.0137	0.041	0.105
Size	0.00209*	-0.067***	-0.062***
	-0.00127	0.005	0.005
BC	0.586	0.437	0.424
	0.361	0.239	0.245
Past Return	0.299	-0.126	0.156***
	-0.268	-0.117	0.0001
Past Vol	0.126***	0.132***	0.145**
	0.00127	0.00012	0.017
ROA	-0.0083	0.167**	0.0156**
	0.013	0.207	0.108
Constant	0.133***	3.491***	2.378***
	0.0001	0.053	0.048
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	835	835	686
R-squared	0.111	0.133	0.104

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

The stock volatility is used as an alternative measure of the market risk measure. The stock return volatility ($StockVol$) is determined using the annualized standard deviation of daily log returns over a year. (Bennett et al., 2015; Campbell & Taksler, 2003) have used the $StockVol$ as a measure of the firm's market risk. $StockVol$ is a forward-looking measure of market risk, same as the standard default risk proxy DtD for the default risk. Generally, a firm having a higher log stock return volatility is more likely to have higher default risk. The panel data regression is performed by replacing DtD with $StockVol$, and the results are reported in Table 6.4. The regression coefficients of RR and other control variables will have the opposite sign when regressed with $StockVol$ as compared to regression with DtD as the dependent variable. The rollover risk of shadow banks is also significantly (at 1%) and positively related to the market distress (measured through stock volatility). A 1% increase in standard deviation of the rollover risk of the firm leads to a increase of 28.31% increase in StockVol of the institution. The economic impact is calculated by multiplying the standard deviation of RR (0.0209 as computed in Table 6.2) with the estimated coefficient of RR (which is 0.654) and then dividing by the mean of $StockVol$ (4.828%). The calculation is (0.654*0.0209)/(0.04828) = i.e. 28.31% The control variables $Cash$, PB, $Profitability, Size$, Idiovol, NPA, Past Vol, $Leverage$, are statistically significant.

The Max%Loss is used as an alternate measure of the systemic risk. The rollover risk of shadow banks is positively related to the systemic risk, but not significant. The control variables Cash, Leverage, PB, Idiovol, Size, Past Return, Past Vol, ROA are statistically significant in affecting the systemic risk of the financial institutions.

6.3 Conclusion

This study analyzes the impact of rollover (refinancing) risk on the default risk, market risk and the systemic risk for the Indian financial institutions. The study is motivated by the sudden defaults in some Indian non-banking finance companies like IL&FS and DHFL, which could not rollover their commercial papers when the market became stressed. This warrants an investigation of rollover risk for the Indian financial institutions. As per the our knowledge, this is the only study that has examined the impact of rollover(refinancing) risk on default risk, market risk and the systemic risk for the Indian firms by taking a comprehensive database of 835 firm-years observations.

The empirical results suggest strong support for the rollover risk hypothesis. The firm that experiences a significant increase in the amount of their long-term debt (divided by assets) payable within the year (i.e., rollover risk) is likely to experience a severe change in distance-to-default (i.e., default risk). When considering the effect of other control variables, a one standard deviation change in the rollover risk can *cetris paribus* decrease the distance-to-default by 4.53%. The rollover risk also impacts the market risk of the financial institutions. When considering the effect of other control variables, a one standard deviation change in the rollover risk can *cetris paribus* increase the market risk by 28.31%. However, rollover risk is not statistically significant in impacting the systemic risk of the financial institutions. It may be due to use of long term debt maturing within one year as rollover risk variable and not the short term debt due to endogeneity problem arising due to short term debt, it may not capture the total rollover risk of the financial institution.

Theoretically, Merton's model and KMV rating methodology use the firm's capital structure and value to ascertain the default risk. Generally, the short-term ratings on instruments are given based on long-term ratings and liquidity profiles. However, the ratings do not account for the rollover risk, which becomes problematic during the stressed market situation. The impact of rollover risk leading to default risk is mainly seen in the NBFCs crisis, where ratings of CPs do not reflect the default risk. Also, these findings are significant to both lenders and investors. The investors bear the entire risk during debt rollover as they experience loss in their equity by rolling over the debt under unfavorable circumstances. Banks can also benefit by taking into account the rollover risk of their client as empirical evidence suggests the rollover risk has a material impact on the firms' default risk.

The limitation of the study is it does not take into account the short-term debt as the measure of the rollover risk due to endogeneity concern. Future research can also consider the interaction of profitability, stress market conditions, industry volatility, and bank dependence on the impact of rollover (refinancing) risk on the firm's credit risk.

CHAPTER 7

EFFECT OF 2018-19 SHADOW BANKING CRISIS ON THE REAL ECONOMY OF INDIA: AN OBSERVATIONAL STUDY

7.1 Introduction

In India, shadow banks are subject to light touch regulation by the RBI as compared to the commercial banks. These institutions play an important role by providing credit to businesses and individuals which are not traditionally served by commercial banks. They also serve as specialized lenders for the MSME, auto, real estate, gold, etc. Commercial banks often use shadow banking services to increase their exposure to some risky asset bases by indirectly holding portfolios of shadow banks and profiting from regulatory arbitrage. Commercial banks are also one of major credit suppliers to shadow banks by direct lending to shadow banks. They also provide liquidity by holding their commercial papers, investing through money market funds, short-term loans, investing in pass-through asset-backed securities and through repurchase agreements.

In 2018, the shadow banking system came under scrutiny after a number of large non-banking financial companies (NBFCs) defaulted on their loans. This led to a loss of confidence in the shadow banking system, and it had a negative impact on the real economy. The real economy refers to the part of the economy that produces goods and services. This includes businesses, households, and government. The shadow banking crisis had a negative impact on the real economy in a number of ways. First, it led to a decline in credit availability. As investors became more wary of the shadow banking system, they were less willing to lend money to these institutions. This made it more difficult for businesses and individuals to get loans, which slowed down economic activity. Second, the shadow banking crisis led to a decline in asset prices. As investors became more concerned about the health of the shadow banking system, they began to sell off assets. This led to a decline in the prices of stocks, bonds, and real estate. This, in turn, made it more difficult for businesses and individuals to raise money, which further slowed down economic activity. Third, the shadow banking crisis led to a decline in consumer confidence. As investors became more concerned about the health of the shadow banking system, they also became more concerned about the health of the economy as a whole. This led to a decline in consumer confidence, which made people less likely to spend money. This, in turn, further slowed down economic activity. The shadow banking crisis had a significant impact on the real economy of India. It led to a decline in credit availability, a decline in asset prices, and a decline in consumer confidence. These factors all contributed to a slowdown in economic activity. The government and the RBI have taken steps to mitigate the impact of the shadow banking crisis on the real economy. These steps include providing liquidity to the shadow banking system and providing guarantees to investors. However, it is still too early to say how effective these measures will be. The shadow banking crisis is a reminder of the importance of financial stability. The shadow banking system is a complex and opaque system, and it is important to have strong oversight in place to prevent crises from happening. The following chapter makes an attempt to study the effect of shadow banking crisis on the real economy of India using observational study and is arranged as follows:

- Time Period of the Study
- Comparison of flow of incremental credit pre and post shadow banking crisis
- Comparison of Gross NPA pre and post shadow banking crisis
- Comparison of non-food credit to GDP pre and post shadow banking crisis
- Sectoral deployment of credit pre and post shadow banking crisis
- Credit deployment to housing sector pre and post shadow banking crisis
- Credit deployment to Industrial sector pre and post shadow banking crisis
- Credit deployment to automotive sector pre and post shadow banking crisis

7.2 Time Period of the Study

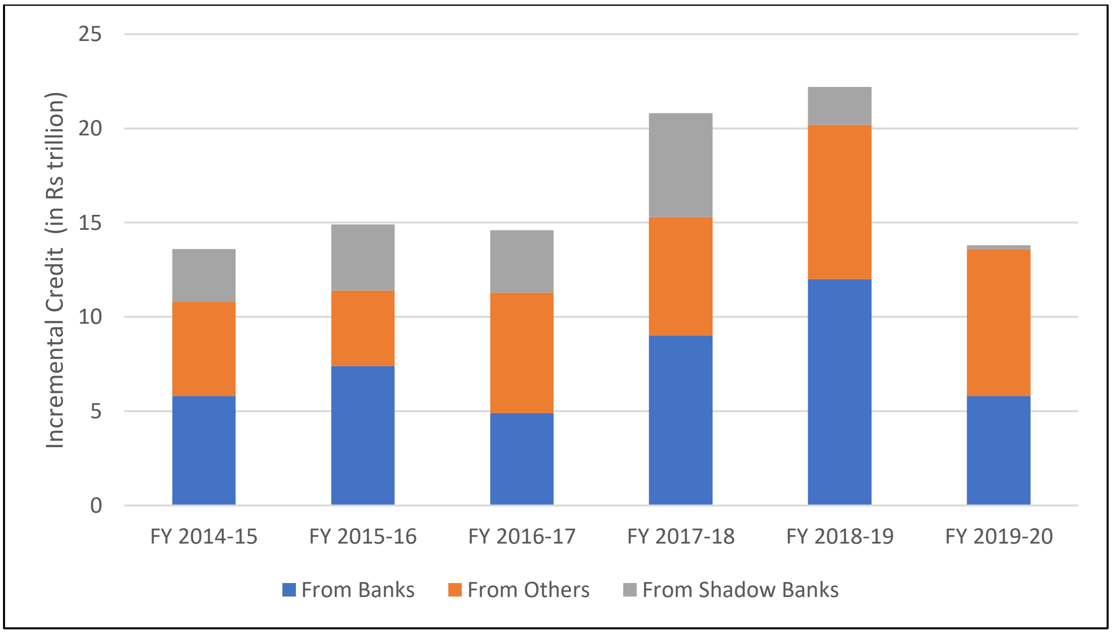
In order to study the impact of systemic risk of Shadow Banking on the real economy of India we have taken the period from FY 2014-15 to FY 2019-2020. The period after

