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Relationship between CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100

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Abstract

The research focuses on relationship between CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100 over a period of 100 days. This paper also determines the volatility of the stock market and the momentum change with other markets. For the purpose of the present study, secondary data is being used. The forecasting is done with the help of Time Series Model, ARCH and Granger Causality. Summary Statistics has been done. The Jarque Bera Test is used to find the Skewness, Kurtosis, and Deviation in the data. Granger Causality test is done to check if one variable can be predicted with the help of another variable. The relationship between Dependent and Independent variable is represented using ARCH Model. From the study it can be found that for every change in the CBOE DJIA Volatility Index, NASDAQ 100 and S&P 100 also shows a change. This means that Volatility in the CBOE DJIA is because of the NASDAQ 100 and S&P 100.

Key words: Emerging Markets, Volatility Index, Momentum, Stock Market

JEL Classification: O16

Paper Classification: Research Paper

Introduction

The main characteristic of any financial asset is its return, which is typically considered to be a random variable. The spread of outcomes of this variable, known as asset volatility, plays an important role in numerous financial applications. All modern option-pricing techniques rely on a volatility parameter for price evaluation. It has been widely recognized that volatility changes stochastically over time and is thus a latent variable which cannot be observed directly. Therefore, forecasting volatility is a crucial task especially for institutions involved in options trading and portfolio management.

Many researchers support the use of implied volatility as it offers a better estimate of future volatility than the realized volatility or ex post standard deviation calculated from the historical returns data. Moreover, past studies assert that historical volatility is traditional and the expectations about future volatility can be predicted based on past behaviour of stock prices and other relevant information.

The implied volatility has developed and elevated as a distinct asset which can be packaged in an index widely known as the implied volatility index. This volatility asset can be traded using futures and options available on it called as the volatility derivatives. This prompted Chicago Board of Options Exchange (CBOE) to introduce first volatility index. This was originally named as VIX (currently known as VXO) to provide latest measure of expected volatility of US equity market. Hence, the information revealed by these indices not only serves the purpose of volatility estimation but can also be utilized in a wide variety of financial decisions such as asset allocation and market timing to variance swap pricing and interdependency of markets.

The research focuses on relationship between CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100 over a period of 94 days. This paper also determines the volatility of the stock market and the momentum change with other markets.

Review of Literature

The survey conducted by Poon and Granger (2003) discusses volatility in general whereas Mayhew (1995) and McAleer & Medeiros (2008) have reviewed the literature on stochastic, option implied and realized volatility respectively.

Typically, a rise in the implied volatilities is observed in times of financial distress, and drop is observed in times of boom. Therefore, IV index is rightly referred as "investor fear gauge". Also the development of worldwide derivative markets signaled towards the need of developing derivatives on based on stock market volatility. For hedging market risk, the IV index can be used as an underlying asset of volatility derivative (Brenner et al. 2006). Koopman et al. (2005) valuated the forecasting value of historical, implied and realised volatility.

Many studies found negative and asymmetric relationship between changes in volatility index (VIX, VXN, VDAX and VSTOXX) and its underlying index (S&P 500, NASDAQ100, DAX, and EURO STOXX 50). Various forecasting methods and trading strategies were used to test the forecast ability of VIX future price, both statistically and economically using the volatility index (VIX, VXO, VXN, VXD, VDAX-New, VCAC and VSTOXX) and the underlying index (S&P 500, NASDAQ 100, DJIA, DAX, CAC 40, and EURO STOXX 50). Bali & Weinbaum (2007), examined that the predictive power GARCH model with GED, student-t and normal distributions is found to be inferior to VIX. Becker & Clements (2008), compared the forecasts performance of VIX index to a range of model-based forecasts and combination forecasts. Daouk & Guo (2004), proposed an urgent need for research on developing derivatives pricing models that account for volatility asymmetry and regime switch. Giot (2005), documented a statistically significant and strong negative relationship between the contemporaneous changes in underlying stock indices and IV index changes for both S&P 100 and NASDAQ 100 indices. Jiang & Tian, found a flaw in the construction methodology of CBOE VIX and showed that the VIX procedure may underestimate the true volatility by as much as 198 index basis points and overestimate by as much as 79 index points. Majmudar & Banerjee (2004) forecasted the revised VIX using a variety of forecasting tools like GARCH, EGARCH, APARCH, GJR and IGARCH.

