Selection of Value-at-Risk Model and Risk-Return Dynamics in Equity Market with Particular Reference to India

A Thesis Submitted to the University of Hyderabad for the Award of the Degree of

Doctor of Philosophy

in Economics

Rajesh P N

Department of Economics
School of Social Science
University of Hyderabad
Hyderabad – 500046

February – 2010

Department Of Economics
University of Hyderabad

Declaration

I hereby declare that the work titled, "Selection of Value-at-Risk Model and Risk – Return Dynamics in Equity Market with Particular Reference to India", is carried out by me under the supervision of Professor Bandi Kamaiah, Department of Economics, University of Hyderabad, is an original piece of work. This dissertation or any part thereof has not been submitted for any other degree at this University or anywhere else.

Hyderabad

01.02.2010 Rajesh P N

Department of Economics

University of Hyderabad

Certificate

This is to certify that the dissertation titled, "Selection of Value-at-Risk Model and Risk – Return Dynamics in Equity Market with Particular Reference to India", submitted by Mr. Rajesh P N in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Economics is original and that the work has been carried out under my supervision. This dissertation or any part thereof has not been submitted for any other degree to this University or anywhere else.

Professor Bandi Kamaiah
Supervisor

Head of the Department of Economics

Dean, School of Social Sciences

Acknowledgement

I express my deep gratitude, respect and affection to my guide and supervisor Professor Bandi Kamaiah for giving me an opportunity to work with him and for introducing me to this happening field as also for sharing his knowledge, experience and time with me. Without his constant guidance and motivation, this work would not have been possible.

I also thank the University Grants Commission for giving me financial support without which I may not have ventured out to undertake this.

I am also deeply indebted to the Head of the Department of Economics, my doctoral committee members and teaching and non-teaching staff of the department for their valuable contribution.

I take this opportunity to express my deep gratitude, respect and love to Mr. Binoy Raphael, former Research Student, Department of Physics, University of Hyderabad and Mr. Shinto P Mathew, Research Scholar, Department of Physics, University of Hyderabad, for the invaluable help given to me in writing Matlab programmes. Without their help, I doubt if I could have met the arduous computational requirements demanded by the thesis.

I also thank Dr. Anver Sadath, Mr. Sreeraj A P, Mr. Jayakrushna Bhoi, Mr. Rajesh Acharyah, Mr. Gouri Sankar Hiremath, Mr. Suresh Naik, Dr. Hussain Yaganti, Dr. P Sakthivel, Ms. Swayamprava Misra, Mr. Zikrullah Khan, Mr. Dinesh Babu P, Mr. Ammathali Naidu and all other colleagues in the department of Economics for their support and encouragement.

I also thank all my friends in the NRS Hostel and the University of Hyderabad for making my stay in the university pleasant and for keeping me intellectually motivated.

I take this opportunity to thank my father, Mr. P Narayanan Nair, mother, Ms. V Vilasini Amma, sister, Ms. Sreeja P N, brother, Mr. Suresh P N as also Nikhil K Das, Neeraj K Das and Gatha Parvathy and all other family members with the deepest affection and respect for their emotional support and unconditional love, particularly during the thesis work and my life in general.

I also thank my fiancée, Ms. Varalakshmi Nair, with lots of love and respect for the assistance given in the proof reading of the materials.

Last but not the least I thank God for being with me.

These hold true only for the strengths of the thesis and its faults and short comings are my own.

Rajesh P N

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Chapter 1

Statement of the Problem

1.1. Introduction

Risk management is defined as, the process by which various risk exposures are identified, measured and controlled (Jorion, 2002). Thus, risk management is concerned with three tasks related to risk viz. identification, measurement and control. Identification is the process of mapping the source of risk as well as the variables that are most closely connected with it. Identification is a difficult issue and usually is tough to quantify. Origin of risk can be from inflation, business cycles, government policies, wars, natural calamities and technological innovation. In a highly integrated financial world, what is happening in one centre is liable to have repercussions in other places as well. If prices go down, we will have problems: problems in the sense of spillover to other areas (Greenspan, 2007). Hence, risk as emerging from foreign market and spilling over to other markets is an important part of the identification of risk and therefore the question whether volatility and return of a foreign market affect the domestic market is an important one in the containment of risk. Therefore, taking all these risk factors as one set and assuming them to be originating in one market and flowing to the others, risk can be thought of as taking the same route and mapped in a similar fashion. Thus, academicians have found spillover of risk from one market to the other as a useful method of quantifying and thereby identifying risk. The second factor in identification of risk is concerned with the variable or proxy that may truly reflect risk. In this regard, volatility has emerged as a standard term to signify risk. It is nothing but the variation of return over a certain period of time. This is amply captured by the variance of return. Hence, combining these two factors may be thought of as a useful way of dealing with identification of risk.

Closely connected with this issue of spillover of volatility is the existence of risk premium. If volatility is spilling over and causing asset prices to fluctuate in the domestic market thereby leading risk levels to soar, investors should be paid a premium to hold these highly fluctuating assets in their portfolio. This mark up is called risk premium. Existence of risk premium is the only rationale for investors preferring securities like stocks over safer bets like bonds, gold and currency. Since measured volatility is equivalent to risk and because financial industry is replete with risk lovers, theoretically, there should be a positive and healthy relation between volatility and return. This study has therefore occupied a pivotal position in financial literature form the 1950's onwards.

The ultimate goal of risk management is the containment or management of risk. It is not possible until the amount of risk that a particular institution is exposed to is not known. Measurement of risk is therefore, an important part of risk management. Proliferation of models dealing with risk measurement and colossal bankruptcy filings has caused an unprecedented boom in this branch of study. Choice of an appropriate model that gives an accurate account of the risk that an institution is exposed to is particularly important for the owners, managers and regulators in particular and financial industry in general. Hence, selection of the model to be used is a very delicate task to be done only after a careful empirical analysis and stringent back testing. Thus, the present study attempts an exhaustive and in-depth analysis in these areas and tries to uncover theoretical relations at empirical level as also seeks to find a benchmark model that would be suitable for all the parties interested for taking decisions at different levels of their operations.

1.2 Evolution of Risk Management

Risk management is a shifting concept that has had different definitions and interpretations. The concept had its origin from insurance industry and focused on damages resulting from accidents. It is defined as the process of protecting one's person or organization intact in terms of assets and income. In the narrow sense it is the managerial function of business, using a scientific approach to dealing with risk. As such, it follows a distinct philosophy and follows well defined sequence of steps (Gallati, 2003). Jorion (2002) defined it as a process by which various risk exposures are identified, measured and controlled. The concept of risk management was in focus from early 1920's, but real developments in this regard happened only in the second part of the last century. These developments were demarcated in to two groups as portfolio theories and capital adequacy measures. The former mainly arose from the academic circles while the latter was popular in the practicing and regulatory circles.