2020 witnessed the corona outbreak and hence not suitable for the study. To analyze the impact, it is necessary to understand the economic situation of the financial institutions during the period. The FY 2014-15 period witnessed the twin deficit problem where the corporate distress spillover to the commercial banks on account of series of defaults and rising interest rates. The period saw the implementation of banking sector reforms by RBI especially regarding the detection of NPAs and classification of the stressed assets where interest or principal are not paid for 30 days or 60 days. For NBFCs, RBI regulations implemented strict disclosures and capital raising norm. NBFCs which are registered as companies also required strict disclosures under new Company Law 2013. NBFCs saw a fall in their credit growth in FY 2014 as compared to FY2012. The period from FY 2015-16 onwards saw economic reforms including financial sector reforms. Banks gradually started unwinding their positions and taking a cautious approach to lending due to strict asset quality norms and monitoring by RBI. NBFCs got a fresh opportunity to fill in this gap and their share in overall credit supply increased. The FY 2016-17 saw the demonetization event in November 2016. The demonetization event caused short term liquidity shock to the economy affecting business cash flows and especially small and medium enterprises and the informal economy. There was a decline in loan disbursal in the second half of FY17 causing short term stress. However, demonetization also led to significant growth in bank deposits, an increase in household participation in mutual funds, and acceleration in the digitization of retail payments. This led to recapitalization and improvement in liquidity in the first half of FY18. Many financial institutions and instruments fetched higher ratings and valuations. All these led to an increase in financial activities and interconnectedness among financial institutions. The period also saw the unearthing of IL&FS crises which spillover to become the entire NBFC crises in June 2018. NBFC crisis led banks to lower exposure to stressed NBFCs and MFs also started exiting the debt papers of NBFCs held by them. This led to a positive feedback loop where many institutions including NBFCs started fire sale of assets held in stressed NBFCs during the FY 2018-19 and FY 2019-20 periods. It led to spillover of the shadow banking crisis on the real sector of the Indian Economy. The real GDP of India slowed down to 4.2% in FY 2019-20 from

6.1% in FY 2018-19. In order to analyze the effect of shadow banking crisis on the real sector of India, we selected flow of incremental commercial credit, Gross NPA, Non-Food Credit to GDP ratio, sectoral wise deployment of credit, Credit deployment to Real Estate, Credit deployment to India Industrial Sector, Credit Deployment to India Automotive sector.

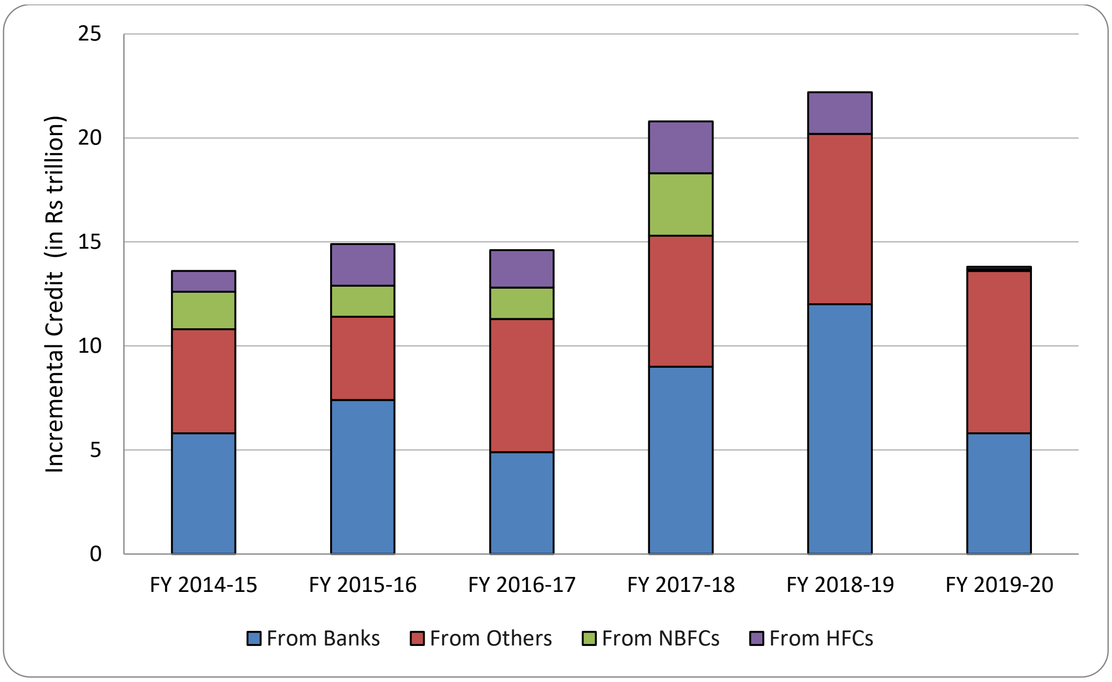
7.3 Flow of Incremental Credit

Commercial credit is defined as the line of credit available to business to pay for a large variety of financial obligations including credit line to pay for inventory, capital expenses, working capital needs to meet day to day operational expenditures, etc. It is often extended as revolving line of credit which business can use anytime. Based on the credit profile of the company, the bank approves a maximum amount of credit, which works like a credit card. The interest charged would be on the amount drawn until it is paid back. This revolving line of credit is either secured or unsecured. Secured commercial credit is backed by a collateral. Unsecured credit is riskier for the lender as there is no collateral attached to it and generally have higher interest rates. The commercial credit can also be used to fund any new business opportunity which typically fall out of the normal business operations. The other type of commercial credit is one which business directly get through bond market or money market through their debt papers. As bond market in India does not have necessary liquidity and depth, they are typically access by large corporates. Thus, popular option of availing credit is through banks and non-bank financial companies (shadow banks). As banks have access to cheap deposits, they channelize the household savings into investments in the form commercial credits. However, most NBFCs do not have access to cheap deposits and often rely on short term borrowings through money market to fund commercial credit. However, in past decade the lending by banks have witnessed slowdown as banks were saddled by asset quality review and higher non-performing asset provisioning by RBI. This led to emergence of shadow banks as alternate source of lending of commercial credit. The shadow banks (which comprised of both NBFCs and HFCs) share in the disbursement of commercial increased rapidly after FY 2014-15 reaching its peak during the FY 2017-18 and then again started falling due to Indian shadow bank crisis. The period from FY 2014-15 to FY 2017-18 saw NBFCs incremental credit to real sector growing at the rate of 13.5% while it is just 8.21% for the banks. This shows that NBFCs attained a prominent space in India financial market as the provider of credit when the banks were saddled with rising NPAs and strict asset quality norms. The comparison of flow of incremental credit pre and post crisis, reveals that shadow banks act as complementary to commercial banks. When the commercial banks were saddled with rising NPAs and higher capital requirements, offloaded a part of their priority sector lending and riskier assets to shadow entities registered as subsidiaries or associate companies on balance sheets. During the shadow bank crisis, the regulatory arbitrage between commercial banks and shadow banks started contracting, resulting in increase in direct lending to aggregate economy by banks and decrease in credit offtake to the shadow banks. Also, annual growth in incremental credit, an indicator of economic activity, shows the complementary nature of shadow banks and commercial banks.



