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Do European, Middle-East and Asian Stock Markets Impact on Indian Stock Market? A Case Study Based on NIFTY Stock Index Forecasting

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Abstract

This paper estimates NIFTY index from Indian stock market by considering a cluster of MSCI European, Middle East and Asian stock market indices. In the forecasting process, we obtain group of independent variables to test its relative impact over dependent variable (NIFTY) considering a sample size of daily observations from January 2000 to December 2021 abstracted from Bloomberg. We run OLS regression, Quantile estimations with additional parameter of VIF and BKW. We found significant impact association with China (Asian index) and Saudi Arabia (Middle East index) during the forecasting process compared to rest of sample indices that exceed unexpectedly out of VIF limits. Further, we recorded strong association of independent variables despite of statistical significance (<1%) in OLS regression estimation.

Keywords: stock market forecasting; inflation; VIF; BKW; OLS regression; EMEA countries; Indian stock market performance.

JEL classification: C22; E44; G12; G41.

1. INTRODUCTION

Financial liberalization resulted positively valuable impact over emerging economics. The growth pattern and inflow in financial markets affected exponentially over the time. Last decade evident for major changes in contribution of international financial market flow, particularly in European, Middle East and Asian countries. Financial markets, which are already under the attention of global investors, sustains potentials to recover from sudden or unexpected impacts. Financial market volatility creates implications for many macro

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dimensions that strongly relates to growth of economy at a larger extent (Singhal & Ghosh, 2016; Akkoc & Civcir, 2019). Henceforth, the detail study, analysis and interpretation of historical property considered as more significant. The interpretation between volatility and its response and recovery over a period adds value as prime assets. Further, several studies that provided evidence for hedging against such events particularly from the risk management perspective (Mum 2007). From the recent COVID – 19 pandemic, all financial market observed under high stress with unpredictable uncertainty.

Indian financial markets have captured attention of international portfolio managers. The number of registered financial institutional investors exceeding 1,600, where more than 325 new FIIs registered after 2008. Further, FII sub-accounts exceed more than 30% in recent year (India Brand Equity Foundation, 2022). This indicates that Indian financial market gained more interest from international investors. Empirical quantitative analysis provides significant statistical parameters, which focuses on various factors such as dependence of a market with other, absorbing changes from other markets, changes in risk factor with changes in quantile, volatility clusters etc., and when asset returns from one market compared with related samples, strong and significant outcome property derived. Which further researchers and investors community can use across the world. For instance, OLS regression that provides estimation and modeling where statistical property of coefficient suggests impact of an independent variable on the mean of dependent variable. Therefore, such statistical approach popularly known as conditional mean modeling (Hao & Naiman, 2007). Even quantile estimation considered as appropriate method to estimate effect at different percentiles (quantiles) which also provides upper and lower tails of achieved distributions (Porter, 2015). Method used widely by international scholars to test dependency of dependent variable over independent variables, for stock markets, oil prices, crypto markets or even commodity markets. Further, such methods also used to measure the relationship between foreign exchange rate and stock prices (Tran, 2016). Parameter of risk and return considered as primary factor for investors. Continuous changes in asset prices creates differences in tomorrow's price, and makes new historical price.

Researchers have studied the relationships between financial markets in the world through numerous studies. The global financial crisis (GFC), the European debt crisis (Mokni & Mansouri, 2017) as well as the recent COVID-19 (coronavirus crisis) pandemic. Many researchers (Azimli, 2020; Sharif *et al.*, 2020; Spulbar *et al.*, 2020; Birau *et al.*, 2021; Coker-Farrell *et al.*, 2021) have investigated the behavior of certain international stock markets. Youssef *et al.* (2021) examined the correlation between the stock market and the uncertainty of economic policies in China, Italy, France, Germany, Spain, Russia, the United States, and the United Kingdom on the COVID-19 pandemic. Their findings show that the direction of the EPU's effect on network connectivity has changed during the onset of the epidemic, suggesting that information overflows from a particular market may indicate good or bad news for other markets, depending on the prevailing economic situation. Outcome of such events creates implications for individual investors, portfolio managers, policymakers, investment banks, and central banks. Poor economic conditions, unstable liquidity platforms and economic crisis affects the overflow of international markets despite the uncertainty of economic policies (EPC) and even changes them Youssef *et al.* (2021). These indices presented by Baker *et al.* (2016) on stock markets, also (Antonakakis *et al.*, 2013; Arouri *et al.*, 2016; Christou *et al.*, 2017; Guo *et al.*, 2018; Hu *et al.*, 2018; Phan *et al.*, 2018; Xiong *et al.*, 2018; He *et al.*, 2020) and its fluctuations (Mei *et al.*, 2018; H. Yu *et al.*, 2018; M. Yu &

