Measuring Resilience Through Systemic Risk with Reference to Indian Indices

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Abstract: *This paper studies financial market resilience indirectly through an important indicator; systemic risk. We propose four measures of systemic risk in important indices of Indian capital market using correlation, principal component analysis (PCA), Granger causality test and the regime switching model. We empirically examined daily return data from 2006 to 2010 in two sub-periods. Results of PCA and correlation suggest existence of a substantial degree of interconnectedness and relatively low liquidity during and after crisis period among three indices i.e., among Nifty 50, Nifty 5Yr G sec and Nifty commodities except for the Nifty bank. However, before crisis, Nifty bank has a positive degree of linkage with three indices except Nifty commodities. Result of pairwise Granger causality test implies more asymmetry of information flow across indices post crisis. This may imply a relatively lower degree of resilience of Indian capital market despite of considerable liquidity of Nifty indices in normal period. We found no evidence of sudden regime change from two state MS GARCH model for all the select four indices during the sample period. This may indicate a relatively stable return generating process. This study will have implications for regulators and policymakers.*

Keywords: *resilience, systemic risk, asymmetry, liquidity, crisis*

Introduction

Liberalization and globalization have facilitated movement of speculative capital across economies in search of short-term profit [Yan (2018)]. Just like any form of benefit comes with its associated cost, this process is also not an exception to it. The process of globalization no doubt has become a boon for economies in terms of faster GDP growth, more employment creation, better socio-cultural adaptation among people of different countries. But at the same time, it comes with challenge like faster spread of economic shock among countries resulting in disruption to functioning of normal economies leading to financial market instability. Fong et al. (2021)

found increasing importance of shadow banking system in facilitating spillover effect across countries during times of tightening global liquidity. In this context, it is important to see how economies withstand such sudden shocks. More particularly, the following two questions arise. First, what defines the ability of an economic system to stand against economic shocks which is more or less a size aspect of shocks on economy [Chabot et al. (2019)]. Second, how fast can economies get around of such shocks [Lo and Hall (2015); Broto and Lamas (2020)]. The premise of answering these questions is what is known as market resilience. Thus, in financial market context, resilience can be defined as ability of market to absorb (size aspect) and recover (time aspect) from external shocks. In general, there should be a high correlation between size aspect and time aspect. This means greater the magnitude of shock, longer the time taken to recover. One strong measure of financial market resilience is systemic risk, originally conceptualized to describe crisis in banking and currency market. Later on, the word 'systemic risk' was used increasingly across sub sectors of financial system. Any event that causes loss of confidence among the economic agents and thereby creating a widespread uncertainty in the real economy can also be thought of as systemic risk according to a report on financial sector by G10 member countries. Uncertainty in the economy can significantly reduce the supply of capital that impact the efficient operation of capital market activity [Acharya et al. (2009)]. Hart and Zingales (2009) defines systemic risk as "*the failure of one institution leads to failure of other institutions in the system, having ultimate spillover effects on the real economy.*" Following these definitions, it is evident that such risk affects the entire system as a whole and not a specific institution or individual. Therefore, in order to effectively contain such risk, starting point is regulatory reforms that must aim at establishing common measure of linkages between key institutions operating in a financial system. Given the complexity of financial system, it would be inappropriate to gauge systemic risk on a single yardstick. Therefore, a combination of statistical measures is used in this paper to contain various aspects of systemic risk.

In the remaining parts, section 2 presents important literatures on the subject domain. Thereafter it is followed by a conceptual underpinning of systemic risk and the methodology in section 3. Section 4 contains the analysis of data, followed by empirical results in section 5. Finally, the study ends with practical implications, scope for future research, limitations and conclusion in section 6.