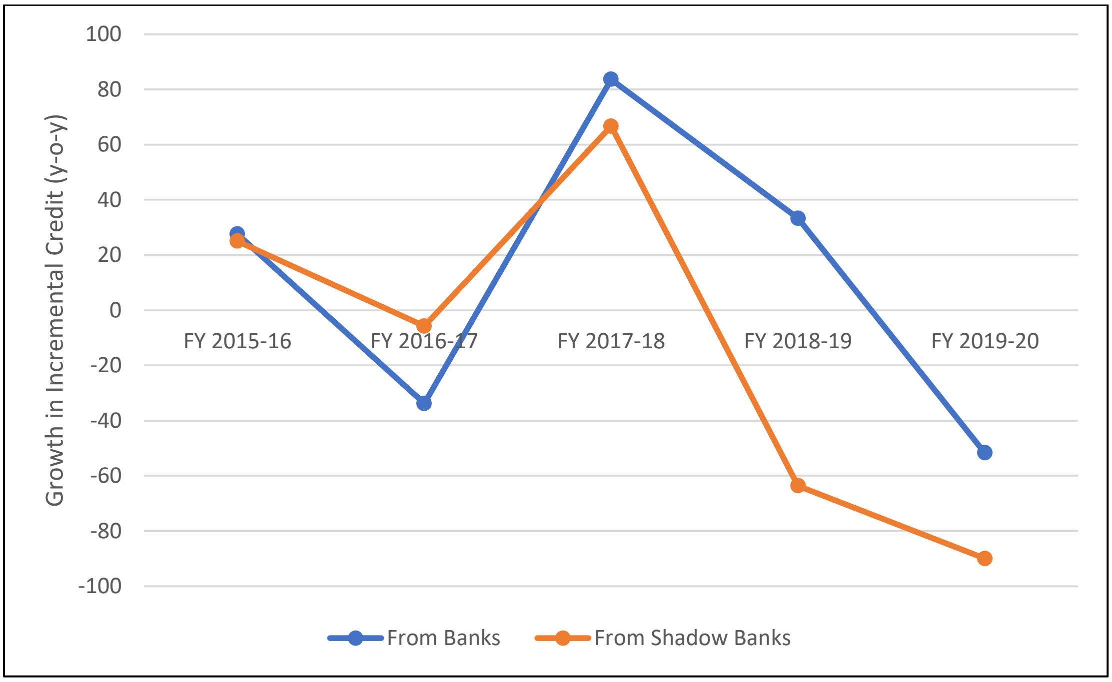
“Others” includes bond issuance to insurance companies, mutual funds, commercial paper issuance, and external commercial borrowings. Source: Reserve Bank of India. 2020. *Handbook of Statistics on the Indian Economy, 2019–20*. Mumbai.

Fig. 7.1: Flow of Incremental Credit from Banks, Shadow Banks and Others



"Others" includes bond issuance to insurance companies, mutual funds, commercial paper issuance, and external commercial borrowings. Source: Reserve Bank of India. 2020. *Handbook of Statistics on the Indian Economy, 2019–20*. Mumbai.

Fig. 7.2: Flow of Incremental Credit from Banks, NBFCs, HFCs and Others



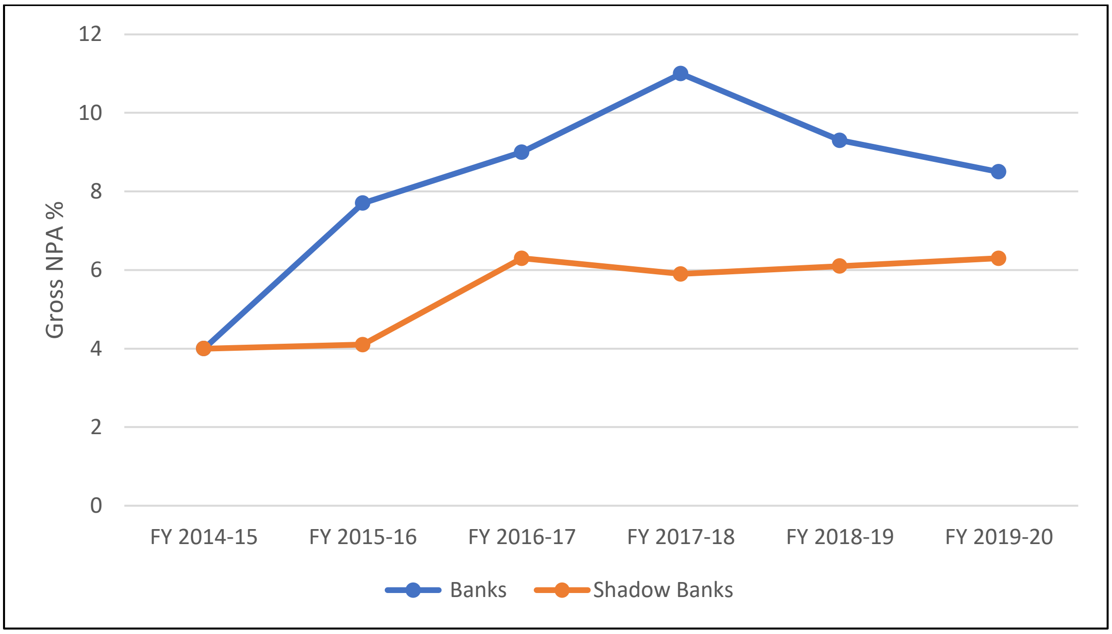
Source: Reserve Bank of India. 2020. *Handbook of Statistics on the Indian Economy, 2019–20*. Mumbai.

Fig. 7.3: Growth in Incremental Commercial Credit Flows (% per year)

7.4 Gross NPA in the Indian Financial Institutions

A non-performing asset (NPA) refers to the classification of the loans or advances that are either considered defaulted or is in arrears. NPA is the sign of distressed assets in the financial institution. NPAs can be classified as a substandard asset, doubtful asset, or loss asset depending on the length of time overdue since the borrower has missed the repayment and the probability of default or non-repayment. RBI classifies a loan account as NPA when the interest or the installment of the principal is overdue for more than 90 days. The Indian commercial banking saw a phase of acceleration and deceleration of credit disbursement from 2000 onwards. The period from 2003 to 2008 witnessed a boom in the credit disbursement of the commercial banks. This was largely due to falling interest rates and expansion of the Indian economy. It also led to rise in subpar loans and "evergreening of loans" by banks due to poor due diligence. All this changed after the global financial crisis of 2008. After global financial crisis, BASEL III got implemented for banks which led to strict classification of distressed assets and higher capital provisioning. After 2014, the "twin balance sheet problem" affecting both the corporates and banks became apparent. It led RBI to introduce new asset quality review norms which coerced banks to recognize and make capital provision for the stressed assets on their balance sheet. These asset quality review norms are applicable to only public and private banks. The gross NPA in the banking sector almost tripled from 4% in FY 2014-15 to 11.5% of the total advances in FY 2017-18 due to wider recognition of stressed assets in the banking sector (Figure 7.4). The twin balance sheet problem caused a vicious circle where banks could not lend corporates due to unprofitable balance sheets and thus both demand and supply of commercial credit declined from FY 2015-16 to FY 2017-18. At the same time bank credit disbursement to shadow banks (NBFCs and HFCs) increased sharply especially from FY 2015-16. It helped banks to increase their exposure to consumer and sensitive sectors through shadow banks. Shadow banks took this opportunity to increase their margins by aggressive lending and by reducing their cost of borrowings through money market instruments. However, they the banks. To maintain margins during this growth phase, NBFCs reduced their costs of borrowing by shortening the maturity of their liabilities.

They began borrowing short term but lending long term, which led to an asset–liability mismatch on their balance sheets. This implied that in the event of a liquidity shock when their creditors were no longer willing to roll over debt or extend new credit, they could default. Increased competition among NBFCs also resulted in some dilution of underwriting and collateral standards as the asset quality of NBFCs deteriorated steadily. Gross NPAs as a percentage of gross advances of shadow banks increased from 4% in FY2014-15 to 6.3% in FY 2019-20. Thus, we do not accept the hypothesis that Gross NPA percentage is negatively related to Gross NPA percentage in shadow banks.



Source: Reserve Bank of India. 2020. *Financial Stability Report: Issue No. 21*. Mumbai (July).

Fig. 7.4: Gross Nonperforming Assets in the Indian Banking Sector and Nonbanking Financial Companies (% of total advances)

7.5 Non-Food Credit to GDP Ratio

The Gross Bank Credit of the financial institutions is composed of Food Credit and Non-Food Credit. The food credit indicates the lending made by banks to the Food Corporation of India (FCI) mainly for procuring foodgrains. It is a small share of the total bank credit. The major portion of the bank credit is the non-food credit which comprises credit to various sectors of the economy (Agriculture, Industry, and

Services) and also in the form of personal loans. The data on bank credit is collected on a monthly basis by the RBI. Shadow Banks have been steadily gaining prominence and visibility in the Indian financial ecosystem. Credit Intensity, as measured by NBFCs' credit to Gross Domestic Product (GDP) ratio has been rising consistently, from 8.9% in FY 2014-15 to 12.2 % in FY 2018-19 reaching an all-time high, before moderating to 11.6% in 2019-20 in the wake of shadow bank crisis (Fig. 7.5.1). Whereas the credit intensity of commercial banks has been steadily falling from 51.7% in FY 2014-15 to 50.7 % in FY 2019-20 and only moderately rising to 51.3% in FY 2018-19 (Fig. 7.5.1). This increase is due to a number of factors including the growth of the Indian economy, the increasing demand for credit from non-banking financial institutions, and the regulatory changes that have made it easier for shadow banks to lend money.

As we can see in Fig. 7.5.2, that shadow bank credit growth rate strongly correlates with the Real GDP growth rates. The effect is much stronger when shadow bank credit growth rate falls it strongly led to decline in GDP growth rates.