Song, 2018; Balcilar *et al.*, 2019; Wang *et al.*, 2020). Which is a transition (Li & Peng, 2017) focused on relationship of bonds and stocks (Li *et al.*, 2015; Fang *et al.*, 2017), commodity and stock markets (Fang *et al.*, 2018; Badshah *et al.*, 2019) and more recently, bitcoin and conventional assets (Matkovskyy *et al.*, 2020) are examples of this effect. Nearly all these studies reported evidence of a negative impact of EPU on the co-movement between these variables, and, in some cases, highlighted a significant portfolio implication related to EPU (Badshah *et al.*, 2019). Previous research has shown that serious issues have devastating effects on the stock markets of different countries. Such as the SARS epidemic (C. Chen *et al.*, 2009; Hsieh, 2013; M. Chen *et al.*, 2018) and the Ebola epidemic (Del Giudice & Paltrinieri, 2017; Ichev & Marinč, 2018). Also, the 9/11 attacks and the Gulf War. Fars in 1991 and the Asian financial crisis in 1997 are other examples of these devastating effects (Hasan *et al.*, 2021).

This paper explores reaction of randomly selected EMEA countries on Indian NIFTY stock index performance of variance inflation factors. We consider UKX, DAX, SMI indices from Europe, SASEIDX, and JALSH from Middle-East and NIFTY, SHCOMP, and NKY indices from Asia. For this purpose, multiple econometric methods being used; ANOVA, OLS regression, Quantile estimations, VIF and BKW, methodologies and process are as follows;

Koenker and Bassett (1978) introduced Quantile regression where each quantiles provides specific values-points at defined locations in the sample populations. It considers "*y*" values in any specific variable distributions at the "q^{th}" quantile. OLS regression model considers residuals of "*y*" for the identically distributions (along with constant population).

Linear regression process is the following:

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} \quad i = 1, \ldots, n \tag{1}$$

We minimize mean square error with:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - (\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip})\right)^2 \tag{2}$$

Percent of variance in dependable variable that explained by all independent variable R^2:

$$R^2 = 1 - \frac{SS\,Error}{SS\,Total} = \frac{SS\,Total - SS\,Error}{SS\,Total} = \frac{SS\,regression}{SS\,Total}$$

$$SSE = \sum_{i=1}^{n} e_i^{\,2} = \sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

$$SS\,Total = \sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2 = \sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 + \sum_{i=1}^{n}\left(\hat{Y}_i - \bar{Y}\right)^2 = \text{SSE + SS} \tag{3}$$

regression process defined for all independent variables selected as sample from MSCI – EMEA countries.

The adjusted $R^2$is the following:

$$R^2{}_{adj} = 1 - \left[\frac{(1-R^2)(n-1)}{n-k-1} \right] \tag{4}$$

Adjusted R^2, which adjusted for seven number of predictors (Sample independent variables) in the model. It particularly tends to overestimate strength of association since the model performs seven independent variables. Quantile estimation;

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \cdots + \beta_p(\tau)x_{ip} \quad i = 1, \ldots, n \tag{5}$$

Quantile estimation is one of the powerful tool that yields robust estimation of independent variables considering presence of dependent variables at different degree of evaluation. Describing impact at different degree of angles and at the same time allows researchers and practitioners to compute the regression estimates bases on the multiple predictors. Collinearity and least squares estimator Belsley *et al.* (1980) of eigenvalues:

$$\begin{gathered} \left(X^T X\right) = \sum_{i=1}^{k} \lambda_i \\ \phi_j = \left(\frac{c_{j1}^2}{\lambda_1} + \frac{c_{j2}^2}{\lambda_2} + \ldots + \frac{c_{jk}^2}{\lambda_k} \right) \end{gathered} \tag{6}$$

