Effect of IT Stock Prices on NIFTY 50 - An Empirical Analysis on Indian Stock Market

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Abstract: NIFTY 50 is National Stock Exchange of India's benchmark broad based stock market index for the Indian Equity Market. Full form of NIFTY is National Exchange Fifty. It represents the weighted average of 50 Indian company stocks in 12 sectors and is one of the two main stock indices used in India. This study is an attempt to find the effects of IT stock prices (NIFTY) on NIFTY 50. IT stocks which are enlisted under NIFTY 50 are TCS, WIPRO, Tech Mahindra, INFOSYS and HCL Technologies. We have collected data mostly from i.) NSE and ii.) Yahoo Finance. Annual Data (daily data) for the period of 2008-2018 have been utilized. This study employs Regression Analysis, Dropping Variable Analysis, Testing of Parameters, Granger Causality Test, Volatility test with ARCH Model. The study will help the rational investors to understand the trend of NIFTY 50 before investing on it. We used the computer program R GUI and EViews-7 for detailed analysis.

Keywords: NIFTY 50, Multiple Linear Regression, Dropping Variable, Granger Causality Test, ARCH

1. Introduction

Generally, stock market across the globe replicates the fluctuation of the market's economy, and attracts the attention of millions of investors. The stock market is characterized by high risk and high yield; hence investors are concerned about the analysis of the stock market and are trying to forecast the trend of the stock market. NSE was incorporated in November 1992, and received recognition as a stock exchange under the Securities Contracts (Regulation) Act, 1956 in April 1993. Since its inception in 1992, NSE of India has been at the vanguard of change in the Indian securities market. This period has seen remarkable changes in markets, from how capital is raised and traded, to how transactions are cleared and settled. The market has grown in scope and scale in a way that could not have been imagined at that time. Average daily trading volumes have jumped from Rs. 17 crore in 1994-95 when NSE started its Cash Market segment to Rs.16,959 crore in 2009-10. Similarly, market capitalization of listed companies went up from Rs.363,350 crore at the end of March 1995 to Rs.36,834,930 crore at end March 2011. Indian equity markets are today among the most deep and vibrant markets in the world. NSE offers a wide range of products for multiple markets, including equity shares, Exchange Traded Funds (ETF), Mutual Funds, Debt instruments, Index futures and options, Stock futures and options, Currency futures and Interest rate futures. Our Exchange has more than 1,400 companies listed in the Capital Market and more than 92% of these companies are actively traded. The debt market has 4,140 securities available for trading. Index futures and options trade on four different indices and on 223 stocks in stock futures and options as on 31st March, 2010. Currency futures contracts are traded in four currency pairs. Interest Rate Futures (IRF) contracts based on 10 year 7% Notional GOI Bond is also available for trading. The role of trading members at NSE is to the extent of providing only trading services to the investors; the Exchange involves trading members in the process of consultation and participation in vital inputs towards decision making. A stock market index is a method of measuring a stock market as a whole. The most important type of market index is the broad-market index, consisting of the large, liquid stocks of the country. In most countries, a single major index dominates benchmarking, index funds, index derivatives and research applications. In addition, more specialized indices often find interesting applications. In India, we have seen situations where a dedicated industry fund uses an industry index as a benchmark. In India, where clear categories of ownership groups exist, it becomes interesting to examine the performance of classes of companies sorted by ownership group.

Stocks are often classified based on the type of company it is, the company's value, or in some cases the level of return that is expected from the company. Below is a list of classifications which are generally known to us Growth Stocks, Value Stocks, Large Cap Stocks, Mid Cap Stocks, and Small Cap Stocks. Stocks are usually classified according to their characteristics. Some are classified according to their growth potential in the long run and the others as per their current valuations. Similarly, stocks can also be classified according to their market capitalization. S&P CNX NIFTY has NIFTY (50), Junior NIFTY (50), CNX IT (20), Bank NIFTY (12), NIFTY Midcap50, CNX Realty (10) and CNX Infra (25). The sectoral distribution of NSE are Financial services or banks, Energy, Information Technology, Metals, Automobile, FMCG, Construction, Media & Entertainment, Pharma, Industrial Manufacturing, Cement, Fertilizers & Pesticides, Textiles, Power and Telecom.

The stock price tends to fluctuate before and after the monetary policy is announced. The monetary policy may have a favorable or adverse impact on the stock market i.e., Nifty is considered as an index depending on how market players analyze it with reference to their expectations. Monetary policy can hence help in achieving economic growth by (i) minimizing fluctuations in the prices and business activities and (ii) providing economic environment conducive for achieving high levels of savings and investments.

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2. Literature Review

Sherman J. Maisel (1968) found that Monetary policy appears to influence the economy primarily through its impact on spending in particular sectors. Spending is influenced through the price, availability, and distribution of credit. Higher interest rates resulting from an increased demand for funds, and/or a slower rate of expansion of the supply of funds, and disintermediation brought contraction in investment. He concluded that movements in the flow of funds among financial institutions and markets may create impacts on spending as great as or even greater than do changes in the general availability and price of credit. Alexandros Kontonikas Christos Ioannidis, (2006)investigated the impact of monetary policy on stock returns in thirteen OECD countries over the period 1972-2002. The results indicate that monetary policy shifts significantly affect stock returns, thereby supporting the notion of monetary policy transmission via the stock market. Shahid Ahmed (2008) investigated the nature of the causal relationships between stock prices and the key macro economic variables representing real and financial sector of the Indian economy for the period March, 1995 to March, 2007 using quarterly data. The variables were index of industrial production, exports, foreign direct investment, money supply, exchange rate, interest rate, NSE Nifty and BSE Sensex in India. The results of the study revealed differential causal links between aggregate macro economic variables and stock indices in the long run. Interest rate seems to lead the stock prices. The study also revealed that the movement of stock prices is not only the outcome of behaviour of key macro economic variables but it is also one of the causes of movement in other macro dimension in the economy.

