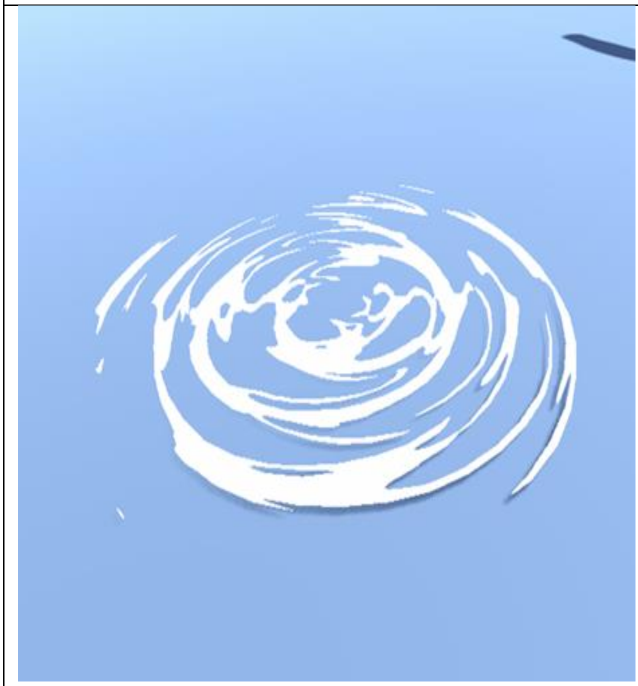
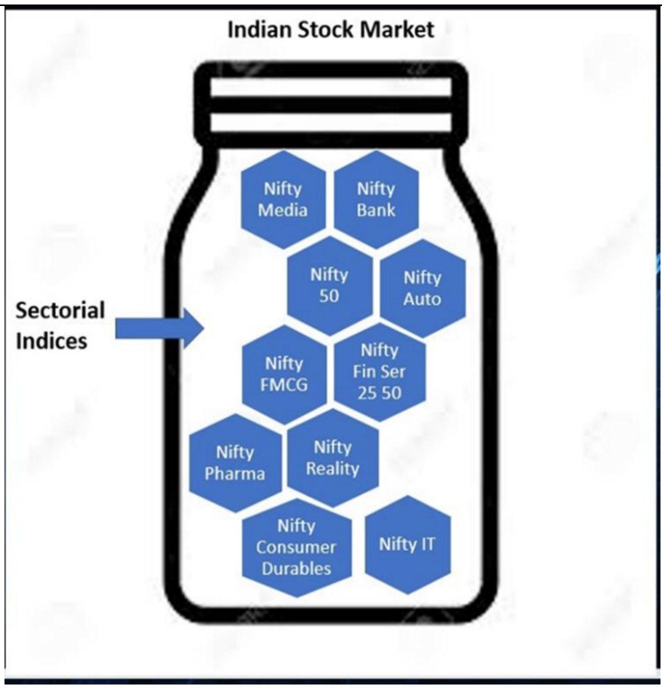
Project Title

Measuring Connectedness & Spill Over
In
Indian Stock Market





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1. Problem Statement & Objective

Problem Statement

Predicting stock prices is a very complex process as the price of a stock depends on macroeconomic factors such as GDP, Unemployment rate etc and factors related to the company such as new investors etc. Taking these into consideration is not enough as many sectors in the stock market are interrelated which means that changes in one sector could have a direct influence and effect on another.

Understanding how markets are connected and shocks are transmitted is an important issue for policymakers and market participants.

Objectives

In our project , we examine the connectedness of various sector indices of Indian Market. Using time-varying connectedness measures, we address the following questions:

(1) How has connectedness in asset returns changed over time? Do markets become more connected during crises periods?

(2) Which sector are major sources and major recipients of shocks? Has there been a shift in terms of the net shock givers and shock receivers (directional connectedness over time)?

Finally, we investigate the connectedness between various Sector Indices since 2007 to Oct 2021 highlighting the importance of one sector indices as a source of shocks

Business prospects

The results have considerable implications for portfolio managers and institutional investors in the evaluation of investment and asset allocation decisions.

The market participants should pay more attention to assess the worth of across linkages among the markets and their volatility transmissions

Additionally, portfolio managers and hedgers may be better able to understand how the returns linkage between various sectors interrelated overtime; this situation might provide them benefit in forecasting the behaviour of one sector by capturing the other sector information.

2. Detailed Design Description

Vector Auto Regressive (VAR):

The vector autoregressive (VAR) model is a multivariate time series model that relates current observations of a variable with past observations of itself and past observations of other variables in the system. VAR models differ from univariate autoregressive models because they allow feedback to occur between the variables in the model. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and for forecasting. It often provides superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model

What makes up a VAR model?

It is a model that is made up of a system of equations that represents the relationships between multiple variables. When referring to VAR models, we often use special language to specify:

- How many endogenous variables there are included
- How many autoregressive terms are included.

Let Yt =(y1t,y2t,…,ynt) denote an (n*1) vector of timeseries variables. The Basic p-lag vector autoregressive (VAR(p)) model has the form

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t, \quad t = 1, \ldots, T$$

Where Π_i are (n *n) coefficient matrix and ε_t is an (n*1) unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix Σ. For example , a bivariate VAR(2) model equation has the form

$$y_{1t} = c_1 + \pi^1_{11} y_{1t-1} + \pi^1_{12} y_{2t-1} + \Pi^2_{11} y_{1t-2} + \pi^2_{12} y_{2t-2} + \varepsilon_{1t}$$

$$y_{2t} = c_2 + \Pi^1_{21} y_{1t-1} + \pi^1_{22} y_{2t-1} + \pi^2_{21} y_1 t - 2 + \Pi^2_{22} y_{2t-2} + \varepsilon_{2t}$$

where $cov(\varepsilon_{1t}, \varepsilon_{2s}) = \sigma_{12}$ for $t = s$; 0 otherwise. Notice that each equation has the same regressors — lagged values of y1t and y2t. Hence, the VAR(p) model is just a seemingly unrelated regression (SUR) model with lagged variables and deterministic terms as common regressors.

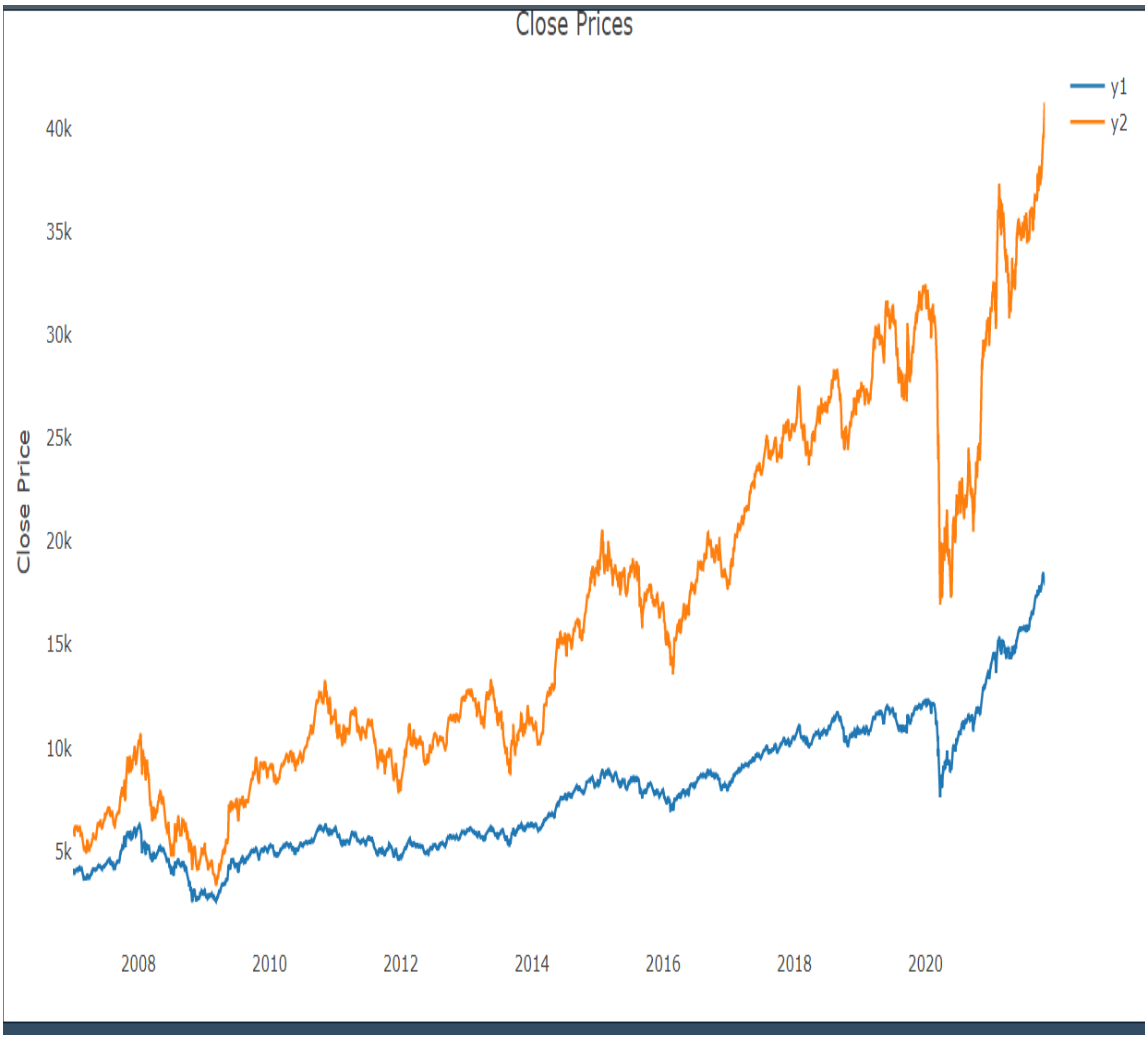
Reduced form VAR models consider each variable to be a function of:

- Its own past values.
- The past values of other variables in the model.

While reduced form models are the simplest of the VAR models, they do come with disadvantages:

- Contemporaneous variables are not related to one another.
- The error terms will be correlated across equations. This means we cannot consider what impacts individual shocks will have on the system.

However, a key issue with reduced form VAR models is that is usually impossible to disentangle what impact a sudden change in one variable will have on the other variables in the model.



Structural VAR models:

- Allow us to examine the causal relationships between variables.
- Use economic theory to add structural restrictions to the VAR model.
- Can be used to examine the impact individual shocks will have on other variables.

The Relationship Between SVAR and Reduced Form VAR Models

Let's take a closer look at the mathematics of the structural VAR and reduced form VAR models. We will do this in a simple bivariate model with two endogenous variables, Y1 and Y2.

Suppose we believe that Y1 and Y2 can both be modelled using:

1. Past observations of Y1 and Y2 going back one period.

2. Random shocks to each variable, $\epsilon 1,t$ and $\epsilon 2,t$.

Mathematically we can represent this in a two-equation system:

$$y_{1,t} = \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + b_{11} \epsilon_{1,t} + b_{12} \epsilon_{2,t}$$
$$y_{2,t} = \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + b_{21} \epsilon_{1,t} + b_{22} \epsilon_{2,t}$$

This structural VAR model includes separate contemporaneous shocks to each variable, $\epsilon 1,t$ and $\epsilon 2,t$. These shocks are:

- Unobservable and zero-mean white noise processes.
- Serially uncorrelated and independent of each other.

In this model the matrix

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

captures the structural impacts the shocks $\epsilon 1,t$ and $\epsilon 2,t$ have on the endogenous variables Y1 and Y2.While this may look like a straightforward system of equations, remember that $\epsilon 1,t$ and $\epsilon 2,t$ are unobserved, leaving us unable to estimate B.

This is where the reduced form VAR comes into play. To see this, let's combine the "shock" components of each equation such that we define:

$$u_{1,t} = b_{11}\epsilon_{1,t} + b_{12}\epsilon_{2,t}$$
$$u_{2,t} = b_{21}\epsilon_{1,t} + b_{22}\epsilon_{2,t}$$

Now our two-equation system becomes a reduced form VAR model:

$$y_{1,t} = \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + u_{1,t}$$
$$y_{2,t} = \phi_{21}y_{1,t-1} + \phi_{22}y_{2,t-1} + u_{2,t}$$

We can use OLS to estimate our unknown parameters in the reduced form VAR model

$$\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$$

However, the residuals from these estimates do not allow us to determine the impacts of the shocks ϵ1,t and ϵ2,t on Y1 and Y2.

To back out the impacts of the shocks ϵ1,t and ϵ2,t on Y1 and Y2 from our reduced form model, it is natural to begin at the relationship

$$u_{1,t} = b_{11}\epsilon_{1,t} + b_{12}\epsilon_{2,t}$$
$$u_{2,t} = b_{21}\epsilon_{1,t} + b_{22}\epsilon_{2,t}$$

or in matrix form

Ut=Bϵt

From this relationship we can derive, using linear algebra and a few statistical relationships, the identity that is at the heart of implementing structural VAR relationships:

Σu=BB′

where Σu is the covariance matrix of the reduced form residuals:

Σu=E[ut′ut]

To see the issue with this, let's again consider what this implies in our two-variable system. First, note that Σu is the covariance matrix of the residuals from our reduced form model:

$$\Sigma_u = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix}$$

This means that Σu=BB′ is equivalent to

$$\begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix}$$

which we can further expand to a system of equations

$$\sigma_{11}^2 = b_{11}^2 + b_{12}^2$$
$$\sigma_{12}^2 = b_{11}b_{21} + b_{12}b_{22}$$
$$\sigma_{21}^2 = b_{11}b_{21} + b_{12}b_{22}$$
$$\sigma_{22}^2 = b_{21}^2 + b_{22}^2$$

Note though,that . $\sigma_{12}^2 = \sigma_{21}^2$ This means we have only 3 unique equations but 4 unknowns - this makes the model *under-identified*. This is the **identification problem** posed by structural VAR models.

To solve this problem, we need more equations -- these equations come in the form of restrictions.

Picking up Restrictions:

Identifying restrictions can take many forms such as:

- No short-run effects.
- No long-run impacts.
- Sign restrictions.

Picking restrictions to identify SVAR models can seem daunting. However, the guiding factor in determining restrictions should always be the theoretical background . In this Model we imposed zero short -run restrictions.

Zero short-run restrictions (Cholesky identification):

This identification scheme assumes that some shocks have no contemporaneous effect on one or more of the endogenous variables. For example, we may believe that shocks to monetary policy do not have an immediate impact on aggregate demand.

How do we implement zero short-run restrictions?

From our previous bivariate structural VAR representation:

$$
\begin{aligned}
y_{1,t} &= \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + b_{11}\epsilon_{1,t} + b_{12}\epsilon_{2,t} \\
y_{2,t} &= \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + b_{21}\epsilon_{1,t} + b_{22}\epsilon_{2,t}
\end{aligned}
$$

If we believe that shocks to y2 have no contemporaneous impacts on y1 this implies that b12=0.

Put in the context of our B matrix:

$$B = \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix}$$

Notice that we can order our variables such that the B matrix is lower triangular. This allows us to use the Cholesky decomposition of Σu for estimation.

Moving average representation of a VAR

If we assume that the VAR(p) model is a stable, we can derive its infinite moving average representation by using either recursive substitution, or lag operators. Since we can easily write any VAR(p) model as a VAR(1), with the aid of the companion-form, we will make use of the VAR model that was formulated in equation . Hence, when given

$$y_t = C + \Pi_1 y_{t-1} + \epsilon_t$$

The same equation can be written as

$$y_t = \mu + A_1 Y_{t-1} + U_t$$

and using recursive substitution, we can show that,

$$y_t = \left\langle 1 + A_1 + A_1^2 + \cdots A_1^j \right\rangle \mu + A_1^{j+1} y_{t-(j+1)}$$
$$+ \left(\bigcup_t + A_1 U_{t-1} + \cdots + A_1^j U_{t-j} \right)$$

Where $A_1^0 = 1$. When the process is stable,$[I + A_1 + \cdots + Aj']\mu \to [I - A_1]^{-1}\mu$ as j→∞. In addition ,as $A_1^{J+1} y_{t-J-1} = 0$ it will be j→∞.Hence ,the equation reduces to

$$y_t = \Psi + \Sigma_{j=0}^{\infty} A_1^j U_{t-J}$$

Where $\psi = (1 - A_1)^{-1}\mu$. Note that equation is called the moving average representation of the VAR. This could be written in terms of the moving average coefficients as,

$$y_t = \psi + \sum_{J=0}^{\infty} B_j U_{t-j}$$

where $B_j = A_1^J$, and $B_0 = I$.