1.2.1 Portfolio Theories

It was Markowitz (1952) who used risk in the financial theory for the first time in a theoretical framework. He linked terms such as return and utility with the concept of risk. It built the foundations for later developments in portfolio and risk theories. The Markowitz approach is based on the assumption of a relation between risk and return and considers the effect of diversification, using the standard deviation or variance as a measure of risk. Portfolio risk was defined as the weighted risk of all the individual assets and the covariance between those assets. His theory was further improved up on by Tobin (1958). Tobin improved the correlation between the assets and the risk aversion by including a risk free position.

Later, Capital Asset Pricing Model originated as a follow up of Markowitz model. It recognized risk as an important factor in portfolio selection and identified systemic risk which was a reflection of market risk and hence non-diversifiable. Risk premium attached to the systemic risk was called the market risk premium. That portion of the risk which could be diversified away was called un-systemic risk or specific risk. It could not be explained by market risk and had a separate origin in position specific factors.

1.2.2 Basel Committee on Banking Supervision

The failure of German bank Herstatt in 1974 created discussion on the need for regulation of banks on an international platform. In accordance with the need of the hour, a standing committee was set up by the central bankers of the G-10 countries under the auspices of the Bank for International Settlement (BIS) in 1975 which came to be called the Basel Committee on Banking Supervision.

1.2.2.1 Need for Regulation

Debates are still going on the need for and the types of regulation to be imposed on financial institutions including banks, pension funds, security houses, insurance companies etc. An argument against regulation is that the owner be allowed to temper risk appetite according to his preference. But regulation is generally viewed as necessary due to two reasons; externalities and deposit insurance. The former refer to the cascading impact the failure of a financial institution can have on the system as whole. This is otherwise called systemic risk. This poses serious threat to the entire financial system. Deposit insurance is the assurance of the government to compensate depositors in case of a bank failure. It seeks to protect small depositors who cannot monitor banks effectively. It also prevents ‘run on the bank’. But this government guarantee creates moral hazard when the banks take excessive risks than they can afford in the hope of government stepping in to their rescue. This amply demonstrates why regulators attempt to control risk taking activity by imposing capital adequacy norms.

1.2.2.2 1988 Basel Accord

The 1988 Basel accord is regarded as a landmark in the regulation of financial institutions. It was agreed up on the 15th of July 1988 by the central bankers of the G-10 countries. The main purposes of this accord were to strengthen the soundness and stability of the international banking system by providing a minimum standard for capital requirements and to create a level playing field among international banks by harmonizing global regulation (Ching, 2004).

1.2.2.3 The Cook Ratio

The 1988 Basel Accord put the capital requirements at a mandatory 8 per cent of the total risk weighted assets. Capital was divided in to Tier 1 and Tier 2. The former included paid up stock issues and retained earnings, while perpetual securities undisclosed reserves, subordinated debt with a maturity of greater than 5 years and shares redeemable at the option of the issuers came under the latter category. Risk weights were classified in to four types from the safest to the riskiest depending on the nature of the asset. Further, positions that exceeded 25 per cent of the bank's total capital was not allowed and the total large risks – positions exceeding 10 per cent of the bank's capital – were to be less than 800 per cent of the bank's total capital. But it had several limitations in that it had inadequate differentiation of the quality of credit disbursed, non-recognition of netting, ignoring the possession of uncorrelated assets and non-recognition of market risks.

1.2.2.4 The amendment of 1996 and Provision for Market Risk

The Basel Committee amended the 1988 Accord in 1996, which came in to effect from 1997 onwards, to incorporate market risks. The capital charge for market risk was based either on the standardized approach of calculation or on the internal models method. The latter allowed the institutions to use their own models subject to test by the Committee. In addition the Committee imposed restrictions like a 99 per cent confidence level, 10 day trading period and at least a year of historical data for the calculation of market charge which was now the sum of credit risk charge and market risk charge. Correlations were allowed in broad categories. A penalty was imposed if the model was found to be lacking in predictive accuracy. Capital requirement was to be a minimum of three times the previous day's Value at Risk or 3 times the average Value at Risk of the last 60 days. The advantage of this model over the GARCH model is that since, $L_n (\sigma^2{}_t)$ is modeled, even if the parameters are negative the result will be positive.

1.2.2.5 Present Scenario

A new generation of guidelines was introduced by the Basel Committee in November 2004 which is periodically amended and is called Basel II accord. This accord has three pillars in operation viz. minimum capital requirements, supervisory reviews and market discipline. The first pillar deals with maintenance of regulatory capital calculated for three major components of risk that a bank faces: credit risk, operational risk and market risk. Other risks are not considered fully quantifiable at this stage. The credit risk component can be calculated in three different ways of varying degree of sophistication, namely, standardized approach, foundation IRB and Advance IRB. IRB stands for "Internal Rating-Based Approach". For operational risk, there are three different approaches – basic indicator approach, standardized approach, and the internal measurement approach. For market risk the preferred approach is Value-at-Risk. The second pillar deals with the regulatory response to the first pillar, giving regulators much improved tools over those available to them under Basel I including those to control residual risks. Third pillar of market discipline is incorporated to promote greater stability in the financial system.

1.2.3 Risk Metrics

The JP Morgan group published its first risk measurement system based on variance model in 1989 which was called RiskMetrics. They had an internal system of reporting the amount of risk that the institution was exposed to at the end of each day. RiskMetrics was a direct outcome of that. The system was revised in 1992 and introduced in the market place which revolutionized the whole gamut of risk management. The methodology is periodically revised and updated and the correlation structure is provided by RiskMetrics itself. This methodology is based on the Exponentially Weighted Moving Average (EWMA) in which the next day’s risk depends on the previous days and weights are attached to the past days based on chronological ordering with the most recent ones getting more weight. Today, many institutions have found this methodology to be simple and at the same time effective and are using it for measuring and controlling risk.

1.2.4 Risk Management in India

Risk management practices in Indian financial institutions in general and banks in particular are in line with international norms. Most of the banks have already migrated in to the simpler standardized approach and are expected to be following the advanced approaches in a year or two at their discretion while simultaneously adhering to the simpler method. The models of risk management used in the Indian financial industry vary from institution to institution as the Basel committee as well as the Reserve Bank of India (RBI) has allowed sufficient elbow room for operation to the participants. Since investment banking is not a developed industry in the country, more advanced and aggressive models of risk management as practiced in the western countries are a rarity.

1.3. Types of Risks

A moderate appetite for risk is desirable to any financial institution from profit point of view but too much of it can be lethal to its very survival. An institution should therefore spend time and effort to understand the types of risks to which it is exposed. The governing body must have a basic understanding of the types of risks, what they mean to the organization and how and when they might appear, before being able to take effective action. To help in this a common understanding of the categories of risk is critical. It allows managers, risk takers and central officers to discuss the issues in common terms and create greater transparency around various risk exposures. Risk in itself is not bad and need not necessarily be avoided at any cost. Temperate risk can benefit organizations by providing healthy returns. But before this can happen, decision makers must understand their risks and types of risk is thus an important part of the identification of risk.