Md. Mahmudul Alam, Md. Gazi Salah Uddin (2009) examined the effect of interest rate on share price and changes of interest rate on changes of share price. Individual country result is mixed for both developed and developing countries. For Malaysia it is found that Interest Rate has no relation with Share price but Changes of Interest Rate has negative relationship with Changes of Share Price. In case of Japan, it is found that Interest Rate has positive relationship with Share price but change of Interest Rate has negative relationship with change of Share Price. Four countries like Bangladesh, Colombia, Italy, and S. Africa showed negative relationship for both Interest Rates with Share price and Changes of Interest Rate with Changes of Share Price. Eight countries like, Australia, Canada, Chile, Germany, Jamaica, Mexico, Spain, and Venezuela has significant negative relationship between Interest Rates and Share price but no relationship between change of Interest Rate and change of Share Price. So, except Philippine all other countries show significant negative relationship either Interest Rates with Share price or Changes of Interest Rate with Changes of Share Price or both. Amaresh Samantaraya (2009) found that Monetary policy is a key constituent of overall economic policy across the industrial and emerging economies for the purpose of stabilization of output and prices. Monetary expansion reduces interest rates and augments aggregate demand through increase in investment and consumption spending. K Raviteja, Mandarapu Tejaswi, Bandla Madhavi, G Ujwala (2013) examined cash reserve ratio effect on stock market returns in India and investigated relative other factors which influence stock market returns in India. It is found that the volatility of the Nifty 50 is more whenever RBI changes the CRR up to 50 basis points. CRR had played vital role in influencing the interest rates and flow of liquidity from the deposit holders into the banks. Monitory policy changes impact is more on the Bank Nifty than the Nifty 50.

Imarhiabel (2010) applied vector-error correlation modelling to study the impact of oil prices on stock prices of selected major oil producing and consuming countries(Mexico, Russia, Saudi Arabia, India, China and the US) with nominal exchange rate as additional determinant. The result showed that in all countries Variance decomposition and impulse response tests confirm existence of oil prices and exchange rates influences over stock prices. Onos (2010) assessed the differences of the impact of oil price futures in stock markets or companies expected earnings among BRIC's and also an unprecedented oil price increases from 1990 to 2010. The finding indicated real oil price for India and industrial production with constants and trend for Brazil cannot be rejected. The existence of a unit root in their levels while on the other hand Null hypothesis (Ho) was rejected real stock price of the unit -root of 1% level in all cases. Consequently, the author believed that real stock returns responded positive to some of the oil price indicators with statistically Significance for China, India, Russia where as no Significant response was observed in the Brazilian real stock returns. Masih, Peter and Mello (2010) analyzed the relationship between oil prices shocks and the Macroeconomic variables by using modern time series techniques in a cointegrating framework. The findings suggested that the financial crises did not affect on the stochastic trend between ip, op, rvol and rsr. In addition the author believed that the oil price movements significantly affect the stock markets and analysis indicates that real stock returns are the main channel of Short-run adjustment to long-run equilibrium. (Industrial production as ip, real stock returns as rsr, interest rates as r, oil prices as op, and oil price volatility as rvol). Impact of crude oil prices in Indian economy growth and the relationship between oil price and inflation was studied by Sharma et.al. (2012) and analyzed the trend in oil price and the factors that affect the crude oil prices. Lis, NeBler, and Retzmann (2007) investigated the impact of oil prices is different on the overall Market and automotive companies. In addition showed the differences in sensitivity among the continents taking Germany, USA and Japan in to account where result pictured a link between the Crude oil price and the share price of cars producing companies in every period as well as every portfolio. Basher and Sadorsky (2006) examined the impact of oil price changes on a large set of emerging stock market returns and found regression for unconditional and conditional models for the relationship between risk returns differences and result showed that oil price risk impacts stock price returns in emerging markets although the exact relationship depend upon the data frequency. Hale and Chang (2011) titled the impact of oil price fluctuation on stock markets in Developed and emerging economies. Suggested that the fluctuations in oil price on stock market is not so statistically significant although the presumption of oil price -stock price relationship seen some reasonable area of Japan. Roselee,

Volume 7 Issue 10, October 2018 <u>www.ijsr.net</u> Licensed Under Creative Commons Attribution CC BY Samad, Fazilah, Bhat and Sonal (2009) examined the effect of oil price movements on the stock price of oil and gas companies in three different market (US, India & UK) and found that some co-integration between oil stocks, oil prices, interest rates, industrial production and the stock index and there is a significant short-run as well as long-run relationship between them which concluded that these variables have co-integrating relationship. Asteriou, Dimitras, Lendewig (2013) assessed the differences in the impact of oil price fluctuations on oil importing countries and on oil exporting countries. The result of the study showed that the oil price interact with the stock markets in a stronger manner than with the interest rates in the short -run as well as in the long-run . Furthermore, the significance of this impacts is higher on oil importing countries than on oil exporting countries. Finally the fluctuation in oil price might present different affects among different countries and a possible explanation for this can be the degree of development of the countries.

The discussion of the potential impact of higher Prices where IMF Research department approved by Mussa (2000), on the topic "The impact of higher oil prices on the Global economy." The researcher suggested some recent development and outlook in oil Markets & impacts on global economy and concluded that 1/4 of the GDP from global oil importers to oil exporters would be a sustained oil price increase of that size & imply a permanent transfer. Christensen (2011) analyzed the impact of oil Price Shocks on Stock Markets where the author investigated linear, nonlinear & asymmetric oil price shocks, where he found that all individual countries dependency on oil will have great impact on the response of the real stock returns. Papaetrou (2001) studied the dynamic linkage between crude oil price and employment in Greece using industrial production and industrial employment as alternative measures of economic activity. His study was modelled in a cointegrated VAR framework and extends out by looking at the generalised variance decomposition and impulse response functions.