Review of Literatures

According to De Bandt and Hartmann (2000) systematic and idiosyncratic shocks are at the heart of systemic risk, that is mainly spread among economies due to contagion effect. It is not only limited to financial system but also covers a health and epidemics sector too. Allen (2011) shown that mispricing of assets, currencies, use of currency swaps particularly in case of cross border banking system in Europe is one major source of systemic risk which was the reason behind 1997 Asian currency crisis. The same cross border transaction between banks was the major cause of 2007-2009 crisis according to the author. This implies that interlinkages among economies, financial system and institutions can cause faster spreading of negative externalities and spiralling of volatilities through network effect. There are many channels which spread these shocks and well documented in vast literatures [Allen and Gale (2000); Diamond and Rajan (2005); Danielsson and Zigrand (2008); May and Arinaminpathy (2010); Patro et al.(2013); Caceres-Santos et al.(2020)]. According to Danielsson and Zigrand (2008), excessive leverage and risk-taking behaviour triggered by free externalities cause systemic risk in a system. The available literatures can be broadly classified into four groups. First group studies systemic risk as contagion effect in banking system due to which failure of some big banks get contaminated to small banks, therefore entire banking system is perceived as risky. Lehar (2005) estimated correlations between portfolios of banking assets and default by each bank as a measure of systemic risk. On the contrary, Bartram et al. (2007) used maximum likelihood estimation method to capture such risk through negative abnormal returns associated with probabilities of bank failures and concluded that Asian crisis of 1997 and the likes didn't create big probabilities to cause failure of global financial system. Second group comprises of studies on banking crisis with use of capital ratio and other accounting variables and macroeconomic factors as a source of systemic risk. Brunnermeier and Oehmke (2013) concentrates on measuring systemic risk at firm level using VaR. Duca and Peltonen (2013) assesses systemic risk with the help of financial stress index. Billio et al. (2016) examined evolution of systemic risk over time and showed entropy measures can be used to predict systemic events in financial system. The third group focuses on spillover effect and market crash as a whole systematic failure through correlation and ARCH type models. Xu (2018) measured systemic risk using CoVaR in Chinese banking sector and found high risk spill over occurred after crash periods. Zhang et al. (2020) found similar type of result in Chinese stock market. Zhao et al. (2019) using cointegration and granger causality test liquidity is badly affected after the market crash. The fourth group focuses on measuring resilience from 'macro-economic' perspective. For instance, Di Caro (2017) examined the employment dynamics of Italian region through a set of factors ranging from financial indicators like export performance, economic diversity to social capital that cause geographical asymmetries in economic resilience. The author concluded worsening aggregate economic conditions have a long-lasting negative effect in terms of employment opportunities and wealth distribution. Eraydin (2016) in his paper applied seemingly unrelated regression technique to determine attributes contributing to regional resilience in Turkey. The study found that enhancement of human capital with continuous innovation in capacity building led to better and stable policies across a region. The same study also found that region wise attributes are responsible for varied capacity to absorb economic shocks. Sanderson et al., (2017) suggested a novel approach of measuring the complex evolution Socio-Economic resilience using Real Option Analysis. They proposed measuring economic resilience through the concept of expected time. In order to examine contagiousness of financial markets Ahmed et al., (2017) concluded that macroeconomic fundamentals can play important role in shock transmission across financial markets. Specifically, they found emerging market economies (EMEs) with better macroeconomic fundamentals can absorb shocks to a great extent, thereby suffers less. Alaoui et al., (2015) examined the linkage between stock market returns using wavelet analysis and found closer markets tend to have a contagion effect indicating a strong correlation with a time delay. The same study also found flight of capital to less risky market during and post crisis periods. Fakhfekh et al., (2016) measured persistence in volatility using FIEGARCH and compared conventional with Islamic banks and found that later are more resilient than former ones with heterogeneity in degree of resilience during calm and crisis periods. Saiti et al., (2016) using a wavelet analysis tested co-movements of selected stock markets as normal or excessive contagious during and after sub-prime mortgage crisis of 2008. The study found evidence of contagion for all the conventional stock indices of non-Islamic countries except Japan. However, indices of Islamic countries did not suffer much except Indonesian MSCI.

This apart, recent research papers focused on studying the effect of pandemic risk on financial market. For instance, Pagano et al., (2023) showed that more resilient firms in terms of adoption of technologies to following robust practices for social distancing outperform less resilient firms. In the similar line, Arif et al., (2021) examined the interconnectedness using time frequency data between different conventional and green markets in the wake of Covid-19 scenario using spillover model of Diebold and Yilmaz (2012) and found that interconnectedness tends to be more pronounced during short run for both normal and covid-19 period except for the bond markets. This implies structural breaks in market returns often causes disruption in transition from conventional to green investments. Elnahass et al., (2021) studied pandemic effect on global banking sectors and found negative impact of Covid-19 on financial performance across different parameters. This even took a toll on financial stability measured through risk-based measures. The study also found that Covid-19 impacts banking sector mediated through institutional factors and the business model. Izzeldin et al., (2021) examined the effect of Covid-19 on performance of stock market covering important sectors of G7 countries using ST-HAR model. The result shows that a non-linear transition happens across all the sectors to crisis period with healthcare and consumer services sector severely affected. Further the US and the UK market were impacted to a large extent with heterogeneity across business sectors. This implies not all the sectors are equally resilient reflecting ambiguity and indecisiveness among market agents. Uddin et al., (2021) examined the market volatility and economic strength during period of Covid-19 which is measured through a set of select variables economic resilience, monetary policy rate, financial development across thirty-four emerging and developed economies. It found an overall decrease in return volatility with more market resilience. This has implications in understanding the fact that in order to avoid effect of any future shock, market has to focus on aggregate resilience measures.