Full Sample Spill over Table And Connectedness Table:

Step 1. Vector Autoregression (VAR)

The difference between spillovers and connectedness is the difference between assuming errors are orthogonal versus correlated. To estimate a model with correlated errors is as simple as feeding a VAR the set of variables one wants to analyze. To estimate a model with orthogonal errors using variables which are correlated requires imposing a structure on the VAR to achieve independent error terms. The vars package in R has VAR and SVAR functions vars The SVAR function estimates a Structural VAR by giving it a matrix that is structured according to a set of assumptions. For this Model we used a lower triangular matrix of coefficients with 1s along the diagonal as the Sims critique stipulates.

Step 2. Moving Average Representation

Any type of autoregression of order p can be converted to a moving average of order q as long as the coefficients of the AR(p) are between -1 and 1. The vars package includes a function Phi which will do this conversion for us by specifying the order q of MA we want to use in this case . From this estimate the MA coefficients are retrieved, along with the residual errors from the VAR, for the next steps.

Lag length selection

The lag length for the VAR(p) model may be determined using model selection criteria. The general approach is to fit VAR(p) models with orders p = 0, ..., pmax and choose the value of p which minimizes some model selection criteria. Model selection criteria for VAR(p) models have the form

$$Ic_{(p)} = \ln\left|\tilde{\Sigma}(p)\right| + c_T\varphi(n, P)$$

where $\tilde{\Sigma}(p) = T^{-1}\Sigma_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t^1$ is the residual covariance matrix without a degrees of freedom correction from a VAR(p) model, cT is a sequence indexed by the sample size T, and φ(n, p) is a penalty function which penalizes large VAR(p) models. The three most common information criteria are the Akaike (AIC), Schwarz-Bayesian (BIC) and Hannan-Quinn (HQ):

$$AIC(P) = \ln\left|\tilde{\Sigma}(P)\right| + \frac{2}{T}Pn^2$$

$$BIC(P) = \ln\left|\tilde{\Sigma}(P)\right| + \frac{\ln T}{T}pn^{\dot{L}}$$

The AIC criterion asymptotically overestimates the order with positive probability, whereas the BIC estimate the order consistently under fairly general conditions if the true order p is less than or equal to pmax.

Impulse Response function

Impulse response functions trace the dynamic impact to a system of a “shock” or change to an input. While impulse response functions are used in many fields, they are particularly useful in economics and finance for a number of reasons:

- They are consistent with how we use theoretical economic and finance models. Theoretical economists develop a model, then ask how outcomes change in the face of exogenous changes.
- They can be used to predict the implications of policy changes in a macroeconomic framework.

- They employ structural restrictions which allow us to model our believed theoretical relationships in the economy.

In stationary systems, we expect that the shocks to the system are not persistent and over time the system converges. When the system converges, it may or may not converge to the original state, depending on the restrictions imposed on our structural VAR model.

For example, Blanchard and Quah(1989) famously demonstrated the use of long-run restrictions in a structural VAR to trace the impact of aggregate supply and aggregate demand shocks on output and unemployment. In their model:

- They allow aggregate supply shocks to have lasting effects on output.
- Assume that aggregate demand shocks do not have lasting effects on long-run output.

As a result, when a positive aggregate supply shock occurs, output converges to a higher level than before the shock.

For the SVAR, the function fevd.matrix in the code implements the IRF and FEVD calculations, taking the covariance matrix of SVAR residuals and MA coefficients as inputs. To find the IRF derive the lower-triangular Cholesky-decomposition of the residuals' covariance matrix. The MA coefficient matrix is impact of the shocks and the lower triangular matrix imposes the independence of the shocks that is assumed in the SVAR.

Forecast error Variance decomposition:

A forecast variance decomposition measures the fraction of the overall forecast variance for a variable that can be attributed to each of the driving shocks. In SVAR model variance decomposition compute the share of a structural shock in the fluctuations of a variable in the VAR, yet this procedure has the important drawback that only the contemporaneous orthonormality of the structural shocks is imposed on the model but the orthogonality of them across time.

$$\theta_{Ij}^{0} = \frac{\Sigma_{l=0}^{n}(e_i' A_h Pej)^2}{\sum_{l=0}^{n}(e_i' A_l \Sigma A_l' e_i)}$$

The numerator is just the impulse response and the denominator is the total forecast error in a system of variables and Σ is the error covariance matrix. The forecast error variance of variable i attributable to variable j is the impulse response of j on i divided by the total forecast error of i.

3. Experiment and Results

Experiment and Results

FINANCIAL CRISIS ANALYSIS – 2008

INTRODUCTION :

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DJIA 10917.51 ▼504.48 -4.4% NASDAQ 2179.91 ▼3.6% NIKKEI Closed(12214.76) DJ STOXX 50 2744.81 ▼4.0% 10-YR TREAS ▲2 3/32, yield 3.482% OIL $95.71 ▼$5.47 GOLD $783.10 ▲$22.80 EURO $1.4310 YEN 104.88

AIG, Lehman Shock Hits World Markets

Focus Moves to Fate of Giant Insurer After U.S. Allows Investment Bank to Fail; Barclays in Talks to Buy Core Lehman Unit

The convulsions in the U.S. financial system sent markets across the globe tumbling, as two of Wall Street's biggest firms looked set to exit the scene and insurance titan American International Group Inc. turned to the Federal Reserve and the state of New York for assistance.

By Susanne Craig, Jeffrey McCracken, Jon Hilsenrath and Deborah Solomon

The U.S. stock market suffered its worst daily point plunge since the first day of trading after the Sept. 11, 2001, terrorist attacks. Financial markets were rattled by the rushed sale Sunday of Merrill Lynch & Co. and the bankruptcy-court filing of Lehman Brothers Holdings Inc., which scrambled Monday to sell its most-prized businesses before too many employees and customers walk out the door. (Please see related article on Page C1.)

All day Monday, top Lehman officials were huddled in Manhattan at their Seventh Avenue headquarters negotiating a sale of the U.S. investment bank—the core part of Lehman—to Barclays PLC of the U.K. People involved in the discussions were increasingly hopeful late Monday evening. For much of the day, the major U.S. market indexes were down 2%, which, while a good-sized decline, was smaller than many had thought would be the case. But in the final hour of trading, a wave of selling hit, driven by concerns about the fate of AIG. The Dow Jones Industrial Average ended down 504.48 points on Monday, off 4.4%, at its daily low of 10917.51, down 18% on the year. Of the Dow industrials' 30 components, all but one—Coca-Cola Co.—fell, led by a 60.8% plunge in AIG.

In Europe, London's FTSE 100 index dropped 3.9%. Several Asian markets, including Japan and China, were closed Monday due to holiday. By Tuesday, Tokyo shares were down 5.1% in early trading, and Hong Kong's Hang Seng index was down 6.1%.

Monday's action was the latest fallout in a widening financial crisis that began a year ago with the fall of American housing prices and is now reordering the U.S. financial system. Steps unveiled by the Federal Reserve to expand its emergency lending arsenal did little to snap the sense of gloom.

Plenty of potential land mines remain. Banks are increasingly hoarding cash, curbing lending at a time when the econ-

AIG Faces Cash Crisis As Stock Dives 61%

BY MATTHEW KARNITSCHNIG, LIAM PLEVEN AND SERENA NG

American International Group Inc. was facing a severe cash crunch last night as ratings agencies cut the firm's credit ratings, forcing the giant insurer to raise $14.5 billion to cover its obligations.

With AIG now tottering, a crisis that began with falling home prices and went on to engulf Wall Street has reached one of the world's largest insurance companies, threatening to intensify the financial storm and greatly complicate the government's efforts to contain it. The company, whose stock fell 61% yesterday, is such a big player in insuring risk for institutions around the world that its failure could shake the global financial system.

The financial crisis of 2007-2008 was years in the making. By the summer of 2007, financial markets around the world were showing signs that the reckoning was overdue for a years-long binge on cheap credit. Two Bear Stearns hedge funds had collapsed, BNP Paribas was warning investors that they might not be able to withdraw money from two of its funds, and the British bank Northern Rock was about to seek emergency funding from the Bank of England.

Yet despite the warning signs, few investors suspected that the worst crisis in nearly eight decades was about to engulf the global financial system, bringing Wall Street's giants to their knees and triggering the Great Recession. It was an epic financial and economic collapse that cost many ordinary people their jobs, their life savings, their homes, or all three.

Sowing the Seeds of the Crisis :

The seeds of the financial crisis were planted during years of rock-bottom interest rates and loose lending standards that fuelled a housing price bubble in the U.S. and elsewhere. It began, as usual, with good intentions. Faced with the bursting of the dot-com bubble, a series of corporate accounting scandals, and the September 11 terrorist attacks, the Federal Reserve lowered the federal funds rate from 6.5% in May 2000 to 1% in June 2003. The aim was to boost the economy by making money available to businesses and consumers at bargain rates.

The result was an upward spiral in home prices as borrowers took advantage of the low mortgage rates. Even subprime borrowers, those with poor or no credit history, were able to realize the dream of buying a home. The banks then sold those loans on to Wall Street banks, which packaged them into what were billed as low-risk financial instruments such as mortgage-backed securities and collateralized debt obligations (CDOs). Soon a big secondary market for originating and distributing subprime loans developed.[4]

Fuelling greater risk-taking among banks, the Securities and Exchange Commission (SEC) in October 2004 relaxed the net capital requirements for five investment banks—Goldman Sachs (NYSE: GS), Merrill Lynch (NYSE: MER), Lehman Brothers, Bear Stearns, and Morgan Stanley (NYSE: MS). That freed them to leverage their initial investments by up to 30 times or even 40 times.

Signs of Trouble :

Eventually, interest rates started to rise and homeownership reached a saturation point. The Fed started raising rates in June 2004, and two years later the Federal funds rate had reached 5.25%, where it remained until August 2007.There were early signs of distress. By 2004, U.S. homeownership had peaked at 69.2%. Then, during early 2006, home prices started to fall.

This caused real hardship to many Americans. Their homes were worth less than they paid for them. They couldn't sell their houses without owing money to their lenders. If they had adjustable-rate mortgages, their costs were going up as their homes' values were going down. The most vulnerable subprime borrowers were stuck with mortgages they couldn't afford in the first place.

As 2007 got underway, one subprime lender after another filed for bankruptcy. During February and March, more than 25 subprime lenders went under. In April, New Century Financial, which specialized in sub-prime lending, filed for bankruptcy and laid off half of its workforce. By June, Bear Stearns stopped redemptions in two of its hedge funds, prompting Merrill Lynch to seize $800 million in assets from the funds. Even these were small matters compared to what was to happen in the months ahead.

August 2007: The Dominoes Start to Fall :

It became apparent by August 2007 that the financial markets could not solve the subprime crisis and that the problems were reverberating well beyond the U.S. borders. The interbank market that keeps money moving around the globe froze completely, largely due to fear of the unknown. Northern Rock had to approach the Bank of England for emergency funding due to a liquidity problem. In October 2007, Swiss bank UBS became the first major bank to announce losses—$3.4 billion—from sub-prime-related investments.[8]

In the coming months, the Federal Reserve and other central banks would take coordinated action to provide billions of dollars in loans to the global credit markets, which were grinding to a halt as asset prices fell. Meanwhile, financial institutions struggled to assess the value of the trillions of dollars worth of now-toxic mortgage-backed securities that were sitting on their books.

March 2008: The Demise of Bear Stearns :

By the winter of 2008, the U.S. economy was in a full-blown recession and, as financial institutions' liquidity struggles continued, stock markets around the world were tumbling the most since the September 11 terrorist attacks.

In January 2008, the Fed cut its benchmark rate by three-quarters of a percentage point—its biggest cut in a quarter-century, as it sought to slow the economic slide.

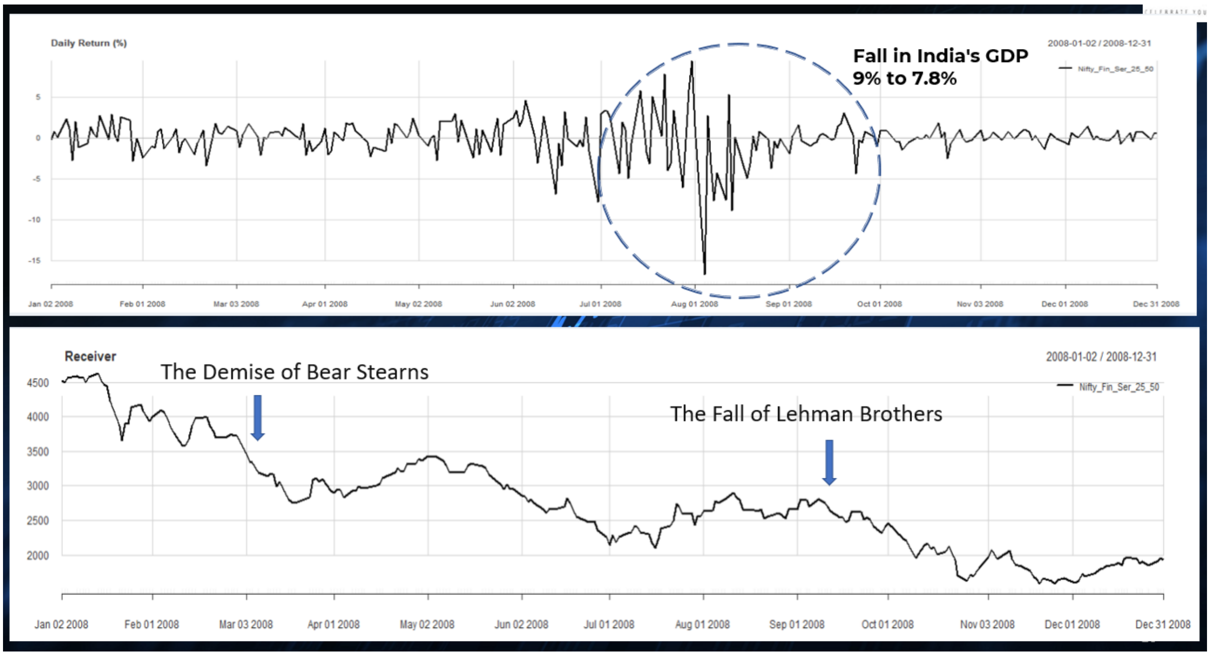
The bad news continued to pour in from all sides. In February, the British government was forced to nationalize Northern Rock. In March, global investment bank Bear Stearns, a pillar of Wall Street that dated to 1923, collapsed and was acquired by JPMorgan Chase for pennies on the dollar.

September 2008: The Fall of Lehman Brothers:

By the summer of 2008, the carnage was spreading across the financial sector. IndyMac Bank became one of the largest banks ever to fail in the U.S., and the country's two biggest home lenders, Fannie Mae and Freddie Mac, had been seized by the U.S. government. Yet the collapse of the venerable Wall Street bank Lehman Brothers in September marked the largest bankruptcy in U.S. history, and for many became a symbol of the devastation caused by the global financial crisis.

That same month, financial markets were in free fall, with the major U.S. indexes suffering some of their worst losses on record. The Fed, the Treasury Department, the White House, and Congress struggled to put forward a comprehensive plan to stop the bleeding and restore confidence in the economy.