1.3.1 Market Risk

Market risk is the risk associated with the adverse move in the value of an asset. It can be a common stock, bond or a commodity or a derivative linked to these assets. Market value of these assets depends on factors like interest rate, exchange rate or even the general economic conditions prevailing at the time. A change in any of these will lead to a corresponding change in the value of the asset. This can be positive or negative depending up on the nature of the change in the variable. Some of the common types of market risks are directional risk, volatility risk, curve risk, time change risk, spread risk, basis risk and correlation risk.

1.3.2 Credit Risk

Credit risk has been in the news recently for the bad reasons. It is the risk arising due to the inability or the unwillingness of a counter party to honor its financial obligation. This leads to default and losses for those extending credit. The credit loss in reality is a worst-case scenario that can be reduced or offset by collateral netting or recoveries. It can appear in the form of direct credit risk, trading credit risk, contingent credit risk, correlated credit risk, settlement credit risk or sovereign credit risk.

1.3.3 Liquidity Risk

It is one of the most important of all risks. Liquidity risk arises due to a mismatch between cash inflows and outflows. It can be an inability to sell a position – asset liquidity risk – and fund a position – funding liquidity risk – or both. In extreme cases any of these two can lead to self fulfilling liquidity crisis when a failure to rollover existing positions may lead to downgrading thereby undermining the willingness of new counterparties to arrange liquidity. This may force the firm to enter in to very expensive arrangement for cash. A combination of asset and funding liquidity risk can lead to huge losses or even bankruptcy.

1.3.4 Operational Risk

According to the Basel Committee operational risk is defined as the risk of direct or indirect loss resulting from inadequate or failed internal process or people and system or from external events. This includes fraud, management failure and inadequate procedures and controls. Technical errors may be due to breakdown in information, transaction processing or settlement systems. Operational risk can also lead to market and credit risks.

1.3.5 Model Risk

Model risk is the risk arising due to the use of inappropriate models and analytical tools to value financial contracts. While some assets can be valued quite precisely using mathematical formulae, other assets rely on much more sophisticated financial mathematics and assumptions. Errors in mathematics or assumptions can lead to model risk losses.

1.3.6 Suitability Risk

Losses can also arise from client transaction suitability issues. This suitability risk most often occurs when a counter party claims financial injury as a result of a particular transaction. It may happen when the deal was riskier than presented or when it was not accompanied by enough disclosures about the downside or when it fails to provide the risk protection sought. The counter party may disown the transaction and sue for damages. While legal proceedings are not always guaranteed to create large settlements, the chances of loss always exist and should be recognized.

1.3.7 Legal Risk

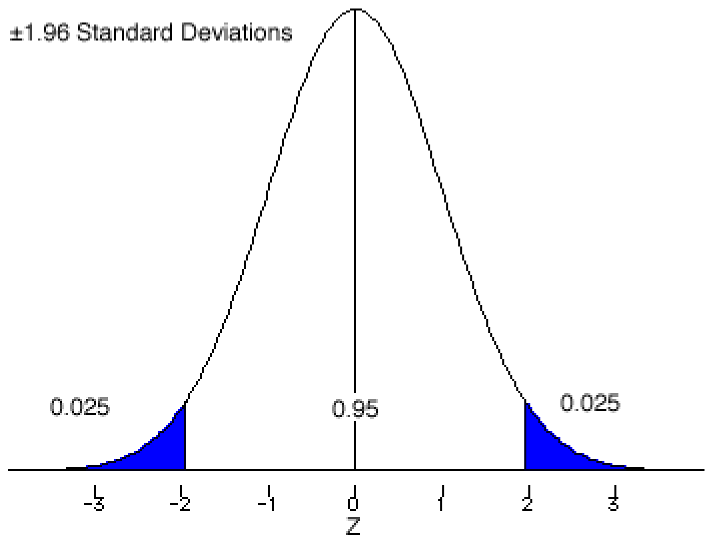
It is the risk of loss due to failure of the legal process. Legal mechanisms like confirmations, master netting agreements and financial covenants are part of most of the financial dealings. They contain important legal provisions that are designed to protect the parties in the event of a dispute or a default. Failure to negotiate proper documentation or obtain necessary protection in the signed agreements can lead to legal risk losses in the event of a default or dispute.

It is clear from the discussion that a firm is susceptible to various types of risks. Risk itself is a kind of dynamic process whereby its nature, sources, causes and consequences keep on changing as the environment in which the entity works changes. So it becomes imperative for any risk management department to keep track of all developments in this front.

1.4. Value-at-Risk

Among the above mentioned types of risks, market risk is the most important one as it is the commonest among them and it is this risk that contributes more to the spread of a crisis through spillover and panic. Hence, controlling this is essential for the health of the entire economy and especially the financial side of it. The one measure that has been widely used and found to be effective for measuring and controlling market risk is Value-at-Risk. For a given portfolio, probability and time horizon, Value-at-Risk is defined as, a threshold value such that the probability that the mark-to-market loss on the portfolio over the given time horizon exceeds this value (assuming normal markets and no trading in the portfolio) is the given probability level (Jorion, 2006). Hence, there are three things to be noted in Value-at-Risk. The first one is the amount of loss, the second one the time horizon and the third is the probability level or the confidence level. Time horizon normally ranges from a single day to two weeks and it can be as low as hours or even run in to months as well in special cases. Similarly, the confidence level can be one, five or ten per cent but in some cases it is extremely tight around 0.05 or 0.01 per cent. But the generally accepted standard is one per cent and is the one recommended by the Basel Committee.

Figure 1.2 Graphical illustration of Value-at-Risk

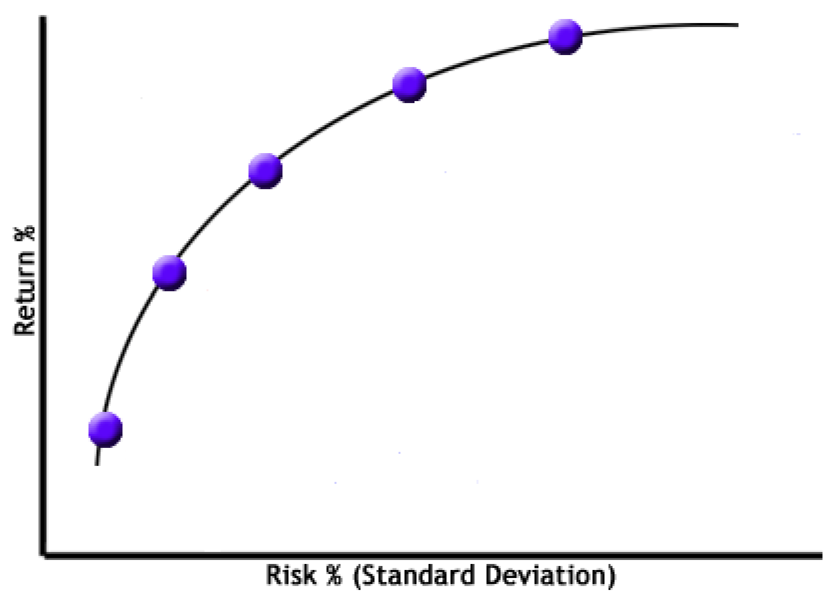


Assuming the returns to be distributed as normal, the above figure shows graphical representation of Value-at-Risk with a two tailed loss scenario. Right side shows possible loss on the upside due to an uncovered short position while the left side shows possible loss on the downside. Both these are at 5 per cent level of significance for a two tailed distribution. But Value-at-Risk normally has to be concerned only with downside loss and is hence to be bothered about the left tail only. The simple logic of Value-at-Risk is to find the value that is likely to lie at the margin of the confidence level on the downside whether that confidence level corresponds to the 95, 97.5 or 99 per cent level of confidence.