One thing is found common to above literatures which support the notion that systemic risk is more or less have umbrella effect and mostly arising due to contagion effect. This has made it futile to study any single aspect of systemic risk on standalone basis and draw conclusion about effect of such risk on functioning of economy. Further most previous studies were undertaken in the context of banking sector assuming the sector to be the origin of all systemic risk across countries. However, evidences suggest there are many sources from which systemic risk arise. For example, multi-billion-dollar CDS and credit derivatives market has caused an acute liquidity crunch in past [See Cont and Minca (2016); Schuldenzucker et al. (2020)]. According to Danielsson and Zigrand (2008), free externalities in search of higher return promote excessive leverage which in turn significantly alter risk taking behaviours of banks and financial institutions ultimately magnifying systemic risk in the system. Moreover, availability of a vast number of techniques of measuring systemic risk is rather confusing one in terms of choosing the best measure for a given situation. Examining systemic risk on standalone basis may not be appropriate especially in a globalised world where economies and financial system are more prone to failure due to fundamental shocks in a given country. This in turn can cause mispricing of assets resulting in sub optimal investment and financing decisions, ultimately translating to real economy. In this context, we therefore revisit systemic risk measurement based on interconnectedness approach of major sectors in a financial system using a host of statistical techniques.

Though there are several important studies in this area covering many aspects of systemic risk measurement, in this paper we try to add value to the existing body of knowledge in the following way. First Indian market is relatively an emerging economy when compared to developed nations like US, Japan, Australia with respect to scope of policy and its implications. Therefore, it is important to measure different aspects of systemic risk in Indian context. Particularly, we want to examine whether there was any significant impact of sub-prime crisis and during that period how selected Indian indices behaved. Further we propose to use two state Markov switching GARCH to examine whether there is any sudden shift in regime during the sample period. With these things in mind, we have selected the following objective for the study.

Objective of the Study

To measure liquidity, leverage and asymmetry in Indian capital market from 2006 to 2010

Theoretical Underpinning

The mechanism of origination of systemic risk can be understood with the following logic. Leverage which many financial institutions regularly use that are often considered as larger than value of collateral can be thought of as the main starting point of risk origination. Leverage has not only the effect of magnifying smaller profit into bigger ones at the same time it also makes smaller loss into larger losses. Under adverse market condition i.e., speculation about war, uncertainties and other macroeconomic phenomenon, when value of collaterals get reduced, that cause forced liquidation of positions in a very short span of time thereby creating randomness in the system. Such randomness has spiralling effect from big to small institutions, thereby affecting the entire economy. Particularly, more the illiquidity of positions, larger will be price impact of liquidations thereby resulting in defaults, bankruptcy finally spreading in the form of unemployment and recession in an economy. This will further get amplified to more economies especially among those which are connected in a much better way. This means degree of contamination of systemic risk depends on correlation among multinational financial institutions, exposure of cash flows to market prices and risk concentration. We tried to examine the effect of systemic risk if any on the most liquid market of Indian capital market segment. i.e., Nifty. We chose to focus on the followings four categories of indices: Nifty 50 (representing equity market), Nifty bank (representing banking sector), Nifty commodities, Nifty 5-year G-sec (representing multi asset class including fixed income categories). Our motivation to select these indices was not random rather based on simple portfolio theory which says investors can benefit most under diversification strategy. Further with liberalisation policies, business strategies of banks have substantially become more aggressive and diversified with blurred distinction among assets, liabilities products. This once again has created a hodgepodge scenario to a much complex interrelationship between different entities.

Research Methods

1. **Correlation as a Measure of Liquidity**

We follow Getmansky et al. (2004) for measuring liquidity through autocorrelation. To see how autocorrelation is an indicator of liquidity, lets recall financial asset pricing which follows a martingale process. In a market which is informationally efficient, asset price should be unforecastable indicating that no serial correlation between successive asset returns. This extreme version of market efficiency can be rejected in real world where different types of market frictions such as borrowing restrictions, transaction cost, cost of obtaining information do exist. These frictions in turn create serial correlation in assets' return. In this context, presence of auto correlation in asset returns can be thought of as a proxy for friction and illiquidity is one such form of friction.

Autocorrelation coefficient at a given lag m (ρm) can be interpreted as

$$\rho m = \frac{\gamma m}{\gamma 0}$$

Where γm is the covariance at lag m and $\gamma 0$ is the variance.

The above equation represents the ratio of sample covariance between two different values (*m* lags apart) to sample variance. It is a unit less figure lies between -1 to +1 similar to any other correlation coefficient.

1. Principal Component Analysis (PCA)

PCA can be used to find commonality between returns of different assets. This helps to provide important information about the degree of correlation among different classes of assets as well as helpful to display similarity pattern, if any. For example, if asset's return is driven by j factor model, then first j principal components should explain most of return variations in selected assets. More formally PCA comprises of two results. Covariance matrix provides information about the proportion of each component (asset) with their respective eigen values and matrix of corresponding eigen vectors. Each eigen value, after being normalised to sum of one, can be understood as fraction of total variance of turnover corresponding to respective principal component. We therefore use PCA to capture the effect of co movement among asset returns. This can provide important information about linkage (an aspect of systemic risk) among chosen assets.