Nifty Financial Services Index – 2008

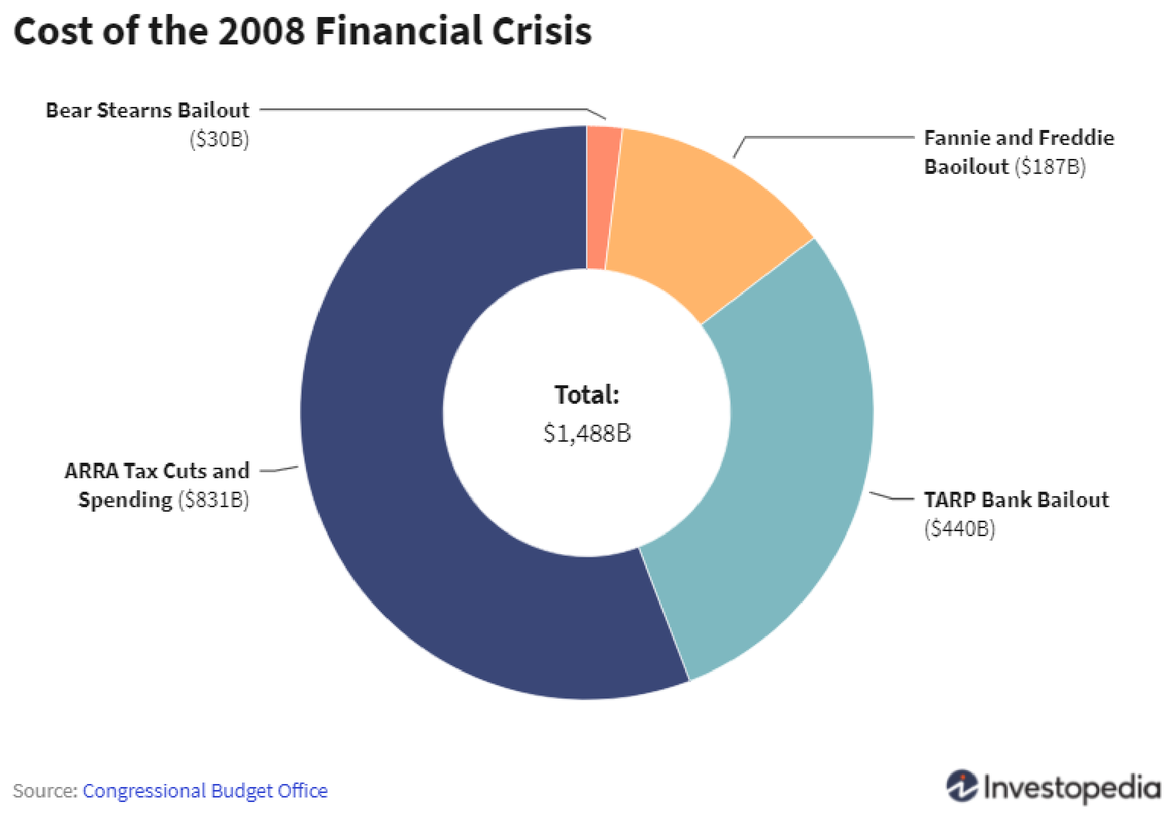


These events had an effect on the **Financial Institutional Investments** (FII's) in India, which effected the Indian Financial Sector, which eventually effected other Indian Sectors. A high volatility can be seen in **Nifty Financial Services** during the crisis due to globalization and integration with global markets. Also there is a fall in India's GDP from 9% to 7.8% during the months of August and September 2008 which eventually decreased in near future.

OTHER EFFECTS :

The Fiscal Deficit of India expanded from **2.7%** in **2007-2008** to **6%** in **2008-2009.** As it expanded, Indian Government provided Fiscal Stimulus. This step reduced Current Account Deficit (CAD).

Another Effect is NPA (Non Performing Assets) in Indian Banks increased. The Loans being provided were being converted into NPA/ stressed Assets. Raghuram Rajan, the former RBI governor mentioned in a public interview that the NPA's mounted in Public Sector Banks (PSB's), their origin is 2008.



DATA :

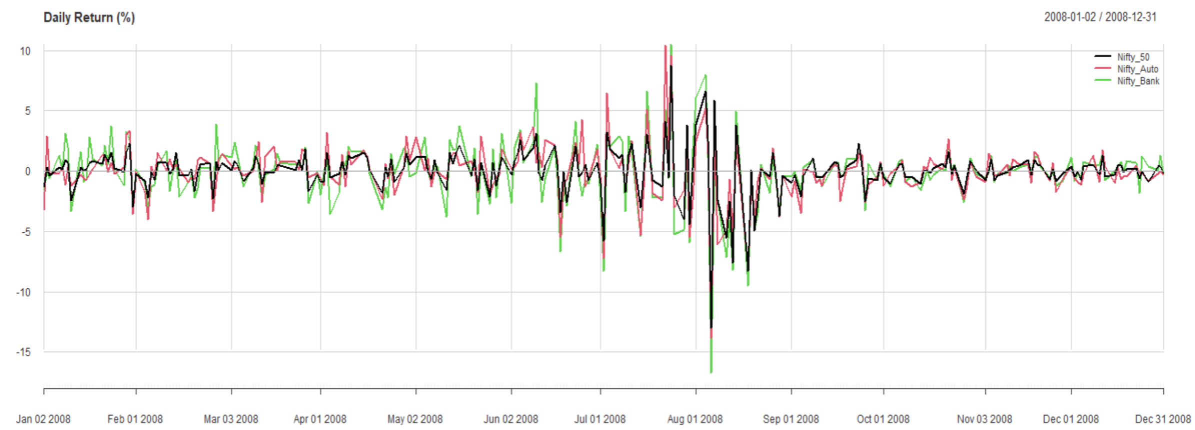
The Data is taken from National Stock Exchange (NSE). Close Prices of 10 Sectoral Indices of Indian stock market during the period 2007- 2021 are chosen for the complete Analysis. These are following Indices:

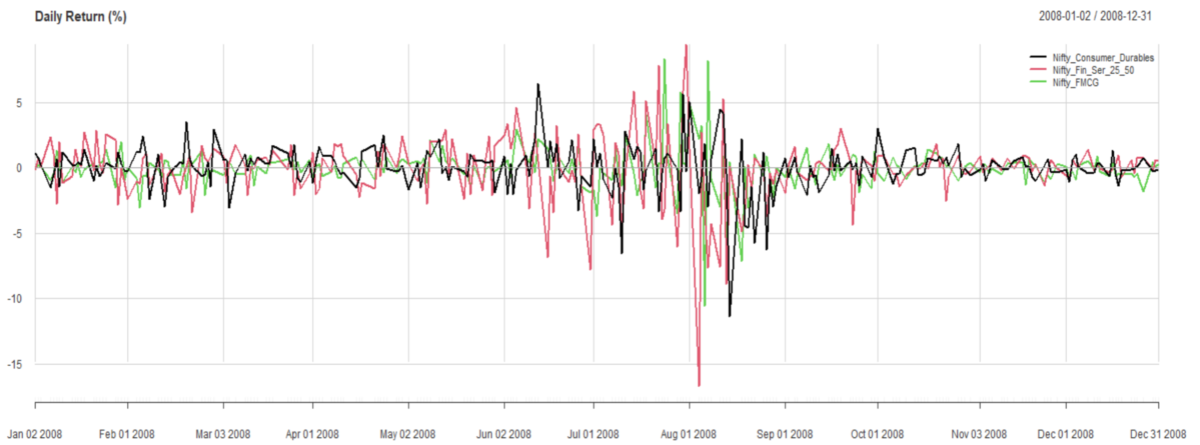
- **Nifty 50**
- **Nifty Auto**
- **Nifty Bank**
- **Nifty Consumer Durables**
- **Nifty Fin_Ser_25_50**
- **Nifty FMCG**
- **Nifty IT**
- **Nifty Media**

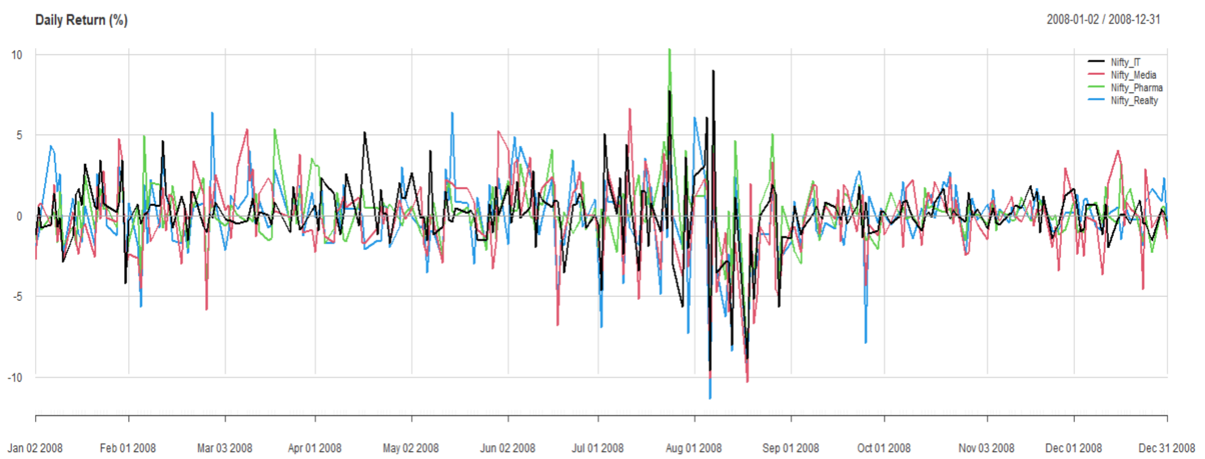
- **Nifty Pharma**
- **Nifty Realty**

Percentage Daily Returns Data :

From the Close prices of the selected indices, Percentage Daily Returns are calculated and the % Returns is plotted.







From the plots, it can be observed that, the Percentage Returns data is stationary. Also volatility is present for the selected time period. But highest volatility is present during the months of August and September due the series of events occurred during that time period.

Summary of the % Returns Data

```
    Index                  Nifty_50       Nifty_Auto
 Min.   :2007-01-02   Min.   : 2524   Min.   :  933.1
 1st Qu.:2010-09-20   1st Qu.: 5232   1st Qu.: 3494.8
 Median :2014-05-26   Median : 7109   Median : 5729.2
 Mean   :2014-05-31   Mean   : 7738   Mean   : 6123.7
 3rd Qu.:2018-02-09   3rd Qu.:10167   3rd Qu.: 8728.5
 Max.   :2021-10-28   Max.   :18477   Max.   :12009.7
   Nifty_Bank     Nifty_Consumer_Durables
 Min.   : 3340   Min.   :  882.1
 1st Qu.: 9566   1st Qu.: 3423.8
 Median :14187   Median : 5448.5
 Mean   :16520   Mean   : 7904.1
 3rd Qu.:23821   3rd Qu.:12662.0
 Max.   :41238   Max.   :30469.0
 Nifty_Fin_Ser_25_50   Nifty_FMCG        Nifty_IT
 Min.   : 1418       Min.   : 4363   Min.   : 2002
 1st Qu.: 3989       1st Qu.: 8668   1st Qu.: 5917
 Median : 5973       Median :17998   Median : 9764
 Mean   : 7163       Mean   :17973   Mean   :10288
 3rd Qu.:10742       3rd Qu.:26652   3rd Qu.:12531
 Max.   :19324       Max.   :41620   Max.   :37106
  Nifty_Media      Nifty_Pharma     Nifty_Realty
 Min.   : 610.5   Min.   : 1969   Min.   : 128.2
 1st Qu.:1525.8   1st Qu.: 4334   1st Qu.: 208.0
 Median :1811.3   Median : 7787   Median : 264.6
 Mean   :1952.3   Mean   : 7454   Mean   : 362.9
 3rd Qu.:2351.7   3rd Qu.:10402   3rd Qu.: 367.1
 Max.   :3642.7   Max.   :14812   Max.   :1878.4
```

Forecast Error Variance Decomposition (FEVD) :

Variance decomposition enables you to determine how much of the variability in dependent variable is lagged by its own variance. In addition, it shows you which of the independent variables is "stronger" in explaining the variability in the dependent variables over time.

Spill Over Table

Returns Spillover Table

Download Spillover Table

	Nifty_50	Nifty_Auto	Nifty_Bank	Nifty_Consumer_Durables	Nifty_Fin_Ser_25_50	Nifty_FMCG	Nifty_IT	Nifty_Media	Nifty_Pharma	Nifty_Realty	From
Nifty_50	44.06	1.20	11.12	0.92	11.18	5.71	10.77	6.41	0.65	7.98	55.94
Nifty_Auto	33.59	21.04	5.32	0.61	9.55	5.68	8.97	5.90	1.97	7.37	78.96
Nifty_Bank	20.65	2.95	25.39	1.77	16.67	6.23	11.54	6.50	0.95	7.35	74.61
Nifty_Consumer_Durables	57.48	8.00	13.17	10.72	1.86	1.37	3.17	1.65	1.27	1.30	89.28
Nifty_Fin_Ser_25_50	25.08	2.22	9.48	1.45	20.85	6.40	14.20	8.91	1.16	10.27	79.15
Nifty_FMCG	51.55	0.76	16.02	0.54	2.52	15.74	5.13	2.36	0.86	4.52	84.26
Nifty_IT	48.18	0.55	16.22	0.91	4.41	4.26	17.26	3.54	0.70	3.98	82.74
Nifty_Media	57.83	1.48	15.33	0.83	3.85	5.19	3.66	8.43	1.43	1.97	91.57
Nifty_Pharma	22.06	0.34	23.64	0.76	6.01	4.84	8.97	4.50	23.14	5.74	76.86
Nifty_Realty	18.99	3.10	10.36	0.98	14.07	9.54	10.66	6.89	2.51	22.88	77.12
To	335.39	20.60	120.67	8.77	70.13	49.22	77.07	46.66	11.49	50.49	79.05

- The Rows indicates the volatility(variance) , each index received from other indices.
- The Column indicates the volatility each index contributed to other indices.
- Spill over from **Nifty Financial Services 25_50 to Nifty Bank** is **16.67%** and spill over from **Nifty Bank to Nifty Financial services 25_50** is **9.48%.**
- So Net spill over of Nifty Financial Services 25_50 - Nifty Bank is **16.67 - 9.48 ie., 7.19%.**
- **Nifty 50** contributed highest spill over of **335.39** ("To" row) to other indices.
- **Nifty 50** received lowest spill over of **55.94** ("From" column) to other indices.

Connectedness Table :

The interpretation of the numerator and denominator is the same as in the orthogonal case.

Connectedness Table

Download Connectedness Table

	Nifty_50	Nifty_Auto	Nifty_Bank	Nifty_Consumer_Durables	Nifty_Fin_Ser_25_50	Nifty_FMCG	Nifty_IT	Nifty_Media	Nifty_Pharma	Nifty_Realty	From
Nifty_50	0.17	0.55	0.34	3.48	85.24	1.63	1.44	2.23	1.49	3.43	99.83
Nifty_Auto	0.15	2.32	0.42	4.08	83.71	1.60	1.13	2.11	1.02	3.48	97.68
Nifty_Bank	0.04	0.35	0.42	2.43	89.11	1.15	0.84	1.92	0.96	2.79	99.58
Nifty_Consumer_Durables	0.33	1.39	0.26	41.18	43.19	3.53	1.78	3.94	1.70	2.71	58.82
Nifty_Fin_Ser_25_50	0.03	0.36	0.38	2.85	88.89	1.03	0.85	1.99	1.05	2.57	11.11
Nifty_FMCG	0.57	1.29	0.37	6.33	71.04	6.30	3.69	2.36	2.87	5.20	93.70
Nifty_IT	0.68	1.13	0.29	6.90	70.16	4.18	8.43	2.10	2.46	3.68	91.57
Nifty_Media	0.14	1.07	0.31	4.54	66.85	2.11	0.61	19.70	1.21	3.46	80.30
Nifty_Pharma	0.52	1.43	0.34	5.02	66.15	2.86	2.26	3.59	13.00	4.84	87.00
Nifty_Realty	0.08	0.80	0.26	3.66	83.01	1.53	1.34	2.36	1.02	5.94	94.06
To	2.52	8.36	2.97	39.29	658.46	19.60	13.94	22.58	13.78	32.16	81.37

- Each value represents a weight or degree of connections between the respective indices.
- The degree of connectedness of each index is measured as the column/row sums, off-diagonal terms.
- The Row sums are the From-Degrees , Column sums are To-Degrees of each index.
- **Nifty Financial services 25_50,** has the highest values**,** indicating maximum strength and direction of connectedness to other Indices.