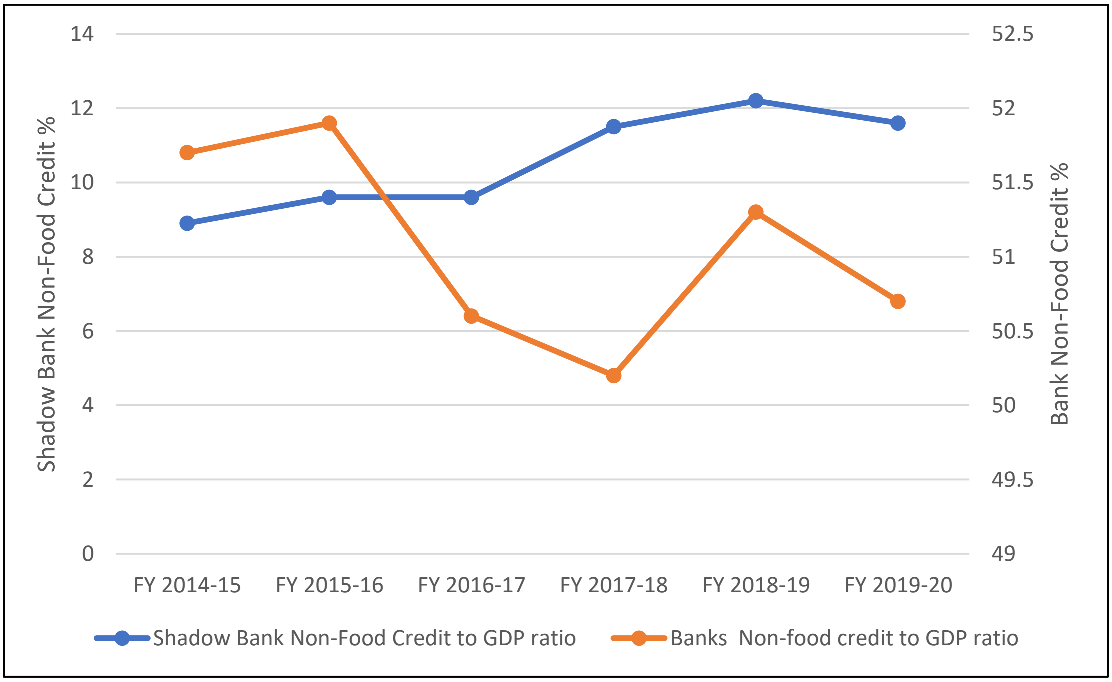


Fig. 7.5.1: Non-Food Credit of Financial Institutions (as % of GDP)

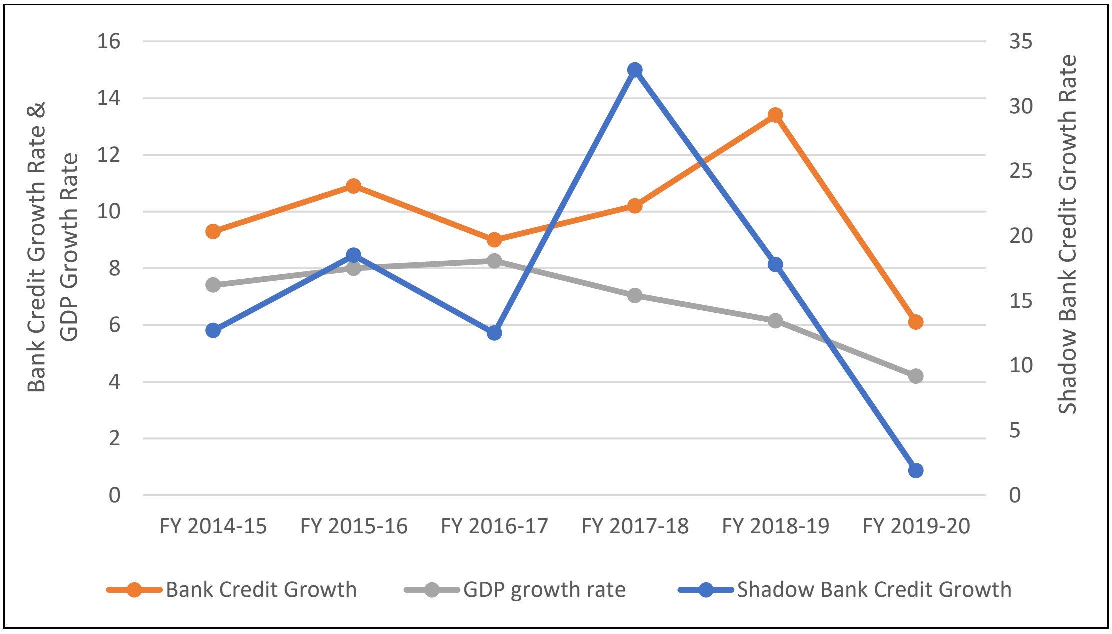


Fig. 7.5.2: Credit Growth Rate of Financial Institutions

7.6 Sectoral Deployment of Credit

Reserve Bank of India (RBI) classifies the non-food credit into the following heads into Agriculture, Micro and Small Industries, Medium Industries, Large Industries, Commercial Real Estate, Retail Trade, Consumer Durables and Housing Loans. The sectors which are highly impacted by the shadow bank crisis are Micro and Small Industries, Medium Industries, Large Industries, commercial real estates and consumer durables (Fig. 7.6). These sectors are highly dependent on shadow bank credit due to their specialized lending. The credit offtake to these sectors fell sharply during the shadow bank crisis, proving the dependence of these sectors on the shadow bank credit. Among these Micro, Small and Medium Enterprises (MSME), Agriculture and Affordable Housing are also the part of priority sector lending (PSL) of commercial banks. However, commercial banks meet their PSL targets by buying PSL certificates from the shadow banks. Shadow banks in turn perform the priority sector lending due to their regulatory advantage, operational efficiency and expertise in specialized lending. These PSL impacts the most vulnerable population and is also strategically important to India. The shadow banking impact on the agriculture and affordable housing is minimum as there are specialized All India Financial Institutions (AIFI) like NABARD and NHB which actively promotes lending in these sectors. However, priority sectors like MSME are most impacted. MSME share in the total gross value added is around 30% over the past 5 years from FY 2015 to FY 2020 and constitute significantly to India's export basket[1]. MSME are also one of the biggest employers in India. Among the MSME, automobile sector was the largest the automotive sector was the largest recipient of credit from the shadow banks in both the pre-crisis and post-crisis periods. The microfinance sector of MSME was the second largest recipient of credit in the pre-crisis period, but it fell to third place in the post-crisis period. The consumer durables sector was the third largest recipient of credit in the pre-crisis period, but it fell to fourth place in the post-crisis period. The consumer durables and microfinance lending is composed of small ticket size loans. Shadow banks mainly depend on volumes to get a significant margin. Thus, there is always a risk that in the period of tightening of liquidity these small ticket loans can default at much higher rates. After the crisis, shadow banks became more cautious in their lending, and they reduced their exposure significantly in MSME and consumer durables. The increase in credit to the housing loans sector was due to the government's focus on affordable housing. The government has introduced a number of schemes to promote affordable housing, and this has led to an increase in demand for housing loans. The overall trend is that NBFCs are shifting their focus to more stable sectors, such as retail trade and housing loans. It is a positive development, as it will help to reduce the risks in the NBFC sector.

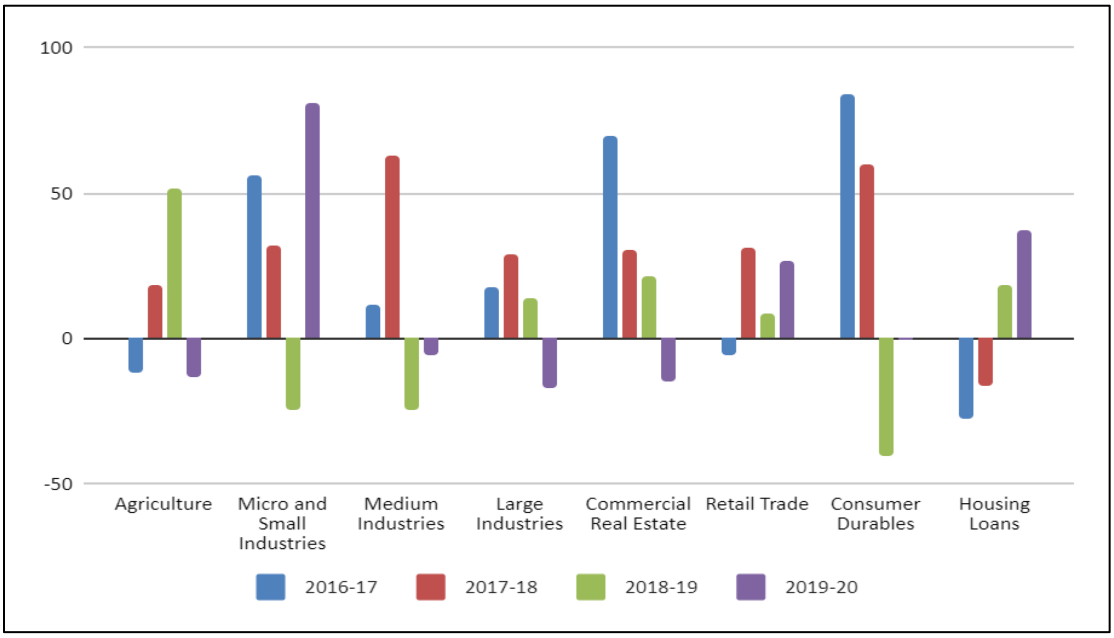


Fig. 7.6: Sectoral wise deployment of credit y-o-y during pre and post crisis

7.7 Credit Deployment to Housing Sector

Housing finance companies (HFCs) together with commercial banks are the main lender of real estates in India. HFCs are considered as a NBFC, shadow bank in India and falls under the purview of RBI. HFCs accounted for 41.7% of credit to the housing sector in the pre-crisis period, and this share declined to 37.9% in the post-crisis period (Fig. 7.7).

