Research Article

Volatility and Firm Size of Banking Sector of National Stock Exchange in India

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Abstract

The paper examines the relationship between the stock market volatility and returns, volatility clustering, leverage effect and the persistence of volatility for the banking sector of the national stock exchange (NSE) in India for the period from 2005–06 to 2013–14. The study further investigates the impact of firm size and volatility on returns. The GARCH–M model is used to examine the volatility clustering and persistence of volatility and the relationship between returns and volatility. The EGARCH model is used to examine the asymmetric effect. A panel regression is estimated to show the relationship among firm size, volatility and returns. The study reveals that the volatility in all the banking sector firms exhibits the characteristics like volatility clustering, asymmetry effect and persistence of volatility in their daily returns. The study also finds the existence of leverage effect in ABL, BOI, CBL, IDBI, ILB, PNB, SBI, YSB and CNX Bank indicating that the negative shocks or bad news have more impact on volatility than that of positive shocks or good news. The relationship between returns and volatility is statistically significant for CBL, ICICI, INGV, J&K and KMB. The study also finds significant small size firms effect on returns.

Key Words: Stock returns, Volatility clustering, Leverage Effect, Firm Size, GARCH–M and EGARCH model.

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Introduction

Industrial development is one of the most significant aspects and the process of economic development of a country. Industrial development depends on capital formation. A vibrant and competitive financial market plays a vital role in the mobilization of saving and investment process. The stock market is an important part of the financial market. The stock market acts as an engine of industrial development. The stock exchange reflects the changing conditions of economic health of a country, as the shares prices are highly sensitive to changing economic, social, and political conditions. During the periods of economic prosperity, the share prices in the stock market tend to rise. Conversely, share prices tend to fall when there is an economic stagnation and the business activities slow down as a result of depressions. The intensity of trading at stock exchanges and the corresponding rise or fall in the share prices of securities reflects the investors' assessment of the economic and business conditions in a country and acts as the barometer which indicates the general conditions of the atmosphere of business. As a result of stock market transactions, funds flow from the less profitable to more profitable enterprises and they avail of the greater potential for growth. Financial resources of the economy are thus better allocated. Stock prices are highly volatile; it is changed in every moment in the stock market due to change in market demand and supply for the share of the companies. If more people want to buy a particular share, the price moves up. Conversely, if more people want to sell their shares, the price would start to fall. Volatility in the stock market price is an integral part of the stock market with the alternating Bull and Bear phases. In the bullish market, the share prices rise high and in the bearish market the share prices fall down and these ups and downs determine the return and the volatility of the stock market.

A common problem plaguing the emerging economies is the shallowness of their financial sector. The financial sector plays an important role in the process of economic growth and development by facilitating savings and channeling funds from savers to investors. While there have been attempts to develop the financial sector, developing economies are facing the problem of high volatility on numerous fronts including the volatility of financial sector. Volatility, which has a dominant influence, impairs the smooth functioning of the financial system and adversely affects economic performance. Similarly the stock market volatility also has a number of negative implications. One of the ways in which it affects the economy is through its effect on consumer spending (Campbell & Martin L., 1999; Poterba et al., 1986). The impact of the stock market volatility on consumer spending is related via the wealth effect. Increased wealth will drive up consumer spending. However, a fall in the stock market will weaken consumer confidence and thus drive down consumer spending. The stock market volatility may also affect business investment and economic growth directly.

A rise in stock market volatility can be interpreted as a rise in risk of equity investment and thus a shift of funds to less risky assets. This move could lead to a rise in the cost of funds to firms and thus new firms might bear this effect as investors will turn to purchase of blue–chip or growth stocks.

While there is a general consensus on what constitutes stock market volatility and, to a lesser extent, on how to measure it, there is far less agreement on the causes of stock market volatility. Some economists investigate the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock (Engle et. al. 1990. Thus, changes in market volatility would merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by changes in trading volume, practices or patterns, which in turn are driven by factors such as modifications in macroeconomic policies, shifts in investor tolerance of risk, and increased uncertainty. The degree of stock market volatility can help forecasters predict the path of an economy's growth and the structure of volatility can imply that "investors now need to hold more stocks in their portfolio to achieve diversification" (Krainer, 2002).

The Indian stock market has faced many microstructure changes such as global capital flow in the form of foreign institutional investor (FII), private equity during last one decade or so. This has helped the market to grow and attract substantial foreign investment. In the last decade, there has been a few market debacles when illegal trade practices manipulated the market to earn an abnormal return. However, few settlement problems have occurred. The market has crashed few times, specifically on May 17, 2004, but the settlement has passed off without any hindrance. This has been possible due to sound and alert risk management practices (systemic and non–systemic) followed by the leading exchanges in the country. Wide price fluctuations are a daily occurrence on the worlds stock markets as investors react to economic, business and political events. Of late, the markets have been showing extremely erratic movements, which are in no way in tandem with the information that is fed to the markets. Thus, chaos prevails in the markets with investor optimism at unexpected levels. Irrational exuberance has substituted financial prudence.

Volatility analysis is important to investigate the behavior of stock market because issues of volatility and risk have become increasingly important in recent times to the financial practitioners, market participants as well as regulators and researchers.

As a concept, volatility is simple and intuitive. It measures variability or dispersion about a central tendency. To be more meaningful, it is a measure of how far the current price of an asset deviates from its average past prices. Greater this deviation, greater is the volatility. At a more fundamental level, volatility can indicate the strength or conviction behind a price move. Despite the clear mental image of it and the quasi–standardized status it holds in the field of finance, there are some subtleties that make volatility challenging to analyze. Since volatility is a standard measure of financial vulnerability, it plays a key role in assessing the risk/return trade–off and forms an important input in asset allocation decisions. In segmented capital markets, a country's volatility is a critical input in the cost of capital. Peters (1994) has noted that stock prices and returns are cyclical, imperfectly predictable in the short run, and unpredictable in the long run and that they exhibit nonlinear and possibly chaotic behavior related to time–varying positive feedback.

Stock return volatility hinders economic performance through consumer spending (Garner, 1988) They believe that the fall in stock prices would reduce consumer spending. The sizeable fall in consumer wealth as a result of fall in stock prices is expected to directly lower consumer spending. In addition, a weakening in consumer confidence could contribute to a further spending reduction.
Stock return volatility may also affect business investment spending (Gertler & Hubbard, 1989). Investors may perceive a rise in stock market volatility as an increase in the risk in equity investments. If so, investors may shift their funds to less risky assets. This reaction would tend to raise the cost of funds to firms issuing stock. Moreover, small firms and new firms might gravitate towards the purchase of stock in larger well–known firms.

Further, extreme stock return volatility could disrupt the smooth functioning of the financial system and lead to structural or regulatory changes. Systems that work well with normal return volatility may be unable to cope with the extreme price changes. Changes in the market rules or regulations may be necessary to increase the resiliency of the market in the face of greater volatility.