Full Sample FEVD as a Network :

DY 2011 demonstrates that net pairwise FEVD (transpose of the connectedness table less the connectedness table) defines a weighted, directed network. Thus the connectedness table can be transformed into a net pairwise connectedness network as shown Figure below.

Each edge shown in the graph represents a node giving volatility to another node. The connections with strength in the top tenth percentile are shown in the graph below.

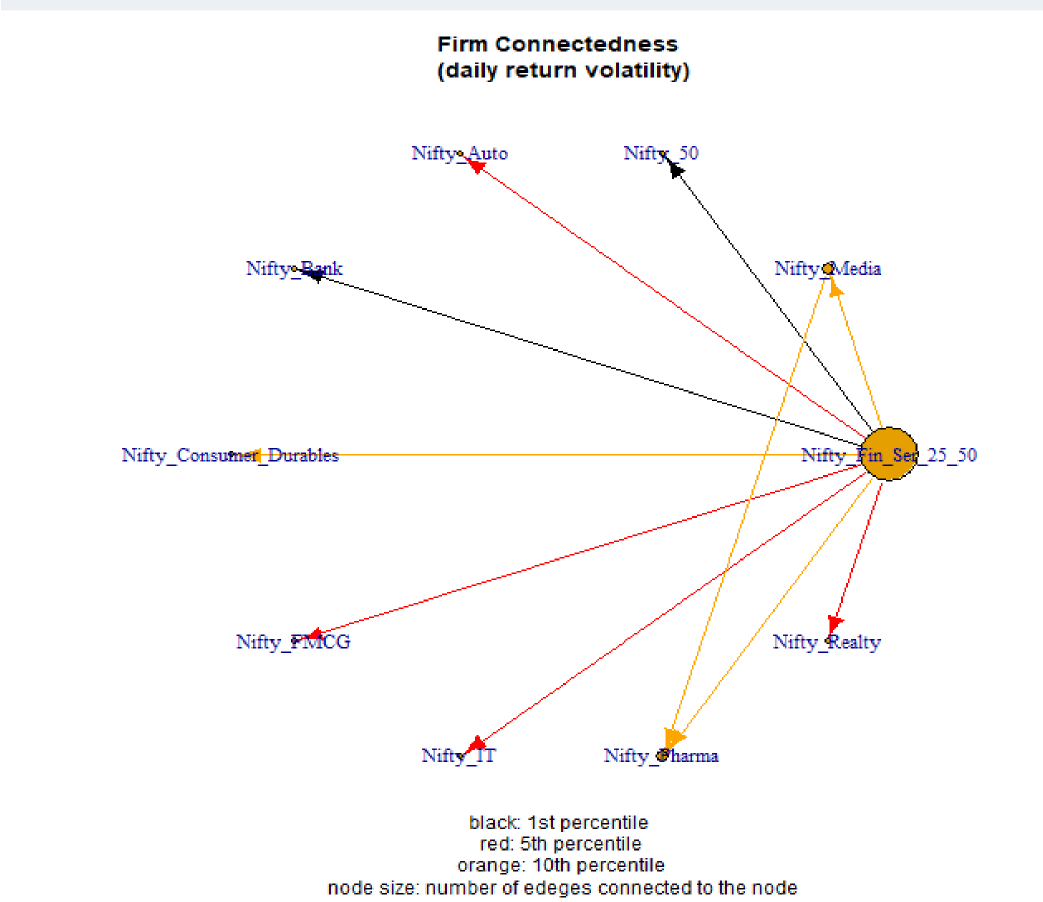


Figure : Full Sample, Net Pairwise Connectedness

- Nifty Financial Services is at the center of the network and connected to all other indices.
- Nifty FinServ is effecting Nifty Auto as people were taking less loans to buy Automobiles due to recession.
- Nifty IT is getting effected due to Forex market getting a hit due to global financial crisis
- Nifty Financial Services and Nifty Bank are strongly connected. This can be because, most of the banks had increased interest rates of the mortgages because of which people found difficulties in repaying the loans.
- Also Financial institutions withdrew their investments which in turn effected the banks. In the time of crisis, Close to 25 Financial Banks and institutions filed bankruptcy protection.
- Nifty Consumer Durables was getting effected, but was significantly less when compared to other indices.

Rolling Window – Spill over Vs. Connected

To apply the methods shown above to a rolling window, it is necessary to only define the size of the rolling window, the size of the increment to move the window, the order q of MA(q), and the number lags in the VAR/SVAR, then loop over the data set. The function **vector_autoreg** in the code snippet takes in the an xts data frame, window size, increment, AR lag order, and MA lag order. The example below uses a window of 100 days, incrementing 10 days, with p=2 (Obtained from VAR metrices) and q=6 (Obtained from ECCM table) .It also calls on function "**make.table**" (to make the spill over and connectedness table) and "**normalize**" (to normalize the connectedness table)

Spill over & Connectedness Indexes (2008) :

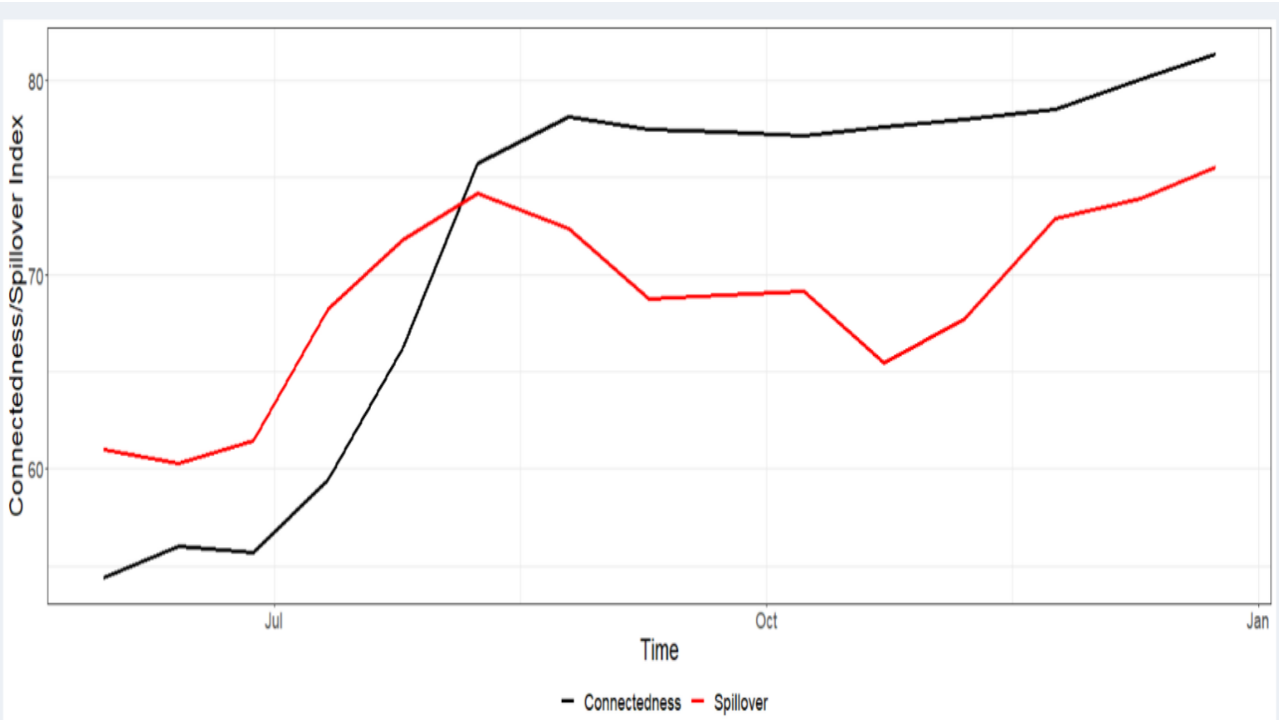


Figure : Spill over(Orthogonal) and Connectedness(Non-Orthogonal) Indexes

Figure shows the percentage of the 10-day ahead forecast error which can be explained by spill overs/connectedness. Mathematically, for each matrix calculated at each point in time the sum of all the off-diagonal entries are divided by the sum of the entire matrix.

- Prior to August Forecast Error is highly explained by Spillover. For the rest of period Connected is explaining the most.

Using the rolling window it is possible to see the network at various points in time.

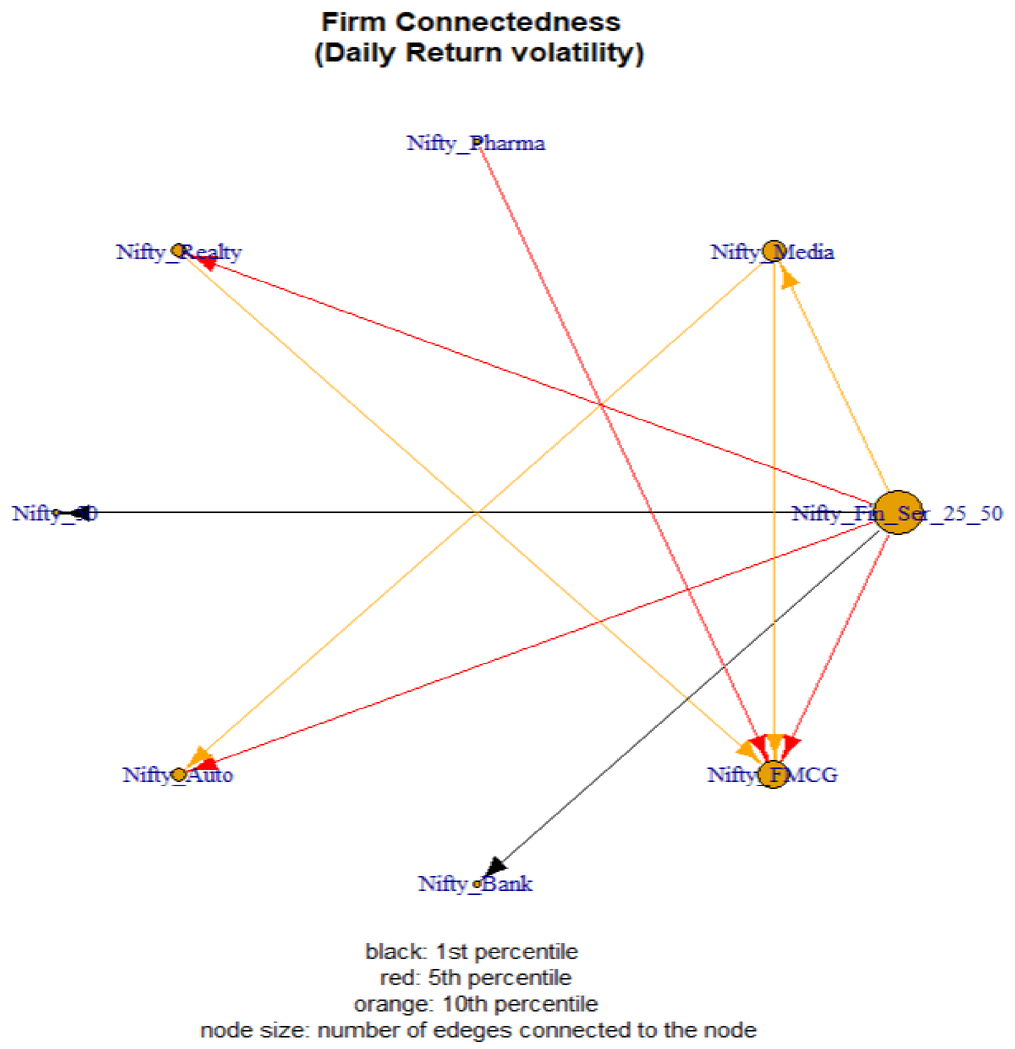
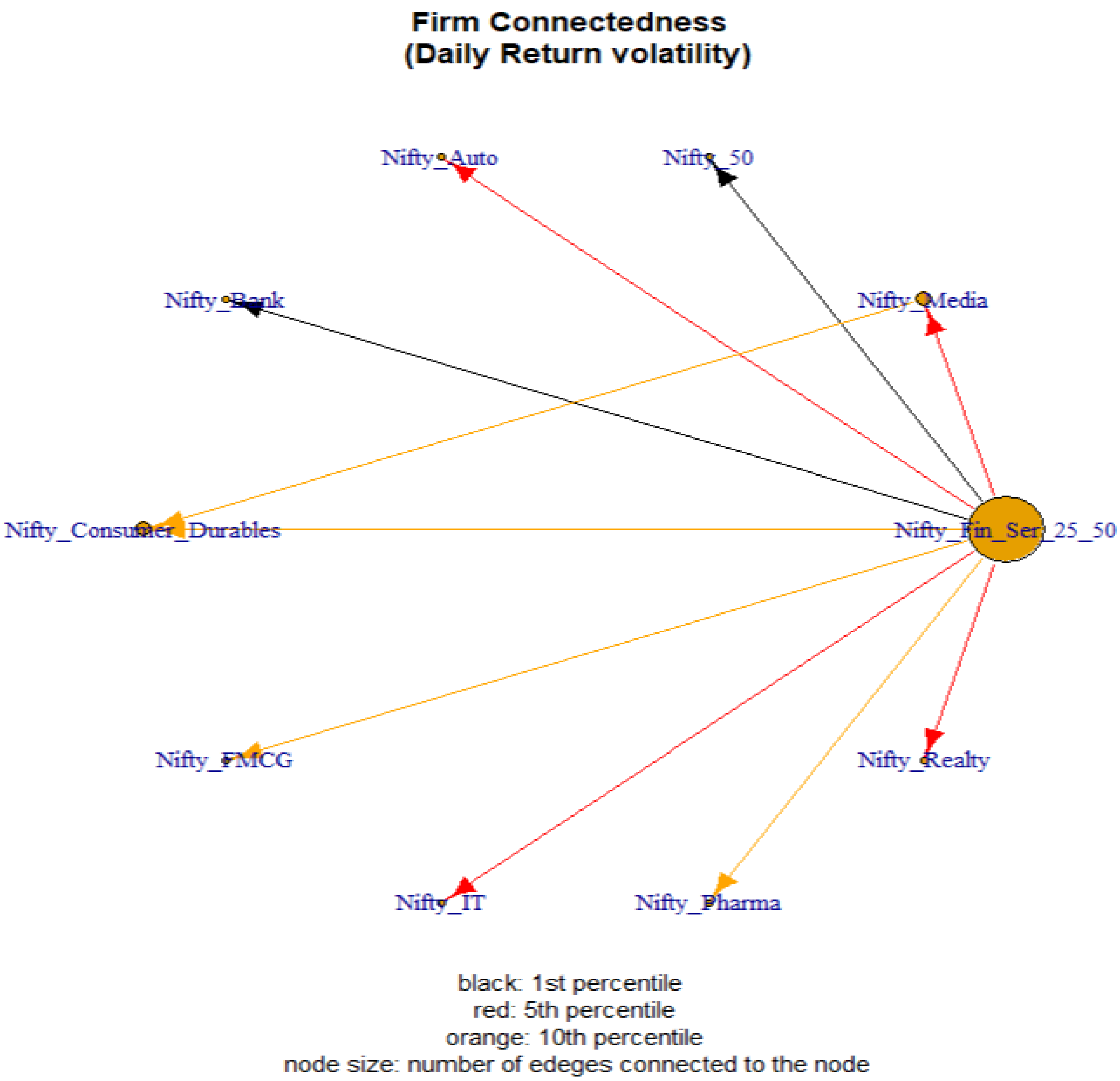


Figure : Financial Interconnectedness: 2008-05-30

- This figure shows the network formation at the beginning of the 2008 financial crisis. Here Nifty_Fin_Ser_25_50 was effecting all other indices due to Global Financial Crisis and Nifty FMCG was getting more effected by all other indices

Figure : Financial Interconnectedness: 2008-10-08



This figure shows the network formation in intermediate stages of the 2008 financial crisis. Here Nifty_Fin_Ser_25_50 effecting all other indices due to the Global financial crisis and Nifty Consumer Durables was getting more effected by all other indices.