3. Objective

The objective of the study is to find the effect of IT stock prices on NIFTY 50. The IT(Information Technology) stocks which are enlisted under NIFTY 50 is taken for consideration. IT stocks which are enlisted are as hereunder:- TCS, Infosys, HCL Technologies, Tech Mahindra and Wipro.

The study is based on Multiple regression, Dropping Variable, Granger Causality Test and ARCH modelling to test the volatility. It was found that the time series data is stationary after doing the root test for first difference. We used R GUI and Eviews-7 for the analysis. The empirical results and analysis are shown in the entire study.

4. Methodology

The study is empirical in nature and the study is limited to Indian stock market represented by NSE. The time frame for the study was ten years beginning from 2008 till end of August' 2018. The sampling elements for the study were TCS, Tech Mahindra, Infosys, HCL Technologies and Wipro stock prices and its impact on NSE NIFTY 50. Purposive sampling was used to complete the study and the data was collected from secondary sources through official website of NSE, Yahoo Finance. Tools for Data Analysis a. Regression Analysis b. Dropping Variable Analysis c. Granger Causality Test d. ARCH Modelling for volatility check. R GUI and EViews - 7 are used for complex data analysis.

The analysis is done based on 2469 data points for the period of 2nd September'2008 till 31st August' 2018. Machine learning technique with R GUI is used for replacing the missing values and validation of Regression Model. The total data set have been divided into training set and test set for validation of model(80 percent training set and 20 percent test set.).

A. Analysis of Data and Discussion:-

		Table	1			
Date	NIFTY	Wipro	TECHM	TCS	INFO	HCL
					SYS	TECH
02-09-2008	4504	135.285	189.788	212	444	125
04-09-2008	4447.75	134.445	193.462	211	447	126
05-09-2008	4352.2998	127.455	189.425	210	428	122
08-09-2008	4482.2998	130.125	193.55	214	438	128
09-09-2008	4468.7002	130.56	198.625	216	437	127
10-09-2008	4400.25	129.57	199.538	213	440	125
11-09-2008	4290.2998	128.04	194.613	209	438	119
12-09-2008	4228.4502	125.895	189.812	203	411	114
15-09-2008	4072.8999	121.17	179.475	190	395	107
16-09-2008	4074.8999	117.465	173.062	187	392	111
17-09-2008	4008.25	119.955	166.938	183	395	105
18-09-2008	4038.1499	119.205	158.462	180	381	106
19-09-2008	4245.25	125.085	168.762	192	406	115
22-09-2008	4223.0498	124.41	164.05	192	407	117
23-09-2008	4126.8999	116.76	159.625	180	386	117
24-09-2008	4161.25	111.135	162.562	178	381	117
25-09-2008	4110.5498	105.63	159.988	172	377	112
26-09-2008	3985.25	103.275	156.288	169	362	106
29-09-2008	3850.05	102.93	152.462	155	348	98
30-09-2008	3921.2	101.97	154.8	166	350	97
01-10-2008	3950.75	104.76	158.738	168	362	103
03-10-2008	3818.3	102.51	155.938	164	348	104
06-10-2008	3602.3501	95.46	144.488	155	330	97
		00.0010				

continued..... till 31.08.2018.

The above data is stationary.

1. Multiple Linear Regression: In multiple linear regression, there are p explanatory variables, and the relationship between the dependent variable and the explanatory variables is represented by the following equation:

$$y_{i} = \beta_{0} + \beta_{1}X_{1i} + \beta_{2}X_{2i} + \dots + \beta_{p}X_{pi} + e_{i}$$

Where: β_0 is the constant term and β_1 to β_p are the coefficients relating the p explanatory variables to the variables of interest. So, multiple linear regression can be thought of an extension of simple linear regression, where there are p explanatory variables, or simple linear regression can be thought of as a special case of multiple linear regression, where p=1. The term 'linear' is used because in

multiple linear regression we assume that y is directly related to a linear combination of the explanatory variables.

 Table 2: Regression Analysis on Training Set

 Residuals:

Activation and a second					
Min	1Q	Median	3Q	Max	
-1907.03	-435.58	11.61	463.53	1820.62	

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2448.1570	84.8348	28.858	< 2e-16 ***
Wipro	1.6534	0.6151	2.688	0.00725 **
TECHM	-1.8092	0.2717	-6.660	3.55e-11 ***
TCS	2.4303	0.1469	16.549	< 2e-16 ***
INFOSYS	1.4574	0.1970	7.400	2.01e-13 ***
HCL.TECH	2.4463	0.2015	12.138	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 690.3 on 1964 degrees of freedom Multiple R-squared: 0.8909, Adjusted R-squared: 0.8906 F-statistic: 3208 on 5 and 1964 DF, p-value: < 2.2e-16

From the above analysis it is seen that except Wipro all are highly statistically significant. So investors can understand that NIFTY is depending on all the IT Stock prices. It's based on training set.

Table 3: Regression Analysis on Test Set

Residuals					
Min	1Q	Median	3Q	Max	
-1804.86	-473.82	-38.85	499.00	1657.91	

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2549.4340	177.6948	14.347	< 2e-16 ***
Wipro	2.2735	1.2749	1.783	0.075149.
TECHM	-1.9076	0.5602	-3.405	0.000716 ***
TCS	2.7015	0.3002	8.999	< 2e-16 ***
INFOSYS	1.0529	0.3884	2.711	0.006950 **
HCL.TECH	2.2259	0.4001	5.564	4.37e-08 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 701.9 on 487 degrees of freedom Multiple R-squared: 0.8844, Adjusted R-squared: 0.8832 F-statistic: 745.2 on 5 and 487 DF, p-value: < 2.2e-16

And again from test set we can analyse that Wipro is less significant.