Review of Literature

There are many kinds of literature on stock market volatility and return. Some literatures are reviewed as follows:

Gahan et al. (2012) examine the volatility pattern of Bombay Stock Exchange (BSE) Sensex and National Stock Exchange (NSE) Nifty during the pre and post derivative period. They estimate volatility by recognizing the stylish features of volatility like persistence, asymmetry, etc. for both pre– and post– derivative period. They use daily closing index levels of BSE Sensex and NSE Nifty over a period of 1992–2012 and 1995–2012, respectively. They find that volatility is lower in the post–derivative period as compared to the pre–derivative period. They also find that recent news has more impact on volatility in the post–derivative period in comparison to the pre–derivative period. They further find that introduction of derivatives has increased the asymmetric effect on volatility.

Nicholas & Nicholas (2011) examine the relationship between stock returns and volatility for the three largest stock markets in Europe i.e. the UK market, French market and the German market. They find that volatility changes for the majority of the stocks rapidly during the crisis period with changes being persistent. They also find that before the crisis more investors are rewarded for market–wide risk and during the crisis fewer stocks exhibit a positive relationship between stock returns and volatility. Finally, they find that most stocks don't exhibit positive and statistically significant leverage effects.

Tripathy et al. (2009) investigate the relationship between leverage effect and daily stock returns, volume, and volatility in the BSE Sensex index in India from January 2005 to June 2009. They find that there exist substantial Auto Regressive Conditional Heteroscedasticity (ARCH) effects in the residuals and the volatility shocks are quite persistent in the market. They also find that both the recent news and the old news have an impact on the volatility of the stock and that bad news generate more impact on the change in trading volumes and volatility of the market. They find the evidence of leverage and asymmetric effect on the stock market and observed that Asymmetric Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model provides a better fit than the Symmetric GARCH model suggesting that systematic variations in trading volume are assumed to be caused only by the arrival of new information.

Sarkar & Banerjee (2006) measure the volatility in the daily return at 5–minute intervals of the NSE from June 1, 2000 through January 30, 2004. They find that the Indian stock market experiences volatility clustering and hence GARCH model predict the market volatility better than simple volatility models like historical average, moving average, etc. They also observe that the Asymmetric GARCH models provide a better fit than the Symmetric GARCH model, confirming the presence of leverage effect. Finally, the study reveals that the change in volume of trade in the market directly affects the volatility of asset returns. Further, the presence of FII in the Indian stock market does not appear to increase the overall market volatility.

Balaban & Bayar (2005) examine the relationship between stock market returns and their forecast volatility derived from the daily observations of stock market indices of 14 countries covering the period December 1987 to December 1997. Both weekly and monthly returns and their volatility are investigated. Expected volatility is derived from the ARCH (p), GARCH (1, 1), Glosten, Jagannathan, & Runkle GJR–GARCH (1, 1) and Exponential Generalized Auto Regressive Conditional Heteroscedasticity (EGARCH) (1, 1) forecast models. Expected volatility is found to have a significant negative or positive effect on country returns in a few cases. Unexpected volatility has a negative effect on weekly stock returns in six to seven countries and on monthly returns in nine to eleven countries depending on the Volatility–forecasting model.

Chang–Jin Kim et al.(2004) investigate whether evidence for a positive relationship between stock market volatility and the equity premium is more decisive when the volatility feedback effects of large and persistent changes in market volatility are taken into account for the period from January 1926 to December 2000. They derive and estimate a formal model of volatility feedback under the assumption of Markov–switching market volatility. They find that a negative and significant volatility feedback effect, supporting a positive relationship between stock market volatility and the equity premium.

Samanta (2003) examines the roles of stock market on excess return and volatility in predicting future output growth of Indian economy from April 1993 to December 2002. He finds that past values pointing to the presence of significant volatility–feedback effects in the stock market. The volatility is also quite strongly related to excess return in recent years. However, roles of stock market return and volatility in predicting future output growth are not clear. Thus, there is a need to undertake further in–depth research for understanding the relationship between stock market return/volatility and future output growth in the context of Indian economy.

Song et al. (1998) examine the relationship between returns and volatility of the Shanghai and Shenzhen Stock Exchanges in China from May 1992 to February 1996. They use GARCH models to analyze the relationship between returns and volatility. They find that there is a positive relationship between returns and volatility. Volatility transmission between the two markets (the volatility spill–over effect) is also found to exist. The results of one month ahead ex–ante forecasts show that the conditional variances of the returns of the two stock markets exhibit a similar pattern.
French et al (1987) examine the relationship between stock returns and stock market volatility. They use daily values of the standard and poor's (S&P) composite portfolio from January 1928 through December 1984. They use Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Conditional Heteroscedasticity (ARCH) and GARCH model. They find that the expected market risk premium is positively related to the predictable volatility of stock returns. They also find that unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns.

Chaibi et al. (2014) evaluates the firm size effect on risk–return on American Stock Market. They select daily traded values of the listed companies in Russell 3000 index for the period 2010–2012. They find different size model by applying the Sharp model and Capital Asset Pricing Model (CAPM) and select Ordinary Least Square (OLS) Regression Method for preparation of each 12 size group. They find that large firms perform significantly better than that of smaller firms during the sample period. They also find that there exists a negative relationship between return and firm size and between return and validity. Further, they observe that small–size firms have low risk–adjusted returns as compared to large–size firms.

Goyal (2014) reinvestigates size anomalies (firm size, price earnings ratio, price to book value, etc.), stock return, and risk associated with financial and non–financial sectors of the US. He selects monthly data of common stocks of the financial and non–financial company from July 1973 to December 2012. He divides financial and non–financial in the separate portfolio on the basis of their respective market capitalization and then sort these portfolio on the basis of size and return. He suggests that if the government gives guarantees about the credibility for large stocks returns then it will not be affected by any anomalies and these guarantees will not change the perception of the shareholders.

Haq & Rashid (2014) examine the relationship between firm size and stock return in Pakistan's stock market. They select 50 companies from Karachi Stock Exchange (KSE) and select yearly data from 2007 to 2011. They construct a set of 10 portfolios based on size, i.e market capitalization, total assets, and sales. They find that firm size affect exists in emerging stock market of Pakistan. They have also observed that there is a prominent size effect where smaller firms are found to have a greater average annual excess return than bigger firms.

Hwang et al. (2014) examines the relationship between size and expected returns on the UK Stock Market. They apply Markowitz mean−variance analysis approach to check the size and expected return effects on the UK Stock Market. They construct portfolios based on size and returns. Moreover, they select monthly data from January 1985 to June 2012 of 612 companies listed in Financial Times Stock Exchange (FTSE) all share index. They suggest that Markowitz Efficiency Frontier is not achieved in larger size portfolio stocks; this suggests that smaller firms operating in the UK have higher risk−adjusted return compared to bigger ones. Overall, these findings suggest that there is a negative relationship between portfolio size and portfolio return during that period.

Minovic & Zikovic (2012) examine the impact of an overall market factor that is firm size, the ratio of book to market value, and liquidity risk on expected asset returns in the Serbian market from April 2008 to March 2011. They suggest that liquidity and firm size have a significant impact on equity price formation; ratio of book to market value does not have an important role in asset pricing.