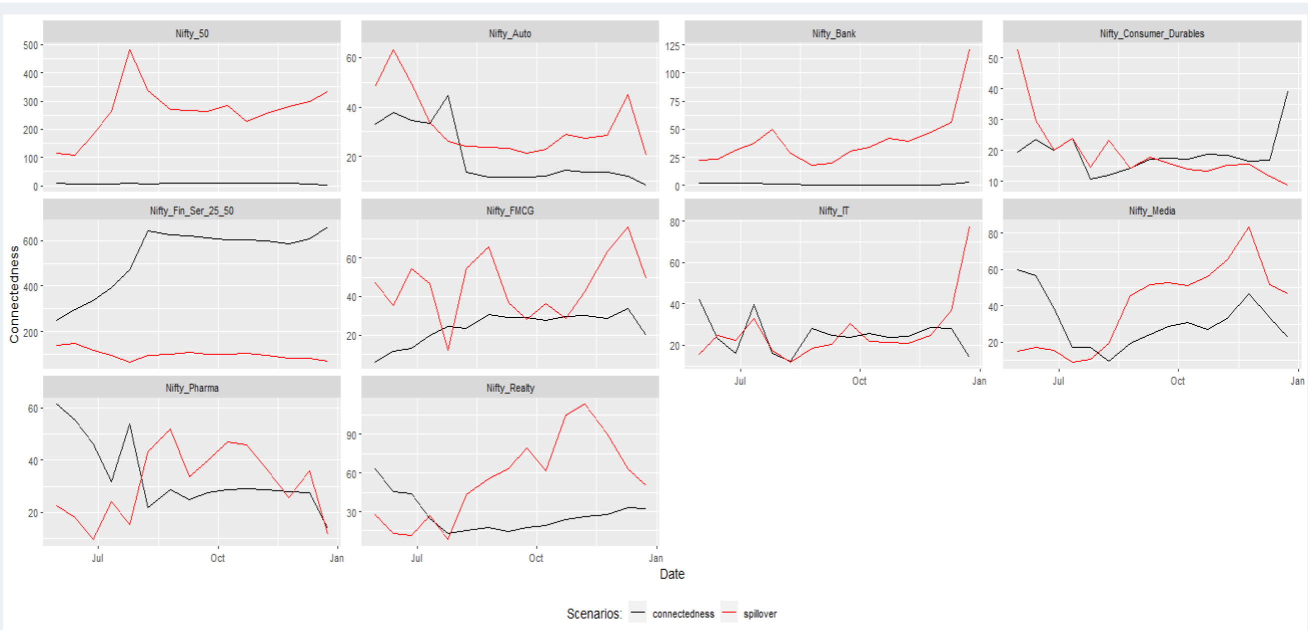
Total Directional Connectedness and Spill over:

Using the time-series of connectedness and spillover tables it is also possible to see how much volatility each stock gave or received, and which ones were net givers/receivers of volatility over time. As with the indexes, the red lines are the spillover measures and the black lines are connectedness.

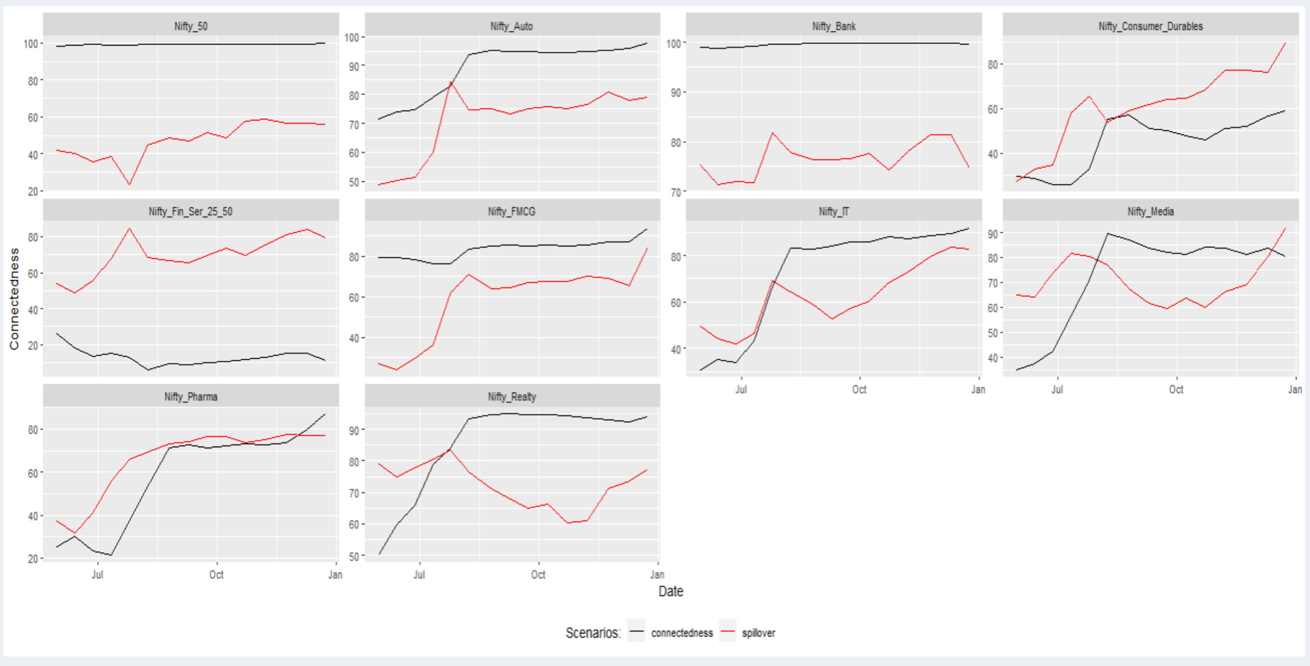
These results show the consequences of the assumptions behind the SVAR and VAR models. During the 2008 financial crisis and in its wake, the Financial Institutional Investments (FII's) in India became less and thus Nifty_Fin_Ser_25_50 and its volatility "giving" is more (the black line).

However, the SVAR (red line) does not pick up on that connection, unlike the "non-orthogonal" VAR, and instead estimates a lower net volatility spill over of Nifty_Fin_Ser_25_50 to the other volatilities. A likely reason is that SVARs are sensitive to the ordering of variables used to satisfy the normality assumption, and, perhaps, a different ordering would deliver a different result.

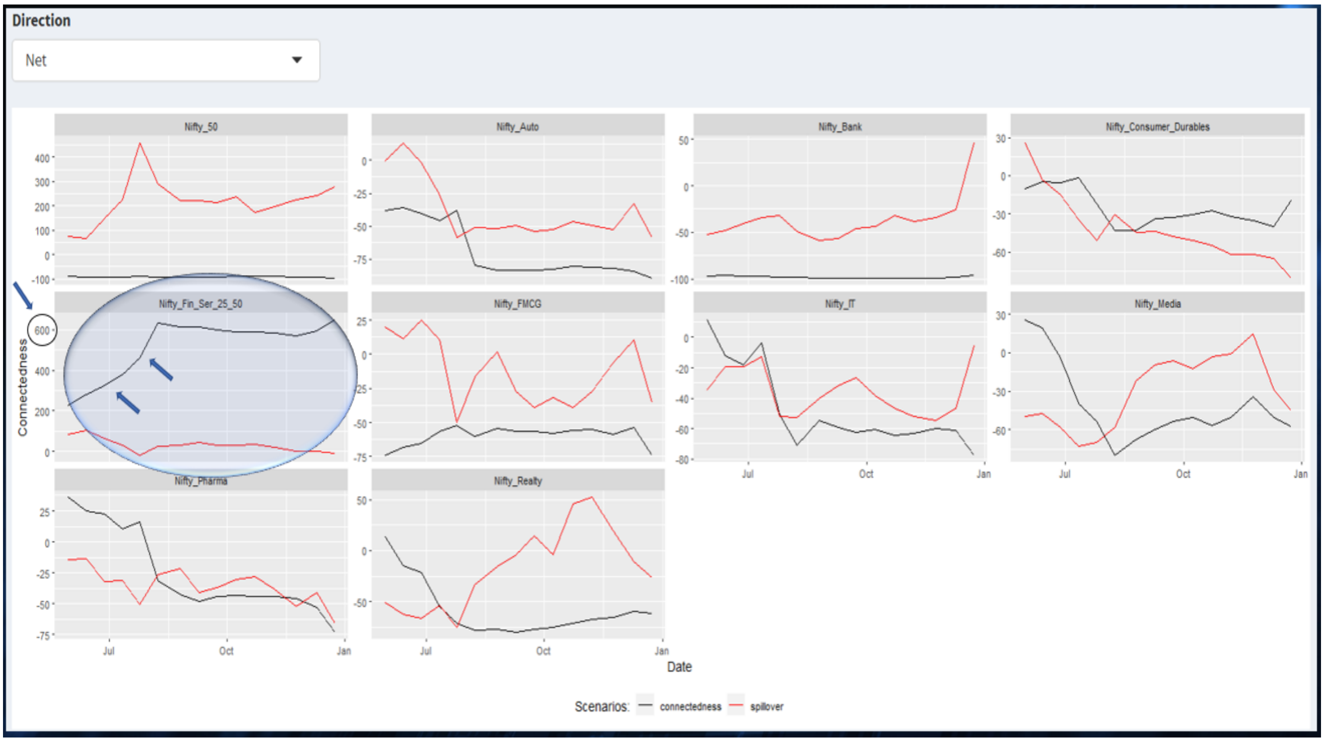
Giving :



Receiving :



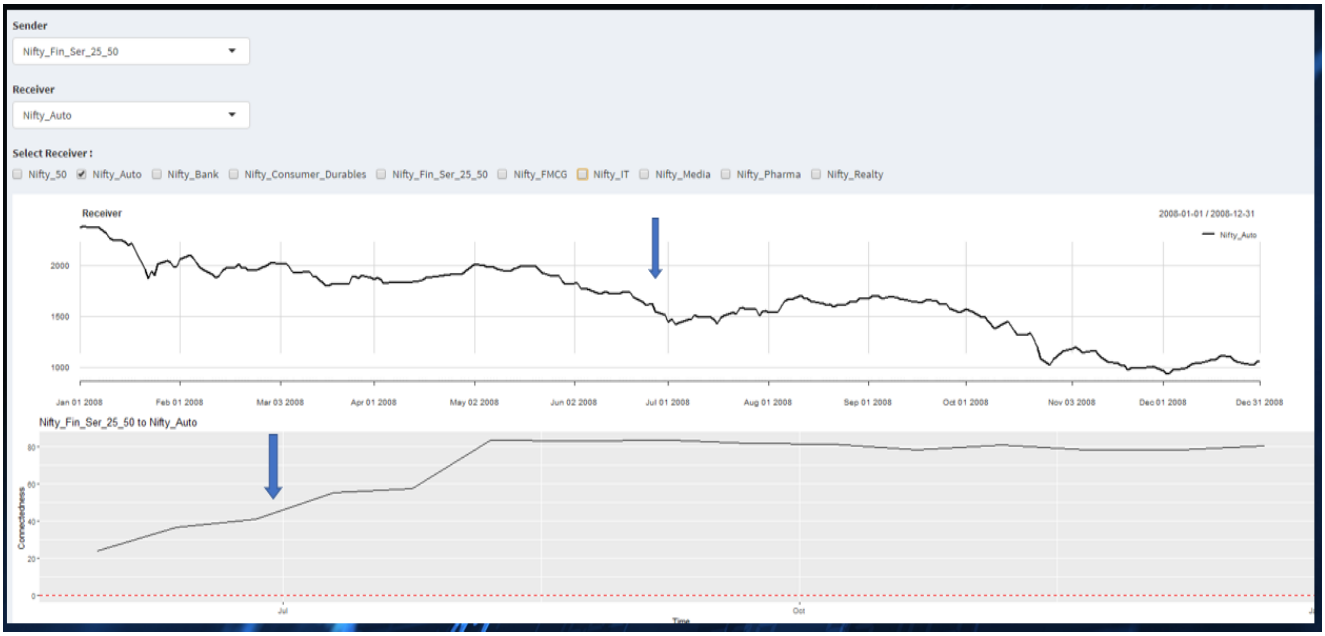
Net :



Rolling Window - Net Pairwise Spill overs & Connectedness :

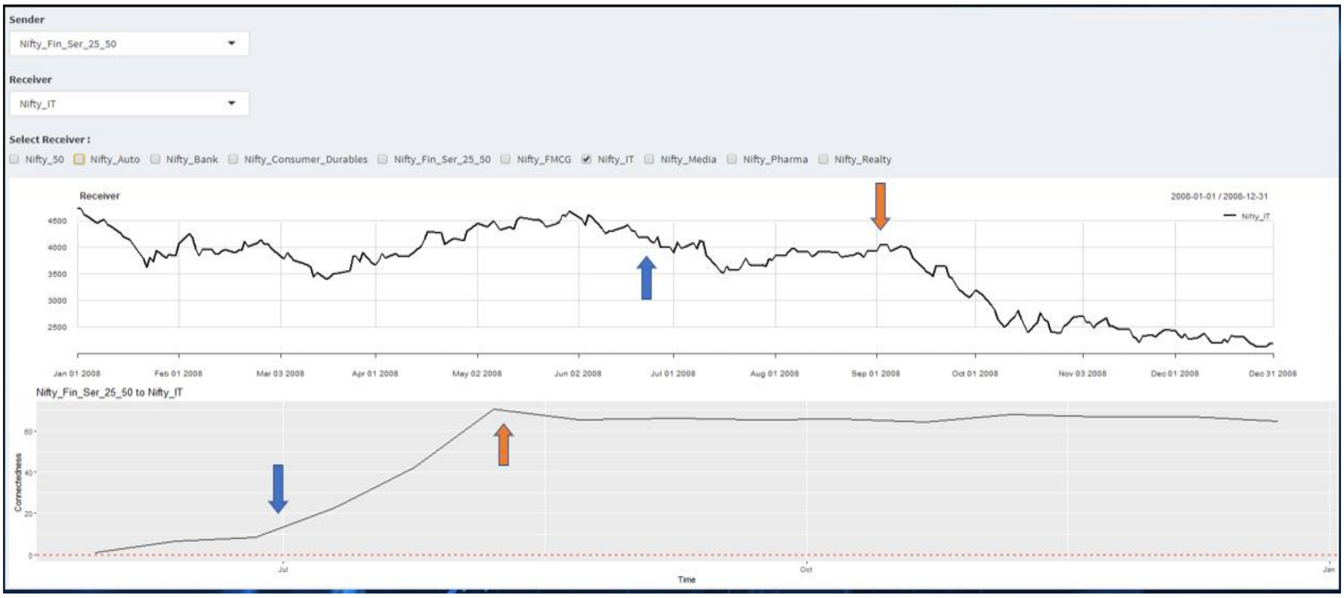
The Pairwise connected diagram can also be analysed through pairwise plot window. The following is some of the significant analysis. The Variation in stock prices can be studied along with the pairwise connectedness variation.