2. Granger Causality Test

In order to effectively measure systemic risk, it is necessary to establish the relationship between two variables with direction of causality along with the degree of correlation as measured through PCA (see above). One popular test in this regard is Granger causality. Fundamentally, a variable A is said to 'granger cause' another variable B if past values of A can help predicting B jointly with past values of B alone. So basically, it is a linear regression of A on B. Once again, in an efficient market framework, current price of a given asset should not be affected by lagged values of other variables. However, in reality, presence of market frictions may granger cause and hence from this viewpoint, this technique can be used as a proxy for measuring transmission of risk among different asset classes.

3. Regime Switching Model

Ability to recoup from black swan events implies the magnitude and depth of systemic risk. Black swan events result in sudden regime shift in pattern of both volatility and return expectations from financial markets. The Asian crisis in 1997, the sub-prime crisis of 2007 to 2009, covid 19, all indicate regime shifts where linear models fail to capture abrupt and unexpected change in return and volatility. These changes can best be described through regime switching models. Fundamentally, in regime switching model, two states can be imagined, where both the parameters characterising each state and the transitioning probability from one state to another are determined from data. Many of earlier studies have used regime switching model for capturing different aspects of financial market. Hamilton (1989) used to study non time series and business cycle. Gonzalez and Hesse (2011) used Markov switching model on key macroeconomic variables to detect any indication of regime change before starting of a crisis. Liu (2017) used regime switching in tails to measure adverse shocks to balance sheet of some large banks in the US. In this paper, we propose to use a two-state MS GARCH for each of the indices separately to measure probability of switching between normal and extreme market states. The generalised equation for index returns which satisfy following stochastic process is given below.

$$R_{i,t} = \mu_i (Z_{i,t}) + \sigma_i (Z_{i,t}) \, u_{i,t}$$

$R_{i,t}$ is index's excess return in time t, $Z_{i,t}$ represents a two state Markov chain with transition matrix $P_{z,i}$ for index i. σ_i represents index's volatility, $u_{i,t}$ is *i.i.d* error term. By convention, value of $Z_{i,t}$ as zero and one indicate low and high volatility regime respectively.

Data and Descriptive Statistics

Daily closing price data were collected from website of National Stock Exchange[1] related to Nifty 50, Bank, Commodity and 5-Yr G-sec. We selected a time period covering pre and post sub-prime crisis i.e., from 3rd January 2006 to 31st December 2010 (total 1239 longitudinal observations) thus, representing better fit for measuring resilience in Indian capital market. The events of 2007-2009 have perhaps been the most devastating one in financial market history of the current century after the Great Depression of 1929. The analysis is carried in two sub- periods (i.e., first period from 3rd January, 2006 to 5th September, 2008 and second period from 8th September, 2008[2] to 31st December 2010) to determine the shift in systemic risk covering the period of financial crisis of 2007-2009. All price data were converted to log returns using $R_t = ln\left(\frac{Pt}{Pt-1}\right)$. The following table (Table 1) shows results of descriptive statistics and stationarity

Table 1: Result of Descriptive Statistics and Stationarity

Panel A: Descriptive Statistics

Parameters	Ret. Nifty 50	Ret. Nifty Bank	Ret. Nifty 5yr Gsec	Ret.Nifty commodities
Mean	0.000623	0.000767	0.000598	0.000725
St. Deviation	0.019409	0.024345	0.010375	0.021133
Skewness	-0.015979	0.057715	-0.375531	-0.400975
Kurtosis	6.835232	3.736831	5.865860	6.411160
JB	2423.2(0.000)	725.78(0.000)	1814.2(0.000)	2165.3(0.000)
ARCH LM test	108.32(0.000)	104.3(0.000)	141.74(0.000)	149.6(0.000)

Note: JB is Jarque-Bera test of normality, p values are in brackets.
Source: *Author's Calculations*

Panel B: Unit Root Tests

Parameters	Ret. Nifty 50	Ret. Nifty Bank	Ret. Nifty 5yr Gsec	Ret.Nifty commodities
ADF	-10.213(0.01)	-10.169(0.01)	-10.409(0.01)	-10.323(0.01)
PP	-1109.4(0.01)	-997.14(0.01)	-1112.4(0.01)	-1099.2(0.01)

Source: *Author's Calculations*

Panel A shows that the mean of the series for all four indices is positive with highest daily standard deviation of 0.024 for Nifty bank series. Except Nifty bank, the skewness is negative for of Nifty 50, Nifty commodity and Nifty 5yr G sec. Negative skewness indicates a relatively small asymmetry in the distribution. Negative skewness may indicate risk of 'black swan events.' All the series appears to be leptokurtic indicating a fat tail, a common characteristic for financial data. JB statistic (significant at 1%) shows non-normality of datasets. Along with this variance during the sample period was found to be heteroscedastic as evident from ARCH LM test. Panel B presents stationarity test results. Both the result of ADF and PP tests reject null hypothesis of presence of unit root, indicating data are suitable for further analysis.