Condition indices and variance proportions distributions;

Considering *Rxx*, as *Rxx* = *VAV*, where A represents diagonal matrix with ordered eigenvalues of RXX and V which is *p* * *p* matrix.

$$\begin{gathered} \boldsymbol{R}_{XX}^{-1} = \boldsymbol{V}\boldsymbol{\Lambda}^{-1}\boldsymbol{V}' \\ VIF_j = \sum_{k=1}^{p} \frac{V_{jk}^2}{\lambda_k} \end{gathered} \tag{7}$$

Condition indicators refers to smallest of eigenvalues which are $\lambda k \approx 0$, confirms collinearity where small values indicate near to collinear relations. VIF equation confirms that only small eigenvalues contribute to variance inflation process. However, for those predictors which have large eigenvector coefficients with effect of small components. The data consists of daily closing index prices from 2000-01-04 to 2021-12-10, downloaded from Bloomberg official website:

Table no. 1 exhibits regression results and the parametric of R^2 indicates that independent variable explains proportion (95.9%) of the variance for a dependent variables (coefficient of determination). Results derived from the regression provides significant understanding about the relationship of movements in NIFTY and samples from Middle-East, Africa and European markets. For instance, it is confirmed that mean of NIFTY tends to have similarity in movements followed by the independent variables from Germany, Saudi Arabia, South Africa, China and Japan. This means that if the value of independent variables increases the mean of dependent variables also respond to increase suggesting a positive symmetry in movement of financial markets between India and China, Japan, South Africa, Saudi Arabia and Germany from the selected samples. At the same time, we find negative coefficients from UK and Switzerland financial markets suggesting a contrasting impact of mean of dependent variables. Henceforth, if the financial markets of UK and Switzerland increases, the dependent variable (NIFTY) tends to decrease. This provides how the correlation coefficient of selected sample markets impact on the movement of Indian specimen (NIFTY).

Table no. 1 – Regression, ANOVA and OLS regression for the sample period from January 2000 to December 2021 (T = 5724)

Regression Statistics					
Mean dependent var	5877.96	S.D.	3963.74		
Sum squared resid	3600	S.E. of reg.	802.303		
R-squared	0.95908	Ad.R-squared	0.95903		
F(7, 5716)	19138.74	P-value(F)	0		
Log-likelihood	−46397.17	A.criterion	92810.4		
Schwarz criterion	92863.57	Hannan-Quinn	92828.9		
rho	0.994717	Watson	0.01157		
ANOVA					
	df	*SS*	*MS*	*F*	*Sig. F*
Regression	7	8620	1230	19138.7	0
Residual	5716	3680	643690.1		
Total	5723	8990			
OLS regression: Dependent variable: India NIFTY					
	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1545.24	97.2464	15.89	<0.0001	***
UKXIndex	−1.18093	0.0250221	−47.20	<0.0001	***
GermanyDAXIndex	0.774263	0.0237351	32.62	<0.0001	***
SwitzerlandSMIIndex	−0.0117955	0.0224215	−0.5261	0.5989	
S.ArabiaSASEIDX	0.091505	0.00503554	18.17	<0.0001	***
S.AfricaJALSH	0.10537	0.00250621	42.04	<0.0001	***
ChinaSHCOMP	0.157896	0.016555	9.538	<0.0001	***
Japan NKY	0.043926	0.00741986	5.92	<0.0001	***

Source: author's computation

NIFTY Index (India) considered as dependable variable, random samples of Morgan Stanley Capital International (MSCI) indices for Europe, Middle-East and Asia (EMEA) includes index from UK, Germany, Switzerland, Saudi Arabia, South Africa, China and Japan performed as independent variables. OLS explores the impact and change on dependent variable with change in independent variables. Statistical property provided in Table no. 1 describes summary of relevance of EMEA countries and confirm the impact on NIFTY index in the sample data for over 20 years. Mean for dependent which suggest index level of 5877.96 with high degree of standard deviation. Measure of R^2 indicates that major proportion of variance of independent variable impact over dependent variable, confirming high relevance of selected samples on NIFTY index returns. Study observed that Germany – DAX and China SHCOMP indices amongst the highest across the samples which creates significantly high influence over movement of dependent variable. ANOVA provides degree of freedom 7 confirming that ll selected seven EMEA samples as independent variable do support predict dependent variable with significant of F property. To check the similarity in movement of indices we run Belsley-Kuh-Welsch (BKW) test as appears in Table no. 2 and property of variance inflation factors summarized in Table no. 3.