 Table 4: Regression Analysis on Data Set

	ŀ	Residuals		
Min	1Q	Median	3Q	Max
-1904.3	-443.5	-0.2	468.1	1815.5

Coefficients

	Estimate	Std. Error	t value	Pr (> t)	
(Intercept)	2466.9422	76.4328	32.276	< 2e-16 ***	
Wipro	1.7824	0.5535	3.220	0.0013 **	
TECHM	-1.8185	0.2440	-7.452	1.26e-13 ***	
TCS	2.4857	0.1317	18.872	< 2e-16 ***	
INFOSYS	1.3752	0.1754	7.841	6.58e-15 ***	
HCL.TECH	2.3954	0.1798	13.324	< 2e-16 ***	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 692 on 2457 degrees of freedom Multiple R-squared: 0.8896, Adjusted R-squared: 0.8893 F-statistic: 3958 on 5 and 2457 DF, p-value: < 2.2e-16

The multiple linear regression model with the data set available is as follows:-

NIFTY 50 = 2466.9422 + 1.7824Wipro + 2.4857

TCS + 1.3752 INFOSYS + 2.3954HCL.TECH - -1.8185 Tech Mahindra + 692

As it has been stated that Wipro is less significant so by dropping variable analysis the Multiple regression model becomes :-

Table 5:	Regression	Analysis	without	Wipro
	Da	stalss a la		

	_	Residuals		
Min	1Q	Median	3Q	Max
-1838.2	-441.9	1.0	461.0	1879.1

COEfficients

Estimate	Std. Error	t value	Pr (> t)
2593.8943	65.6058	39.538	< 2e-16 ***
-1.7657	0.2439	-7.238	6.05e-13 ***
2.4662	0.1318	18.708	< 2e-16 ***
1.6656	0.1507	11.054	< 2e-16 ***
2.4703	0.1786	13.831	< 2e-16 ***
	Estimate 2593.8943 -1.7657 2.4662 1.6656 2.4703	Estimate Std. Error 2593.8943 65.6058 -1.7657 0.2439 2.4662 0.1318 1.6656 0.1507 2.4703 0.1786	EstimateStd. Errort value2593.894365.605839.538-1.76570.2439-7.2382.46620.131818.7081.66560.150711.0542.47030.178613.831

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 693.4 on 2458 degrees of freedom Multiple R-squared: 0.8891, Adjusted R-squared: 0.8889 F-statistic: 4926 on 4 and 2458 DF, p-value: < 2.2e-16

The multiple linear regression model without Wipro as the data set available is as follows:-

NIFTY 50 = 2593.8943 + 2.4662 TCS + 1.6656 INFOSYS + 2.4703 HCL.TECH - 1.7657 Tech Mahindra + 693.4 The level of significance is already defined in the above table which states that its highly significant.

2. Granger Causality Test :- The Granger causality test, first proposed by Granger, is commonly used to examine causality relationship between two time series variables. It is a statistical hypothesis test in order to determine if one variable affects the other. Technically speaking, x and y are two time-series variables. If "x causes y" by means of a set of statistics, it indicates that the current y can be explained by past values of x and that adding lagged values of x to the model can enhance the explanation.

The null hypothesis in the first regression is that "x does not Granger cause y". Similarly, the null hypothesis in the second equation is that "y does not Granger cause x".

Fable 6: Granger Causality Re	esult
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Pairwise Granger Causality Tests				
Date: 10/23/18 Time: 19:38				
Sample: 9/02/2008 8/31/2018				
Lags: 2				
	F-			
Null Hypothesis:	Statistic	Prob.		
WIPRO does not Granger Cause NIFTY 2461		0.36032	0.6975	
NIFTY does not Granger Cause WIPRO		15.6480	2.E-07	
TCS does not Granger Cause NIFTY 2461 1.43431 0.2385				