Zhang & Zhu (2006) VIX found that VIX data could be used to estimate the volatility structural parameters in the VIX future-pricing models. Turhan & Cevik (2009) investigated the effect of CBOE VIX on 15 emerging stock markets with the application of GJR-GARCH model and found that the emerging stock markets had leverage effect in conditional variance.

Yang & Liu (2012) explored the predictive power of the volatility index (VIX) in emerging markets from December 2006 to March 2010. The results of the study show that the models including both the volatility indicator and the option market information have a stronger predictive power.

Sarwar (2012) analyzed that VIX act as an investor fear gauge for the equity markets of U.S., Brazil, India, and China. Nishina et al. (2010), found that Implied volatility index was highly correlated with realized volatility and it contains some useful information that beyond that conveyed by historical returns. Lin & Chang (2010) introduced a model that identified relationship between stylized features on S&P 500, VIX and derivatives on VIX.

Data and Measurement of Variables

The research focuses on relationship between CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100 over a period of 100 days. This paper also determines the volatility of the stock market and the momentum change with other markets. For the purpose of the present study, secondary data is being used. The forecasting is done with the help of Time Series Model, ARCH and Granger Causality. Summary Statistics has been done. Granger Causality test is done to check if one variable can be predicted with the help of another variable. The relationship between Dependent and Independent variable is represented using ARCH Model. The time period for the study spans from 30th November 2017 to 17th April 2017. The data source is taken from Federal Reserve Economic Data – St. Louis Fed Res. The time series model is tested using E-views Software for Time series.

The objectives for the study are :

- To estimate the relationship between CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S & P 100.
- To find momentum change in the CBOE DJIA Volatility Index and its effect on the other Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100.

Table 1: Summary Statistics

	CBOE_DJIA	CBOE_EMERGING MARKETS	CBOE_NASDAQ	CBOE_S_P
Mean	11.90117	18.20085	13.3683	11.11436
Median	11.845	18	13.125	10.885
Maximum	14.58	22.94	17.18	14.4
Minumum	7.58	13.97	10.31	9.07
Std.Dev	0.97614	1.881829	1.394598	1.111211
Skewness	-0.345775	0.317029	0.51444	0.851462
Kurtosis	6.464532	2.716294	3.11693	3.611117
Jarque-Bera	48.8848	1.889864	4.199846	12.82086
Probability	0	0.388706	0.122466	0.001644
Sum	1118.71	1710.88	1256.62	1044.75
Sum Sq. Dev	88.61497	329.3391	180.8761	114.8355
Observations	94	94	94	94

There are 94 observations of CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100 from 30-11-2017 to 17-04-2017 The mean and median CBOE Volatility Index is more for Emerging markets from 30-11-2017 to 17-04-2017 and the least is for S&P100 VIX. The standard deviation is more for Emerging markets. The skewness for all CBOE DJIA Volatility is on the negative side. The Kurtosis for all the countries is greater than zero. The p-value of JarqueBera Test is less than 0.05, indicating data is normally distributed for CBOE DJIA Volatility Index and S&P 100.