Table no. 2 – Belsley-Kuh-Welsch collinearity diagnostics for the sample period from January 2000 to December 2021

lambda	cond	const	UK	Germany	Switz.	S.Arabia	S.Africa	China	Japan
7.612	1	0	0	0	0	0.0001	0	0.001	0
0.173	6.663	0.016	0.001	0.002	0	0.077	0.027	0.001	0.001
0.006	8.108	0.01	0.002	0	0	0.403	0.008	0.065	0
0.059	11.383	0.001	0.001	0.002	0.003	0.036	0.007	0.563	0.033
0.03	15.9	0.0084	0.013	0	0.002	0.05	0.092	0.298	0.075
0.006	35.4	0.546	0.376	0.026	0.011	0.022	0.111	0	0.161
0.003	51.647	0.036	0.157	0.027	0.982	0.096	0.035	0.072	0.232
0.002	61.52	0.308	0.45	0.943	0.002	0.315	0.72	0	0.498

Source: author's computation

Table no. 3 – Variance Inflation Factors (VIF) 2000-01-04:2021-12-10

Variance Inflation Factors	
UK	5.63
Germany	55.17
Switzerland	13.39
S.Arabia	2.1
S.Africa	19.44
China	1.9
Japan	14.42

Source: author's computation

We consider Variance Inflation Factor (VIF) for independent variable = 1/ (1-R(j)^2), considering R (j) as multiple correlation coefficient factor (MCC) among variable (j) together with all samples of EMEA independent variables. Further, variance inflation factors also consider standard minimum value =1.0, and exceeding parameter of collinarity issues considered where VIF exceeds value >10.0.

Figure no. 1 exhibits the normal probability plots of selected residuals and explains that error terms are normally distributed across the samples and provides graphical visualization of the residual behavior. This confirms that selected indices samples follow a normal distribution with mean (μ) and the variance (σ^2) indicates approximately linear behavior. The coefficient of regression equation which defines the relationship between the selected indices and impact on dependent variable plotted and exhibited in Figure no. 2. The plot explains the constrictive relationship between NIFTY and response variables from the sample markets from Europe, Asia and Africa.