1.5. Volatility, Risk and Return

In finance, volatility is a statistical measurement of up and down asset price fluctuations over time. If an asset has rapid and dramatic price swings, volatility will be high. If prices are consistent and rarely change, volatility is low. Volatility can be measured as the annualized standard deviation. Volatility is often used to measure risk. Many common measurements of risk, such as beta, utilize volatility in calculations. It makes sense that an asset that has had huge price swings is more risky than an asset that is not volatile. In literature, volatility and return are inversely related. High volatility preceding a bear market is shown as a classic example for this phenomenon. It is common in the financial industry during these days to observe traders buying volatility index as a means of protecting their portfolio.

Figure 1.2 Risk and Return



This is how the relation between risk and return has been defined in the literature. The investor is expected to get an increasing amount of return as he/she assumes extra risk but after a certain point a level of saturation is attained and no more extra returns can be expected.

1.6. Recent Financial Failures

Examples of financial failures are many in history. But the single important point to note in all those failures is the impotency of the risk management wing. Functions concentrating in a single person, taking hugely leveraged positions or assuming greater risks in the hope of cornering higher returns are some of the usual culprits for these failures. A short glance at four of the major financial failures over the last two decades would be interesting as a prelude to the study. This would give an explanation to the huge importance attached to this branch of study and to its ever increasing appeal.

1.6.1 Barings

Barings was a reputable British merchant bank with branches over most of the major financial centers. In 1990, Nick Lesson, a settlement specialist in the bank's London branch was transferred to Singapore where he was given the additional responsibility of looking the bank's futures brokerage division. It is usually a low risk – low return job where the duty is to accept and execute customer orders and to return or call for margins accordingly. Clerical errors cause brokers to own positions unknowingly in this type of business, but these are closed instantly at minor losses. But Lesson kept all these positions in a separate account in the hope of settling them profitably in the future. Through this manipulation he was able to show a more than normal profit which raised his image and access.

The losses in his accounts kept accumulating but due to his credentials Lesson was able to get margin from the head office and his margin fund slowly exceeded the bank's capital. In 1995, Lesson sold a large amount of straddles in a last attempt to cover all the losses. This strategy depended on a calm market where the buyers will not exercise their positions. But due to a massive earthquake the market turned volatile and Lesson's attempt failed miserably. As a result of his huge positions, Barings failed and was bought by ING for a nominal £1. This incident depleted the value of Barings by £860 million. In this case a single person was given control over the front and back offices and nobody cared to enquire the source of his abnormal profits or the rationality of funding his margin. This was a foremost case of operational risk strengthened by market and liquidity risks.

1.6.2 Long Term Capital Management

It was a hedge fund managed by the best financial and modeling experts available in the industry during the early 1990's. Initially, it traded in fixed income securities and garnered stunning margins by managing the pricing discrepancies of the financial instruments to their advantage. As the fund became too unwieldy, it returned $2.7 billion to investors which compromised its liquidity. Later, as competition increased, they had to venture in to new areas like equities to keep delivering their past returns. The operation of the fund was in such a way that it owned position far in excess of its capability and pledged its assets for more funds with which it took new commitments. The suppliers of fund were often very lenient in hair cuts to keep a good client in healthy humor. Competition among suppliers also led to lax issue of loans. The fund was holding virtually uncorrelated assets in equity, bond and currencies.

The East Asian and the Russian crises of the late 1990's caused turmoil in the financial markets and as it deepened all assets began to lose value as investors preferred liquidity and the benefits of diversification became a mere theory. This exacerbated the margin calls on Long Term Capital Management (LTCM). Several of the supposedly uncorrelated LTCM trading strategies simultaneously created the need to repay loans, raise money and pledge more assets. Its lenders panicked as they had relaxed their norms and knew the fund's hugely leveraged position. As competitors came to know about the trouble they began to push around the positions of LTCM. Thus, a combination of tight liquidity and over leveraged position led to the demise of LTCM.

1.6.3 Orange County

Bob Citron, a treasurer with Orange County, was entrusted with $7.5 billion portfolio. In addition he purchased about $12.5 billion on reverse purchase agreements to create more profits through leverage and invested the money in Treasury Notes with a maturity greater than 4 years. The strategy worked well when the short term funding costs were lower than the medium term yields. But interest rates began to rise from 1994 and caused margin calls from short term fund providers. Finally the county defaulted on collateral payments and brokers started liquidating the collateral with them. This resulted in Orange County going bankrupt. This bankruptcy represents the most extreme case of uncontrolled market risk. The treasurers never had to disclose the market value of the portfolio because of regulatory loopholes and it was allowed to keep accumulating till reaching a lumpy $1.7 billion when the fund suppliers started demanding margin. Had the positions been valued at current market value on a mark-to-market basis, the risky positions would have been revealed much earlier.

1.6.4 Lehman Brothers

The largest bankruptcy filing so far in the world is that of Lehman Brothers which took place in September 2008. The collapse of Lehman started with the boom in US housing market. It acquired five mortgage backed lenders including Aurora Loan Services which made loans without proper documentation. The firm reported record revenues and profit over 2005 to 2007. But cracks began to appear in the US housing market even as Lehman continued to report record profits. However, failure of Bear Sterns Hedge Funds made the situation worse and Lehman had to close some of its mortgage units. But it continued underwriting mortgage backed securities accumulating a portfolio which was 4 times its shareholder's equity. Its leverage ratio spiraled up to 31 and it reported $2.8 billion loss for second quarter of 2008 and its cash dwindled to $1 billion by second week of September. Attempts by many banks to rescue Lehman failed and it filed for bankruptcy on September 15 2008. Thus, the failure of Lehman can be attributed to a combination of credit, operational and regulatory risk.