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	a		0.000
NIFTY does not Granger Cause TC	S	2.52263	0.0805
TECHM does not Granger Cause NIFTY	2461	1.31348	0.2691
NIETV doos not Granger Cause TEC		2 19962	0.0922
NIFT T does not Granger Cause TEC		2.48803	0.0852
INFOSYS does not Granger Cause			
NIFTY	2461	0.23455	0.7909
NIETV does not Granger Cause INEO	CVC	1 33173	0.0132
	313	4.33423	0.0132
HCL_TECH does not Granger Cause			
NIFTY	2461	0.60033	0.5487
NIETY does not Granger Cause HCL	TECH	2 04082	0.0530
NIFT T does not Oranger Cause TICL_I	LCH	2.94082	0.0550
TCS does not Granger Cause WIPRO	2461	13.8561	1.E-06
WIPRO does not Granger Cause TC	S	2.01071	0.1341
TECHM does not Granger Cause			
TECHIVI does not Granger Cause			
WIPRO	2461	9.26128	0.0001
WIPRO does not Granger Cause TEC	HM	0.82583	0.4380
INFOCVC data and Cranger Course		0.02303	0.1500
INFOSTS does not Granger Cause			
WIPRO	2461	24.5238	3.E-11
WIPRO does not Granger Cause INFO	SYS	2 35317	0.0953
	515	2.33317	0.0755
HCL_TECH does not Granger Cause			
WIPRO	2461	13.5483	1.E-06
WIPPO does not Granger Cause HCL	FECH	0 43296	0.6486
will RO does not Glanger Cause HCL_		0.43270	0.0480
TECHM does not Granger Cause TCS	2461	3.14871	0.0431
TCS does not Granger Cause TECH	М	3.82347	0.0220
INFOSVS does not Granger Cause TCS	2161	2 08112	0 1250
The of the second secon	<u>∠</u> 401	2.00113	0.1230
TCS does not Granger Cause INFOS	YS	6.82763	0.0011
HCL TECH does not Granger Cause			
	2461	1 20766	0.07(1
105	2401	1.28/00	0.2761
TCS does not Granger Cause HCL_TH	ECH	4.07595	0.0171
INFOSYS does not Granger Cause			
	0461	0.04770	0.0524
TECHM	2461	0.04772	0.9534
TECHM does not Granger Cause INFC	SYS	4.48649	0.0114
HCL_TECH does not Granger Cause			
	0461	0.50600	0.55(1
IECHM	2461	0.58688	0.5561
TECHM does not Granger Cause HCL_'	TECH	8.46128	0.0002
HCL_TECH does not Granger Cause	-		
HCL_TECH does not Granger Cause	0461	2 75 6 40	0.0627
HCL_TECH does not Granger Cause INFOSYS	2461	2.75649	0.0637
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_	2461 TECH	2.75649 0.92191	0.0637
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause	2461 TECH	2.75649 0.92191 sts	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL Pairwise Granger Causa	2461 _TECH 	2.75649 0.92191 sts	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time	2461 TECH lity Te : 19:40	2.75649 0.92191 sts	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3	2461 _TECH llity Te : 19:40 51/2018	2.75649 0.92191 sts	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4	2461 TECH lity Te : 19:40 51/2018	2.75649 0.92191 sts	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4	2461 TECH lity Te : 19:40 51/2018	2.75649 0.92191 sts	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4	2461 TECH lity Te : 19:40 51/2018	2.75649 0.92191 sts F-	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis:	2461 TECH lity Te : 19:40 51/2018	2.75649 0.92191 sts F- Statistic	0.0637 0.3979
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY	2461 _TECH llity Te : 19:40 11/2018 Obs 2459	2.75649 0.92191 sts F- Statistic 0.23382	0.0637 0.3979 c Prob. 2 0.9194
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY	2461 TECH lity Te : 19:40 01/2018 Obs 2459	2.75649 0.92191 sts F- Statistic 0.23382	0.0637 0.3979 c Prob. 2 0.9194
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause WIF	2461 TECH lity Te : 19:40 01/2018 Obs 2459 PRO	2.75649 0.92191 sts F- Statistic 0.23382 11.7304	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause WIF TCS does not Granger Cause NIFTY	2461 TECH ility Te : 19:40 1/2018 0bs 2459 PRO 2459	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause WIF TCS does not Granger Cause NIFTY NIFTY does not Granger Cause TC	2461 TECH ility Te : 19:40 1/2018 0bs 2459 PRO 2459 CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 5 0.1990
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Causa Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause WIF TCS does not Granger Cause NIFTY NIFTY does not Granger Cause TC	2461 TECH lity Te : 19:40 1/2018 Obs 2459 RO 2459 CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 5 0.1990 8 0.1600
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause WIF TCS does not Granger Cause NIFTY NIFTY does not Granger Cause TC TECHM does not Granger Cause NIFTY	2461 TECH ility Te i19:40 01/2018 0bs 2459 PRO 2459 CS 2459 CS	2.75649 0.92191 sts F- Statistic 0.23382 11.730- 0.85605 1.50176 1.64593	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC	2461 TECH Ility Te : 19:40 51/2018 0bs 2459 RO 2459 RO 2459 CS 2459 CS 2459 HM	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434	0.0637 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause	2461 TECH lity Te : 19:40 51/2018 Obs 2459 PRO 2459 CS 2459 CS 2459 HM	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause TEC	2461 TECH lity Te : 19:40 1/2018 Obs 2459 PRO 2459 CS 2459 HM 2459	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5120
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause NIFTY	2461 TECH ility Te : 19:40 01/2018 0bs 2459 PRO 2459 CS 2459 CS 2459 HM 2459	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877	0.0637 0.3979 0.4896 0.1990 0.1600 0.1600 1.600 1.600 1.600 0.05130 0.1600 0.05130 0.05150 0.05130 0.05150 0.0
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause NIFTY	2461 TECH Ility Te : 19:40 0bs 2459 RO 2459 RO 2459 C 2459 HM 2459 SYS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877 2.20173	0.0637 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 8 0.0664
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause	2461 TECH lity Te : 19:40 0bs 2459 PRO 2459 CS 2459 CS 2459 HM 2459 SS 2459 SS 2459 CS CS CS CS CS CS CS CS CS CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85602 1.50176 1.64593 3.01434 0.81877 2.20173	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 6 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause TEC INFOSYS does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause	2461 TECH lity Te : 19:40 1/2018 Obs 2459 PRO PRO PRO PRO PRO PRO PRO PRO	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877 2.20173	0.0637 0.3979 c Prob. 2 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause WIF TCS does not Granger Cause NIFTY NIFTY does not Granger Cause NIFTY NIFTY does not Granger Cause NIFTY NIFTY does not Granger Cause TEC TECHM does not Granger Cause TEC INFOSYS does not Granger Cause TEC INFOSYS does not Granger Cause NIFTY NIFTY does not Granger Cause INFO HCL_TECH does not Granger Cause NIFTY	2461 TECH ility Te : 19:40 01/2018 0bs 2459 PRO 2459 CS 2459 CS 2459 HM 2459 SYS 2459 2459	2.75649 0.92191 sts F- Statistic 0.23382 11.7302 0.85605 1.50176 1.64593 3.01432 0.81877 2.20173 0.32682	0.0637 0.3979 0.4896 0.1990 0.1600 0.1600 0.05130 0.0664 4.0.8601