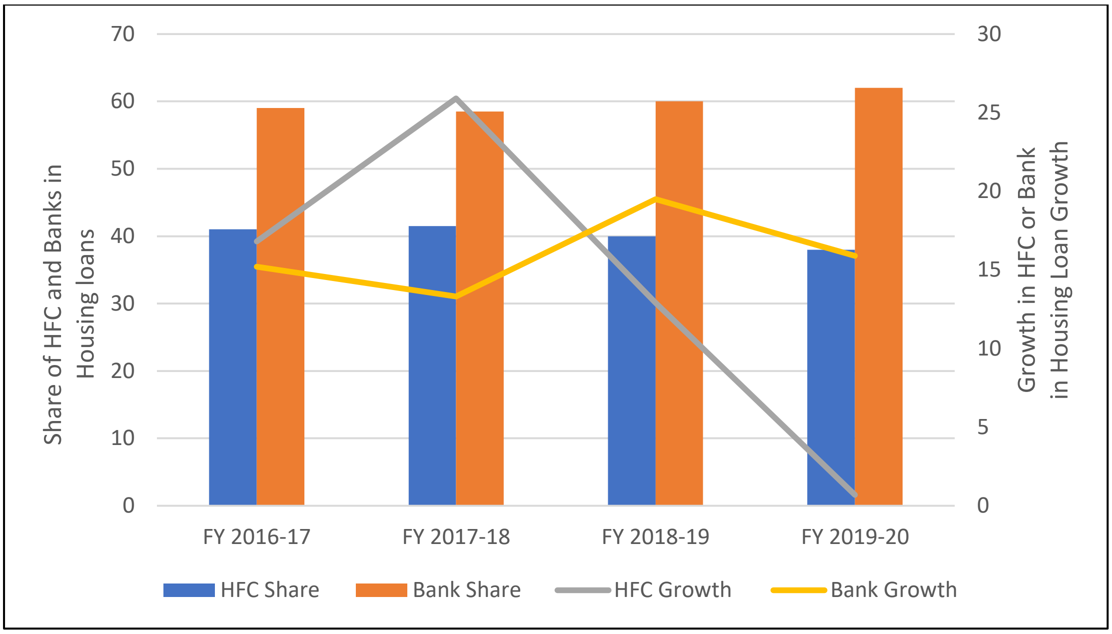


Fig. 7.7: Credit deployment to Housing Sector by Housing Finance Companies and Commercial Banks Pre and Post Shadow Banking Crisis

Commercial Banks accounted for 50.8% of credit to the housing sector in the pre-crisis period, and this share increased to 53.1% in the post-crisis period. The decline in the share of HFCs in credit to the housing sector was due to the NBFC crisis of 2018-19. The crisis led to a loss of confidence in the HFC sector, and this made it more difficult for HFCs to raise funds. As a result, HFCs had to reduce their lending, and this led to a decline in their share of credit to the housing sector. In case of housing loans, both commercial and shadow banks are acting as substitute to each other. During the periods of economic growth, commercial banks use shadow banks' securitization services to offtake the risky long term real estate loans and get liquidity. Also, shadow banks intermediates and transform cheap bank loans to long term real estate loans. For shadow banks these long-term real estate loans are profitable as they charge a higher rate from borrowers than banks. However, during the shadow bank crisis, banks loans to housing sectors offset the decline in shadow bank credit offtake. The increase in the share of Commercial Banks in credit to the housing sector was due to the government's focus on affordable housing.

7.8 Credit Deployment to Industrial Sector

Shadow Banks are a major source of credit to the industrial sector in both the pre-crisis and post-crisis periods. Shadow Banks accounted for 23.2% of credit to the industrial sector in the pre-crisis period, and this share declined to 19.2% in the post-crisis period (Fig. 7.8). The IIP series, which measures the industrial production index, also declined in the post-crisis period. The crisis led to a loss of confidence in the shadow banking sector, and this made it more difficult for shadow banks to raise funds. As a result, shadow banks had to reduce their lending, and this led to a decline in their share of credit to the industrial sector. The decline in the IIP series was due to a number of factors, including the shadow banking crisis, the trade war between the US and China, and the slowdown in the global economy. The overall trend is that shadow banks have become a less important source of credit to the industrial sector in the post-crisis period. This is a negative development, as shadow banks played an important role in financing small and medium-sized enterprises (SMEs).

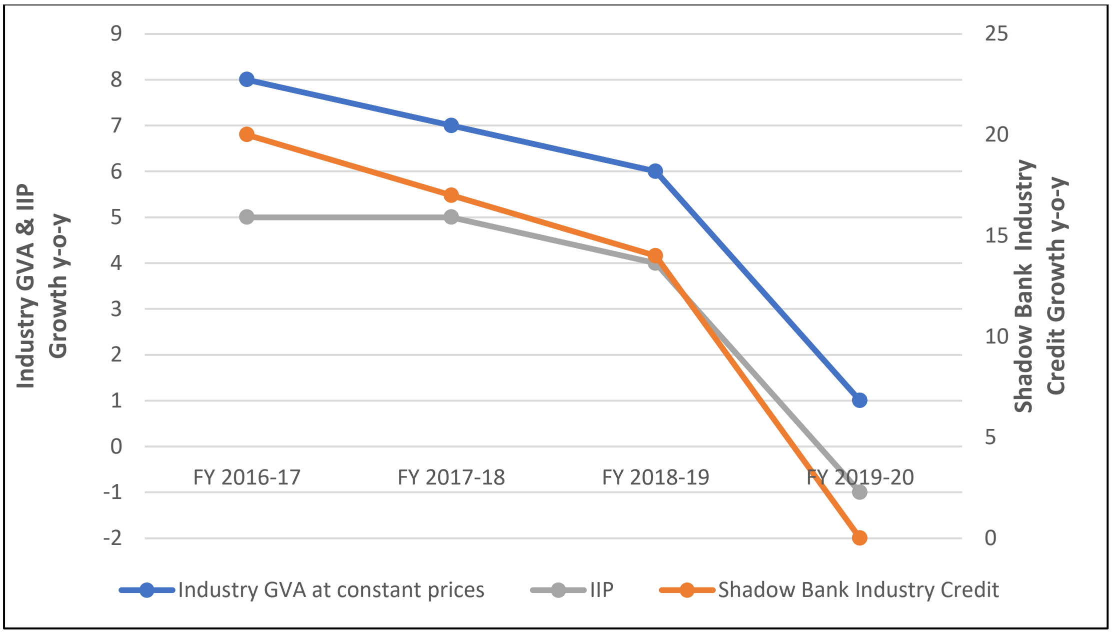


Fig. 7.8: Credit deployment to Industrial Sector Y-o-Y growth by Shadow Banks Pre and Post Shadow Banking Crisis

7.9 Credit Deployment to Automotive Sector

As you can see, shadow banks were a major source of credit to the automotive sector in 2018-19, but their share declined significantly in 2019-20. Shadow banks accounted for 13.3% of credit to the automotive sector in 2018-19, and this share declined to 6.3% in 2019-20 (Fig. 7.9). The decline in the share of shadow banks in credit to the automotive sector was due to the NBFC crisis of 2018-19. The crisis led to a loss of confidence in the shadow banking sector, and this made it more difficult for shadow banks to raise funds. As a result, shadow banks had to reduce their lending, and this led to a decline in their share of credit to the automotive sector. The decline in credit to the automotive sector also had a negative impact on the automobile industry. The automobile industry is a major driver of economic growth in India, and the decline in credit to the sector led to a slowdown in the industry. The overall trend is that shadow banks have become a less important source of credit to the automotive sector in the post-crisis period. This is a negative development, as the automotive sector is a major driver of economic growth in India.