Nateson et al. (2012) examine the volatility of the NSE sectoral indices from January 2, 2007 to December 31, 2011. The NSE sectoral indices comprise sectors like energy, finance, fast moving consumer goods (FMCG), information technology (IT), media, metal, multinational companies (MNC), pharma, public sector undertaking (PSU) banks, realty, auto, and bank. They find that a wide range of fluctuation in daily returns could be witnessed in all the sectoral indices. The fluctuations are high in the realty sector. The average daily return for the study period is highest for the FMCG sector and is graded as Rank 1, and next comes the crisil nifty index (CNX) pharrma sector which holds graded 2. The lowest grade 12 is assigned to CNX realty, as it has the lowest return. The key point to be noted is that for all the years of study from 2007 to 2011, the volatility is high for the CNX realty sector.

Apergis et al. (2011) examine the relationship between stock returns and volatility for the three largest stock markets in Europe, i.e., the UK market, the French market, and the German market. They find that volatility changes for the majority of the stocks rapidly during the crisis period with changes being persistent. They also find that before the crisis more investors are rewarded for market−wide risk and during the crisis fewer stocks exhibit a positive relationship between stock returns and volatility. Finally, they find that most stocks don't exhibit positive and statistically significant leverage effects.

Bettman et al. (2011) examine the existence of firm size, shares trading strategy, January and July effects of 500 small market capitalization stocks listed on Australian Stock Exchange (ASX). Monthly data of market capitalization, stock returns, risk–free rate of returns, dividend, leverage, operating profit, bid price, ask price, and trading volume of the particular stocks from January 1990 to December 2008 is selected for investigation. They find that firm size, January and July effect exist on stock returns of the companies operated in Australian stock market. However, illiquidity and relative large transaction costs of small stocks eliminate the potential for economic profit on trading. Filis et al. (2011) examine the option listing effect on stock returns and volatility. The daily price of the Athens General Index and the four option index: Greek Telecommunication Organization, Intracom, National Bank of Greece and Alpha Bank are used for the period December 1999 to February 2002. They test asymmetric information hypothesis by using a Standard Event Study Methodology and Asymmetric GARCH type models. Event study results indicate that abnormal returns existed in the pre–listing period, but tend to disappear in the post–listing period. Asymmetric component Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) models with Generalized Error Distribution (GED) show that the introduction of stock options lead to increase volatility (positive effect) for Greek Telecommunication Organization, Intracom and National Bank of Greece only whereas Alpha Bank shows a positive but insignificant effect.

Kasman (2009) investigates the volatility behavior and persistence in the stock markets of Brazil, Russia, India, and China (BRIC) countries to provide new and additional evidence on the impact of sudden changes on the persistence in volatility. He uses daily closing prices of the five indices from the four BRIC countries for the period 1990 to 2007. He uses integrated control and safety system (ICSS) algorithm to detect sudden changes in volatility and also uses GARCH models to examine the behavior of volatility persistence. The study shows that when endogenously determined sudden shifts in variance are taken into account in the GARCH model, the estimated persistence in return volatility is reduced significantly in every return series.

Manjunatha & Mallikarjunappa (2009) test the empirical validity of the firm– specific factors model as envisaged by Fama & French (1992) and the market model as envisaged by Kothari, et al. (1995) in the Indian context over the period from 1978 to 1979 to June 30, 2005. They use a standard form of Capital Asset Pricing Model (CAMP). They find that the result of their study is consistent with the studies undertaken by Fama & French (1992) and Kothari et al. (1995).

Nair et al. (2009) examines the relevance of factors other than the CAMP beta that significantly explain equity returns in the Indian stock market. The time period of analysis is from January 1993 to August 2004, collecting weekly data of 82 companies comprising BSE 100 index. They use Fama & Mac Beth cross–sectional regression, pooled regression and least square dummy variables. They find that size, value, and leverage are significant anomalous factors other than the beta that significantly explain asset returns in Indian stock market.

Patev & Kahayan (2009) examine the influence of the Asian and Russian market crises on the temporal behavior of the four Central European Markets (CEM), viz Hungary, Poland, the Czech Republic, and Slovenia. They use four CEM indices—the Hungarian BUX, the Polish WIG 20, the Czech PX50, and the Slovenian SBI over the period April 30, 1996 to August 31, 2001. They use GARCH estimation technique. They find that the influence of the Asian Crisis over the CEMs is more severe than the influence of Russian crisis. During crises, CEM exhibits an increase in correlation between stock market volatility and return initially and a decrease afterward. They find that the correlation never reaches the pre–crisis level. They also find increasing persistence for CEM not only during the crisis but also after the crisis. After the crisis, the market reaction was much weaker to the current market news than to the past information. They do not find a positive relation between stock market volatility and expected returns. During the crisis period, the relationship is positive.

Ray (2009) identify whether there exists a causal relationship between net investment made by FIIs and the equity return in the Indian stock market. He analyzes the relationship between FII and stock returns in India (BSE) with the aid of daily data from January 2006 to June 2008. The stationary condition for the time series data consider for analysis has been tested using Augmented Dickey Fuller (ADF) test and Phillips–Perron (PP) test. The Granger Causality test suggests that the equity returns granger cause FII investments, but not the reverse.

Objectives

The study is based on the following objectives:

- To examine the nature of volatility of the banking sector firms of NSE India.
- To examine whether the asymmetric effect or leverage effect exist in the banking sector firms of NSE India.
- To examine the relationship between returns and volatility of the banking sector firms of NSE India.
- To examine the impact of firm size and volatility on returns of banking sector firms.

Data Source and Methodology

The study is based on the closing index value of the CNX Bank and 15 banking sector firms which are enlisted in the banking sector of NSE in India. The selected banking sector firms are Axis Bank Ltd. (ABL), Bank of Baroda (BOB), Bank of India (BOI), Canada Bank Ltd. (CBL), HDFC Bank Ltd. (HDFC), ICICI Bank Ltd. (ICICI), IDBI Bank Ltd. (IDBI), IndusInd Bank Ltd. (IBL), ING Vysya Bank Ltd. (INGV), The Jammu & Kashmir Bank Ltd. (JK), Kotak Mahindra Bank Ltd. (KMB), Punjab

National Bank (PNB), State Bank of India (SBI), Standard Chartered Bank (SCB), and Yes Bank Ltd. (YBL). The period of the study is from March 31, 2005 to April 1, 2014. The data is collected from the NSE website, www.nseindia.com.

Methodology

The stock return is calculated using the following formula (Eq. 1):

$$r_t = ln\left(\frac{c_t}{c_{t-1}}\right)$$

$$r_t = [\ln(c_t) - \ln(c_{t-1})] \quad .... \quad (1)$$

Where r_t = stock market return

c_t= closing price at time period t

c_{t-1} = closing price at time period t−1.

ln = natural logarithm

The data is first tested for normality by using Jarque–Bera (JB) test and to test unit root Augmented Dickey–Fuller (ADF) and Philips Perron (PP) test is used.