Pairwise plot - Nifty_Fin_Ser v_25_50 vs Nifty Auto



- It can be observed that there was an increase in connectedness after July 2008 and more fall of prices for Nifty Auto.This is because people were taking less loans from Financial Institutions and Banks to buy Automobiles which led to decrease in sales of Automobiles, which in turn led to decrease in stock prices of Automobile industry.

Pairwise plot – Nifty_Fin_Ser_25_50 vs Nifty IT

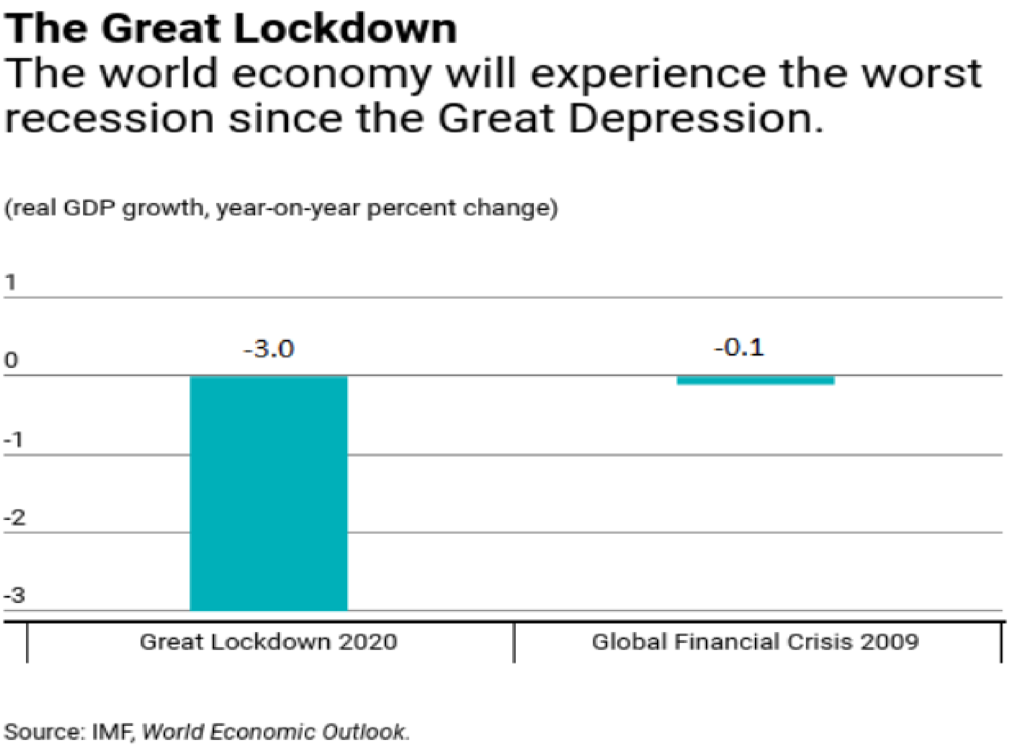


- The Foreign Institutional Investments (FII's) in IT sector got reduced which led to decrease in stock prices of IT sector.
- Also due to economic crisis people were loosing jobs and forex market got effected, which also led to decrease of in IT sector stock prices.

Summary : The above analysis shows how the Global Financial crisis effected various sectors in Indian Stock Market. Thus A portfolio Manager can diversify a client's portfolio by understanding the connectedness and risk of association between different sectors.

Impact of Covid-19 on Indian Stock Market- 2019

The corona virus outbreak, which originated in China, has infected nearly 8,75,000 people. Its spread has left businesses around the world counting costs. The corona virus is going global, and it could bring the world economy to a standstill. COVID-19 that began in the depths of China's Hubei province is spreading rapidly, persuading the World Health Organisation to declare it as a pandemic. There are now significant outbreaks from South Korea to Italy and Iran, from America to Britain. The ongoing spread of the new corona virus has become one of the biggest threats to the global economy and financial markets. Even though, time and again our Indian economists have assured the country that Indian economy stands relatively insulated from the global value chain, but being integrated into world economy, there has to be some impact. This was reflected in the Nifty when the stock market took a great plunge down in last week of February, 2020. The present study is an attempt to examine the impact of COVID-19 on Indian Stock market. The study takes into consideration a time period of four months, from December 1st, 2019 to March 31st, 2020. The study focuses on the Nifty and sectoral indices of Nifty along with India Volatility Index. Tools used for the study involves correlation, regression, ANOVA, variance analysis and moving averages. The study concludes with the statement that volatility is higher in medium run than in short run and also there is significant impact of COVID-19 on Indian stock market.



List of Events during the Covid – 19 in India :

SN	Date	Event
1	January 30	India's first novel corona virus patient was reported
2	March 12	India reports first fatality due to Covid-19
3	March 25	A nationwide lockdown was imposed till April 14
4	March 27	RBI allows moratorium on loan repayment
5	April 29	1,000 confirmed deaths recorded
6	May 12	PM announces Rs 20 lakh crore Atmanirbhar package,
7	May 15	India Records 100 COVID-19 Deaths in 24 Hours.
8	May 19	Total Covid-19 cases in India cross 1 lakh
9	May 31	India records 5,000 deaths
10	June 1	India is now the 7th-most-infected country
11	June 8	Unlock 1.0
12	June 12	India overtakes UK to become 4th worst corona virus-hit country
13	June 27	Total cases cross 5 lakh
14	July 1	India enters Unlock 2.0
15	July 6	India overtakes Russia to become third worst corona virus-hit country,
16	July 15	Phase-1 clinical trials of India's first indigenous Covid-19 vaccine, Covaxin
17	August 29	Centre issues Unlock 4.0 guidelines
18	August 31	India's Gross Domestic Product (GDP) growth contracts 23.9 per cent in the April-June quarter
19	September 7	India overtakes Brazil to emerge as the country with the second largest

Nifty 50 Behaviour during Covid – 19 :

Figure 2: NSE Nifty50 during different phases of lockdown

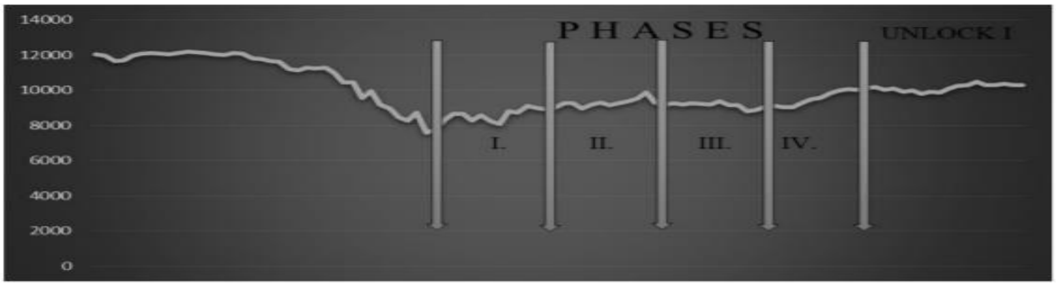
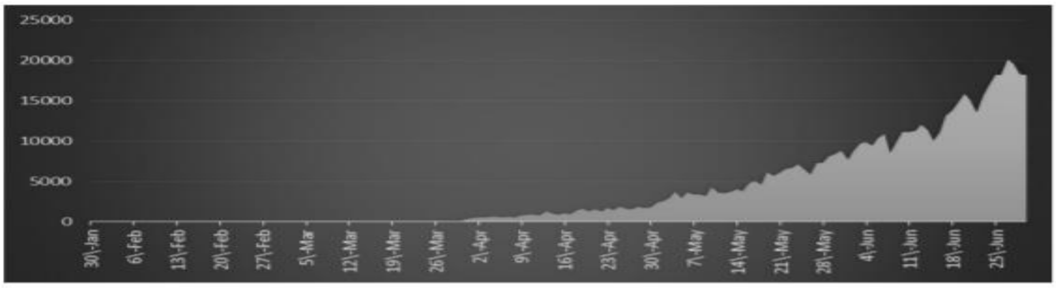
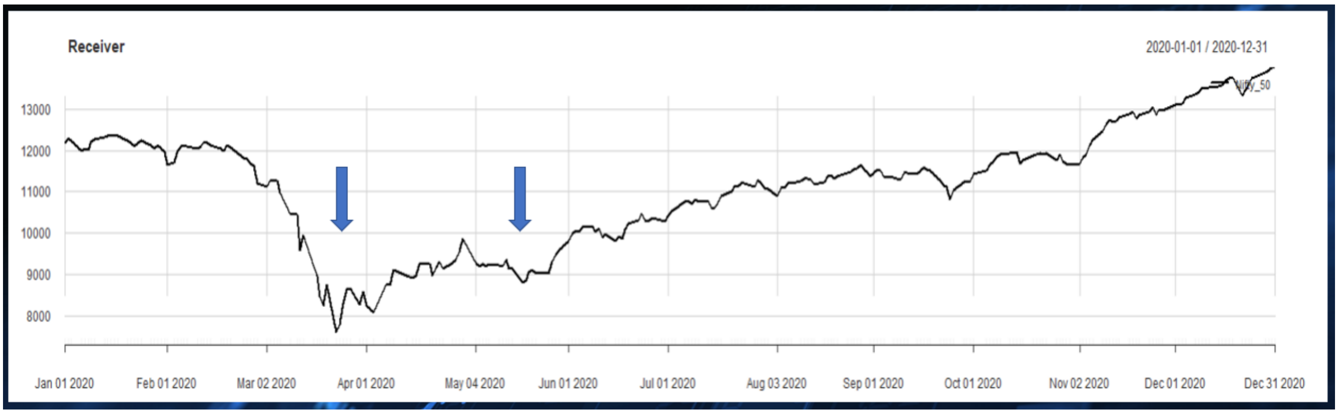


Figure 3: Daily coronavirus cases during various phases of lockdown

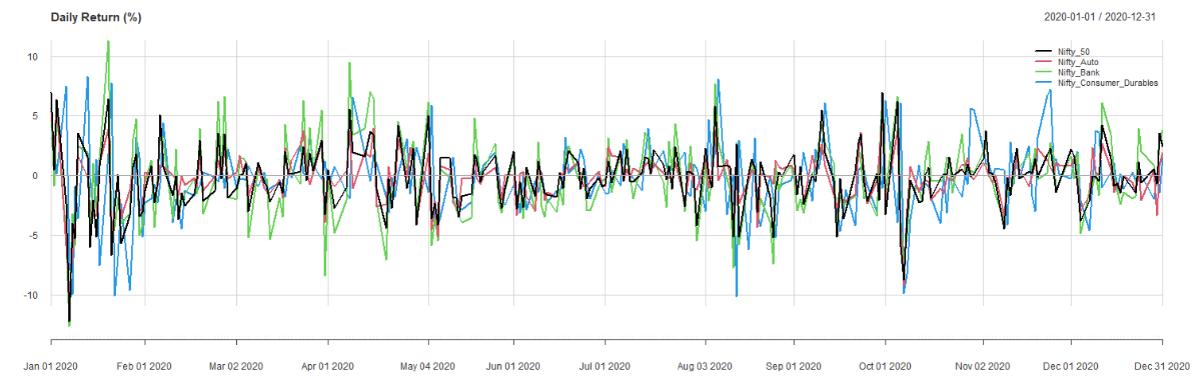


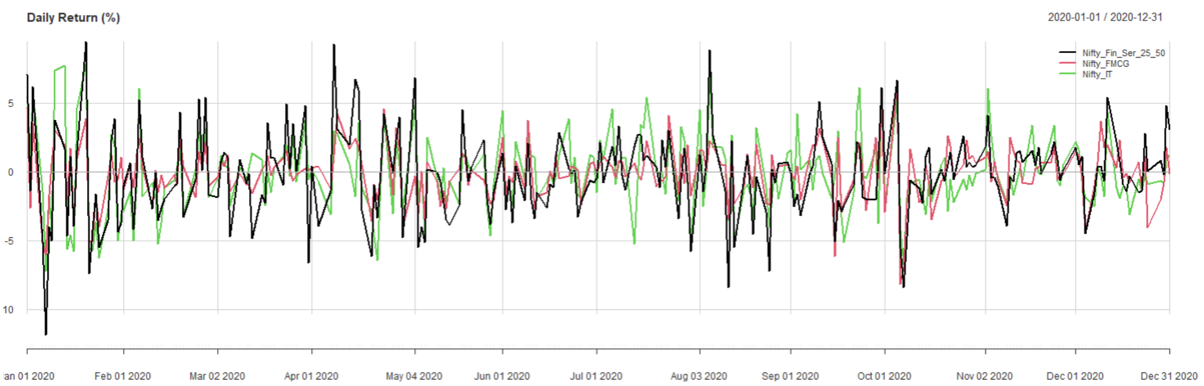
Source: covid19india.org

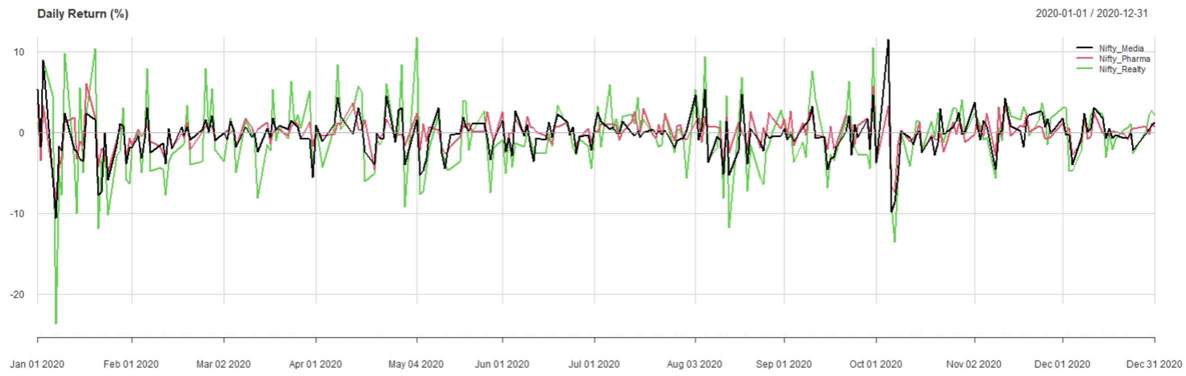


Nifty 50 index went down in March as India reported its first fatality due to covid-19 on 12th of March and also because of the announcement of Nationwide lockdown on 25th of March.

Percentage Daily Returns Data :

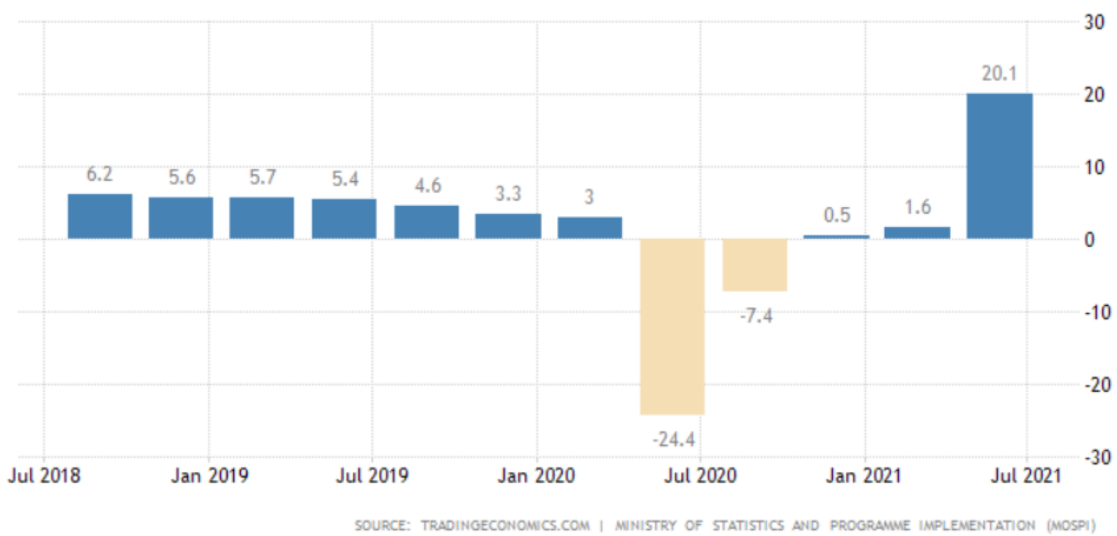






It can be observed that there is high volatility during the month of January, April, August and September. High volatility in January because the first covid case in India was reported. Volatility in April was because of the announcement of **Great Lockdown** nationwide in India.