Table 2: ARCH Model

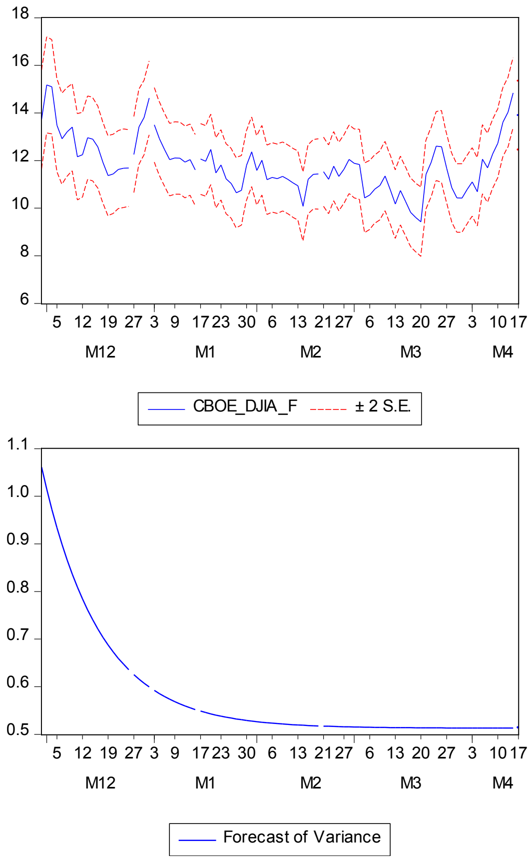
Dependent Variable: CBOE_DJIA_VOLATILITY_IND
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 04/24/17 Time: 12:16
Sample: 11/30/2016 4/1 7/2017
Included observations: 94
Convergence achieved after 59 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2+C(6)*GRACH(-1)

Variable	Coefficient	Std. Error	z-Statistc	prob
CBOE EVE-RGING MARKETS ET	-0.091 767	0.074954	-1.224311	0.2208
CBOE NASDAQ 100 VOLATILI	0.601343	0.1 0531 7	5.709866	0.0000
CBOE S P 100 VOLATILITY	0.495007	0.087597	5.650975	0.0000
		Variance Equation		
C	0.043171	0.024009	1.798126	0.0722
RESID(-1)^2	0.48504	0261 505	1.854798	0.0636
GARCH(-I)	0.430772	0.194702	2.212471	0.0269
R-squared	0.652944		Mean dependent var	11.90117
Adjusted R-squared	0.645316		S.D. dependent var	0.97614
S.E. of regression	0.581343		Akaike info criterion	1 .547256
Sum squared resid	30.75437		Schwarz criterion	1 .709594
Log likelihood	-66.72104		Hannan-Quinn criter	1.612829
Durbin-Watson stat	1 .1 83079			

**The dependent variable for this test is CBOE DJIA Volatility Index.*

R-squared value of 0.6529 indicates that every independent variable like Emerging markets, NASDAQ 100, S&P 100 and Chicago illuminates 65.29% of the deviation from the dependent variable. Adjusted R-squared value of 0.645 indicates that there is 64.5% of the total variation in these variables. S.E. of regression is 0.581 means that the average distance of the residual points i.e. the difference between actual and predicted values of relationship and fitted line is 0.581. Lesser the fit, better is the fit. Sum of squared residuals is 30.75 which indicates the amount of error remaining between regression function and data set. Smaller the value better will be our estimation. Log likelihood is used to determine the optimal values of the estimated coefficients and compare the fit of different coefficients and so higher value is better. In the study the log likelihood is -66.72. Durbin-Watson stat is used to identify the existence of autocorrelation between residuals. The standards should lie between zero and four where values approaching zero indicates positive and four indicates negative autocorrelation. Here the value is approaching towards 1.18 which means there is a positive autocorrelation between the past and present relationship between independent and dependent variables. Akaike Info Criterion gives the least value, so it is the best method.