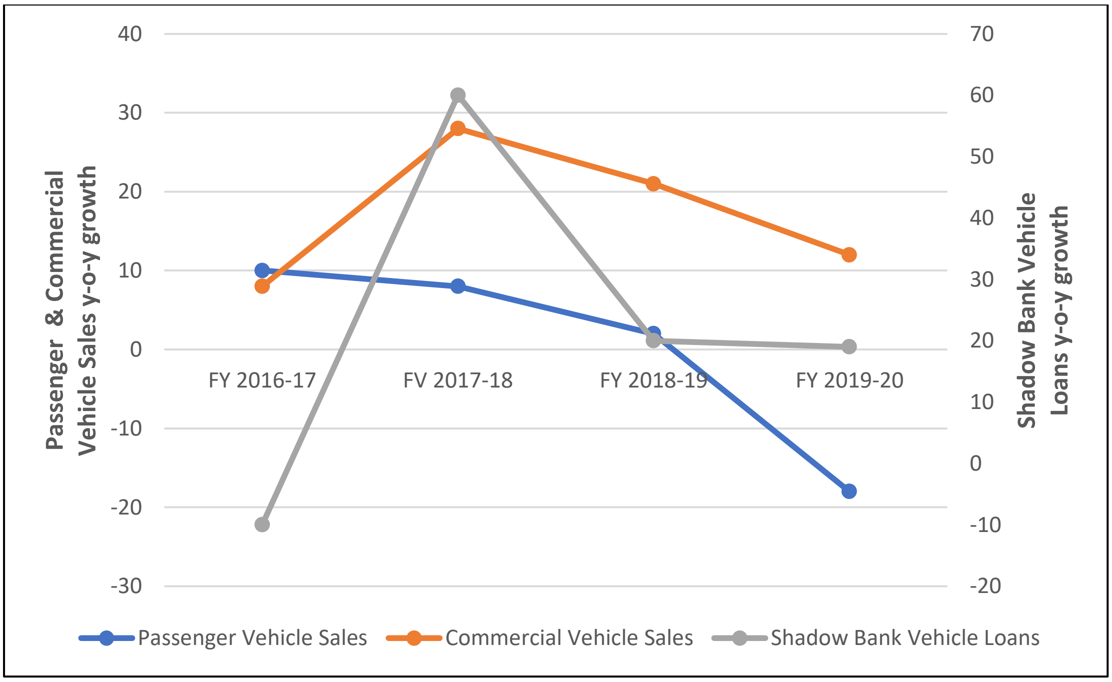


Fig. 7.9: Credit deployment to automotive sector pre and post shadow banking crisis

7.10 Conclusion

The shadow banking crisis of 2018-19 had a significant impact on the real economy of India. It led to a decline in credit availability, a decline in asset prices, and a decline in consumer confidence. These factors all contributed to a slowdown in economic activity. The comparison of flow of incremental credit pre and post crisis, reveals that shadow banks act as complementary to commercial banks. Isayev and Bektas (2023) also corroborated the existence of complementary relationship between shadow banks and commercial banks in the emerging market. The Gross NPA to total advance of commercial banks and shadow banks are also positively related. As the incremental credit flow decline and distressed assets soar on the balance sheet of the commercial banks, it led to low value of loans securitized and credit offtake on the balance sheet of shadow banks. The complementary relationship between incremental credit and distressed assets of both commercial banks and shadow banks is also simulated by (Meeks et al., 2017); that balance sheets of both commercial banks and shadow banks are tightly coupled and correlated with each other. Also, over the past years the credit intensity of shadow banks is increasing and commercial banks is decreasing. Also, the decline in GDP mirrors the decline in credit growth rate of the shadow banks. The results coincide with the studies of (Greenwood and Scharfstein, 2013; Le et al., 2021; and, Feve, Moura, and Pierrard, 2022); stating that period of contraction in real GDP strongly correlates with period of contraction in non-bank credit intermediation. Also, the sluggish recovery after the GFC is mainly due to collapse of shadow banking. The sectoral deployment of credit provides clearly highlight the role of shadow banking in supporting key strategic and sensitive area of the economy like MSME, affordable housing and consumer durables. The shadow banking crisis affects the most vulnerable sections and the real asset-output relationship of the economy (Geanakoplos, 2010). The shadow bank crisis impacted the credit flow to the various sectors. The sectors like MSME, consumer durables and commercial real estate took the severe hit. These sectors are highly dependent on the shadow bank credit. Particularly, in case of housing sector the credit offtake of banks and shadow banks offset each other. During the periods of economic boom, the commercial banks used shadow bank channels to increase the credit supply to the housing sectors as there was a lot of push by the government. During the shadow bank crisis, the banks offset the decline in credit supply by shadow banks, by directly lending to the housing sectors. This substitute behavior of commercial banks and shadow banks are also seen in emerging economy like China. In India, shadow banks are one of the main drivers of the industrial and automotive credits. The decline in shadow bank lending to industrial sectors negatively impacted the industrial gross value added, a measure of productivity. It also hurts the sentiment of the industrial outlook which further led to decline in productivity and economic activities. (Han, Hus and Li, 2019) found the positive effect of shadow banking in increasing the industrial productivity in China. The automobile industry is also one of the largest recipients of shadow bank credits. As automobile industry sits on the top of supply chain, it helps in developing other industries for its components and raw material. Thus, it generates a large number of jobs directly or indirectly. As we can see, both the passenger vehicles and commercial vehicles sales slowed down during the Indian shadow bank crisis. However, passenger vehicle sales were severely impacted as lot of prospective customers depend on shadow banks to access funds. Thus, any slowdown in automobile sales can indirectly effect a large number of industries and employment rates in India.

Overall shadow banking plays an important role as financial intermediary in the Indian financial system. It acts as both the substitute and complement to the existing traditional commercial banking. Over the last decade its role as lender has gained importance. The present study has also highlighted shadow bank role in directly or indirectly affecting the key macros like GDP, industrial productivity, household credit, real estate, automobile, unemployment, etc. By analyzing the changes in credit flows and sectoral allocations, it provides a comprehensive understanding of the impact of the shadow bank crisis on the real economy. The findings can inform policymakers, regulators, and industry participants in their efforts to ensure the stability and resilience of the shadow banks in the future. The shadow banking crisis is a complex issue with no easy solutions. There is need for strengthening oversight of the shadow banking system; providing more liquidity to the shadow banking system; providing guarantees to investors, and promoting transparency in the shadow banking system. By doing these policymakers can help to mitigate the impact of future crises and promote financial stability in India.

CHAPTER 8
CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

8.1 Discussion of the Results

The Global Financial Crisis has established the role of shadow banking in amplifying the crisis through its intricate and complex products and operations with other entities. Bilateral information about their trades is either confidential or not readily available as they are mostly unregulated. To this end, we constructed a complex shadow bank network based on granger-causality relations of financial institutions' stock return information, which is publicly available. The complex network graph of the crisis period is denser than the tranquil period indicating that institutions are more tightly coupled during the crisis period. Also, the Dynamic Causality Index (DCI), which measures total interconnectedness, remained elevated and above the cut-off during the crisis period. The increase in causality measure shows that both correlation and co-movement of institutions' returns increased during the crisis. The DCI crosses the threshold at the onset of the crisis, demonstrating its use as a systemic risk indicator. In the recent shadow bank crisis, the shadow institutions were much closer to the center of the network, thereby decreasing the path of spreading contagion and increasing their role as a transmitter of risk. Comparing centrality measures, the financial institutions are closer to the center of the network and have higher systemic vulnerability during the crisis. These core positions give some institutions a dual role as both transmitter and receptor of contagion, making them systemically important nodes. The shadow bank complex network also depicts small-world phenomena. The network has embedded nodes that divide graphs into small cliques where some cliques are more systemically vulnerable due to their connections. The rank-based regression shows out-of-sample properties of network-based measures in predicting financial institutions' loss of market capitalization in the crisis period. Overall, the more connected, more central, and more prestigious institutions suffered significant losses in their market capitalization during the shadow bank crisis. The commonality in institution ranking on network-based measures from the pre-crisis period and market capitalization loss from the crisis period demonstrated that the Granger-causal network-based measures could serve as an early warning tool when systemic risk increases.