1.7. Need for the Study

There are a large number of bank and investment company failures over the last two decades or so. Most of these are connected to faulty risk management practices as is already clear from the examples above. These failures have led to a spurt in the interest of risk management tools. Creation of RiskMetrics by JP Morgan Chase was a case in point. It was followed by a number of studies on the topic. However, studies on volatility and risk premium have been in existence since long back. Portfolio diversification was seen as an effective strategy for reaping maximum profit at minimum risk. It was the study of

Grubel (1968) which created interest in international diversification of portfolio. Since then, a number of studies have analyzed whether international diversification is beneficial or not. An important criterion for the benefit was minimization of risk which was achieved because of low correlation among markets. This came to be questioned later when due to opening up of financial markets over the world, stock markets became highly integrated leading to co-movement of prices. With emergence of risk management as an important area, studies began to be diverted to linking international diversification and spillover of risk. These studies were concentrated more or less in the Pacific Rim area involving USA, European markets and Japan. Two notable studies involving India are Nath (2003) and Mukherjee (2008). However, both of them concentrated on the interlinkages of India with Asian markets. Moreover, Nath used only co-integration and vector auto regression analysis and covered the period till 2002 only while Mukherjee used only the naive conditional heteroscedasticity model. The present study is an improvement over the two in terms of coverage, time period and methods used.

Researchers have shown interest in risk premium from the early 1950's onwards. In fact, only after the paper by Markowitz (1959) did financial literature started in an organized manner with studies on risk premium taking a leading role. This work by Markowitz later developed to become the Capital Asset Pricing model which essentially dealt with the tradeoff between risk and return. Initial studies showed a positive relation between risk and return but towards the early 1980's this trend changed and a negative or no relation began to emerge. Subsequent studies have given mixed results. As far as India is concerned, there are no serious studies on risk premium. All the studies are elementary arithmetical operations by subtracting risk free return from stock return and showing an arithmetical risk premium. Hence, there is a need for a comprehensive study which is seen as an improvement over the previous studies in terms of techniques employed as well as period and market covered.

A rapidly evolving area in risk management in particular and finance in general is the modeling of risk. This started, as already mentioned, by the publication of RiskMetrics by JP Morgan Chase. Since then, a large number of models have come out as modifications of existing models after claiming to have plugged the loop holes that they were subject to. A major problem of risk manager or regulator is to decide which model should be used considering the particular objective of the institution. A good model should be one that ensures biggest operating room for the institution with least possible risk. The present study is an extensive analysis of the models, distributions and window sizes with the latest back testing methodology used in the Indian context. In the light of the above background, the objectives of the study are set as follows.

1.8. Objectives

i) The first objective has been to analyze the transmission of volatility across international markets. For this purpose the study uses the markets of India (Nifty), Japan (Nikkei) and USA (S&P 500).

ii) The second objective deals with risk-return dynamics in the Indian equity market by analyzing the existence of risk premium.

iii) The third objective has been to identify a model that predicts Value-at-Risk at highest possible precision. Daily returns of three markets viz. Nifty, Nifty Junior and Nikkei, are used for this purpose.

As per theory it is expected that there is a positive spillover of volatility as well as return from one market to the other. This is supported by a number of studies for other markets as well as by the expectations prevalent in the industry. This comes under identification of risk as originating in the foreign markets. The study takes Nifty and Nifty Junior as the two markets to test whether there is any risk premium in them. The study seeks to verify the existence of a positive risk premium as the investors need to be compensated adequately for the additional risk that they are taking. The study analyzes 7 models and their different varieties and subjects them to back testing against real world returns in the third objective. The study runs these models accounting for asymmetric information as well with assumptions of fat tailed distribution. The study includes both parametric and non-parametric models and does 2.5 million one day ahead forecasts and subjects all of these single values to back testing using the technique developed by Christoffersen (1998).

1.8.1 Hypotheses of the Study

i) The study hypotheses the existence of a positive risk premia for equity markets as it is absolutely necessary for the participants to take on additional risk. This is borne by theory as well.

ii) It is expected that there will be a spillover of volatility as well as return from one market to the other as nations are getting more and more integrated in terms of flow of capital as well as trade relations.

iii) It is also expected that the return as well as volatility shocks are originated in US markets as it has the largest turn over and is the leader in international trade as also the financial centre of the world.

1.9 Chapterization Scheme

The thesis is organized in to five chapters. The first chapter is an introduction to the topic of risk management in general and Value-at-Risk in particular, dealing with the background of the study. The chapter also connects the three objectives that the study deals with. The second chapter deals with transmission of volatility across Japan, India and USA. It does a review of the available literature on the issue and also a preliminary analysis of the data followed by empirical analysis and concludes by giving a detailed account of the findings of the study. The third chapter is on risk-return relation and follows the pattern of the second chapter. It includes a review of the Capital Asset Pricing Model (CAPM) which is a basic building block for any study on risk-return relation. The fourth chapter presents a review of the major models used for risk management at present. It acts as an appetizer for the larger study of model selection and is in fact cut off from the other chapter so that the flow of the main and larger chapter is not impaired. The fifth chapter is on model selection and the scheme of things is very similar to the second and third chapters. Results of various models are presented in tabular form with brief explanation for each table given at its end.

1.10 Scope and Limitations

The study basically aims at identification and measurement of risk and analyzes how much risk is being generated abroad and if this (risk) has any influence on return as also selecting a best performing Value-at-Risk model. Model selection basically revolves around most popular available ones. It has implications for academicians, practitioners, regulators and common investors. In this sense it has an all encompassing scope. The study has got limitations of its own. It does not use all the available models; first to avoid a feeling of redundancy and secondly because of the huge computing costs involved in terms of time and technology. The study also does not conduct a back testing of the models separately from a regulator's and manager's point of view which would have been ideal as their interest may in most cases be vastly different if not really competitive. Another improvement could have been made by having a look at the third pillar of risk management, i.e. control of risk which is ignored by the present study to take care of identification and measurement in an exhaustive way.

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Chapter 2

Spillover of Volatility among Equity Markets: An Empirical Study of Nikkei, Nifty and S&P 500

2.1 Introduction

Defining equity returns as the percentage change in prices between successive days, equity volatility can be defined as the variation observed in returns calculated over the relevant period of time and volatility spillover as the persistence of volatility across international boundaries or over financial assets in active operation simultaneously or in different periods of time. The present chapter concentrates on transnational spillover of volatility and returns in equity markets. There are variety of reasons for the spillover of volatility between international markets but all of them come together to the degree of integration between the concerned economies and hence the markets that are referred to. This trend towards integration of national economies got a boost after the collapse of the Brettonwoods and the subsequent liberalization of international capital markets in a phased manner. This has led to enormous amount of capital being moved across international boundaries. A major chunk of this is portfolio investment. This has made equity markets interlinked on a scale never seen before and made them responsive to pulses in any other market. Consequently, the benefits of diversification have begun to be questioned and volatility studies have become an integral part of identification of risk as generated in a particular market as a result of adverse foreign market movement. With this background, the present study has built a model of volatility spillover connecting Japan, India and USA. This study is expected to throw light on the behavior of mean and volatility spillover across these markets and identify the risk present in each of these markets that is being generated in the other two. The selection of markets is based on the trend of past studies as well as on the strategical importance of each of the markets. Nikkei and S&P 500 are two of the biggest markets in terms of market capitalization and trading activity. They also operate on either side of the opening of the Indian market thereby making it easy to capture the mutual impact. It will enable to establish transnational spillover of return and volatility without any ambiguity.