Figure 1: Residual Graph



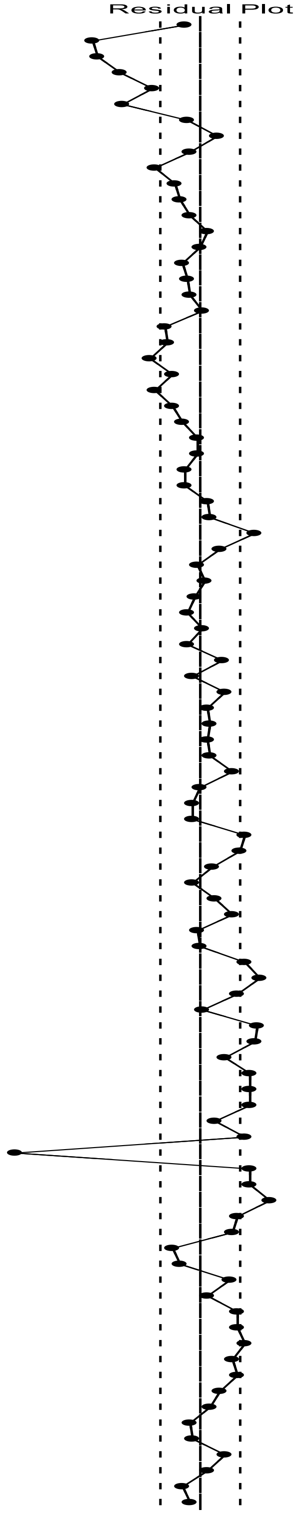
Forecast: CBOE_DJIA_F	
Actual: CBOE_DJIA_VOLATILITY_IND	
Forecast sample: 11/30/2016 4/17/2017	
Included observations: 94	
Root Mean Squared Error	0.571991
Mean Absolute Error	0.406784
Mean Abs. Percent Error	3.529798
Theil Inequality Coefficient	0.023964
Bias Proportion	0.002896
Variance Proportion	0.117323
Covariance Proportion	0.879781
Theil U2 Coefficient	0.679170
Symmetric MAPE	3.487935

Interpretation

Root mean squared value is 0.571. Mean absolute error is 0.406. This denotes the value of errors in the forecast. The mean absolute percentage error in the data set is 3.52%. The inequality coefficient is 0.0239. It is perfectly fit if U = 0, and imperfect if U = 1. Bias is 0.0028 is an indication of systematic error. If it is close to 0, it is a perfect fit model. Systematic over or under prediction happens with large bias. Variance of 0.117 is an indicator of degree of variability to forecast. The movement of variance proportion is not equated to the forecasted proportion. Covariance is 0.879 is a tandem movement between actual value and the forecasted value.