To examine the nature of volatility and the relationship between returns and volatility Generalized Auto Regressive Conditional Heteroscedasticity in Mean (GARCH–M) model is used. Engle (1982) introduced the ARCH model in his study "Autoregressive Conditional Heteroscedasticity with estimates of the Variance of United Kingdom Inflation" as the first formal model, which seemed to capture the phenomena of changing variance in time series data. Bollerslev (1986) extends Engle's (1982) ARCH process by allowing the conditional variance to follow an ARMA process. This model is known as a Generalized ARCH model or GARCH model. Engle et al. (1987) extend the basic ARCH framework to allow the mean of a sequence to depend on its own conditional variance. This class of model, called the ARCH in mean (ARCH–M) model, is particularly suited to the study of asset market. The basic insight is that risk–averse agents will require compensation for holding a risky asset. The GARCH–M model form as follows (Eq. 2):

$$r_t = \omega + \theta h_t + \sum_{i=1}^{p} \emptyset_i \, r_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \delta_i \quad \dots\dots(2)$$

Where rt is the daily returns on equity and r_(t-i) represents lag returns and ht represents conditional variance which are considered as regressors and ε_t represent random shocks.

The conditional variance equation is formed as

$$\square_t = v_t\sqrt{h_t} \qquad v_t \sim iid(0,\ 1)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, h_{t-i} \qquad \text{GARCH (p, q)} \quad \dots. \quad (3)$$

Where, $\alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_j \geq 0$ and $\alpha_i + \beta_j < 1$.

A significant ARCH coefficient (α_1) indicates that there is a significant impact of previous period shocks on current period volatility. The ARCH coefficient (αi) is also treated as recent "news" component which explains that recent news has a significant impact on price changes which implies the impact of yesterday's news on today's volatility.

The GARCH coefficient (β_i) measures the impact of last period variance on current period volatility. A significant GARCH coefficient (β_i) indicates the presence of volatility clustering. A positive β_i indicates that positive stock price changes are associated with further positive changes and vice versa. A relatively higher values of β1implies a larger memory for shocks. The GARCH coefficient (β_1) is also treated as old "news" component, which implies that the news, which is old by more than 1 day, plays a significant role in volatility. The sum of the ARCH and GARCH coefficients i.e. (α_i+ β_i) indicates the extent to which a volatility shock is persistent over time. A persistent volatility shock raises the asset price volatility. A positive θ indicates that the return is positively related to volatility process. In other words, a higher value of θ represents greater the impact of conditional variance on returns.

To examine the leverage effect EGARCH model can be used. Though ARCH and GARCH models respond to good and bad news or positive and negative shocks and are quite useful in forecasting and measuring volatility but these models are unable to capture the "leverage effect" or asymmetric information. The rational and underlying logic of asymmetric or "leverage effect is that the distribution of stock return is highly asymmetric." An interesting feature of asset prices is that "bad news" (negative shocks) seems to have a more pronounced effect on volatility than that of "good news" (positive shocks) of the same magnitude, that is, bad news is followed by larger increase in price volatility than good news of the same magnitude. It is known that the magnitude of the response of asset prices to shocks depends on whether the shock is negative or positive. To demonstrate this point Engle et al., (1990) mapped the relationship between the conditional variance of asset returns to exogenous shocks, which resulted in what they termed a "news impact curve." Nelson (1991) proposed an exponential GARCH model or EGARCH model that is the earliest extension of the GARCH model that incorporates asymmetric effects in returns from speculative prices based on a logarithmic expression of the conditional variability of variable under analysis. The conditional variance equation in the EGARCH (1, 1) model is as follows (Eq. 4)

$$\ln(h_t) = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \lambda_1 \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta_1 \ln(h_{t-1}) \dots\dots\dots (4)$$

Where ht is an asymmetric function of past $\mathscr{E}$t and α_0, $\alpha 1$ λ_1 and β_1 re constant parameters.

Note that the left–hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic and that forecasts of the conditional variance are guaranteed to be nonnegative. In this model specification, β_1 is the GARCH term that measures the impact of last period's forecast variance. A positive β_1 indicates volatility clustering implying that positive stock price changes are associated with further positive changes and vice versa. If ε_(t-$_1$)/√(h_(t-$_1$)) is positive the effect of the shock on the log of the conditional variance is $(\alpha_1+\lambda_1)$. If ε_(t-$_1$)/(√(h_(t-$_1$) is negative, the effect of the shock on the log of conditional variance is $(-\alpha_1+\lambda_1)$. λ_1 measures the leverage or asymmetric effect. λ_1 is expected to be negative implying that bad news has a bigger impact on volatility than that of the good news of the same magnitude.

To examine the relationship between firm size, volatility, and returns the study here employs the following panel regression model (Eq. 5)

$$r_{it} = \alpha_1 + \theta_1 D_1 + \theta_2 D_2 + \beta_1 h_{it} + \delta_1 P_1 + \delta_2 P_2 + \varepsilon_{it} \dots\dots\dots (5)$$

Where
i stands for i th cross–sectional unit, i = 1, 2, ..., N
t stands for t th time period t = 1, 2, ..., T
D_1 = 1 for small–size firm or 0 otherwise
D_2 = 1 for medium–size firm or 0 otherwise
P_1 = ht for small–size firms or 0 otherwise
P_2 = ht for medium–size firms or 0 otherwise
D_1 and D_2 are intercept dummies and P_1, and P_2 are slope dummies.

Result and Discussion

The analysis is started with descriptive statistics of daily returns of selected banks and banking sectoral index which are reported in Table 1.

Table 1: Descriptive statistics

Bank's ame	Mean	Standard Deviation	Maximum	Minimum	Skew Ness	Kurtosis	JB Statistic	P–Value
BOB	0.00054	0.002	0.012	–0.009	0.101	5	300	0
BOI	0.00035	0.004	0.014	–0.012	0.013	3	11	0.003
CBL	0.00011	0.003	0.014	–0.016	–0.219	4	188.	0
HDFC	0.00013	0.000	0.001	–0.013	–27.019	959	6,291	0
ICICI	0.00052	0.004	0.031	–0.018	0.333	8	1,989	0
IDBI	–0.00016	0.003	0.013	–0.018	–0.078	5	432	0
ILB	0.001	0.004	0.019	–0.016	0.007	7	1,155	0
INGV	0.00061	0.002	0.009	–0.007	0.044	4	250	0
KMB	0.00038	0.003	0.013	–0.012	0.015	4	165	0
PNB	0.00028	0.002	0.010	–0.010	0.152	4	261	0
SBI	0.00047	0.003	0.019	–0.012	0.247	5	587	0
JK	0.00062	0.002	0.015	–0.010	0.553	8	1,937	0
YSB	0.00084	0.006	0.036	–0.027	0.232	6	952	0
ABL	0.00059	0.002	0.012	–0.010	0.064	5	350	0
CNX Bank	0.00055	0.003	0.023	–0.016	0.297	7	1,197	0

Source: Computed data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014

From Table 1, it is observed that the daily mean return of Induslnd Bank (ILB) is relatively higher than that of other banks. The daily mean return of CNX Bank, i. e. banking sector index is 0.00055 (0.055%). The mean returns ILB, YSB, INGV, J&K, and ABL are relatively higher than banking sector index. But the mean returns of BOB, BOI, CBL, HDFC, ICICI, IDBI, KMB, PNB, and SBI are relatively lower than banking sector index. The lowest even negative mean return is shown in IDBI bank. Except for IDBI bank all other banks including CNX Bank show positive returns. In the banking sector (within selected banks) the return fluctuates between 0.036 and –0.018. The highest standard deviation or volatility is shown in Yes Bank whereas the lowest is shown in HDFC bank. The risk of

[1]Axis Bank Ltd. (ABL), Bank of Baroda (BOB), Bank of India (BOI), Canada Bank Ltd. (CBL), HDFC Bank Ltd. (HDFC), ICICI Bank Ltd. (ICICI), IDBI Bank Ltd. (IDBI), IndusInd Bank Ltd. (IBL), ING Vysya Bank Ltd. (INGV), The Jammu & Kashmir Bank Ltd. (JK), Kotak Mahindra Bank Ltd. (KMB), Punjab National Bank (PNB), State Bank of India (SBI), Standard Chartered Bank (SCB), Yes Bank Ltd. (YBL).