2.2. Review of Literature

International market integration and the spillover of mean and variance has been an important topic of discussion in financial literature. The seminal works of Tobin (1958) and Markowitz (1959) showed that the efficiency of portfolios could be optimized by combining assets based on the correlation in their return. International diversification was, therefore, just a step away from being seen as an effective way of minimizing the risk on the given return of a portfolio.

The twist in literature was provided by Grubel (1968), who, following the footsteps of Tobin and Markowitz, explained the phenomenon of diversified asset holdings and empirically analyzed the case of 11 national stock markets to see if, there was any gain from international diversification of portfolios. He used a static model as well as a dynamic model in which foreign assets grew over time. The study used monthly data from January 1959 to December 1966 for 11 countries that included USA, Canada, UK, West Germany, France, Italy, Belgium, Netherlands, Japan, Australia and South Africa. Using the mean variance analysis, the study was able to show that a US investor could earn a greater return on his investment through an internationally diversified portfolio of common stocks at a lower variance than what he could earn by holding only local assets. Dropping Japan, Australia and South Africa from the portfolio reduced the mean return considerably to 8.9 from 12.6 as compared to the 7.5 realizable from a monolithic US portfolio. This gain was in addition to the potential gains from interest rate and productivity differentials. However, the variance of the study was subdued due to the inability to quantify some of the risk factors like war and confiscation. The result, though not path breaking, extended the portfolio diversification benefits to the international scenario.

In a study centered on the abnormal crash of the US stock market in October 1989 and the subsequent ripple effects around the world, King and Wadhwani (1989), examined a 'rational expectations price equilibrium' and a model of contagion between markets as an outcome of rational attempts to use imperfect information about the events relevant to equity value. The result, as interpreted using simple variance across markets and volatility coefficients of Tokyo, London and New York, supported the contagion hypothesis. There was a substantial rise in variance across the markets during the crash period providing evidence that contagion was likely to be more pronounced during high volatility periods. Further, the jumps in variance and volatility coefficients in London around US market opening was found to be significantly higher during the crash than either side of it. The analysis of New York and London markets during 1968-1975, when US markets were closed on Wednesdays, showed that variance in London was only 2/3rd

during the New York holidays as a proportion to the variance on other week days. This strengthens the result that volatility actually flowed from New York to London. The study arrived at the conclusion that, in a market in which investors infer information from price changes in other countries is also one in which a mistake in one market can be transmitted to other markets and if a failure in the market mechanism of USA exacerbated the 1987 crash, this would have transmitted itself to the other markets. Thus, the study provided valuable information on the 1987 melt down.

Eun and Shim (1989) used a Vector Auto Regression framework to analyze whether, equity movements in one market can be explained by innovations in other markets and how rapidly information gets transmitted from one market to the other. The model included nine developed markets, Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, UK and USA with daily return in local currency being collected for the period from December 1979 to December 1987. The US market was found to be the most influential of all as it explained error variance ranging from 6.43 per cent of Hong Kong to 42.03 per cent of Canada. It was followed by Switzerland and UK with average figures of 2.56 per cent and 2.15 per cent respectively. Similarly, among all the markets, US market accounted for the highest percentage of its own error variance. Switzerland was found to be the most interactive market with its high degree of integration, whereas, Japan was found to be a follower in the international scenario. Analyzing the impulse responses, it was found by the study that the innovations to US returns transmitted on the next day itself to the European markets, whereas the Asian markets were found to be sluggish in response. This testifies to the higher information processing capacity of the European markets vis a vis their compatriots in Asia-Pacific. Based on these results, the study concluded that a substantial amount of interdependence existed among international markets with about 26 per cent of error variance of a market being explained by foreign markets on an average. It also added to the literature that the US market was the biggest producer of information.

In a study of Tokyo, London and New York stock markets on volatility spillover, Hamao *et al.* (1990) used Generalized Auto Regressive Conditional Heteroscedasticity in mean to analyze daily data ranging from April 1985 to March 1988. The study divided the period in to pre-crash and post-crash and within the close to close return, a bifurcation was made between close to open and open to close returns to analyze the impact of an immediately closed foreign market on the domestic market and the combined effect of the two foreign markets on the domestic market. The results indicated that while there was volatility spillover from London to New York and from New York to Tokyo, the latter was not able to exert any significant effects on the volatility of the other two markets. This trend was significant in the pre-crash period also but with much weaker effect. Almost a similar result was obtained for mean spillover effect but with the difference that Tokyo market had a positive and significant impact on the mean return of New York. The result did not change much for the close to open returns. The study, thus, underlined the importance of New York as the most influential financial centre. The greater volatility spillover from London to New York was assigned to the over lapping of trading hours between them. Further, the explanatory power of the foreign market was found to be noticeably higher during the crash period, substantiating the argument that markets moved more in tandem during periods of heightened volatility.

Mathur and Subramanyam (1990) used Granger causality to see if the Nordic markets of Sweden, Norway, Denmark and Finland were integrated. The US market data was used as a control variable. Monthly data from 1974 to 1985 was collected for these markets and a Granger causality test applied on this. The result showed that the US market had limited influence on the Nordic market with its hold restricted to Denmark, while there was no causality running from any of the Nordic markets to the US market. Among the Nordic markets, Swedish market showed influence on the Norwegian and Finnish markets, but not on the Danish market. The stock markets of Norway, Denmark and Finland did not cause any change in the return behavior in any of the other three markets in the region. The study thus concluded that the Nordic markets were not fully integrated. This may be due to the market inefficiencies as these markets have very few stocks traded thinly in them.

Engle and Ng (1993) investigated behavior of volatility in 18 international markets covering East Asia, Europe and North America. The study looked at the univariate statistics and fitted a univariate ARCH model to the 18 markets and observed some similarities including that the second moments might be related for some of the countries on a bilateral basis and as a group. They also tested if a group of countries had similar time varying volatility and for this purpose, they implemented a common ARCH feature test to these 18 markets. They found two groups of countries with similar time varying volatility characteristics. The first group composed of Belgium, Germany, Norway and Sweden and the second group composed of the East Asian and Oceanic markets of Australia, Hong Kong and Singapore. For these, groups of countries, common regional factors were important in determining the time varying volatility. But there was found to be an ARCH effect in US return when regressed against Canada and its own past return. This was put to the very similar portfolios of stocks that existed in the USA and Canadian exchanges.