Empirical Results

1. Result of Autocorrelation Plot

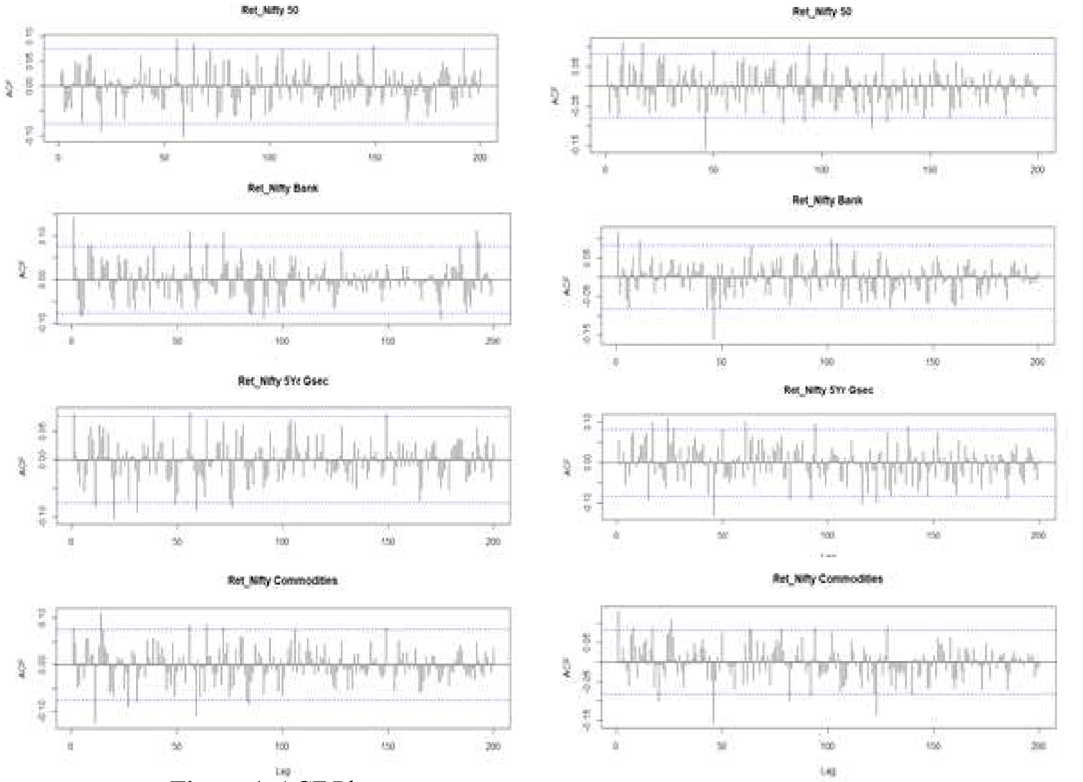


Figure 1: ACF Plot

The above figures (Figure 1) show autocorrelation function (ACF) plot for four indices over the sample period. Left hand side panel shows ACF plot of period 1 (from 3rd January, 2006 to 5th September, 2008) and right-hand side panel shows that of period 2 (from 8th September, 2008 to 31st December 2010). More early spikes breaking the threshold limit (set on either side) in case of Nifty 50, Nifty 5yr G sec and Nifty commodities (in right hand side panel) indicate a likely correlation value (statistically significant at 95% confidence interval) at early lags. This may be interpreted as relatively lower resilience due to low liquidity in these three indices post sub-prime crisis. This means sub-prime crisis has considerable impact on these three indices.

2. Result of Principal Component Analysis

The above figure (Figure 2) represents correlation matrix among four indices. It is clear that there exists a high positive correlation among these four indices over the sample period. But in order to select which among these are mostly correlated, the following table (Table 2) is useful.

This shows the proportion of total variance with cumulative proportions of each index. It is evident that Nifty 50 and Nifty bank explain around 97% in period 1 and 92% in period 2 of total variance. Table 3 presents loading matrix of two components (i.e., Nifty fifty and bank Nifty). This shows that Nifty fifty has high positive values for all except Nifty bank (negative value) in both the periods. So far as the second component (Nifty bank) is concerned, it has negative value for Nifty commodities in period 1 and for Nifty 5-Yr G sec in period 2. This suggests Nifty 50 is highly impacted by other three except Nifty bank in both the periods. This can be interpreted as presence of strong linkage among these indices except Nifty bank. However, for Nifty bank, the linkage is positive in period 1 with other three indices except Nifty commodity which gets altered after crisis period. In period 2 the loading value of 0.759 for Nifty commodity indicates that most investors might have included commodity post crisis period since commodities investment are good hedge against inflation and perceived to have negative correlation with financial assets. The proportion of total variance is presented in scree plots of two periods (Figure 3).