YSB, ILB, ICICI, and BOI are relatively higher than that of banking sector index. From this, it can be said that the investor can invest in those companies which provides good returns with lower risk. Except for CBL, HDFC, and IDBI banks all other selected banks are positively skewed. A positively skewed return series indicates that it has higher possibility to generate positive returns while negatively skewed implies higher probability to generate negative returns. The kurtosis of all the return series is greater than three (excess kurtosis) thus, they are leptokurtic; i. e. the frequency distribution assigns a higher probability of either very high positive or negative returns. From Table 1, it is also observed that the JB statistic for all the return series are highly significant even at less than 1% level of significance which indicates that the return series are not normally distributed implying the presence of heteroscedasticity. Hence, GARCH model is suitable for testing the hypothesis.

Table 2. Unit root test

Bank name	ADF Statistic	P Value	PP Statistic	P Value
ABL	−18.32	0.00	−146.88	0.00
BOB	−28.07	0.00	−36.28	0.00
BOI	−42.10	0.00	−18.06	0.00
CBL	−26.28	0.00	−47.08	0.00
HDFC	−21.48	0.00	−46.91	0.00
ICICI	−27.34	0.00	−69.12	0.00
IDBI	−21.03	0.00	−71.13	0.00
IBL	−38.88	0.00	−18.88	0.00
INGV	−30.25	0.00	−21.98	0.00
JK	−21.00	0.00	−62.73	0.00
KMB	−49.48	0.0001	−13.82	0.00
PNB	−22.77	0.00	−63.68	0.00
SBI	−30.19	0.00	−180.84	0.00
SCB	−21.03	0.00	−71.13	0.00
YBL	−76.78	0.0001	−77.89	0.00
Banking Sector Index	−41.43	0.00	−41.23	0.00

Source: Computed data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.

For the time series analysis, the first important task is to check whether the data series of the concerned variables are stationary or not. To check whether the data series are stationary or not the study employs the unit root test. For the test of unit root, the present study applies the ADF and PP test. From Table 2, it is observed that the ADF and PP test statistics for all the return series of the banking sector is greater than their critical values even at less than 1% level of significance. Both ADF and PP test statistic confirms that there is no unit root. Therefore, the null hypothesis that the return series has unit root is rejected for all the return series and thus data for all return series are found to be stationary.

Table 3. ARCH–LM test

Bank name	**F– Statistic**	**P Value**	**LM Statistics**	**P Value**
ABL	109.59	0.00	102.85	0.00
BOB	26.96	0.00	103.08	0.00
BOI	19.94	0.00	77.19	0.00
CBL	24.91	0.00	95.59	0.00
HDFC	0.00095	0.97	0.00095	0.97
ICICI	56.76	0.00	206.51	0.00
IDBI	111.17	0.00	371.49	0.00
IBL	14.12	0.00	55.23	0.00
INGV	77.75	0.00	273.50	0.00
JK	20.17	0.00	78.03	0.00
KMB	185.42	0.00	557.63	0.00
PMB	29.56	0.00	112.54	0.00
SBI	30.24	0.00	115.00	0.00
YBL	59.79	0.00	216.46	0.00
Banking Sector Index	33.42	0.00	126.39	0.00

Source: Computed data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.

To check ARCH effect the study here employs the ARCH LM test of Engle (1982). The ARCH LM test regress the squared residual of the mean model ($\varepsilon t/2$) on lagged squared residual (ε_{t-1}^{2}) and a constant. The ARCH LM test provides two statistics, that is, F–statistic value and Observed R square value. From Table 3, it is observed that the F–statistic and the observed R square value is greater than their critical values for all the return series of banking sector except HDFC bank, as indicated by their corresponding P–value which is less than 1% level of significance. Therefore, the null hypothesis that is no ARCH effect is rejected for all the return series except HDFC bank indicating that there is ARCH effect for all the return series of banking sector except HDFC bank. Thus, it is confirmed that the study can apply ARCH or GARCH model.

Result of Generalized Auto Regressive Conditional Heteroscedasticity in Mean Models

The most popular member of the ARCH class of model, i.e. GARCH−M (p,q) model is used to model volatility of banking sector return series. The Maximum Likelihood Estimation technique is used for the estimation of GARCH−M model. For this technique the model selection is based on Akaike Information Criterion and Schwarz Information Criterion (AIC & SIC). The model with a lower value of AIC and SIC fits the data best. The return series of BOI, CBL, KMB, and PNB fits the GARCH−M (2, 1) model and IDBI fits GARCH−M (2, 2) model whereas ABL, BOB, ICICI, ILB, INGV, J&K, SBI, YSB, and CNX Bank fits the GARCH−M (1, 1) model.

In the estimation of GARCH type models, we start with a general specification of the mean Eq. (5) and the variance Eq. (6).

$$r_t = \omega + \theta h_t + \sum_{i=1}^{p} \phi_i \, r_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \delta_i \, \varepsilon_{t-i} \tag{5}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, h_{t-i} \tag{6}$$

As far the stationarity of the variance process is concerned, it is observed that the summation of αi and βi for all return series are less than one and hence the stationary condition is satisfied for all the return series of banking sectors except INGV bank. However, the sum is rather close to one which indicates a long persistence of shock on volatility. The summation of α1 and β1 is greater than one for INGV bank which implies that the persistence of shocks on volatility is unstable.