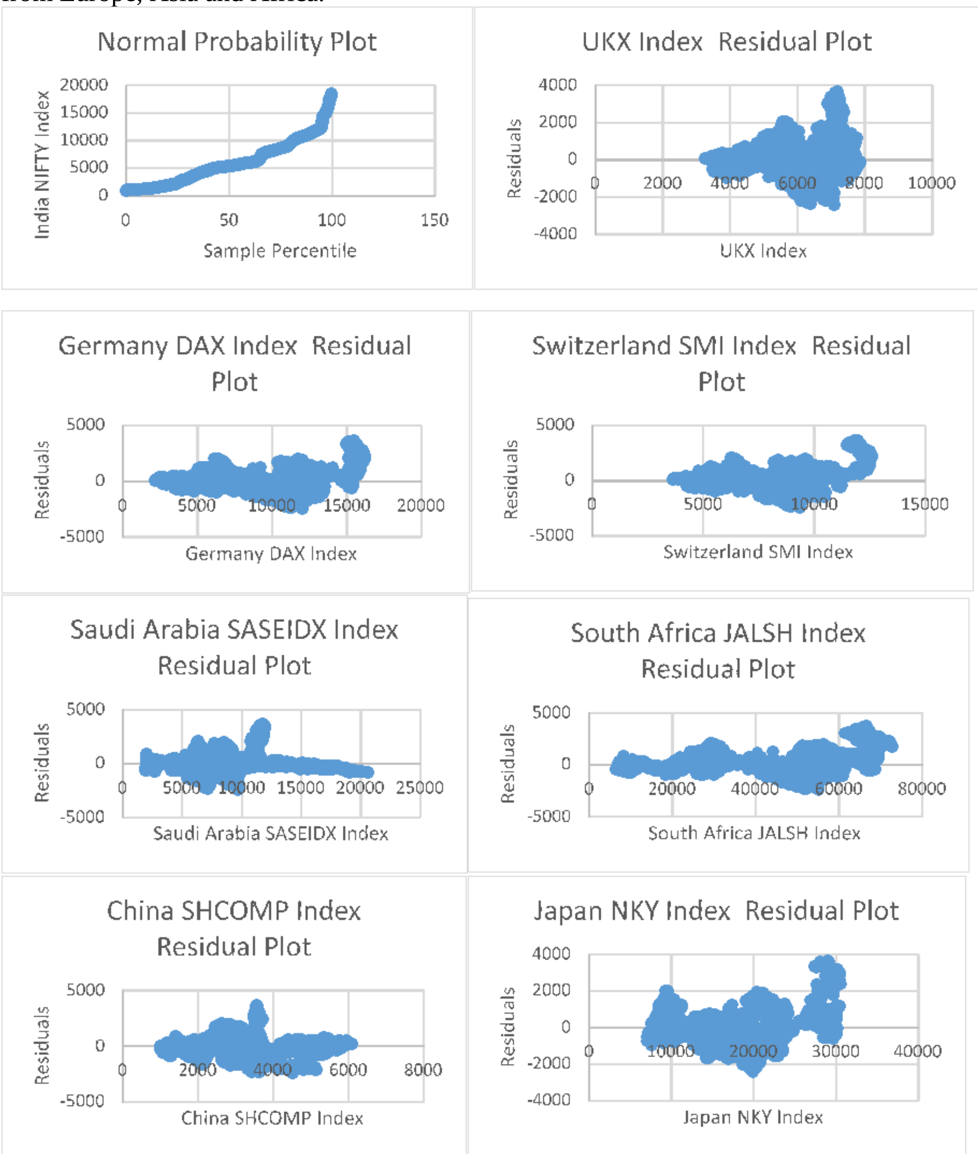

Figure no. 1 – Normal probability and independent indices residual plot for the sample period from January 2000 to December 2021
Source: author's computation