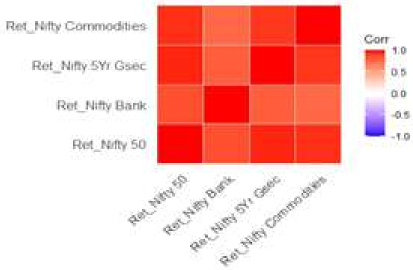


Figure 2: Correlation Matrix

Table 2: Importance of Components

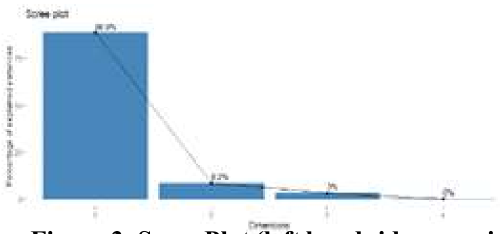
Parameters	Period 1				Period 2			
	Nifty fifty	**Bank Nifty**	**Nifty 5yr G sec**	**Nifty commodities**	**Nifty fifty**	**Bank Nifty**	**Nifty 5yr G sec**	**Nifty commodities**
Standard Deviation	0.14843	0.04515	0.02719	0.00000	0.10911	0.05833	0.03441	0.00000
Proportion of Variance	0.88800	0.08219	0.02980	0.00000	0.72188	0.20629	0.07181	0.00000
Cumulative Proportion	0.88800	0.97019	1.00000	1.00000	0.72188	0.92818	1.00000	1.00000

***Source**: Author's Calculations*

Table 3: Loading Matrix

Indices	Period 1		Period 2	
	Nifty fifty	**Bank Nifty**	**Nifty fifty**	**Bank Nifty**
Nifty 50	0.32305	0.493605	0.196930	0.3244045
Nifty bank	-0.598306	0.346477	-0.674862	0.1437398
Nifty 5Yr G sec	0.465149	0.655960	0.5561682	-0.5455418
Nifty Commodity	0.566831	-0.453897	0.443234	0.7592659

***Source**: Author's Calculations*



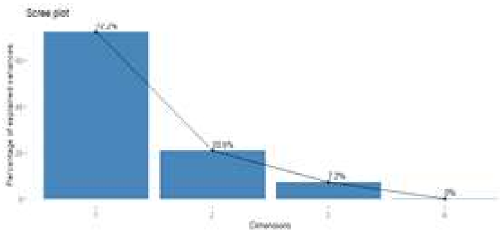


Figure 3: Scree Plot (left hand side pre-crisis period and right-hand side post-crisis period)

3. Result of Granger Causality Test

In the following two tables (Table 4 and Table 5), results of pairwise Granger causality tests are presented for two lags. We can see that there is more causality in post crisis period between indices (at lag 3) compared to Pre-crisis period. This is an indication of more asymmetry of information flow across indices post crisis. This implies relatively lower resilience of Indian capital market despite of considerable liquidity of Nifty indices in normal period. Past returns on Nifty bank effects Nifty 50 before crisis period, however during crisis period it only affects Nifty 5Yr G-sec returns.

Table 4: Pre-crisis Period

Null hypothesis	Lag2		Lag 3	
	F-statistic	Prob.	F-statistic	Prob.
Nifty 5Yr GSec ? Nifty 50	2.20242	0.1113	1.68200	0.1696
Nifty 50 ? Nifty 5Yr Gsec	3.42423	**0.0332**	2.59858	0.0513
Nifty bank ? Nifty 50	4.61458	**0.0102**	3.26339	**0.0211**
Nifty 50 ? Nifty bank	2.43799	0.0881	1.64605	0.1775
Nifty commodities ? Nifty 50	1.35947	0.2575	1.67557	0.1710
Nifty 50 ? Nifty commodities	1.87439	0.1543	1.70489	0.1647
Nifty bank ? Nifty 5Yr Gsec	2.82428	0.0601	2.03421	0.1078
Nifty 5 Yr Gsec ? Nifty bank	2.27132	0.1040	1.70656	0.1644
Nifty commodities ? Nifty 5 Yr Gsec	0.24959	0.7792	2.40155	0.0666
Nifty 5Yr Gsec ? Nifty commodities	0.02242	0.9778	2.27081	0.0792
Nifty commodities ? Nifty bank	3.63669	**0.0269**	2.26390	0.0799
Nifty bank ? Nifty commodities	4.07747	0.0174	2.55233	0.0546