Table 4: Result of GARCH–M model

	Coefficients of Mean Equation						Coefficients of Variance Equation						Diagnostic Test			
Bank's name	θ	⍰!	ϕ_1	ϕ_2	δ_1	δ_2	α_0	α_1	α_2	β_1	β_2	$\alpha_i + \beta_i$	Adj. R^2	Log like	F–statistic	AIC
ABL	−5.32 (0.61)	0.00060*** (0.00)	−1.59*** (0.00)	−0.91*** (0.00)	1.05*** (0.00)	0.07* (0.01)	0.00000** (0.02)	0.09*** (0.00)		0.91*** (0.00)		0.99	0.81	9,418	793.24*** (0.00)	−11.45
BOB	2.79 (0.81)	0.00051*** (0.00)	1.31*** (0.00)	−0.54*** (0.00)	−0.88*** (0.00)		0.00000*** (0.00)	0.06*** (0.00)		0.93*** (0.00)		0.99	0.30	10,944	121.55*** (0.00)	−9.78
BOI	1.65 (0.58)	0.00034*** (0.00)	1.36*** (0.00)	−0.97*** (0.00)	−0.70*** (0.00)		0.00000*** (0.00)	0.23*** (0.00)	−0.16*** (0.00)	0.91*** (0.00)		0.99	0.95	12,933	4,380.39* (0.00)	−11.55
CBL	16.21* (0.07)	−0.61564*** (0.00)	−0.95*** (0.00)	0.82*** (0.00)	0.89*** (0.00)		0.00000*** (0.01)	0.14*** (0.00)	−0.10*** (0.00)	0.96*** (0.00)		0.99	0.35	10,460	1.98	−9.34
ICICI	0.00 (0.11)	0.00184 (0.03)	0.81*** (0.00)	−0.12*** (0.00)	−0.88*** (0.00)		0.00000*** (0.00)	0.08*** (0.00)		0.91*** (0.00)		0.99	0.66	9,892	18.81*** (0.00)	−8.83
IDBI	25.76* (0.06)	−0.00025*** (0.00)	−1.68*** (0.00)	−0.79*** (0.00)	1.42*** (0.00)	0.68*** (0.00)	0.0000* (0.07)	0.16*** (0.00)	−0.12*** (0.00)	1.37*** (0.00)	−0.41** (0.03)	0.99	0.31	10,611	91.75*** (0.00)	−9.48
ILB	0.58 (0.83)	0.00100*** (0.00)	1.38*** (0.00)	−0.95*** (0.00)	−0.58*** (0.00)	−0.05** (0.03)	0.00000*** (0.00)	0.08*** (0.00)		0.92*** (0.00)		0.99	0.93	12,771	3,250.22*** (0.00)	−11.40
INGV	−15.17** (0.03)	0.00055*** (0.00)	0.27*** (0.00)	0.43*** (0.00)	0.25*** (0.00)	0.42*** (0.00)	0.00000*** (0.00)	0.40*** (0.00)		0.79*** (0.00)		1.19	0.66	12,978	490.68*** (0.00)	−11.59
J&K	0.00* (0.05)	−0.00101 (0.22)	−0.82*** (0.00)		0.56*** (0.00)		0.00000*** (0.00)	0.16 (0.00)		0.70** (0.00)		0.86	0.13	11,180	48.99*** (0.00)	−9.99
KMB	−0.11** (0.02)	−0.00024 (0.41)	−0.10*** (0.00)	0.83*** (0.00)	0.75*** (0.00)		0.00000** (0.03)	0.19*** (0.00)	−0.10** (0.03)	0.92*** (0.00)		1.00	0.72	12,121	631.40*** (0.00)	−10.83
PNB	0.03 (0.59)	0.00026*** (0.00)	−0.97*** (0.00)	−0.42*** (0.00)	0.67*** (0.00)		0.00000** (0.002)	0.15*** (0.00)	−0.10*** (0.00)	0.95*** (0.00)		1.00	0.18	11,441	56.31*** (0.00)	−10.22
SBI	−1.13 (0.83)	0.00048*** (0.00)	0.75*** (0.00)	−0.07*** (0.00)	−0.96*** (0.00)		0.00000*** (0.00)	0.06*** (0.00)	0.93*** (0.00)			0.99	0.12	10,445	39.68*** (0.00)	−9.33
YSB	0.00 (0.28)	−0.00069 (0.63)	−0.51*** (0.00)				0.00000*** (0.00)	0.10*** (0.00)		0.87*** (0.00)		0.98	0.20	8,224.85 4.26	89.52*** (0.00)	−8.17
Bank	0.55 (0.73)	0.00085 (0.14)	−0.71*** (0.00)	0.10*** (0.01)	0.85*** (0.00)		0.00000*** (0.00)	0.07** (0.00)		0.92*** (0.00)		0.99	0.01	5,779.88	5.01*** (0.00)	−5.15

Source: Estimated based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.
*Note: ***denotes the level of significance at 1% or less than 1% level of significance; ** denotes at 5% or less than 5%; and *denotes 10%.*

From Table 4, it is observed that for all the return series of banking sector the ARCH coefficient is statistically significant at less than 1% level of significance which indicates that previous period shocks influence the current period volatility Bank name. For some return series, the second period lag shocks (ε^2_{t-2}) has some impact on current period volatility as the ARCH coefficient (α_2) is also statistically significant.

From Table 4, it is observed that the GARCH coefficient β1 is statistically significant for all the return series of banking sector indicating that h_{t-1} has influenced the current period volatility (h_t) Bank name. However, for IDBI return series the GARCH coefficient β_2 is also significant indicating that h_{t-2} is also influenced by the current period volatility. A relatively large value of GARCH coefficient indicates that shocks to conditional variance take a long time to die. However, the low value of ARCH coefficient suggests that market surprises induce relatively small revision in future volatility. A large sum of these coefficients implies that a large positive and negative return will lead future forecasts of the variance to be high for a particular period. So an investor can take advantage of the same and by analyzing recent and historical news can forecast the future market movement and can take their investment strategies accordingly.

In the GARCH–M model in the mean equation, the most important variable is ht i.e. conditional variance. Here, the coefficient of ht i.e. θ is the risk parameter. A significant positive coefficient of volatility (θ) indicates that there is a positive relationship between predicted return and volatility. If volatility increases then expected return will also increase and vice versa. From Table 4, it is observed that θ is statistically significant for the return series of CBL, ICICI, INGV, J&K, and KMB. But the coefficient θ is positive only for CBL, ICICI, and J&K while it is negative for INGV and KMB. For the rest of the companies such as ABL, BOB, IDBI, ILB, PNB, SBI, YSB, and CNX Bank the coefficient θ is statistically insignificant. From this, it can be said that when volatility rises expected return also rises for CBL, ICICI, and J&K banks. On the other hand, when volatility rises, predicted return falls for INGV and KMB. The result of banking sector is partially inconsistent with the theory of asset pricing. In the mean equation, the autoregressive (AR) and moving average (MA) coefficients are statistically significant for all banks which indicate that one, two, or three period lag return and one or two period lag residual has some impact on current period return.

A high value of R_2 depicts a very high degree of explained variation. Apart from this AIC and SIC is used in the study indicating lower for the regression which is quite reasonable and fit for our models. A high value of F–statistic states that the statistical models that are used are fit and appropriate.

To check whether the estimated models capture the ARCH effect or there remains further ARCH effect, the study here employs the ARCH–LM test. To check the adequacy of the mean models the

Ljung–Box Q–statistics of the standardized residual is used and that of the square standardized residual is used to check the adequacy of variance models.

From Table 4, it is further observed that the Ljung Box Q–statistic of standardized residuals is insignificant for all the return series of banking sector except INGV, KMB, and PNB indicating that the estimated mean models of each company fit the data well except INGV, KMB, and PNB. For these three companies, different models are used but there still remains serial correlation. Finally, we have selected those mean models for these companies which have lowered AIC and SIC. However, the Ljung–Box Q statistic of the square standardized residual is highly insignificant for all the return series of banking sector except ICICI, INGV, and J&K indicating that the estimated variance models fit the data very well. That is the GARCH–M models are suitable for the return series of the banking sector.