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause INFC HCL_TECH does not Granger Cause HCL_' NIFTY NIFTY	2461 TECH Ility Te : 19:40 0bs 2459 RO 2459 2459 2459 HM 2459 SYS 2459 HM 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS CS 2459 CS CS 2459 CS CS CS CS CS CS CS CS CS CS CS CS CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85609 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56663	0.0637 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1805
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause INFC	2461 TECH lity Te : 19:40 0bs 2459 RO 2459 RO 2459 CS 2459 HM 2459 SYS 2459 CS CS CS CS CS CS CS CS CS CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56665 10.8682	0.0637 0.3979 0.3979 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1805 2 1 E-08
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause INFO HCL_TECH does not Granger Cause INFO HCL_TECH does not Granger Cause INFO NIFTY does not Granger Cause INFO HCL_TECH does not Granger Cause HCL_	2461 TECH lity Te : 19:40 0bs 2459 PRO 2459 CS 2459 HM 2459 SYS 2459 ECH 2459 255 255 255 255 255 255 255 2	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85602 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56663 10.8682 10.8682	0.0637 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1805 2 1.E-08 0 0.225
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause TEC INFOSYS does not Granger Cause INFO HCL_TECH does not Granger Cause INFO HCL_TECH does not Granger Cause MIFTY NIFTY does not Granger Cause NIFTY NIFTY does not Granger Cause INFO HCL_TECH does not Granger Cause MIFO HCL_TECH does not Granger Cause MIPRO WIPRO does not Granger Cause WIPRO	2461 TECH lity Te : 19:40 1/2018 Obs 2459 PRO 2459 CS 2459 HM 2459 SYS 2459 ECH 2459 2459 CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56663 10.8682 1.26010	0.0637 0.3979 0.3990 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.30000 0.3000000000 0.30000000000
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HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause INFC HCL_TECH does not Granger Cause HCL_ TCS does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO	2461 TECH Ility Te : 19:40 0bs 2459 RO 2459 2459 2459 2459 HM 2459 2459 ECH 2459 2459 CS 2459 TECH 2459 CS 2459 TECH	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56663 10.8682 1.26010 6.40809 0.77184	0.0637 0.3979 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1805 2 1.E-08 0 0.2835 9 4.E-05 4 0.5434
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HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause INFC HCL_TECH does not Granger Cause HCL_ TCS does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO	2461 TECH ility Te i1/2018 0bs 2459 2459 2459 2459 2459 2459 2459 ECH 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS CS 2459 CS CS CS CS CS CS CS CS CS CS CS CS CS	2.75649 0.92191 sts F- Statistic 0.23382 11.730- 0.85605 1.50176 1.64593 3.0143- 0.81877 2.20173 0.3268- 1.56663 10.8682 1.26010 6.40809 0.7718- 17.0769	0.0637 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.4896 0.1990 0.4896 0.1990 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1805 2 1.E-08 0 0.2835 0 4.E-05 4 0.5434 0 8.E-14
HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFC HCL_TECH does not Granger Cause INFC HCL_TECH does not Granger Cause HCL_ TCS does not Granger Cause WIPRO WIPRO does not Granger	2461 TECH Ility Te : 19:40 0bs 2459 RO 2459 2459 2459 2459 2459 2459 ECH 2459 2459 2459 2459 2459 2459 2459 2459	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85609 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56663 10.8682 1.26010 6.40809 0.77184 17.0769 1.7547	0.0637 0.3979 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.0664 4 0.8601 3 0.1805 2 1.E-08 0 0.2835 9 4.E-05 4 0.5434 9 8.E-14 1 0 1353
HCL_TECH does not Granger Cause INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause HCL_ Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFO HCL_TECH does not Granger Cause INFO HCL_TECH does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause TEC INFOSYS does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause TEC INFOSYS does not Granger Cause TEC INFOSYS does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause TEC INFOSYS does not Granger Cause INFO WIPRO does not Granger Cause INFO	2461 TECH ility Te : 19:40 0bs 2459 RO 2459 RO 2459 CS 2459 HM 2459 CS CS CS CS CS CS CS CS CS CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85605 1.50176 1.64593 3.01434 0.81877 2.20173 0.32684 1.56665 10.8682 1.26010 6.40809 0.77184 1.7.0769 1.75471	0.0637 0.3979 0.3979 0.3979 0.3979 0.9194 4 2.E-09 5 0.4896 5 0.1990 3 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1805 2 1.E-08 0 0.2835 9 4.E-05 4 0.5434 0 8.E-14 1 0.1353
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HCL_TECH does not Granger Cause INFOSYS INFOSYS does not Granger Cause HCL_ Pairwise Granger Cause Date: 10/23/18 Time Sample: 9/02/2008 8/3 Lags: 4 Null Hypothesis: WIPRO does not Granger Cause NIFTY NIFTY does not Granger Cause INFO HCL_TECH does not Granger Cause INFO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause INFO HCL_TECH does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause WIPRO WIPRO does not Granger Cause INFO HCL_TECH does not Granger Cause INFO WIPRO does not Grang	2461 TECH Ility Te : 19:40 01/2018 2459 RO 2459 CS 2459 HM 2459 2459 FECH 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS 2459 CS CS 2459 CS CS 2459 CS CS CS CS CS CS CS CS CS CS CS CS CS	2.75649 0.92191 sts F- Statistic 0.23382 11.7304 0.85609 1.50176 1.64599 3.01434 0.81877 2.20173 0.32684 1.56663 10.8682 1.26010 6.40809 0.77184 17.0769 1.75477 9.77268 0.39022	0.0637 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.3979 0.4896 0.4896 0.1990 0.4896 0.1990 0.1600 4 0.0171 7 0.5130 3 0.0664 4 0.8601 3 0.1605 2 1.E-08 0 0.2835 0 4.E-05 4 0.5434 1 0.1353 3 8.E-08 3 0.8158
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TCS does not Granger Cause INFOS	4.45049	0.0014	
HCL_TECH does not Granger Cause			
TCS	2459	2.53441	0.0384
TCS does not Granger Cause HCL_TECH		2.33593	0.0534
INFOSYS does not Granger Cause			
TECHM	2459	0.70665	0.5873
TECHM does not Granger Cause INFOSYS		2.54907	0.0375
HCL_TECH does not Granger Cause			
TECHM	2459	0.22657	0.9236
TECHM does not Granger Cause HCL_7	FECH	4.48329	0.0013
HCL_TECH does not Granger Cause			
INFOSYS	2459	3.95259	0.0033
INFOSYS does not Granger Cause HCL_	TECH	3.97936	0.0032