Figure 2: Residual Plot

obs	Actual	Fitted	Residual
11/30/2016	13.5000	13.7326	-0.23260
12/01/2016	13.6200	15.1727	-1.55273
12/02/2016	13.5800	15.0962	-1.51624
12/05/2016	12.3200	13.4859	-1.16591
12/06/2016	12.2200	12.9168	-0.69678
12/07/2016	12.0700	13.2087	-1.13868
12/08/2016	13.2100	13.4038	-0.19382
12/09/2016	12.4100	12.1580	0.25205
12/12/2016	12.0900	12.2432	-0.15318
12/13/2016	12.2900	12.9613	-0.67135
12/14/2016	12.5400	12.8969	-0.35692
12/15/2016	12.3000	12.5700	-0.26997
12/16/2016	11.7700	11.9159	-0.14594
12/19/2016	11.4800	11.3653	0.11474
12/20/2016	11.4500	11.4411	0.00892
12/21/2016	11.3600	11.6251	-0.26507
12/22/2016	11.4900	11.6803	-0.19027
12/23/2016	11.5400	11.6831	-0.14307
12/27/2016	12.3100	12.2535	0.05648
12/28/2016	12.9100	13.4151	-0.50508
12/29/2016	13.3200	13.8084	-0.48841
12/30/2016	13.8800	14.6292	-0.74920
1/03/2017	13.0800	13.5038	-0.42384
1/04/2017	12.2700	12.9191	-0.64906
1/05/2017	12.0400	12.4569	-0.41695
1/06/2017	11.7900	12.0356	-0.24559
1/09/2017	12.0500	12.1061	-0.05611
1/10/2017	12.0500	12.0949	-0.04490
1/11/2017	11.7000	11.9359	-0.23593
1/12/2017	11.8300	12.0394	-0.20941
1/13/2017	11.7300	11.6060	0.12401
1/17/2017	12.2200	12.0676	0.15238
1/18/2017	12.7900	11.9735	0.81654
1/19/2017	12.7400	12.4694	0.27064
1/20/2017	11.4700	11.4827	-0.01272
1/23/2017	11.8800	11.8182	0.06184
1/24/2017	11.1600	11.2324	-0.07243
1/25/2017	10.8500	11.0370	-0.18699
1/26/2017	10.6700	10.6496	0.02040
1/27/2017	10.5600	10.7470	-0.18698
1/30/2017	12.1300	11.8031	0.32685
1/31/2017	12.2500	12.3642	-0.11423
2/01/2017	11.9300	11.5853	0.34470
2/02/2017	12.1000	12.0142	0.08578
2/03/2017	11.3600	11.1950	0.16503
2/06/2017	11.3900	11.2900	0.10001
2/07/2017	11.4000	11.2352	0.16478
2/08/2017	11.8100	11.3324	0.47755
2/09/2017	11.2200	11.2125	0.00753
2/10/2017	10.9800	11.0643	-0.08435
2/13/2017	10.8400	10.9414	-0.10143
2/14/2017	10.7200	10.0768	0.64316
2/15/2017	11.7900	11.2128	0.57720
2/16/2017	11.6000	11.4231	0.17693
2/17/2017	11.3300	11.4393	-0.10933
2/21/2017	11.7400	11.5312	0.20876
2/22/2017	11.7100	11.2148	0.49518
2/23/2017	11.7100	11.7658	-0.05582
2/24/2017	11.3400	11.3312	0.00880
2/27/2017	12.3200	11.6387	0.68133
2/28/2017	12.9400	12.0487	0.89134
3/01/2017	12.4100	11.8817	0.52830
3/02/2017	11.8600	11.8341	0.02592
3/03/2017	11.2600	10.4331	0.82689
3/06/2017	11.3400	10.5530	0.78703
3/07/2017	11.1500	10.8000	0.34996
3/08/2017	11.6800	10.9574	0.72264
3/09/2017	12.0700	11.3477	0.72227
3/10/2017	11.5200	10.7871	0.73290
3/13/2017	10.3700	10.1695	0.20052
3/14/2017	11.4000	10.7385	0.66154
3/15/2017	7.58000	10.2889	-2.70889
3/16/2017	10.5600	9.81926	0.74074
3/17/2017	10.3300	9.60353	0.72647
3/20/2017	10.4600	9.42650	1.03350
3/21/2017	11.9800	11.4186	0.56139
3/22/2017	12.3800	11.9221	0.45786
3/23/2017	12.2100	12.6099	-0.39989
3/24/2017	12.3100	12.5820	-0.27203
3/27/2017	12.1200	11.6768	0.44319
3/28/2017	10.9800	10.8590	0.12095
3/29/2017	10.9900	10.4307	0.55933
3/30/2017	10.9700	10.4255	0.54447
3/31/2017	11.4400	10.7812	0.65884
4/03/2017	11.5900	11.1019	0.48812
4/04/2017	11.2300	10.6874	0.54260
4/05/2017	12.3300	12.0561	0.27395
4/06/2017	11.8600	11.6991	0.16090
4/07/2017	12.1400	12.2752	-0.13523
4/10/2017	12.6400	12.7261	-0.08606
4/11/2017	13.9800	13.6147	0.36530
4/12/2017	14.1300	14.0330	0.09701
4/13/2017	14.5800	14.8440	-0.26403
4/17/2017	13.7100	13.8747	-0.16474



Interpretation

Actual value of the dependent variable shows a good pattern with a positive movement. This indicates that the linear model provides a good fit to the data set. Fitted value of the dependent variables shows a positive movement above the regression line. This indicates that the linear model provides a good fit to the data set. Residual value of the dependent variable shows a random pattern with positive and negative movement. This random pattern indicates that a linear model provides a decent fit to the data. The line at zero level is the regression line. The residual is the difference between actual and fitted. The residual values above the regression line indicate that actual values are greater than fitted. The residual values below the regression line indicate that actual values are less than fitted. The sum of positive and negative residual values is zero.