Table 5: ARCH LM test after estimation

ARCH LM TEST After Estimation					**Standardized Residuals**		**Squared Standardized Residuals**	
Bank's Name	F–Statistics	P–Value	LM (T^*R^2) statistic	P–Value	Q–Statistic (36)	P–Value	Q–Statistic (36)	P–Value
ABL	0.65	0.63	2.59	0.63	26.53	0.74	23.70	0.86
BOB	0.33	0.57	0.33	0.57	27.82	0.72	24.66	0.85
BOI	0.04	0.85	0.04	0.85	35.46	0.35	25.77	0.81
CBL	0.00	0.97	0.00	0.97	29.67	0.59	34.08	0.37
ICICI	1.36	0.24	1.36	0.24	39.15	0.21	48.93	0.04
IDBI	1.05	0.30	1.06	0.30	40.63	0.12	37.39	0.20
ILB	0.60	0.44	0.60	0.44	24.74	0.82	24.26	0.84
INGV	1.58	0.21	1.58	0.21	3,265.40	0.00	3,265.40	0.00
J&K	0.64	0.43	0.64	0.42	32.72	0.53	47.50	0.06
KMB	0.00	1.00	0.00	1.00	13,426	0.00	8.084	1.00
PNB	0.02	0.89	0.02	0.89	13,269.00	0.00	5.85	1.00
SBI	0.00	0.95	0.00	0.95	30.25	0.61	41.54	0.15
YSB	0.04	0.84	0.04	0.84	33.20	0.56	29.26	0.74
CNX Bank	0.02	0.88	0.02	0.88	24.30	0.86	40.63	0.17

Source: Estimated data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.

To check the adequacy of the mean models the Ljung–Box Q statistics of the standardized residual is used and that of the square standardized residual is used to check the adequacy of variance models. The diagnostic test for model adequacy as shown in Table 5 suggests that the Ljung–Box Q statistic of standardized residuals is insignificant for all the return series of banking sector indicating that the estimated mean models of each bank fit the data well. Moreover, the Ljung–Box Q statistic of the square standardized residual is highly insignificant for all the return series of banking sector indicating that the estimated variance models fit the data well, that is the GARCH–M models are suitable for the return series of the banking sector.

To check whether the estimated models capture the ARCH effect or there remains further ARCH effect, the study here employs the ARCH–LM test. From Table 5, it is also observed that the ARCH–LM test statistic, i.e. F–statistic and $T^*.R_2$ value for all the return series of the banking sector is less than their critical values imply that the null hypothesis of no ARCH effect is accepted. This implies that there is no further ARCH effect. That means the estimated models are appropriate.

Result of Exponential Generalized Auto Regressive Conditional Heteroscedasticity model

Though ARCH and GARCH models respond to good and bad news and are quite useful in forecasting and modeling volatility but these models have not captured leverage effect and information asymmetry. The rational and underlying logic of asymmetric or leverage effect is that the distribution of stock returns is highly asymmetric. Bad news (negative shocks) is followed by a larger increase in price volatility than that of good news (positive shocks). Because when stock prices fall the value of the associated company's equity declines. As a result, the debt–equity ratio of the company rises, thereby signaling that the company has become riskier. The increased risk is considered an indicator of higher volatility (Black, 1976). So it is important to use EGARCH model to test asymmetric shocks to volatility.

$$\ln(h_t) = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \lambda_1 \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta_1 \ln(h_{t-1}) \qquad (7)$$

Table 6 presents the result of EGARCH model for the return series of the banking sector. The EGARCH model takes the leverage effect into account. Table 6 presents that the asymmetric term ($\lambda 1$) is negative and statistically significant for ABL, BOI, CBL, IDBI, ILB, PNB, SBI, YSB, and CNX Bank indicating that the volatility is high when there is bad news or negative shocks in the market than that of good news or positive shocks for these banks. But the asymmetric term ($\lambda 1$) is positive and statistically significant for ILB indicating that the volatility is high when there is good news or positive shocks in the market than that of bad news or negative shocks for this bank. However, the asymmetric term or leverage effect ($\lambda 1$) is statistically insignificant for BOB, ICICI, INGV, J&K, and KMB indicating that these companies have not significant asymmetric or leverage effect. In the variance equation, the ARCH and GARCH coefficients are statistically significant for all the return series of automobile sector implying greater shocks on volatility.

To check whether the estimated models capture the ARCH effect or there remains further ARCH effect, the study here employs the ARCH–LM test. From Table 6, it is observed that the ARCH–LM test statistic, i.e. Obs. R2 for all the return series of the banking sector is less than their critical values imply that the null hypothesis of no ARCH effect is accepted. This implies that there is no further ARCH effect. That means the selected models are appropriate.

Table 6: Result of EGARCH model

	Variance Equation					Diagnostic Test						ARCH– LM
Bank's Name	α_0	α_1	α_2	λ_1	β_1	R^2	Adj. R^2	Log like	F–statistic	AIC	SIC	Obs.R^2
ABL	−0.32137*** (0.00)	0.16*** (0.00)		−0.05*** (0.00)	0.99*** (0.00)	0.81	0.81	9,422	793*** (0.00)	−11	−11	0.04 (0.84)
Bank name	−0.34467*** (0.00)	0.15*** (0.00)		−0.02 (0.23)	0.98*** (0.00)	0.30	0.30	10,946	122*** (0.00)	−10	−10	0.32 (0.57)
BOI	−0.63431*** (0.00)	0.37* (0.00)	−0.18*** (0.00)	−0.05*** (0.00)	0.97*** (0.00)	0.95	0.95	12,940	4,380*** (0.00)	−12	−12	0.06 (0.80)
CBL	−0.30024*** (0.00)	0.26*** (0.00)	−0.16*** (0.00)	−0.03*** (0.01)	0.98*** (0.00)	0.35	0.35	10,457	2*** (0.00)	−9	−9	1.04 (0.31)
ICICI	−0.23283*** (0.00)	0.24*** (0.00)	−0.08* (0.10)	−0.01 (0.34)	0.99*** (0.00)	0.06	0.66	9,891	16*** (0.00)	−9	−9	0.10 (0.75)
IDBI	−0.66663*** (0.00)	0.22*** (0.00)		−0.04*** (0.01)	0.96*** (0.00)	0.31	0.31	10,601	112*** (0.00)	−9	−9	13.25*** (0.00)
ILB	−0.30372*** (0.00)	0.16*** (0.00)		0.02* (0.08)	0.99*** (0.00)	0.93	0.93	12,775	3,251*** (0.00)	−11	−11	0.85 (0.36)
INGV	−0.6117*** (0.00)	0.26*** (0.00)		0.01 (0.50)	0.97*** (0.00)	0.80	0.80	13,845	972*** (0.00)	−12	−12	2.23 (0.14)
J&K	−1.82756*** (0.00)	0.29*** (0.00)		−0.03 (0.20)	0.87*** (0.00)	0.13	0.13	11,183	50*** (0.00)	−10	−10	0.12 (0.73)
KMB	−0.343*** (0.00)	0.35*** (0.00)	−0.14*** (0.00)	0.01 (0.47)	0.99*** (0.00)	0.72	0.72	12,128	633*** (0.00)	−11	−11	0.31 (0.58)
PNB	−0.1439*** (0.00)	0.21*** (0.00)	−0.13*** (0.01)	−0.05*** (0.00)	0.99*** (0.00)	0.19	0.18	11,455	56*** (0.00)	−10	−10	0.85 (0.36)
SCP	−6.67E01*** (0.00)	0.22*** (0.00)		−0.04*** (0.01)	0.96*** (0.00)	0.31	0.31	10,601	112*** (0.00)	−9	−9	0.67 (0.41)
SBI	−0.34124*** (0.00)	0.14*** (0.00)		−0.03*** (0.02)	0.98*** (0.00)	0.12	0.12	10,448	40*** (0.00)			1.89 (0.17)
YSB	−0.48773*** (0.00)	0.20***		−0.07*** (0.00)	0.97*** (0.00)	0.20	0.20	8,866	89***	−8	−8	1.32