GDP(%)- INDIA



In July and August, a record 24.4% slump in GDP explains the volatility. In September the volatility is because India become 2nd largest country in covid cases as India went into Un-Lockdown.

Forecast Error Variance Decomposition (FEVD) :

Spill Over Table

Returns Spillover Table

Download Spillover Table

	Nifty_50	Nifty_Auto	Nifty_Bank	Nifty_Consumer_Durables	Nifty_Fin_Ser_25_50	Nifty_FMCG	Nifty_IT	Nifty_Media	Nifty_Pharma	Nifty_Realty	From
Nifty_50	27.99	2.52	27.10	1.20	38.39	0.66	0.65	0.34	0.55	0.59	72.01
Nifty_Auto	12.81	21.79	28.45	2.33	32.37	1.33	0.28	0.13	0.49	0.03	78.21
Nifty_Bank	11.72	3.94	39.03	1.21	40.16	0.66	0.65	0.47	1.13	1.03	60.97
Nifty_Consumer_Durables	13.43	3.80	32.61	10.90	34.73	1.07	0.80	1.41	0.52	0.74	89.10
Nifty_Fin_Ser_25_50	14.64	3.26	27.56	1.92	49.05	0.88	0.62	0.49	0.73	0.85	50.95
Nifty_FMCG	18.04	4.02	22.77	2.00	27.69	21.99	0.06	1.85	0.59	0.99	78.01
Nifty_IT	16.92	0.96	26.99	1.15	32.18	1.59	19.27	0.13	0.36	0.46	80.73
Nifty_Media	9.62	4.36	30.00	1.22	34.97	2.06	2.28	14.49	0.60	0.40	85.51
Nifty_Pharma	11.02	1.98	24.36	1.87	31.25	1.15	1.10	0.99	26.24	0.05	73.76
Nifty_Realty	9.50	2.43	31.04	1.23	44.51	0.94	2.11	0.64	0.71	6.90	93.10
To	117.71	27.26	250.88	14.11	316.24	10.33	8.56	6.44	5.68	5.13	76.24

- Spill over from **Nifty Financial Services 25_50 to Nifty Bank** is **40.16%** and spill over from **Nifty Bank to Nifty Financial services 25_50** is **27.56%.**
- So Net spill over of Nifty Financial Services 25_50 - Nifty Bank is **40.16 – 27.56 ie., 12.6%.**
- **Nifty Financial Services 25_50** contributed highest spill over of **316.24** ("To" row) to other indices.
- **Nifty Financial Services 25_50** received lowest spill over of **50.95** ("From" column) to other indices.

Connectedness Table :

The interpretation of the numerator and denominator is the same as in the orthogonal case.

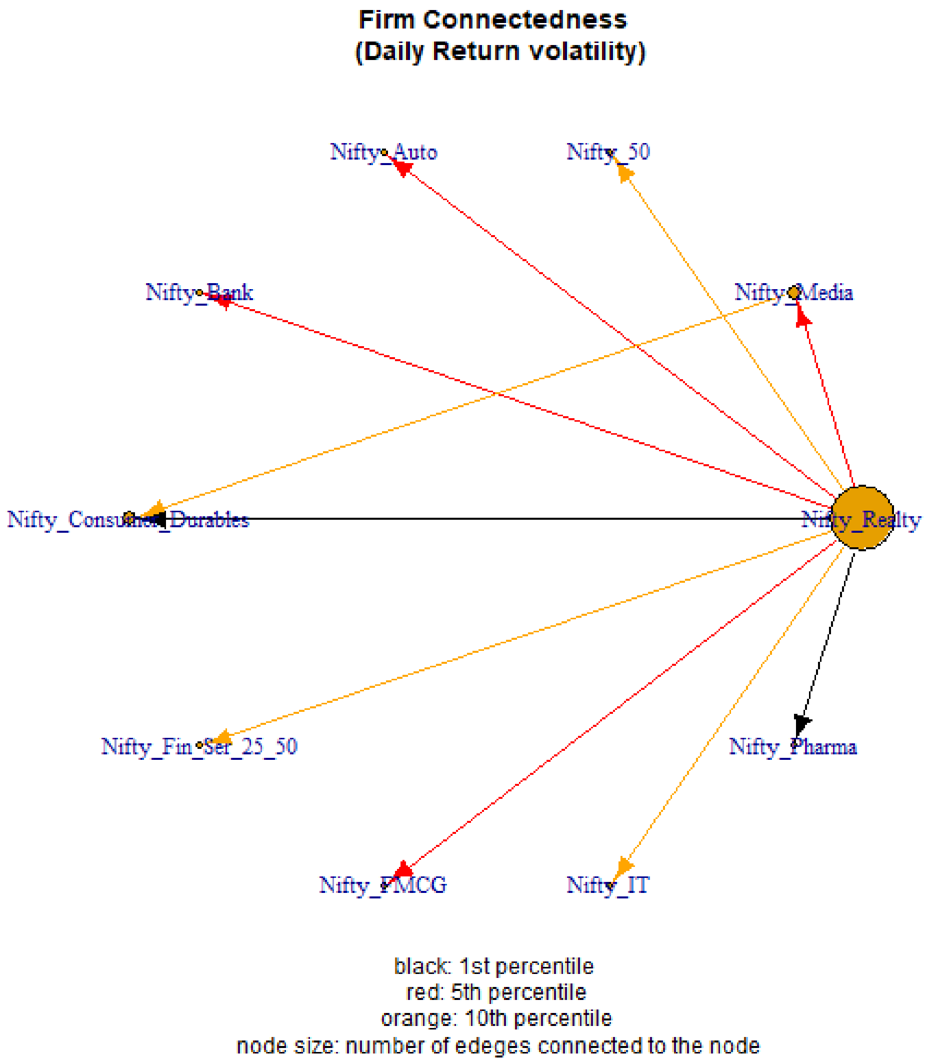
Connectedness Table

Download Connectedness Table

	Nifty_50	Nifty_Auto	Nifty_Bank	Nifty_Consumer_Durables	Nifty_Fin_Ser_25_50	Nifty_FMCG	Nifty_IT	Nifty_Media	Nifty_Pharma	Nifty_Realty	From
Nifty_50	13.45	5.54	10.70	0.21	12.09	7.41	9.88	8.87	5.21	26.65	86.55
Nifty_Auto	11.62	9.46	10.16	0.17	11.71	7.97	8.48	10.74	5.51	24.19	90.54
Nifty_Bank	10.91	5.19	17.56	0.40	16.69	5.73	6.63	7.58	3.57	25.72	82.44
Nifty_Consumer_Durables	10.42	6.10	8.20	3.28	10.64	7.52	7.36	13.41	4.89	28.19	96.72
Nifty_Fin_Ser_25_50	11.18	5.34	14.93	0.27	16.38	6.48	7.40	8.38	4.03	25.60	83.62
Nifty_FMCG	12.50	5.95	8.73	0.24	10.75	15.19	6.45	10.76	5.75	23.67	84.81
Nifty_IT	13.26	5.34	8.91	0.28	10.55	5.06	24.44	6.55	5.25	20.36	75.56
Nifty_Media	10.38	5.63	8.18	0.34	9.71	7.36	6.73	20.07	4.84	26.77	79.93
Nifty_Pharma	12.75	5.85	8.24	0.21	9.62	7.71	10.14	9.31	11.51	24.67	88.49
Nifty_Realty	10.93	4.67	9.77	0.19	10.75	5.96	6.75	9.77	4.28	36.94	63.06
To	103.95	49.61	87.83	2.31	102.51	61.19	69.81	85.37	43.33	225.82	83.17

- **Nifty Realty,** has the highest values**,** indicating maximum strength and direction of connectedness to other Indices.

Full Sample FEVD as a Network :

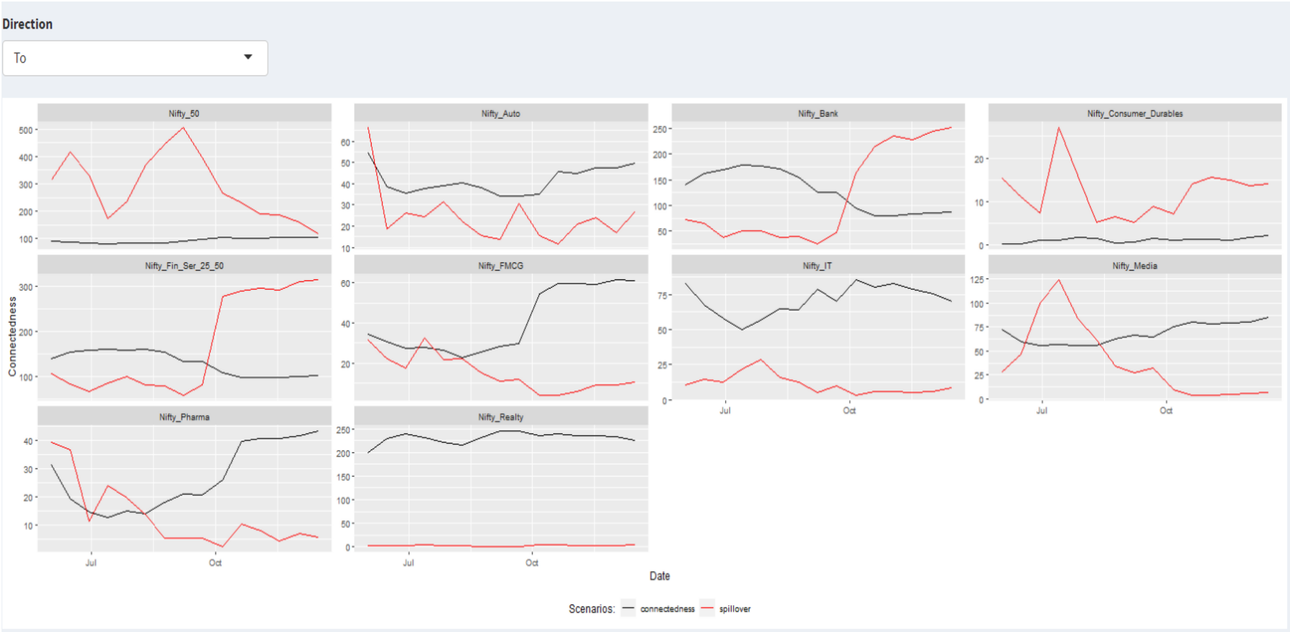


- **Nifty Realty** is at the center of the Network and effecting all other indices. This was during 2020 covid crisis realty stocks were effected as there were lockdowns and work from home became relevant so people were buying less properties.
- **Nifty Realty** was effecting nifty pharma and nifty consumer durables in the first percentile as less new houses will lead to sale of less consumer durables like TV, AC, fridge, etc.
- **Nifty Realty** was effecting **Nifty Bank, Nifty Media, Nifty FMCG and Nifty Auto** in the **5th percentile,** as less sales of houses effected banks as people were taking less number of loans.
- **Nifty Realty** was effecting **Nifty IT, Nifty Financial Services and Nifty 50 in the 10th percentile**

- **Nifty Media** is effecting **Nifty Consumer Durables in the 10th percentile**, which is because of lockdowns people are moving to TV entertainment and watching movies and shows on Netflix like platforms and this increased the sale of Smart TV's and online classes of children have increased the sales of smartphones and laptops.

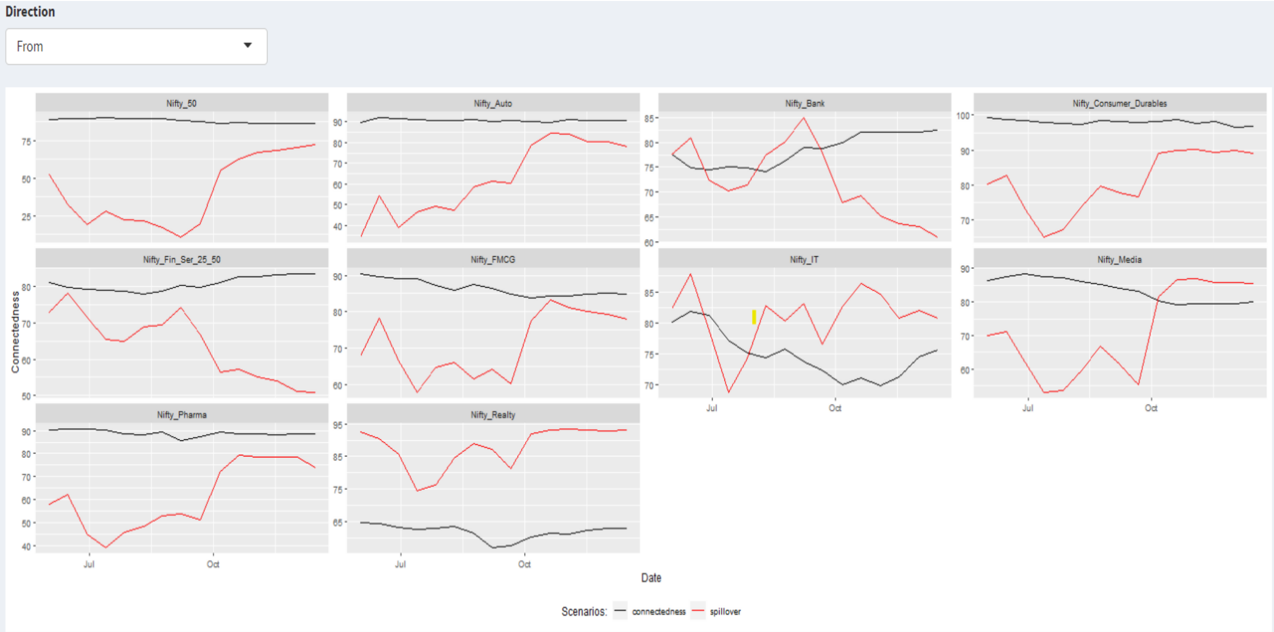
Total Directional Connectedness and Spill over:

Giving:



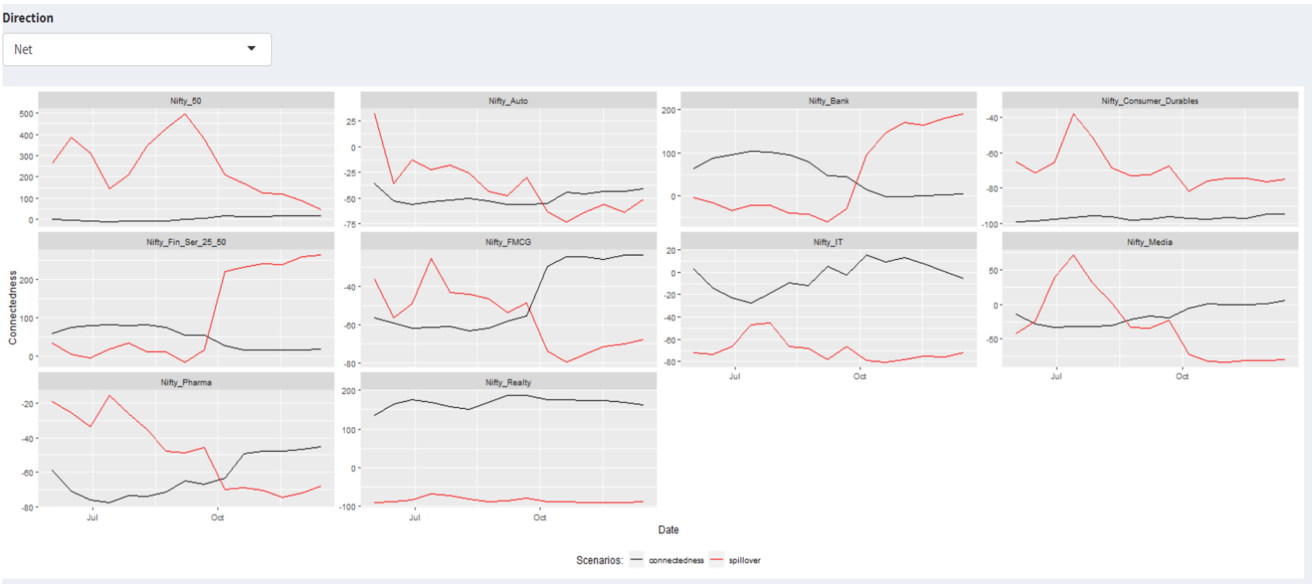
- **Nifty Realty** has more connectedness which was observed from Network Diagram.
- **Nifty 50**'s spill over is more which was observed from spill over table.