This data is not Normally Distributed since the curve comes out of the stripes.

Table 3: Granger Causality Test

Pairwise Granger Causality Test			
Null Hypothesis	Obs	F-Statistic	Prob
CBOE_EMERGING_MARKETS_ET does not Granger Cause CBOE_DJIA_ VOLATILITY_ IND	92	1.36455	0.2609
CBOE_DJIA_VOLATILITY_IND does not Granger Cause CBOE_EMERGING_ MARKETS_ET		0.51761	0.5978
CBOE_NASDAQ_100_VOLATILITY does not Granger Cause CBOE_DJIA_ VOLATILITY_ IND	92	2.26918	0.1095
CBOE_DJIA_VOLATILITY_ IND does not Granger Cause CBOE_NASDAQ_100_ VOLATILITY		1.09861	0.3379
CBOE_S_P_100_VOLATILITY_does not Granger Cause CBOE_DJIA_VOLATILITY_ IND	92	1.7509	0.1797
CBOE_DJIA_VOLATILITY_ IND does not Granger Cause CBOE_S_P_100_ VOLATILITY		5.84308	0.0042
CBOE_NASDAQ_100_VOLATILITY does not Granger Cause CBOE_EMERGING_ MARKETS_ET	92	1.73034	0.1833
CBOE_EMERGING_MARKETS_ET does not Granger Cause CBOE_NASDAQ_100_ VOLATILITY		0.84515	0.433
CBOE_S_P_100_VOLATILITY does not Granger Cause CBOE_EMERGING_ MARKETS_ET	92	2.71243	0.072
CBOE_EMERGING_MARKETS_ET does not Granger Cause CBOE_S_P_100_ VOLATILITY		1.94065	0.1498
CBOE_S_P_100_VOLATILITY does not Granger Cause CBOE_NASDAQ_100_ VOLATILITY	92	2.34924	0.1015
CBOE_NASDAQ_100_VOLATILITY does not Granger Cause CBOE_S_P_100_ VOLATILITY		5.67773	0.0048

The p-value should be less than 0.05 for the relationship to be significant. So it is seen that the relationship between CBOE DJIA Volatility index and NASDAQ 100, and NASDAQ 100 and S&P 100 Volatility Index is significant.

Findings

Summary Statistics has been done. The Jarque Bera Test is used to find the Skewness, Kurtosis, and Deviation in the data. Granger Causality test is done to check if one variable can be predicted with the help of another variable. The relationship between Dependent and Independent variable is represented using ARCH Model. From the study it can be found that for every change in the CBOE DJIA Volatility Index, NASDAQ 100 and S&P 100 also shows a change. This means that Volatility in the CBOE DJIA is because of the NASDAQ 100 and S&P 100. This means that CBOE Emerging Markets doesn't impact CBOE DJIA Volatility Index.

Conclusion

The study focuses on CBOE DJIA Volatility Index, compared with Volatility Index of Emerging Markets, NASDAQ 100 and S&P 100 over a period of 94 days. Any change in CBOE DJIA Volatility Index reflects the change in other markets as well and thus it acts as a major factor in the share index. This indicates the market movement among the shares. From the analysis it is concluded that every change in the blue-chip shares that are listed in the DJIAA Index, will have an impact on the other share indices.

Bases on the findings in this study, it is seen that CBOE DJIA Volatility index has major impact on other indices so traders and investors should prefer this while making financial and investing decisions.

There is a scope for further studies related to this topic with respect to analyzing relationship between other volatility indices.

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