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Management

Dynamics of stock volatility and opportunity for returns in Indian Mid-Cap stocks

Jatin Trivedi Associate Professor, Amity University.

Amol Gawande Ph.D Scholar at JJT University.

ABSTRACT Mid-cap stocks represent the company structure which established well and performing at steady and standard level towards growth. In general, Mid-cap covers the companies with market capitalization from $2 billion to $10 billion. Such stocks assumed to be more volatile and riskier compared with large-cap stocks. This research work investigates the volatility, risk and investment prospects by forecasting volatility, presence of leverage effects and forecasting impact of news on stock market. We select NIFTY Midcap 50 index for computing process and employ exponential generalized autoregressive conditionally heteroskedasticity model (EGARCH) and GJR-GARCH. Main results indicates presence of strong and persistent volatility, presence of leverage effects and financial asset returns of NIFTY Midcap 50 captures strong impact of negative news at greater magnitudes.

KEYWORDS :

Introduction:

Investments in large-cap (Large market capitalization i.e. more than $5 billion) assumes to perform less volatile and comparatively less risky than investment in Mid-Cap stocks. Mid-cap stocks represent companies which now perform at stable level and moving towards better growths. Such positioning of companies captures more focus of investors and their annual returns are at higher side. This interests investors and creates more volumes during the day trading. This study investigates the performance and volatility of NIFTY Midcap 50 index which captures the movement of midcap segment of the Indian financial market. NIFTY Midcap 50 covers top 50 companies consisting full market capitalization from NIFTY Midcap 150 index. This research work empirically investigates the volatility and stock movement performance, the degree of risk for the investors, prospects for returns and the performance of impact of good and bad news on NIFTY Midcap 50. The estimations of such results will add better value to evaluate the performance of NIFTY Midcap 50. For this objective we employ asymmetric GARCH models such as EGARCH and GJR – GARCH. There are plenty of scholarly articles with the use of EGARCH and GJR-GARCH for estimation and forecasting of financial series returns, exchange rates, oil prices etc. and delivered by several known scholars from all over the world.

The structure of this research starts with discussion of previous work which presented in introduction section which is first section. Further, second section covers data and methodology part which discloses the details of the methodology and also details for asymmetry models. Third section covers result and discussion part which empirically explains all detail outcomes of computed results. The last section concludes the outcome of this research.

Exponential generalized conditional heteroskedasticity model known as EGARCH introduced by Nelson in 1991 and GJR-GARCH introduced by Glosten, Jagannathan and Runkle in 1993. Xu, J. G. (1999) modeled volatility for Shanghai stock market considering symmetric (GARCH) and asymmetric (EGARCH and GJR-GARCH) models. Similarly, Ederington, L. H., & Guan, W. (2010) worked with comparative analysis of outcomes amongst GARCH, EGARCH and GJR- GARCH. Whereas, Ou, P. H., & Wang, H. (2010) predicted volatility using Relevance Vector Machine to predict GARCH, EGARCH and GJR considering Hang Sang Index financial series return. The study on forecasting performance using various GARCH (1,1) models such as GARCH, EGARCH, GJR-GARCH and APARCH investigated by Peter J.P. (2001) considering FTSE100 and DAX30 financial series returns. He suggests that improvement of overall estimation improvised when asymmetric GARCH used and concludes that GJR-GARCH and APARCH delivers better forecast compared to symmetric GARCH model.

An interesting research work by Su, Y. C., Huang, H. C., & Lin, Y. J. (2011) confirms the performance of GJR-GARCH to forecast ability. In their research work they introduce an asymmetric Generalized Autoregressive Conditional Heteroscedastic (GARCH) model, Glosten, Jagannathan and Runkle-GARCH (GJR-GARCH), in Value-at-Risk (VaR) to observe whether or not GJR-GARCH is a good method to assess the market risk of financial properties.

Whereas, McAleer, M., Chan, F., & Marinova, D. (2007) contributed research work on analysis of asymmetric volatility using various asymmetric econometric models. The objective of their paper presents an econometric analysis of the symmetric and asymmetric volatility of the patent share which is based on the number of registered patents for the top 12 foreign patenting countries in the USA. Their empirical results deliver an analytic authentication of the regularity conditions underlying the GJR (1, 1) model which precisely the log-moment condition for steadiness and asymptotic ordinariness of the QMLE. That also is computationally more upfront but sturdier second and fourth moment conditions. Black F. (1976) introduced the detail content matter and stylized facts such as leverage effects in financial series returns. It suggests that the volatility in market is higher in the bad news compared to good news.

Data and methodology

The financial returns of daily closing index for NIFTY Midcap 50 index is from 26th September to 31st December, 2016 consisting 2293 daily observations. Research objectives are more focused on detail part of volatility analysis such as cluster effects, leverage effect etc. and for the purpose we employ two asymmetric generalized autoregressive conditional models such as EGARCH by Nelson and GJR by Glosten, Jagannathan and Runkle. Before modeling the asset returns, the series converted in to logs and considered first difference of log returns. The converted series follows Augmented Dickey Fuller (ADF) test to measure the significance of the data and confirms stationarity of series returns. ADF test conducted with constant and maximum lag 4 following AIC criterion. The result rejects null hypothesis of unit root and confirms the stationary in financial series returns of NIFTY Midcap 50 index.