***Source**: Author's Calculations*

Table 5: Post-crisis Period

Null hypothesis	Lag2		Lag 3	
	F-statistic	Prob.	F-statistic	Prol
Nifty 5Yr GSec ? Nifty 50	2.83689	0.0594	3.74209	**0.01**
Nifty 50 ? Nifty 5Yr Gsec	3.58444	**0.0284**	5.03235	**0.00**
Nifty bank ? Nifty 50	1.83266	0.1609	1.25840	0.28
Nifty 50 ? Nifty bank	0.85385	0.4263	0.76766	0.51
Nifty commodities ? Nifty 50	0.79669	0.4513	0.58587	0.62
Nifty 50 ? Nifty commodities	0.68764	0.5032	0.35483	0.78
Nifty bank ? Nifty 5Yr Gsec	3.69805	**0.0254**	2.97574	**0.03**
Nifty 5 Yr Gsec ? Nifty bank	1.64819	0.1933	1.31821	0.26
Nifty commodities ? Nifty 5 Yr Gsec	1.37058	0.2548	2.97735	**0.03**
Nifty 5Yr Gsec ? Nifty commodities	1.52311	0.2189	1.85649	0.13
Nifty commodities ? Nifty bank	1.87322	0.1546	1.45908	0.22
Nifty bank ? Nifty commodities	2.30489	0.1007	1.37315	0.25

***Note**: Does not granger cause is represented through Ï!*

***Source**: Author's Calculations*

4. Result of Two State Markov Switching GARCH

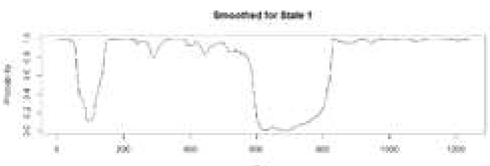
In the following table (Table 6) estimates of two state Markov switching GARCH are presented. α_0 is intercept term which has zero mean in both first and second states for all the four indices. α_1, the lagged squared error is significant for both the states. A high $\beta_,$ the lagged variance term is very high for all the indices under both states. $p_{\_1\_1}$ and $p_{\_2\_1}$ refer to transition probabilities between two states. The result indicates that there is high likelihood of being in a given state for all the four indices. For instance, in case of Nifty 50, estimate of $p_{\_1\_1}$ is 0.9968 which implies that there is 99% probability that it will remain in state 1 with only 1% chance of being changing into state 2. The same states are presented below (Figure 4) showing two-state regime switching plot for all the four indices covering both pre and post sub-prime crisis.

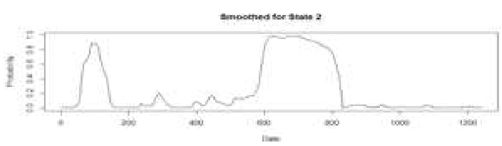
Table 6: Estimates of Two State MS GARCH

Parameters	Nifty fifty	Bank Nifty	Nifty 5yr G sec	Nifty commod
α_{0_1}	0.0000(0.0000)	0.0000(0.0097)	0.0000(0.0021)	0.0000(0.0011)
α_{1_1}	0.0935(0.0002)	0.0234(0.0188)	0.0907(0.0050)	0.0683(0.0040)
$\beta_{\_1}$	0.8786(0.0000)	0.9597(0.0000)	0.8615(0.0000)	0.8952(0.0000)
$?_{\_1}$	5.3848(0.0000)	5.1480(0.0000)	23.8246(0.0158)	6.4184(0.0000)
α_{0_2}	0.0000(0.0000)	0.0000(0.0065)	0.0000(0.0013)	0.0001(0.0036)
α_{1_2}	0.1344(0.0116)	0.0814(0.0199)	0.1685(0.0041)	0.1764(0.0087)
$\beta_{\_2}$	0.8222(0.0000)	0.8994(0.0000)	0.7524(0.0000)	0.7681(0.0000)
$?_{\_2}$	90.8242(0.0297)	99.9343(0.0000)	6.4552(0.0000)	9.8968(0.0042)
$p_{\_1\_1}$	0.9968 (0.0000)	0.9846(0.0000)	0.9932(0.0000)	0.9962(0.0000)
$p_{\_2\_1}$	0.0112(0.0000)	0.0221(0.0015)	0.0088(0.0044)	0.0081(0.0010)
LL	3375.9387	3023.2866	4155.2385	3289.0125
AIC	-6731.8773	-6026.5731	-8290.477	-6558.025
BIC	-6680.6567	-5975.3525	-8239.2564	-6506.8044