Receiving:



- **Nifty Consumer Durables** is receiving more connectedness which is observed in Network diagram
- **Nifty Realty** is receiving more spill over (**93%**) from other indices.

Net:

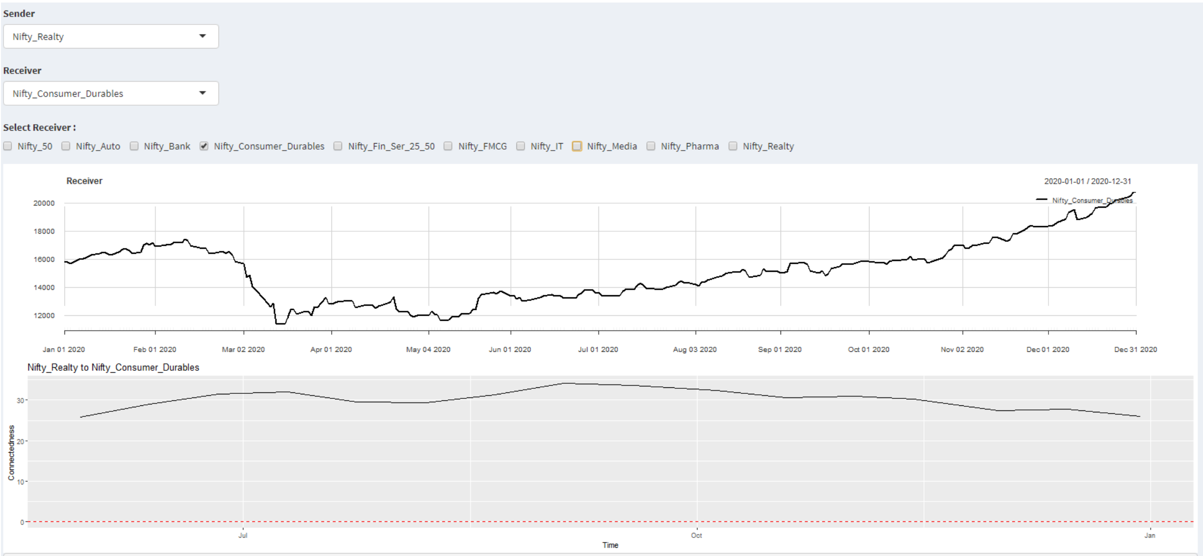


- **Nifty Realty** has the highest Net Connectedness
- **Net Spill over** initially was more for **Nifty 50,** but in second half of the year **Nifty_Fin_Ser_25_50** and **Nifty Bank.**

Rolling Window - Net Pairwise Spill overs & Connectedness :

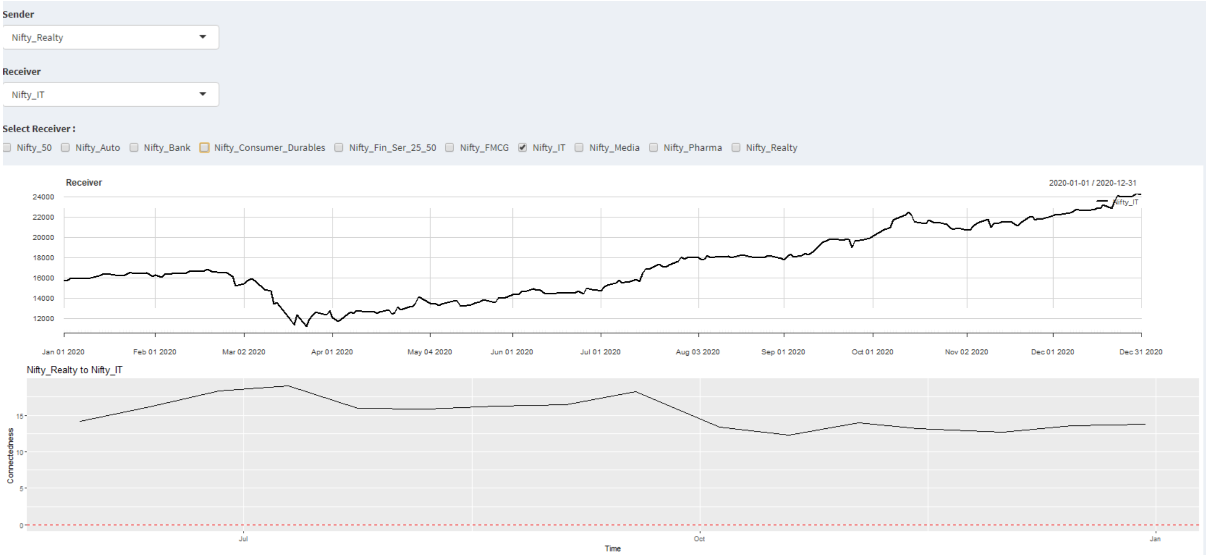
The Pairwise connected diagram can also be analysed through pairwise plot window. The following is some of the significant analysis. The Variation in stock prices can be studied along with the pairwise connectedness variation.

Pairwise plot – Nifty Realty vs Nifty Consumer durables



- **Sender** is **Nifty Realty** and **Receiver** is **Nifty Consumer Durables**.
- It can be observed that the connectedness in the below graph and price fluctuations of Nifty Consumer Durables in the above graph.
- From the below graph it can be seen that the connectedness of the indices and we can see a sharp increase in the connectedness after 22-07-2020 so accordingly we can see the price increase and do the hedging.

Pairwise plot – Nifty Realty vs Nifty IT



- **Sender** is **Nifty Realty** and **Receiver** is **Nifty IT.**
- Here we can observe sharp decline in connectedness after 17-09-2020 and increase in price of Nifty IT so accordingly we can buy or sell Nifty IT to make our portfolio balanced.

4. Creative Approaches

APPROACH -1 :

USING EXTENDED CROSS CORRELATION MATRICES (ECCM)TO CHOOSE MA LAGS INSTEAD OF PACF (PARTIAL AUTO CORRELATION FUNCTION) GRAPHS

```
p-values table of Extended Cross-correlation Matrices:
Column: MA order
Row   : AR order
       0      1      2      3      4      5      6
0 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
1 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.9987
2 0.0000 0.0000 0.0000 0.0000 0.6421 0.3217 0.9999
3 0.0000 0.7923 0.4089 0.9990 0.9999 1.0000 1.0000
4 0.9926 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
5 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
```

The Extended Cross Correlation Matrices is in MTS package in R language. Instead of traditional and difficult way of choosing MA lags from PACF plots, we have chosen ECCM matrices. The advantages are ECCM table is easy to interpret when compared to PACF plots which are very confusing.

In ECCM table, the columns indicate MA order and rows indicate AR order. When p- value is greater than 0.05 for the first time, we choose the MA lag value. AR lag can also be chosen in the same manner.

APPROACH -2 :

INCLUSION OF VAR METRICS TAB TO CHOOSE AR LAGS

Index | Network Visual | Give/Receive Graphs | Give/Receive Table | Pairwise Plot | Data Viz | Returns Data | VAR Metrics

Accuracy	1	2	3	4	5	6	7	8	9	10
AIC(n)	3.53384835403237	3.8812130100712	4.11125472020977	4.43391254491277	4.65132825403546	4.90813378599851	4.66638863905431	4.8406439031462	4.84588007222018	4.751749411173
HQ(n)	4.28139636891974	5.30835012940165	6.21798094398328	7.22022787312935	8.1172326866951	9.05362732310122	9.49147128060009	10.345315649135	11.0301409226521	11.615599366048
SC(n)	5.38015579732474	7.40598176544755	9.31448478767008	11.3156039244571	13.2114809456637	15.1467477897107	16.5834639548505	18.4361805310264	20.1198780121843	21.7042086632211
FPE(n)	34.2966381974815	48.8912254104925	62.7057565985452	89.7992268788685	118.598209185095	168.190955681072	150.879995456174	215.934639865957	278.259979758788	351.926297910653

Instead of the traditional ACF plots, AR lags can be chosen based on the metrices from the Criteria function present in **VAR Select** in '**vars'** package. This option enables users who has good knowledge on Time Series concepts do experiments on the AR lag values based in different metrices. The value of lag is chosen for which the metric value is low. In our Analysis, SC (also called BIC) was chosen as a metric to determine the AR lag value.

Ex : As SC values is less for AR lag 1, it is chosen.

APPROACH -3 :

INCLUSION OF ORIGINAL TIME SERIES DATA OF THE INDICES ABOVE THE CONNECTEDNESS DIAGRAM IN PAIRWISE PLOT TAB TO STUDY THE MOVEMENTS OF PRICES OF INDICES IN ACCORDANCE WITH PAIRWISE CONNECTEDNESS

This is similar to DJI index in stock market. From the above tab, inclusion of original time series of all indices in the study will allow us to study the price movements of receiver in accordance with pairwise connectedness of sender and receiver. This analysis will help in hedging.

5. Shortfall & Future prospects

MAKING THE DATA SELECTION DYNAMIC TO USER BY INTEGRATING DASHBOARD WITH FINANCIAL WEBSITES

For our Analysis, we have chosen fixed data from 2007 to 2021 and extracted the data as a csv file, which makes the user to analyse indices in different time periods in that time frame i.e, from 2007 to 2021. Instead of choosing the fixed data, the dashboard can be integrated with some of the financial websites , which gives the user to choose the dynamic time period data for his/her analysis.

VAR- METRICS AND MA LAG SELECTION

Problem 1 :

If the user does not have knowledge of time series concepts, it become difficult for him/her to read the VAR metrics table to choose the AR lag value.

Solution :

The AR lag selection can be automated in such a way that the model chooses the AR lag value for which the evaluation metrics are giving less value.

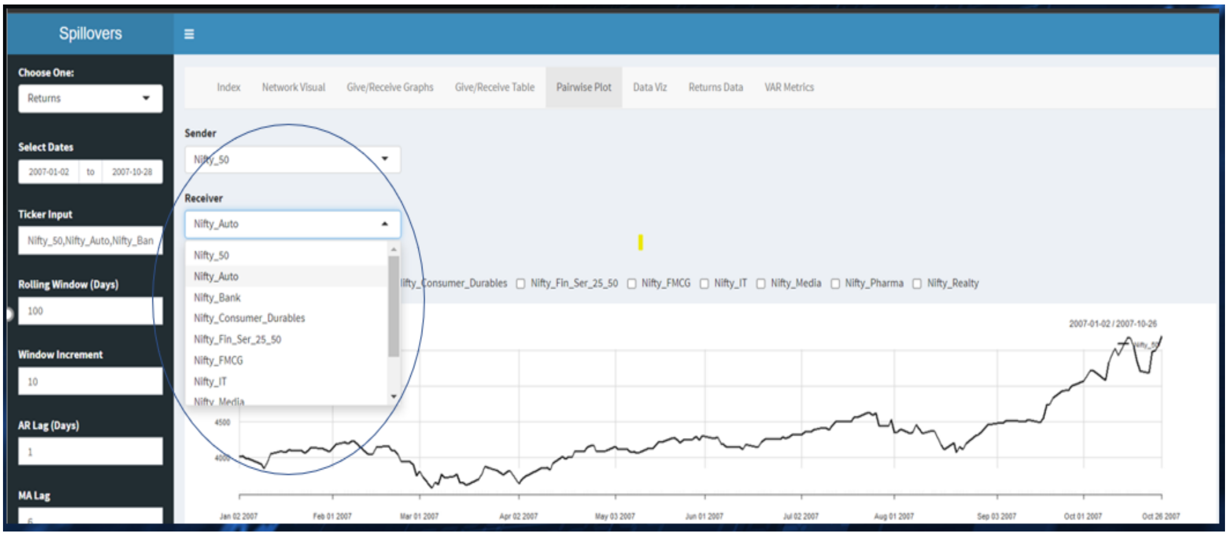
Problem 2 :

For the data chosen (2007-2021) the MA lag is fixed as 6. But if the time period is further extended ECCM might give a different MA lag value.

Solution :

The MA lag selection process can be automated such that the model choses the MA lag from ECCM table for which the p-value is greater than 0.05 for the first time.

1. MULTIPLE INDICES SELECTION OPTIONS IN DROP DOWNS IN PAIRWISE PLOT TAB



Multiple options selection can be helpful to analysis the connectedness of different combinations of selected indices, which can give more insights such that a portfolio can be balanced and risk of losses can be reduced.

Future Prospects

- Commodity Market
    - We can use volatility connectedness of commodity futures market by decomposing the connectedness at high medium and low frequencies Commodity volatility spillovers at medium and particularly low frequency account for over 40% of the total volatility connectedness, which can be significantly explained by economic factors related to broad economic conditions; however, this is not the case at high frequency.

- Stock Prices Movement Study
    - Though this study cannot directly do the stock price prediction but can be well well utilized to study the stock prices movement
- Derivative and Intraday Trading
    - This model will have a significant implication for intraday traders in implementing hedging and arbitrage trading strategies and policymakers in assessing market stability this can be achieved by taking intraday data(hourly).
- World Market Connectedness and spill over
    - This study also helps us understand the link between different international markets during shock so during a time of crisis we know exactly how different markets will react based on the connectedness and return spillover.
- Bank Connectedness and Spillier
    - This study can be applied to understand the connectedness and spillover among banks and for the fact between any business

6. Summary

After taking inspiration from the work of Diebold and Yilmaz we noticed that the papers describe how to quantify in an index the amount of forecast error that can be attributed to shocks of the error terms of each dependent variable in vector autoregression. Consider a set of stocks for which we want to estimate and forecast either returns or volatility, and control for the systematic, or common, factor driving each one, then whatever cannot be explained by common factors is an idiosyncratic error. The first key question which arises is if this idiosyncratic error can affect the forecast of another stock or index. In other words, do idiosyncratic errors spillover into common factors' ability to forecast? These "spillovers" are found using standard time-series techniques for finding impulse-response functions and forecast error variance decompositions. The research paper also shows how the effects of these shocks can be represented as a network when one relaxes the assumptions that vector autoregressions have normally distributed. When we look at the error terms and the shocks each variable must be orthogonal to the other shocks. We have taken the sectorial indices of the Indian market to better understand the connectedness between these indices.

We followed these steps; we first described the data source and summarize the data. We then use a rolling window over the time-series data, applying the same concepts from the full sample analysis to derive an index of spillover, connectedness and measure the behavior of the network over time; We finally then use these spillover and connectedness table to create our network diagrams to give us a beautiful graphical representation of the connectedness and links between the selected indices. We then use our prior financial knowledge to interpret these results especially during times of economic crisis such as the 2008 recession and the covid pandemic to name a few examples.

7. References

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- Better to Give than to Receive: Predictive directional measurement of volatility spillovers| Francis X. Diebold and Kamil Yilmaz| November,2008

8. Code and Data

https://github.com/abhinil12