International Equity Correlations among 17 markets was analyzed by Erb *et al.* (1994) which revealed that correlation is time varying and depended largely on the phase of the business cycle. It was found to be more in times of recession than during booms. It also brought in to light the asymmetric behavior of correlation; implying a substantially higher correlation during down markets as compared to up markets. Since the period of study included the abnormal 1987 market crash, the model was re-estimated after dropping the observations during the crash period but the results did not change noticeably. The study tried to forecast correlations using variables applied in measuring persistence of volatility and return – expected business cycles in the respective countries and the differential in the expected returns in those two countries – and found variability in correlation through time to be predictable. This, according to Erb, has important implication for cross country allocation of investment funds for reaping the benefits of diversification. This was possible through predicting the future correlations and investing in markets that are least likely to be correlated.

An investigation exclusively focused on the transmission of stock return and volatility in the North American market was conducted by Karolyi (1995). The study used conditional heteroscedasticity family models along with Vector Auto Regression to assess the transmission mechanism of volatility for the US and Canadian markets for the period from April 1981 to December 1989 using daily data of New York Stock Exchange (NYSE) and Toronto Stock Exchange (TSE). The study found bivariate GARCH model to be doing better in modeling volatility after examining the residuals. The main fall out of the study was the uncovering of the declining volatility and mean spillover from NYSE to the TSE. The study found that volatility originated in USA and spilled over in to Canada, but its magnitude fell from early 1980's to the late 1980's. The study also checked for volatility spillover from US to Canada on interlisted and non-interlisted stocks and found the latter to be affected more – up to three times – by spillover. The analysis of impulse responses also brought out similar results. Further, the impulse responses showed that the foreign shocks were much more important to Canada than it was to USA. In fact, shocks to the foreign return caused greater ripples than those to the domestic return in the Canadian case. Vector Auto Regression models fared poorly compared to the conditional volatility models and the significance of their lagged variables extended up to the 5^{th} lag whereas those of the conditional volatility models were significant only up to the 2^{nd} lag at the most.

An extreme value – Vector Auto Regression (VAR) model was used by Booth *et al.* (1997) in a study of the volatility transmission among US, UK and Japanese markets. The variable used in the VAR model was the extreme value variance obtained by using the Garman and Klas technique. The study used the intraday data of the stock index futures of these markets for the period 1988 to 1994. The result indicated that the volatilities of the US and UK markets was affected not only by idiosyncratic factors but also by the volatility of variance in foreign market. Most of the markets were subject to information generated in the market that operated prior to their opening. But Japanese market was found to be immune to spillover from other markets in that the volatility of Japanese market was able to be explained by its own past volatility rather than by the volatility in the other two markets. Application of multivariate GARCH (1, 1) for the same data produced a different result. It showed USA also to be immune to volatility spillover in addition to Japan.

Christensen (2003) investigated volatility spill over in European bond market using AR-GARCH models. He separated the shocks to individual country effects in to three: local – own effect, regional – European effect and global – US effect. The mean and volatility equation of individual countries included the lagged US and European returns and residuals of both returns to account for mean and volatility spillover respectively. The study found weak mean spillover from USA and Europe in to the individual markets, while there was significant volatility spillover. The proportion of variance of unexpected return caused by US effects was negligible for European monetary union members as compared to the countries out of it, while the effects generated by European shocks had a comparatively larger effect on the monetary union countries. The non monetary union countries had a proportionately larger spillover from US and their idiosyncratic effects were also much larger than those of the monetary union members. The European spillover effect was seen to be increasing for the monetary union countries over time. Doing the same exercise before and after the introduction of Euro showed lower US effects on monetary union countries post Euro and was unchanged in the case of non monetary union countries. The non monetary union member Denmark was found to be behaving in a similar fashion as monetary union members. This was probably due to the pegging of Danish Krone to the Euro.

Baele (2004) investigated regional and global spillover effects in to the European equity markets and found the regime switches in spillover intensities to be statistically and economically important. For all European countries, the probability of high regional and global – using USA as a proxy – spillover was found to have increased significantly over the 80's and 90's with European shocks having an increasing effect. The European shock spillover intensity increased primarily in the second part of 1980's and the first part of 1990's, suggesting that economic integration and efforts to liberalize European capital markets were more important in bringing markets closer than the process towards monetary integration and the introduction of Euro. USA continued to be the dominating influence in Europe but the relative importance of regional European markets were seen to have increased considerably. According to him, the noticeable rise in the importance of common factors for explaining local equity market returns did not only suggest an increase in the degree of market integration but also a reduced potential for international diversification. The study also found evidence of contagion effect from USA to a number of European local markets in times of high equity market volatility.

A structural system approach to examine the direction and nature of volatility transmission was used by Gannon (2004). The study utilized intra-day 15 minute interval data and found significant spillover of volatility from Hong Kong futures market to cash market. US volatility parameter was included to check the influence of US on Hong Kong and the result showed that it was highly significant in explaining the volatility in Hong Kong market. A positive volatility shock on the US market was found to have a dampening effect on the trading volume as well in the Hong Kong market. The effect of US market was found to be more pronounced in the Hong Kong futures in that, many of its explanatory variables lost significance once the US volatility parameter was introduced in to the equation. This was hardly a surprising result as the futures market usually has high liquidity and low transaction cost. This also pointed to the market efficiency improving characteristics of futures market.

In a study involving Nikkei, FTSE 100 and S&P 500, Veiga and Michael (2004), used Vector Auto Regressive Moving Average – Asymmetric Generalized Auto Regressive Conditional Heteroscedasticity model to analyze mean and volatility spillover among these markets for intra daily data from October 1992 to July 2003. The study found significant mean spillover among all the three markets and also observed that the market with the more recent trading time is likely to have more influence on the return of the next market to open for trading to such an extent that in two cases it even overshot the auto regressive term in its scale of importance. S&P 500 was found to have the strongest spillover effect in to Nikkei and FTSE 100, while Nikkei had the weakest spillover effects. Volatility equation showed that the conditional volatility of Nikkei was affected by both its short run positive and negative shocks. Conditional volatility of FTSE 100 was seen to be affected only by their own short run negative shocks while conditional volatility of S&P 500 was affected by short run shocks to FTSE 100 and by its own short run negative shocks. These findings stood intact for long run persistence of shocks as well. The study also confirmed the well documented theory that all the markets behaved differently to positive and negative shock. A negative shock was seen to produce a higher degree of volatility than a positive shock of the same magnitude. Thus, the study differed from earlier studies on volatility spill over by rejecting the US superiority.