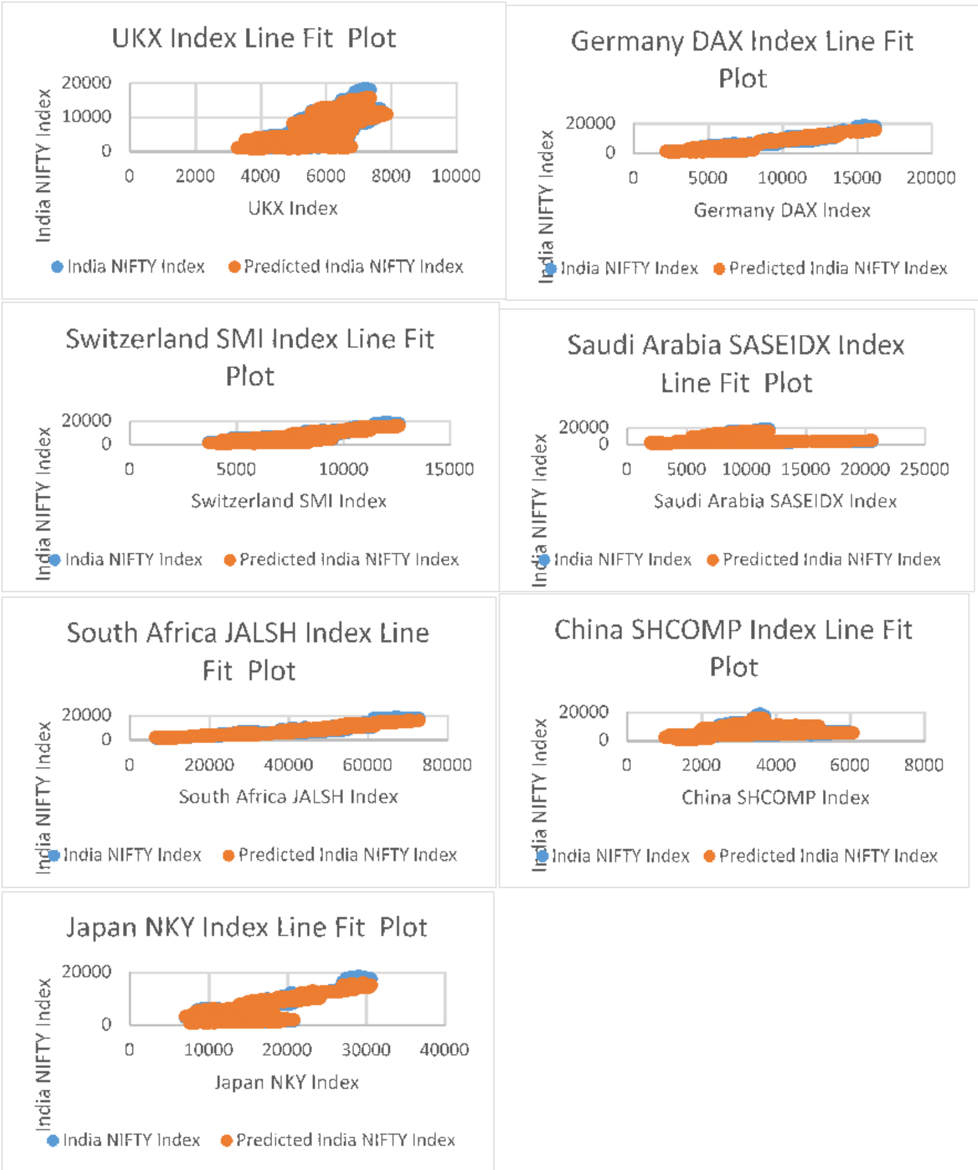

Figure no. 2 – Predictability of independent variable on NIFTY India Index
Source: author's computation

Selected and performed indices of MSCI – EMEA countries expresses a strong linear relationship confirmed in Table1. Collinearity statistics provides vital input to understand that considering all samples as independent variable whether the properties are correlated, or association of same movement patterns. Collinearity analysis confirms that there is high correlation or deep association between selected seven independent variables which considered as potential predictor variable. We observe dramatic increase in VIF with BKW diagnosis test. We found evidence of deep association in movement of selected independent variables. This means that one predictor variable is correlated with another predictor variable the same is also confirmed by variance inflation factor which provides high measure of the degree of collinearity between independent variables. Such VIF factors demonstrate high collinearity to extreme collinearity, resulting multicollinearity among all selected independent variables except China (1.9000), Saudi Arabia (2.106) and UK (5.638) and Switzerland, Japan and South Africa confirms medium collinearity. Germany index demonstrates extreme collinearity with VIF value of (55.144) exceedingly far from exceed parameter of 20. In this multicollinearity condition, where the tolerance i.e. estimated by 1- R^2 (where R^2 is computed by regressing independent variables), exhibits that index from China, Saudi Arabia and UK certainly considered as predictor variables.

Belsley *et al.* (1980) indicated that if VIF number results around 10, it is considered as weak dependencies between independent variable and dependent variable and exceeding 10 may not be suitable for forecasting based on regression estimates.

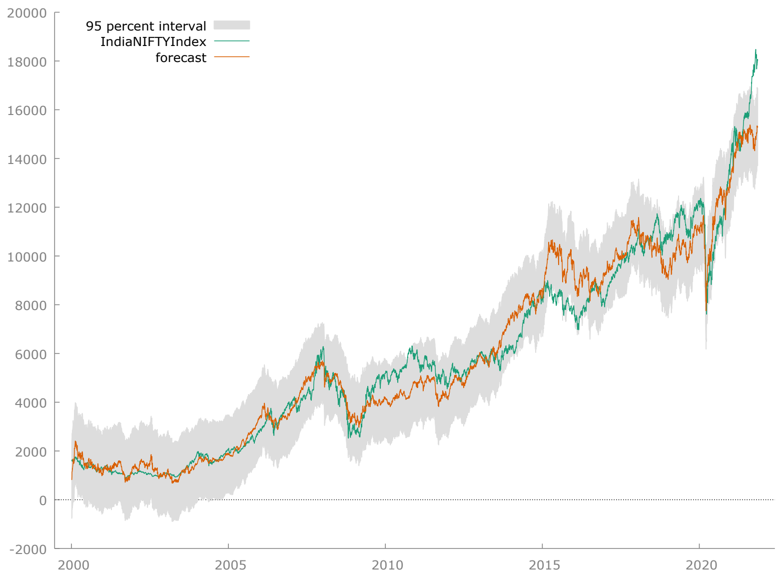

Figure no. 3 – Forecasting of NIFTY India Index based on regression analysis
Source: author's computation