Source: Estimated data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.

Note: *denotes the level of significance at 1% or less than 1% level of significance; **denotes at 5% or less than 5%; and ***denotes 10%.

Return and Firm Size

The study here investigates the relationship between return and firm size. Firm size is classified into three categories, viz, small–size firm, medium–size firm, and large–size firm based on a composite index constructed by using market capitalization, net sales, and profit after tax. The study also shows the relationship between firm size and return from the investment. It also explains the effect of a change in volatility on expected return for each category of firm size.

Table 7. Random–effects GLS regression (REM)

Group variable: PI		Number of observation = 23,465		
		Number of groups = 11		
R–Square:	Within = 0.0010	Observation per group: min = 1,645		
	Between = 0.1015	Average = 2,133.2		
	Overall = 0.0017	Maximum = 2239		
Corr.(u_i, X) = 0 (assumed)		Wald $chi^2(5)$ = 23.63		
Dependent Variable = Return		Prob. > chi^2 = 0.0000		
Coefficients	Value of Coefficients	Std. Error	t–statistic	P–Value
β_1	0.092856	0.043293	2.14	0.032
θ_1	−0.000049	0.00028	−0.17	0.862
θ_2	−0.000129	0.00028	−0.46	0.645
δ_1	−0.1010317	0.043339	−2.33	0.020
δ_2	−0.0243486	0.0688117	0.35	0.723
α_1	0.0004654	0.0002135	2.18	0.029
Sigma u		0.0003571		
Sigma e		0.00289136		
Rho		0.01502421 (fraction of variance due to u_i)		

Source: Estimated data is based on secondary data retrieved (12/06/2014) from www.nseindia.com, 2014.

From Table 7, it is observed that the intercept term ($\alpha 1$), which captures the structural factors for large–size firms of the banking sector, is significant at less than 5% level of significance. This implies that there would be a positive return (0.046%) from investment in large–size firms without any risk. The intercept differential impact of small–size firm ($\theta 1$) and medium–size firm ($\theta 2$) as compared to large–size firm is negative but statistically insignificant. This indicates that small–size firm and medium–size firm has no statistically significant effect on return.

There is statistically significant effect of a change in volatility of small–size firms on expected return for the banking sector as the estimated coefficient of volatility ($\beta 1$) is positive and statistically significant at less than 5% level of significance. The slope differential effect of medium–size firm as compared to small–size firm ($\delta 1$) is negative and statistically significant at less than 5% level of significance. This indicates that if volatility increases by 1% for medium–size firms then expected return may decreases by approximately 10% as compared to small–size firms. The slope differential effect of large–size firms compare to small–size firms ($\delta 2$) is negative but statistically insignificant.

Conclusions

From the analysis discussed earlier, it can be concluded that the volatility in all the banking sector firms exhibits the characteristics like volatility clustering, asymmetry effect, and persistence of volatility in their daily returns. The study also observed that the asymmetric term ($\lambda 1$) is negative and statistically significant for ABL, BOI, CBL, IDBI, ILB, PNB, SBI, YSB, and CNX Bank (sectoral index) indicating that the volatility is high when there is bad news or negative shocks in the market than that of good news or positive shocks for these banks. The relationship between returns and volatility is statistically significant for the return series of CBL, ICICI, INGV, J&K, and KMB. However, the coefficient θ is positive only for of CBL, ICICI, and J&K while it is negative for INGV and KMB. The study also finds significant small–size firm effect on returns.

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Appendix

Table 1.2 A. Banks selected based on market capitalization

Sector	Bank Symbol	Bank Name	Market Capitalization
Banking Sector	HDFC	HDFC Bank Limited	1,73,939.73
	ICICI	ICICI Bank Limited	1,39,806.51
	SBI	State Bank of India	1,22,792.10
	ABL	Axis Bank Limited	65,632.86
	KMB	Kotak Mahindra Bank Limited	57,205.39
	BOB	Bank of Baroda	27,750.51
	ILB	IndusInd Bank LTD	24,584.40
	PNB	Punjab National Bank	22,220.24
	YSB	Yes Bank Limited	13,172.01
	BOI	Bank of India	12,784.19
	CBL	Canara Bank Limited	10,876.51
	INGV	ING Vysya Bank Limited	10,706.37
	IDBI	IDBI Bank Limited	9,535.42
	SCP	Standard Chartered PLC	7,910.24
	J&K	The Jammu & Kashmir Bank Limited	7,393.20

Source: Secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.

Classification of firm size

Name of Bank	DI of Net Sale	DI of Net Profit	DI of Market Capitalization	Composite index
ABL	0.25	0.74	0.35	0.45
BOB	0.30	0.45	0.12	0.29
BOI	0.28	0.13	0.03	0.15
CBL	0.28	0.15	0.02	0.15
HDFC	0.34	1.00	1.00	0.78
ICICI	0.22	0.91	0.80	0.64
IDBI	0.19	0.02	0.01	0.07
ILB	0.04	0.11	0.10	0.08
INGV	0.00	0.00	0.02	0.01
J&K	0.01	0.01	0.00	0.01
KMB	0.07	0.21	0.30	0.19
PNB	0.33	0.35	0.09	0.26
SBI	1.00	0.95	0.69	0.88
YSB	0.06	0.14	0.03	0.08

Note: DI means Dimensional index

Source: Calculated data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.

Classification of firm size

BANKING Sector		
Name of Bank	**Composite Index**	**Firm Size**
INGV	0.006631	SMALL
J&K	0.007446	SMALL
IDBI	0.073233	SMALL
YSB	0.080326	SMALL
ILB	0.08334	SMALL
BOI	0.148807	MEDIUM
CBL	0.150312	MEDIUM
KMB	0.191663	MEDIUM
PNB	0.256144	MEDIUM
BOB	0.291164	MEDIUM
ABL	0.446643	LARGE
ICICI	0.640372	LARGE
HDFC	0.77965	LARGE
SBI	0.882179	LARGE

Source: Calculated data is based on secondary time series data retrieved (12/06/2014) from www.nseindia.com, 2014.