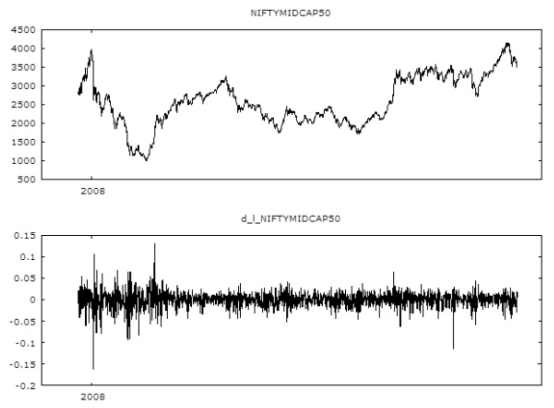
EGARCH or Exponential GARCH was developed and introduced by Nelson (1991) which is asymmetric GARCH model that capture stylized facts in financial returns such as leverage effect.

Another asymmetry model GJR GARCH introduced by Glosten, Jagannathan and Renkle (1993) that also capable to identify effect of news on volatility and presence of leverage effect in series returns of NIFTY Midcap 50 index..

Result and discussion

The summary of basic statistics computed considering 2292 daily observations that provide vital information about the series movement pattern and asset returns. The mean value derived merely zero as expected with standard deviation of 0.0180 and negatively skewed return. The ex-kurtosis indicates high degree i.e. 7.6812 compared to normal (3). This creates long fat tailed for NIFTY Midcap 50 index returns.

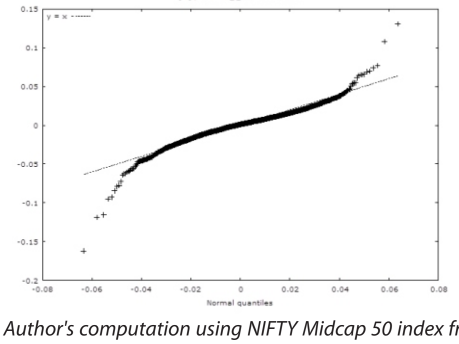
Fig1 – NIFTY Midcap 50 index returns (actual) and (stationary)



Source: Author's computation using NIFTY Midcap 50 index from 26th September to 31st December, 2016

The series returns of NIFTY Midcap index movement ranges from merely 1000 points to 4000 points and several unpredictable volatility shocks appears in graphical results. The degree of negative skewed returns and high kurtosis creates leptokurtosis impacts in asset returns (see quantile – quantile plots).

Fig2 – Quantile – Quantile plot for NIFTY Midcap index returns



Source: Author's computation using NIFTY Midcap 50 index from 26th September to 31st December, 2016

GJR by Glosten, Jagannathan and Runkle modeled with normal distributions to dependable variables of NIFTY Midcap 50 index. GJR fits perfect at significant level of 1% considered to second logged difference of NIFTY Midcap 50 index and computation process includes 2291 daily observations. GJR result indicates negative mean equation. The conditional variance equations indicate positive values and provide significant evidence for presence of leverage effects in financial returns. The good news indicator suggests 0.2151 degree of magnitude and bad news creates impact of 0.6380. In this financial outcome it means that bad news creates almost three times more volatility in the market as compared to good news impact. In case there is news for instance the same can create 0.2151 magnitude volatility if positive (good news) and may create 0.6380 magnitude of volatility in case negative impact. The market volatility movement found overreacting for bad news and creates leverage effects in returns. This may be good sign for sell side traders or short sellers to gain better prospects for the impact course.

EGARCH (1,1) model by Nelson modeled with normal distributions considering dependent variable of second logged difference of NIFTY Midcap 50 index. EGARCH (1,1) computed using 2291 daily observations. The result property indicates negative conditional mean equation and conditional variance equation also indicates negative value except alpha and beta property. The negative gamma value rejects hypothesis of no leverage effect. EGARCH confirms the presence of leverage effects in series returns of NIFTY Midcap 50 index at significance of 1% considering second logged difference. The market reacts more volatile for longer time and captures more interest for sellers.

Conclusion

Application of EGARCH (1, 1) and GJR-GARCH resulted successfully at significant level and both the models confirm the presence of leverage effect in series returns of NIFTY Midcap 50 index. The volatility found reacting almost three times higher in case of negative news impact or bad news. The property of descriptive statistics finds negatively skewed returns with high kurtosis which creates leptokurtosis impact on series returns. The index movement pattern found unpredictable and no out of risk while making investments. The return prospects remain higher with high degree of risks. The financial series returns of NIFTY Midcap 50 can be modeled with EGARCH and GJR GARCH. The series return distributions found unexpected and volatile where several upper and down side shocks found in the index returns. It increases the probability for greater return in short time or otherwise.

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