In the recent financial crises, attention has shifted towards identifying “Too-big-to-fail,” “Too-connected-to-fail,” and “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 NBFC crisis highlighted the role of smaller institutions in perpetuating and amplifying the crisis. Thus, we also analyzed the predictive capability of firm-level variables in identifying the systematically vulnerable institutions and compared it with interconnectedness-based measures’ prediction capability. For this, we used the leverage ratio, size, non-performing assets, non-interest income, and short-term funding of the financial institution. We once again employed rank-based correlation to identify systematically vulnerable institutions based on the firm-level variables and compared them with the actual institutions that faced losses. The size of the financial institution is negatively related and significant (at 1%), implying that smaller institutions suffered the most losses during the crisis. Short-term funding is positively related and significant (at 5%), indicating that an over-reliance on short-term funds increases the systemic vulnerability of the institutions due to an increase in uncertainty when accessing refinancing at the next rollover dates of the short-term debt instruments. This negatively affects the credit risk of these institutions. During the shadow bank crisis, investors dumped these securities, which had higher credit risk. Thus, a high dependence on short-term funding can increase the systemic vulnerability of financial institutions during the crisis. Non-interest income is positive and significant at 10%, identifying most of the institutions that suffered losses during the crisis period. This shows that the non-interest income activities of financial institutions increase earnings and cash flow volatility due to their unpredictable business operations. To our surprise, the leverage ratio and non-performing assets do not have significant predictive values in the out-of-sample analysis. When we compare the prediction results with interconnectedness and centrality-based Granger-causal network measures, we can see that the #In_Degree, #Out_Degree, #In+Out_Degree, #Eigenvector_Centrality, and #PageRank_Centrality are all positively related and significant (at 1%). Additionally, #Closeness_Centrality is positively related and significant (at 5%) in predicting the institutions that suffered the maximum losses during the crisis. Thus, we can conclude that interconnectedness and centrality-based measures perform better than firm-level variables in out-of-sample analysis when identifying systematically vulnerable institutions. Therefore, we can use firm-level variables along with network-based measures to identify systemic risk ex-ante and also individually analyze the role of nodes in the financial network. As network-based measures exhibit better out-of-sample performance, we can conclude that the "too-connected-to-fail" and "too-central-to-fail" hypotheses are at work during the shadow bank crisis.

The shadow banks perform credit intermediation, maturity transformation and liquidity management through their specialized lending and securitization services. This web of financial contracts often leads to asset-liability mismatches on the balance sheet of shadow banks. It gets exacerbated by the use of short-term debt. In normal time period they stabilize the financial market and help in increasing the real output of the economy. However, during abnormal time this short-term debt leads to rollover risk which impacts the financial market and even spillover to the real economy. Thus, we modeled the rollover risk of the shadow banks to the default risk, market distress and the systemic risk of the financial institution. After controlling for the firm level variables and the fixed effects, we find that the rollover risk is significantly and negatively effects the Distance-to-Default of the financial institutions. A 1% increase in the standard deviation of RR can lead to 4.53% decrease in the distance-to-default or increase in default risk. The rollover risk of shadow banks is also significantly (at 1%) and positively related to the market distress (measured through stock volatility). A 1% increase in standard deviation of the rollover risk of the firm leads to a increase of 28.31% increase in market risk of the institution. This corroborates with the Rollover Risk Hypothesis (He and Xiong, 2012) which states that that rollover risk intensifies the conflict between shareholders and debtholders, where shareholders have to fund the rollover losses to prevent bankruptcy while the debtholder receives full payments. It motivates shareholders to declare a firm insolvent earlier thereby increasing default risk (the rollover risk hypothesis). Since short-term debt rollovers are more frequent than long-term debt, the rollover risk impacting default risk gets amplified for firms issuing more short-term debt. However, we could not find any effect of rollover risk on the systemic risk as measured by Max%Loss of the financial institution. The systemic risk as denoted by Max%Loss of the financial institution is dependent on leverage and linkage of the financial institution. Thus, the short-term debt incorporated by the financial institution does not alone justify the systemic exposure of the financial institution.

The shadow banks strongly impact the real economic variables through specialized lending, credit intermediation and maturity transformation activities. Thus, we used observational study by using real economic variables like flow of incremental commercial credit, Gross NPA, Non-Food Credit to GDP ratio, sectoral wise deployment of credit, Credit deployment to Real Estate, Credit deployment to India Industrial Sector, Credit Deployment to India Automotive sector and compared with the bank. The share of shadow bank in the incremental flow of credit to real economy increased consistently over the years with period between FY 2015 to FY 2017 having more than 100% growth rate in the credit offtake of the shadow banks. However, the Shadow Bank crisis negatively impacted the flow and it faced with negative credit growth during FY 2018 and FY 2019 period. The discovery of Non-Performing Assets in the Shadow Banks also increased during FY 2018 and FY 2019 period when activities of shadow banks were under heavy scrutiny due to the crisis. The share of Shadow bank credit to GDP ratio have increased during the past decade with slightly dipping during FY 2020 period when GDP also declined, while the share of bank credit to GDP ratio have declined in the same period. The credit deployment of shadow banks to the MSME, Large industries, Commercial Real estate, and consumer durables declined during crisis, while the retail trade, agriculture and housing sector saw growth in credit even during the crisis. This shows that flight-to-quality problem where shadow banks investing in stable sectors where they have co-lending agreements with the banks or have insurance facility. The credit deployment to the housing sector by shadow banks decreased relatively to the commercial banks during the crisis period. The sale in passenger vehicle segment is positively related to the credit deployed by the shadow banks to the automotive sector. During crisis the passenger vehicle sale dipped due to the subdued financing by shadow banks to the vehicle loans. The Index of Industrial Production (real output indicator) is positively related to the growth in shadow banks financing of industrial credit. During the shadow bank crisis the shadow bank industrial credit fallen from 15% Y-o-Y growth in FY 17 to almost 0% Y-o-Y growth in FY 19 and at the same time IIP series growth fallen from 5% in FY 17 to -1% in FY 2019.

8.2 Practical Implications

Supervisors and financial regulators can use the proposed measures to monitor the development of systemic risk and swiftly identify and isolate contagious financial institutions in the event of a crisis. Also, it is helpful to policymakers and researchers of an emerging economy where bilateral exposures' data between financial institutions are often not present in the public domain, plus there is a gap or delay in financial reporting. The study also showed the importance of the graph-based measure in comparison to firm-level variables in predicting buildup of systemic risk in the financial institutions. Thus, policymakers should use "too-connected-to-fail" and "too-central-to-fail" approach rather than "too-big-to-fail" hypothesis alone in identifying SIFI nodes in the financial network. Regulators should also monitor the rollover risk in the shadow bank institutions, as they posses' serious systemic risk to the stability of the financial institutions. The investors of shadow banks should consider the dependence on liquidity and default premia while calculating the credit risk of the financial instrument of the shadow banks. The rollover risk of the shadow banks also explains the flight-to-quality problem during the event of market distress as many investors flock to investable grade securities creating fire-sale problem in shadow bank collaterals and securitized products. This can amplify the crisis. Policymakers and Regulators should monitor the funding and market liquidity profiles of shadow bank networks to prevent the rollover risk and financial crisis. Also, policymaker should develop shadow bank network as shadow bank credit is positively correlated with GDP growth rate and real economic output. Also, the degrowth in shadow bank credit critically hampers the real economic productivity of nation. Thus, a robust and well-functioning shadow bank network is needed for transitioning India from developing to developed nation and for the financial inclusion of all sectors of the economy.

8.3 Limitations

The present study underscores several noteworthy limitations warranting consideration and suggesting avenues for future research. Initially, it is imperative to acknowledge that the investigation exclusively focuses on the publicly listed financial institutions, thus overlooking unlisted shadow banks. Furthermore, the selection of a systemic risk predictor variable is subject to scrutiny, particularly concerning its susceptibility to variations in window size and return frequency, be it daily, weekly, or monthly. Additionally, the determination of the significance level for Granger-causality introduces a notable influence on the quantification of interconnectedness, as evidenced by the study's utilization of a 5% threshold. Moreover, the temporal scope of the study is circumscribed to the period spanning from 2016 to 2020 for the pursuit of objectives 1, 2, and 3, a choice necessitated by the evolving regulatory milieu surrounding shadow banks.

Also, the viability of backtesting the proposed systemic risk measure is impeded by the rarity of shadow banking crises in India and the concomitant dearth of suitable data. Nonetheless, it is envisaged in the future work we will endeavor to conduct such backtesting exercises utilizing historical data or leveraging emergent systemic risk events. Moreover, the idiosyncratic nature of shadow banking operations and regulatory frameworks across different jurisdictions precludes generalization of findings. In summation, the elucidation of these limitations underscores the imperative for future research endeavors to address these lacunae and refine the understanding of systemic risk within the context of shadow banking.

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LIST OF PUBLICATIONS AND THEIR PROOFS (Reprint/Acceptance Letter/Mail)

Examining the interconnectedness and early warning signals of systemic risks of shadow banks: an application to the Indian shadow bank crisis

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Abstract

Purpose

The paper models the financial interconnectedness and systemic risk of shadow banks using Granger-causal network-based measures and takes the Indian shadow bank crisis of 2018–2019 as a systemic event.

Design/methodology/approach

The paper employs pairwise linear Granger-causality tests adjusted for heteroskedasticity and return autocorrelation on a rolling window of weekly returns data of 52 financial institutions from 2016 to 2019 to construct network-based measures and calculate network centrality. The Granger-causal network-based measure ranking of financial institutions in the pre-crisis period (explanatory variable) is rank-regressed with the ranking of financial institutions based on maximum percentage loss suffered by them during the crises period (dependent variable).