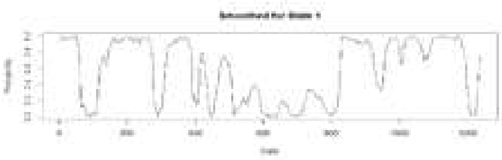
Note: *Figures in bracket indicate p values.*
Source: *Author's Calculations*

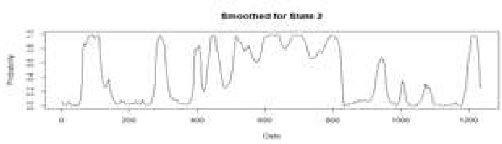
Nifty 50



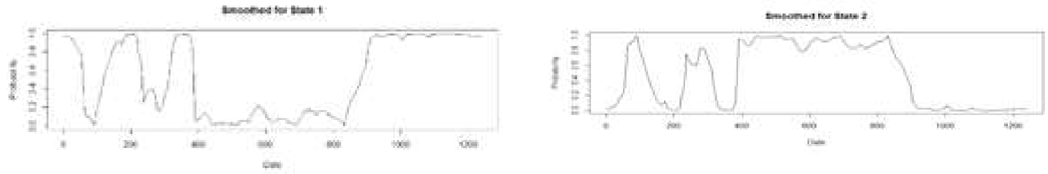


Nifty bank





Niftv 5 Yr Gsec



Nifty commodity

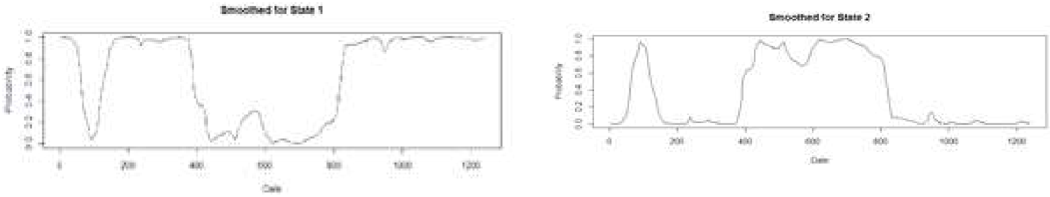


Figure 4: Smoothed state plots of state 1 (left) and state 2 (right) for each of the four indices

Implications and Conclusion

We measure statistically three different aspects of such risk; liquidity, degree of interconnectedness and asymmetry using daily data of four main indices representing equity, banking, fixed income and commodities sector. We strongly believe that measuring resilience directly of financial market is very difficult due to inherent characteristics of financial markets. In this paper, we didn't measure resilience but provided an alternative way of gauging resilience through measurement of systemic risk. Quantifying systemic risk assess the present state of financial market and thus giving indication about speed of recovering from a crisis.

The findings of the study have the following implications. First, classical efficient market theory assumes reflection of all available information instantaneously into the asset price. However, Adaptive Market Hypothesis of Lo (1994) assumes the evolution of market over time under EMH framework. This is confirmed from output of Granger causality test which implies more asymmetry of information flow across chosen indices post crisis. However, the result of two states MS GARCH is indicative of no sudden regime change during and after the crisis period. This contradiction of increasing asymmetry and steady regimes may have behavioural implications. Second, post 1991 reforms in Indian financial market, particularly the banking sector has been beneficial which integrated its different segments to a greater extent. This results in easy and quick information flow across different markets segments not only within an economy but also across countries. This is confirmed from results of correlation studies. Third, liquidity in market is a good proxy for measuring market depth. With more randomness, liquidity is supposed to be dried up and vice versa according to Noise theory. The theory suggests mispricing; market inefficiencies measured through a large bid-ask spread and trading cost during and after crisis. The same is also confirmed from results of PCA and correlation. Empirical results from PCA and Granger causality test indicate that during and after crisis period, equity market other than banking sector, can be an important source of systemic risk. Results of Markov switching GARCH has however given no indication of regime change during sample period.

The subject of this kind is definitely helpful to policymakers, especially in judging the effectiveness of existing ones and accordingly planning for desired policy interventions to mitigate any future systematic risk in financial market. This apart, the study gives important cues about measuring market risk which helps portfolio managers to optimise their investment allocation decisions.

Scope for Future Research

The present study is based on the framework of efficient market notion where readymade price data are used as input variables to measure systemic risk in Indian market. The same study can be further to include more market segments within or across countries to get more meaningful conclusion about the source systematic risk. The same study could be undertaken using time varying models so as to effectively capture the dynamic nature of datapoints. This will be helpful in understanding interrelation among financial variables in a much better way. This apart, there is a scope to examine the impact of key macro-economic variables such as income distribution, employment, inflation and policy rates on financial market return and risk. The study can also be further with application of artificial intelligence techniques in measuring and predicting systematic risk. This will unearth any hidden pattern and early warning indicators in data which would not only be helpful in comparison of model performances, but also to reconfirm theories of statistical models used in this paper.

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