Regression estimates further processed to forecast NIFTY index considering supporting historical prices throughout the period and demonstrates for the last month forecast. The forecast exhibits at 95% confidence interval where predicted variables communicate strong response to actual index returns (See Figure no. 3). The predictability of all independent variables for NIFTY (India) index exhibited in Figure no. 2, where two line-fit plot appears which demonstrates actual movements and predicted movement of the index with support of respective independent variables. We observed (lambda) performance as eigenvalues of inverse covariance matrix providing 0.001669 suggests strong linear dependence of Germany with other associated indices in the samples. The parameter estimates high linear dependences confirming unfit to model forecast for dependent variable NIFTY index.

Table no. 4 – Quantile estimates, using observations for the sample period from January 2000 to December 2021 (T = 5724). Dependent variable: India NIFTY Index

var	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
const	1207.940	63.243	19.1	<0.0001
UKXIndex	−0.885729	0.016	−54.43	<0.0001
Germany DAX	0.569	0.015	36.86	<0.0001
Switz. SMI	−0.119902	0.015	−8.223	<0.0001
S.Arabia SASEIDX	0.066	0.003	20.09	<0.0001
S.AfricaJALSH	0.123	0.002	75.43	<0.0001
China SHCOMP	0.245	0.011	22.75	<0.0001
Japan NKY	0.068	0.005	14	<0.0001
Median depend. var	5280.8	S.D. dep. var		3963.737
Sum absolute resid	3314724	SSR		4.00E+09
Log-likelihood	−46104.58	Akaike criterion		92225.16
Schwarz criterion	92278.38	Hannan-Quinn		92243.69

Note: *Asymptotic standard errors assuming identically distributed means
Source: Author's computation* tau = 0.5

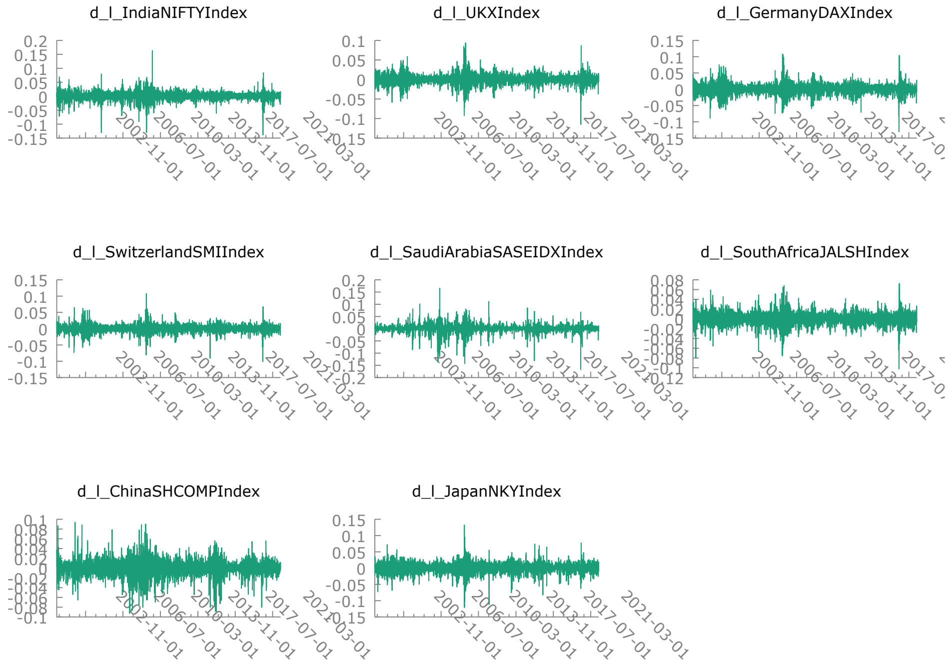

Figure no. 4 – Volatility shocks from sample series returns for the sample period from January 2000 to December 2021 (T = 5724)