Findings

The empirical result demonstrated that the shadow bank complex network during the crisis is denser, more interconnected and more correlated than the tranquil period. The closeness, eigenvector, and PageRank centrality established the systemic risk transmitter and receiver roles of institutions. The financial institutions that are more central and hold prestigious positions due to their incoming links suffered maximum loss. The shadow bank network also showed small-world phenomena similar to social networks. Granger-causal network-based measures have out-of-sample predictive properties and can predict the systemic risk of financial institutions.

Research limitations/implications

The study considers only the publicly listed financial institutions. Also, the proposed measures are susceptible to the size of the rolling window, frequency of return and significance level of Granger-causality tests.

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

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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.

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Acceptance of your paper

16 messages

Dr Md Abdul Wadud <wadud68@yahoo.com> Fri, Dec 22, 2023 at 8:51 AM
To: anurag chaturvedi <canurag17@gmail.com>

Dear Dr. Anurag,

We have managed to receive the referees' reports on your paper, "**An empirical study of the effect of Rollover Risk on Default Risk of Indian Firms**". The scholar raises and discusses issues rightly and competently. Econometric analysis has been done properly. The paper is found to be suitable for publication. Comments of the referees are also favourable. The paper has also been read by one of the editors. It gives me immense pleasure to inform you that your paper has been accepted for publication in ***Empirical Economics Letters***. Congratulations!

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PERSONAL PROFILE

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With total experience of 10+ years, I am currently working as Assistant Professor in the University School of Management and Entrepreneurship at Delhi Technological University. I have 6+ years of teaching and research experience in finance and financial risk management related areas.

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- *PhD thesis: "Interconnectedness and Systemic Risk of Indian Shadow Banks-Detection Measures and Effect Analysis"*
- *Published paper "Examining the interconnectedness and early warning signals of systemic risks of shadow banks: An application to the Indian shadow bank crisis. Kybernetes. ISSN 0368-492X. https://doi.org/10.1108/K-12-2021-1280*
- *Published paper "Examining Systemic Risk using Google PageRank Algorithm: An Application to Indian Non-Bank Financial Companies (NBFCs) Crisis." International Journal of Mathematical, Engineering and Management Sciences. ISSN: 2455-7749.* DOI: 10.33889/IJMEMS.2022.7.4.037
- *Published paper "The role of crowdfunding in endorsing responsible open innovation for shared value co-creation: a systematic literature review", European Journal of Innovation Management, ISSN: 1460-1060, DOI: https://doi.org/10.1108/EJIM-03-2022-0131*

Conference Paper Presented

- *Presented "An empirical study of the effect of Rollover Risk on Default Risk of Indian Firms", 1st International Conference on Behavioural Finance, 2022. IIIT Allahabad*
- *Presented the paper titled "The Impact of Interaction between Industry Competition and Rollover Risk on Corporate Financial Default Risk" at 4th SEBI-NISM Conference at NISM Mumbai from 2nd-3rd March 2023.*
- *Presented the paper titled "Unveiling the impact of ONDC on DEI in E-commerce: Creating a diverse and inclusive digital marketplace" at the 1st International Conference on Diversity, Equity and Inclusion: Cultures, Practices and Policies in Management, Entrepreneurship and Economics (ICMEE) during September 15-16, 2023 at USME, DTU*

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- *Presented the paper titled "Examining the Internet of Things products adoption by Millennial in India from the perspectives of Unified Theory of Acceptance and Use of Technology and Privacy Risk", International Conference on Business and Management 2019, DSM, DTU*
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Teaching Experience

- *MBA : Financial Derivatives, Financial Risk Management, International Financial Management*
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- *Cultural Committee Coordinator*
- *Library Committee :- Member*
- *Alumni Relation Cell :- Coordinator*
- *BoS(Board of Studies):- Member*
- *Coordinator for the student Management Fest (Traction), Freshers Party (INIZIO), Farewell and Alumni Meet*
- *Coordinator for Orientation Programs, Specialization and Elective Finalization and Major Research Project for MBA*
- *Coordinated for MBA syllanus update in May 2020 and transformation of MBA program as per new NEP guidelines from 2022 onwards*
- *Worked as a coordinator/examiner/paper setter for various U.G. and PG Courses.*
- *Worked as invigilator during end-semester examinations for B. Tech, BBA, BA(H) Eco, MBA, and Ph.D.*
- *Responsibility of Student Registration, enquiry and Arrangement distribution Orientation Program*
- *Faculty Advisor:- Vittleshan (Finance Club)*
- *Member, Discipline Committee, USME, DTU*
- *Member Anti ragging committee for USME,DTU*

TRAINING/ SUMMER SCHOOL/FDP ATTENDED				
S.No.	***Name of Course/Summer/ Winter School***	***Place***	***Duration***	***Sponsoring Agency***
01	*4 Weeks Orientation Program OR-93*	*CPDHE, DU*	*4 Weeks 03/07/2018-30/07/2018)*	*DTU*
02	*TEQIP- FDP on "Advances in Research Methods & Teaching Pedagogy"*	*Delhi School of Management, DTU*	*2 weeks*	*Delhi School of Management, DTU*
03	*Advanced Pedagogy, IPR, Sponsored Research and Entrepreneurship*	*Engineering Staff College of India (ESCI) & DTU*	*1 week (16/7/2019-20/7/2019)*	*Engineering Staff College of India (ESCI) & DTU*
04	*Research Summer School on Empirical Finance And Accounting Research*	*The Financial Research and Trading Laboratory (FRTL), Indian Finance Association (IFA) at IIM Calcutta*	*2 weeks (29/4/2019-07/05/2019)*	*The Financial Research and Trading Laboratory (FRTL), Indian Finance Association (IFA) at IIM Calcutta*
05	*Refresher Course in Commerce and Management*	*Ramanujan College, Delhi University*	*2 weeks (27/5/2022-09/05/2022)*	*Ramanujan College, Delhi University*
06	*5th Summer School on Behavioural Finance*	*IIIT Allahabad*	*1 week (13/6/2022-17/06/2022)*	*IIIT Allahabad*
07	*Two Weeks Industrial Training at Ornate Solar on "Inventory Control Management"*	*Ornate Solar*	*2 weeks (23.06.2022 – 07.07.2022)*	*Ornate Solar, Delhi*
08	*Completed 8 Modules of NITTTR Chennai*	*Online*	*2021-22*	*NITTTR Chennai*

PROFESSIONAL QUALIFICATIONS

- Qualified FRM LEVEL-1
- Qualified JRF NET for Assistant Professor in 2017
- Member of GARP (Global Association of Risk Professional)
- Member of AIMA (All India Management Association) and DMA (Delhi Management Association)

CORPORATE WORK EXPERIENCE

JUNE 2017-DEC 2017 **HIS MARKIT**

IMPLEMENTATION SERVICE ANALYST

Responsible for after sales membership procedures, on boarding new clients and providing demo for the product and services.

APRIL 2014- JULY 2015 **TATA MOTORS**

CUSTOMER SUPPORT MANAGER

Handled 4 to 5 Tata Motors' service networks. Responsible for achieving dealership profitability, service targets, customer satisfaction & process adherence.

- *Improvement in JD Power Customer Service Index by 25 points (2014) and 49 points (2015)*
- *Oriented approximately 50 service manpower with service targets and service processes.*
- *Improvement in Turnaround Time (TAT) for complaints resolution from 45% to 95%.*
- *Used data analytics for segregating and targeting customers from Business for customer communications, events and service targets*
- *Analyzed CAPEX & OPEX reports & consult the Dealer Principal/ Channel Partners for business profitability.*
- *Coordinating with sales team for New Product Launches and Before the Launch (BTL) activities promotion.*

JUNE 2013- MAR 2014 **TATA MOTORS**

PURCHASE PROGRAM MANAGER-TM1

Responsible for price settlement and purchase of Unique Parts for new Commercial Vehicles and the parts availability before Start of Production.

- *Driven as PPM Manager for ULTRA FESLF 650mm, CNG DMRC, LPT 2518 55WB, LPK 2518 G1150.*
- *Taken key decisions of Commonization vs Purchase for new parts*

AUG 2012- MAY 2013 **TATA MOTORS**

MANAGEMENT TRAINEE

- *Panther Project- JDP Champion - To improve CSI in Lucknow (Feb 2012- May 2013)*
- *Digitization of Process Audit on Manufacturing Execution System in Sanand Plant, Ahmedabad.(Dec 2012- Jan 2013)*
- *Market Survey of Nano Customers for resolving Product issues of Nano in Coimbatore. (Aug 2012- Nov 2012)*

EDUCATIONAL QUALIFICATIONS			
Ph.D. (Financial Risk Management)	*2018-2024*	*Delhi School of Management, Delhi Technological University (Formerly DCE)*	Ph.D.
Master of Business Administration (M.B.A)	*2015-17*	*Delhi School of Management, Delhi Technological University (Formerly DCE)*	CGPA: 8.23
B.Tech (Electronics and Communications)	*2008-2012*	*NIT SURAT*	*8.54/10*
XII th	*2008*	*ARMY SCHOOL, GORAKHPUR*	*92%*
X th	*2006*	*H.P.CHILDREN'S ACADEMY*	*91.33%*