From the above test i.e granger causality test it has been found that none of the above IT stocks effect NIFTY independently rather it's found that they jointly effect the NIFTY 50. But from the above analysis it was found that NIFTY 50 granger cause Tech Mahindra stock price and Wipro stock price so we can come to a point as NIFTY 50 gets effected these two stock prices also gets effected.

3. ARCH: An ARCH (autoregressive conditionally heteroscedastic) model is a model for the variance of a time series. ARCH models are used to describe a changing, possibly volatile variance. Although an ARCH model could possibly be used to describe a gradually increasing variance over time, most often it is used in situations in which there may be short periods of increased variation. (Gradually increasing variance connected to a gradually increasing mean level might be better handled by transforming the variable.)

ARCH models were created in the context of econometric and finance problems having to do with the amount that investments or stocks increase (or decrease) per time period, so there's a tendency to describe them as models for that type of variable.

To apply ARCH modelling the following conditions should be checked:-

- a) Clustering Volatility.
- b) ARCH test should be rejected as NULL hypothesis.

Table 7: ARCH Effect results						
	NIFTY and TCS					
	Test Eq	uation:				
Depe	ndent Vari	able: RES	ID^2			
N	Aethod: Le	ast Square	es			
Dat	e: 10/23/18	Time: 20):16			
Sample (adjusted):	9/04/2008	8/31/2018			
Included obs	ervations:	2462 after	adjustme	nts		
Variable	Coefficient	Std. Error	t-Statistic	Prob.		
С	7442.206	3124.066	2.382218	0.0173		
RESID^2(-1)	0.986107	0.003356	293.8456	0.0000		
R-squared	0.972299	Mean depe	endent var	543345.8		
Adjusted R-squared	0.972288	S.D. depe	ndent var	756027.5		
S.E. of regression	125856.1	Akaike inf	o criterion	26.32448		
Sum squared resid	3.90E+13	Schwarz	criterion	26.32920		
Log likelihood	-32403.43	Hannan-Q	uinn criter.	26.32619		
F-statistic	86345.21	Durbin-W	atson stat	2.056425		
Prob(F-statistic)	0.000000					

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From the above analysis it is seen that the probabilistic value is less than 5% so the Null Hypothesis that there is no ARCH effect is rejected and alternative hypothesis that it has ARCH effect is accepted. So clustering volatility and ARCH effect is present in the above model.

ARCH model where dependent variable is NIFTY and independent Variable is TCS with all other stocks as regressors.

Dependent Variable: NIFTY					
Method: ML - AR	Method: ML - ARCH (Marguardt) - Student's t distribution				
Date: 10/24/18 Time: 14:34					
Sai	mple: 9/02/2	2008 8/31/2	2018		
Inc	cluded obser	vations: 2	2463		
Failure to im	prove Likel	ihood afte	er 46 iteratio	ons	
Presample va	ariance: bac	kcast (pa	rameter = 0	.7)	
t-distribution de	egree of free	dom para	meter fixed	l at 10	
GARCH = C(4) +	C(5)*RESII	$D(-1)^{2} + 0$	C(6)*GARC	H(-1) +	
	C(7)*W	IPRO +			
C(8)*TECHM -	- C(9)*HCL	TECH +	C(10)*INFC	OSYS	
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
@SQRT(GARCH)	0.084193	0.038386	2.193322	0.0283	
С	2997.047	41.93611	71.46697	0.0000	
TCS	4.171147	0.022657	184.1000	0.0000	
	Variance I	Equation			
С	549268.8	.8 135297.6 4.059708 0.0000			
RESID(-1)^2	1.173354	0.201344	5.827608	0.0000	
GARCH(-1)	-0.390129	0.045724	-8.532328	0.0000	
WIPRO	-464.0286	700.7707	-0.662169	0.5079	
TECHM	-53.15360	196.1283	-0.271014	0.7864	
HCL_TECH	15.80545	144.5019	0.109379	0.9129	
INFOSYS	-264.8679	98.92195	-2.677544	0.0074	
R-squared	0.873770	Mean dependent var 6786.95			
Adjusted R-squared	0.873667	S.D. dependent var 2080.322			
S.E. of regression 739.4154 Akaike info criterion 15.35301				15.35301	
Sum squared resid 1.34E+09 Schwarz criterion 15.37659					
Log likelihood	1 -18897.23 Hannan-Quinn criter. 15.36158				
Durbin-Watson stat 0.010895					

@SQRT(GARCH) is actually the risk of NIFTY. RESID(-1)² is also known as ARCH and GARCH(-1) are the internal causes of Volatility of NIFTY 50 and from the above analysis it is significant as the Prob. Value is 0. GARCH effects in a negative manner. And the external causes are WIPRO, TECHM, HCL_TECH and INFOSYS. But it is seen that only INFOSYS is significant to some extent. But other external factors are insignificant. As the value of INFOSYS is negative so volatility of NIFTY can be influenced to certain extent but negatively. Akaike info criterion = 15.35301 and Schwartz criterion = 15.37659 with **Students distribution with fixed 10 degrees of freedom**. Lower the value of Akaike info criterion and Schwartz criterion better will be the model.