Quantile estimates considering 0.5 percentile confirms significance of all dependent and independent variables less than 1%. The constant coefficient (NIFTY) estimated at 1207 with having negative coefficients of UK and Switzerland indices. We explore heterogeneity issues from the sample response with implementation of quantile regression as natural statistical tool along with generalized interpretation of quantile regression results for selected samples of EMEA indices. We estimate the median of selected samples of which UK and Switzerland provides negative results suggesting investors over a period of time resulted no profit or probably loss of some of their investments. We find that index of Germany, China and South Africa have larger effect than other samples with highly significant (SD of selected regression) SSR. The provided coefficients demonstrate estimated quantile at 50% or 0.5 percentile with confirms significant differences in derived values of coefficients. Throughout the center of distributions of independent variables, minor differences noticed compared with weight of dependent variable of NIFTY index. Quantile at 0.5 percentile predicts the inferences among the samples considering as dependent variable which performing as center to rest of indices.

2. DISCUSSIONS

Volatility sketches indicates sharp drop during the COVID-19 pandemic period. It is interesting to note that Japanese stock market relatively less volatile across the sample during the pandemic period. Further, the model for the volatility sketches also provides significant information that volatility in sample stock markets remained higher during the global financial crisis compared to the COVID-19 pandemic. In the situation of global financial crisis all sample stock markets responded negative trend where Chinese stock market performed over volatile that has create strong volatility cluster for longer period of time. This indicates that during global financial crisis Chinese stock market remained comparatively more unpredictable. On the other side, stock market of Switzerland responded least to global financial crisis. It is also observed that sample stock market of Saudi Arabia and Germany indicated sharp drop responding to pandemic period.

Regression considering NIFTY as dependent variable against rest of sample returns as independent variable provides high measure of standard deviation 3963.74 whereas all coefficients except from Switzerland and UK found to be positively correlated and creates impact over movement of dependent variable. We found that DAX index of Germany significantly develops strong impact compared to rest of sample indices. Surprisingly, NKY from Japan and SHCOMP from China impacts even less than five times despite of being Asian continents. This means that dependent market is significantly more correlated and contagious to European indicator than the Asian indicator. Considering statistical outcome of BKW test and measure of VIF, it is confirmed that financial indices of Germany, South Africa and Japan significantly strong correlated and provided evidence for collinearity. It means that these indices have stronger pattern of associated movements unlike alternate index from China or Middle-East index of Saudi Arabia or European indicator UK. The provided Figure no. 4 exhibits log differences of sample returns and make all volatility sketches visible. The generalized international integration of pattern clearly demonstrates global financial crisis and COVID – 19 pandemic effect where responses of selected sample indices reported. Predictable line-plot for Germany, Switzerland, Saudi Arabia and South Africa provides similar forecast-pattern with the difference in respective index trading levels.

3. CONCLUSIONS

We attempted to estimate the impact on NIFTY movements considering random sample indices from MSCI – EMEA countries such as UK, Switzerland, Germany, South Africa, Saudi Arabia, China and Japan. We confirm association of sample variables and impact on movement of NIFTY index at significance level of less than 1%, forecasts regression parameters, exhibits forecasting parameter considering all sample markets, demonstrates quantile estimation suggesting weight of index over independent variables. Firstly, there are two sample indices that found with negative correlation coefficients with the dependent variables. This suggests that NIFTY index performed contrasting movement and derived opposite mean coefficient during the sample period. On the other hand, China, South Africa, Saudi Arabia strongly impact over asset price of NIFTY index with significantly positive correlation coefficients. Variance Inflation Factor found in favor only for indices from China, Saudi Arabia and UK with medium collinearity, for rest we found multicollinearity indicating peer association of independent variables with similar index movement. Therefore, we conclude that with the use of quantile regression as a natural statistical method and a broader interpretation of the results for selected samples of EMEA indicators. Further, we investigate heterogeneity issues arising from the sample response and its impact on the dependent variable, results for NIFTY estimated based on the mean of selected samples. Financial markets of UK and Switzerland found to be with unfavorable impact, indicating that contrasting movement. With the BKW diagnosis test, we notice a sharp increase in VIF; VIF factors exhibit strong to extreme collinearity, leading to multicollinearity among all chosen independent variables with the exception of China. This shows that the Chinese stock market remained relatively more unpredictable during the global financial crisis.

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