Diagnostic Checking:

Heteroskedasticity Test: ARCH					
F-statistic	695.3816	Prob. F(1,2460)		0.0000	
Obs*R-squared	542.5745	Prob. Chi-Square(1)		0.0000	
Test Equati	on:				
Dependent	Variable: W	GT_RESID	^2		
Method: Least Squares					
Date: 10/24/	18 Time: 1:	5:18			
Sample (adj	usted): 9/04/	2008 8/31/2	018		
Included observ	vations: 246	2 after adjus	tments		
Variable	Coefficient	Std. Error	Prob.		
С	0.332834	0.014488 22.97368		0.0000	
WGT_RESID^2(-1)	0.469454	0.017803	26.37009	0.0000	
R-squared	0.220380	Mean dependent var		0.627235	
Adjusted R-squared	0.220063	S.D. dependent var		0.518756	
S.E. of regression	0.458134	Akaike info criterion		1.277503	
Sum squared resid	516.3218	Schwarz criterion		1.282221	
Log likelihood	-1570.606	Hannan-Quinn criter.		1.279217	
F-statistic	695.3816	Durbin-Watson stat		2.352901	
Prob(F-statistic)	0.000000				

From the ARCH test it is found that as the probabilistic value is less than 5 % so ARCH effect is present. As our Null hypothesis that there is no ARCH effect.

Correlogram Squared Residuals analysis diagnose that there is serial correlations in the model. But we have to do further analysis with **Students t distribution**.

Dependent Variable: NIFTY					
Method: ML - ARCH (Marquardt) - Student's t distribution					
Date: 10/24/18 Time: 15:42					
Sa	ample: 9/02/	2008 8/31/2	2018		
Ir	ncluded obse	ervations: 2	463		
Failure to in	nprove Like	lihood afte	r 39 iteratio	ns	
Presample	variance: ba	ckcast (par	rameter = 0.'	7)	
GARCH = C(4) +	C(5)*RESI	$D(-1)^{2} + 0$	C(6)*GARC	H(-1) +	
	C(7)*W	/IPRO +			
C(8)*TECHM	+ C(9)*HCI	L_TECH +	C(10)*INFC	DSYS	
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
@SQRT(GARCH)	-0.001683	0.072030	-0.023368	0.9814	
С	2938.873	68.82128	42.70297	0.0000	
TCS	4.256515	0.033248	128.0245	0.0000	
	Variance	Equation			
С	549329.4	118511.5 4.635241		0.0000	
RESID(-1)^2	0.887802	0.198313 4.476780 0.00			
GARCH(-1)	-0.341914	0.055383 -6.173670 0.00			
WIPRO	-147.8865	602.4652	-0.245469	0.8061	
TECHM	-134.6540	150.4113	-0.895239	0.3707	
HCL_TECH	-125.4220	119.1680	-1.052481	0.2926	
INFOSYS	-193.0556	91.83881	-2.102113	0.0355	
T-DIST. DOF	667.6723	24260.70	0.027521	0.9780	
R-squared	0.870838	Mean dependent var 6786.			
Adjusted R-squared	0.870733	S.D. dependent var 2080.3			
S.E. of regression	747.9538	Akaike info criterion 15.38436			
Sum squared resid 1.38E+09 Schwarz criterion 15.41030					
Log likelihood	-18934.83	3 Hannan-Quinn criter. 15.39378			
Durbin-Watson stat	0.010787				

@SQRT(GARCH) is actually the risk of NIFTY which is insignificant in this model.. RESID(-1)² is also known as ARCH and GARCH(-1) are the internal causes of Volatility of NIFTY 50 and from the above analysis it is significant as

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the Prob. Value is zero. GARCH effects in a negative manner. And the external causes are WIPRO, TECHM, HCL_TECH and INFOSYS. But it is seen that only INFOSYS is significant. But other external factors are insignificant. As the value of INFOSYS is negative so volatility of NIFTY can be influenced to certain extent but negatively. Akaike info criterion = 15.38 and Schwartz criterion = 15.41.

So from the above analysis and from further analysis i.e by changing the independent variable from TCS to INFOSYS or TECH MAHINDRA or Wipro or HCL Technologies same results are being analysed. There are certain internal causes of volatility is present and INFOSYS is one of the external causes of effecting the volatility of NIFTY 50 whereas other external factor that is stock prices of TCS, Wipro etc are not effecting the volatility of NIFTY 50.

5. Conclusion

From the above analysis i.e multiple regression analysis, dropping variable analysis, granger analysis and ARCH it has been found that NIFTY 50 is having a multiple linear regression with Wipro, TCS, INFOSYS, Tech Mahindra and HCL Technologies. But from Granger Causality test it has been found that none of the above IT stocks effect NIFTY independently rather it is found that they jointly effect the NIFTY 50. Similarly it was found that NIFTY 50 granger cause Tech Mahindra stock price and Wipro stock price so we can conclude as NIFTY 50 gets effected , these two stock prices also gets effected. So if there is a fluctuation in NIFTY 50 it effects the Tech Mahindra and Wipro stock prices. Similarly from ARCH model it is found that certain internal causes of volatility is present, and INFOSYS is one of the external causes of effecting the volatility of NIFTY 50 whereas other external factor that is stock prices of TCS, Wipro etc are not effecting the volatility of NIFTY 50.

6. Recommendations

To provide a 1-suitable investment environment in India through more incentives and facilities to investors away from the bureaucracy and the removal of the obstacles faced by these investors. 2- To work on creating investment opportunities to attract more foreign investment in the Indian Stock Market 3 - It's very essential for decision -makers to take a look at the results of this research. 7- This study is subject to a limitation and might be explored in future research. It adopted multiple regression analysis, granger test and ARCH for volatility test. While ARCH models limiting the choice of methodology, as further analysis can be done from case to case basis. Thus could be varied from one study to another one that depends on the effect of different kinds of stocks on NIFTY 50. Despite this limitation, this study has provided several important insights into issues relating to empirical analysis on effects of IT Stock prices on NIFTY 50. Hopefully, this study will encourage researchers to conduct further studies about effect of different stock prices on NIFTY 50 in Indian Stock market. The data which are taken are the closing price of stocks daily wise. For further analysis we can use Low price, High Price, Volume traded or opening price as the case may be.

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