An investigation in to the volatility spillover among the rather neglected Gulf Cooperation Countries (GCC) was undertaken by Al-Deehani (2005). He found that the highest correlation coefficients of the disturbances of the random components and the disturbances of the levels of the trends were between Bahrain and Kuwait, Bahrain and UAE, Bahrain and Oman, Kuwait and Saudi Arabia, Kuwait and UAE, Saudi Arabia and UAE and UAE and Oman. Therefore he expected largest volatility spillover between these markets. Qatar, which did not feature in any of these combinations, was expected to behave independently. Using the stochastic volatility model the study found that the volatility of these markets was explained by factors other than the volatility in the foreign markets. The potential factors accounting for volatility were identified as local financial or economic factors or volatility of other international markets. The study found strong evidence of contemporaneous volatility spillover among the GCC countries. Bahrain, Kuwait, Saudi Arabia and UAE were found to have bi-directional contemporaneous effect on each other. Oman was found to have a bi-directional contemporaneous effect with Bahrain, Kuwait and UAE but not with Saudi Arabia or Qatar, although it was found to have contemporaneous effect on Kuwait. Qatar was not seen to be influenced by any of the other five markets. The study also found weak evidence for lagged volatility spillover. These findings point to the comparative insignificance of local historical factors and the need to look for other factors having a say on the volatility of these markets.

Ozun (2007) analyzed the transmission of volatility from the US exchange rate market to the equity market return of 14 world markets of Asia-Pacific, Europe and South America. The study made use of naïve GARCH model with normal and student – t distributional assumption. The attempt revealed that the time value of US Dollar had a positive and significant influence on the return volatility of emerging markets studied except that of Argentina. This exception was seen as a result of the country being subject to heavy economic and political upheavals during the period of study. Testing for the more developed European markets, it was seen that the impact was much stronger in this case and also accounted for much greater amount of volatility in these markets. This was thought to be a direct fall out of the impact that the interest rate changes were having on US Dollar – Euro exchange rate. A similar result was obtained for the domestic US market. Using the GARCH model with student – t distributional assumption produced a similar result though the coefficients showed a marginal increase. Doing a similar exercise for the world bond market showed much stronger negative impact.

2.2.1 Studies on India

Studies on the volatility spillover of Indian market have been far and few. In one of the earliest studies, Sharma and Kenndy (1977) examined the price behavior of Indian market with US and London markets. The objective of their study was to test the random walk hypothesis by runs analysis and spectral densities for Bombay Variable Dividend Industrial Share Index (BVDISI), New York S&P 425 common stock Index (S&P 425) and the London Financial Times Actuaries 500 (London FTA). The test period covered 132 monthly observations from 1963 to 1973. The study found that the behavior of BVDISI was statistically indistinguishable from that of London FTA and S&P 425. In the runs analysis the expected distribution of lengths turned out to be very similar, with probability equal to 0.5 for rise or fall. Further, the spectral densities estimated for the first difference series of each index confirmed the randomness of the series with no evidence for the existence of symmetric cyclical component neither was there any periodicity found to be present. Based on these tests, the study observed that the stocks on the BVDISI obeyed a random walk and were equivalent in this sense to the behavior of stock prices in more advanced industrial countries.

The short run dynamic interlinkages between the US and Indian stock markets using day time and overnight returns of NSE Nifty and NASDAQ Composite for a two year period from July 1999 to June 2001 was investigated by Kumar and Mukhopadyay (2002). The study employed a simple univariate ARMA-GARCH model as well as the two stage GARCH model for the purpose of examining spillover effect on mean and variance between these markets. The study found the simple GARCH model to be outperforming the two stage GARCH model. Granger causality test conducted on these markets showed a unidirectional causality running from the US index to the Nifty. The NSE Nifty overnight return was found to be significantly influenced by the previous day time NASDAQ and Nifty returns. However, it found the volatility spillover effect in Nifty to be directly imported from the NASDAQ. The contribution of day time NASDAQ volatility was found to be 9.5 per cent while that of Nifty was a mere 0.5 per cent. The study also found the inclusion of NASDAQ day time trading information to be useful in predicting the movements in NSE Nifty next day returns but not volatility.

Nair and Ramanathan (2002) analyzed the co movements between NASDAQ and Dow Jones on the one hand Nifty and Sensex on the other. The study used causality tests developed by Granger, Sims and Hsiao. It covered the period from January 1996 to February 2002. The result invalidated the existing notion that Dow Jones Industrial Average caused movements in Indian indices and found NASDAQ to be more instrumental in accounting for movements in Indian indices. The co-movements of the markets were explained by the study as an outcome of the liberalization of the economy. The rather surprising result of NASDAQ led movement of Nifty was assigned by the study to the increasing importance of technology, media and telecommunication companies in Indian indices the price of which rose by 90 per cent, 100 per cent and 170 per cent during the period of study as compared to the 65 per cent rise in the overall market. This co movement, according to the study, was possible also because of the fact that 75 per cent of the stocks listed in NASDAQ composed of firms operating in technology, media and telecommunication fields. The subdued impact of Dow Jones Industrial Average was ascribed by the study to the composition of the index as well as to its methodology of computation.

Analysis of the level of capital market integration by examining the interlinkages of market movements among the three major stock markets of Asia viz. India, Singapore and Taiwan, during the period 1994 to 2002 was performed by Nath and Varma (2003) in a study titled, 'Study of Common Stochastic Trends and Co-integration in the Emerging Markets: A Case Study of India, Singapore and Taiwan'. The study was divided in to different periods in order to account for the large scale changes that had taken place during the period. The findings were against the existing literature which supported massive co-movements among international equity markets. Using Johansen's maximum likelihood method to examine the presence of co-integration with a lag of 5 days, it was found that there was no co-integrating vector in the underlying series and hence no long run equilibrium existed among the three markets. Pair wise Johansen co-integration test by placing each market against one of the others also produced same result. Using the pair wise Granger causality test, the study found very few significant causating relationships. Out of 42 models tested for different periods only 8 turned out to be significant. Using the variance decomposition it was observed that the Singapore market explained the error variance in the other two markets but there was no feedback from

India or Taiwan. It became more pronounced towards the later periods. Impulse responses also certified for Singaporian superiority. The study concluded by saying that investors can reap the benefits of diversification by investing in the three markets, as there was no significant co-movement among them.

Applying the simple GARCH (1, 1) model to the intraday data over a period from November 1997 to April 2008, an attempt was made to investigate stock market integration and volatility spillover between India and 12 other Asian markets by Mukherjee and Mishra (2008). The study tried to document evidence for mean and volatility spillover. Empirical analysis for intraday data showed that there was bi-directional spillover in mean among almost all of the markets studied, but this was found lacking in the case of volatility. Volatility of only a handful of Asian markets was found to have any impact on the Indian market. Taking overnight return and doing the similar exercise, the study found weaker mean spillover and even negligible volatility spillover from Asia to India, whereas there was no spillover from India to the Asian markets except to those of Sri Lanka and Pakistan. This anomaly in overnight return may be due to the subsequent trading in Europe and USA which might be having a separate influence on the Asian markets. Repeating the exercise to lagged return showed that, spillover – both mean and volatility – persisted in to later days. Information to India was found to be flowing mainly from Hong Kong, Korea, Singapore and Thailand.

Most of the literature so far on volatility has been concentrated on developed countries. Studies on the volatility spillover involving Indian equity markets have been very few. Whatever studies have taken place so far attests to the spillover of mean and volatility from one market to the other. And a majority of the studies found that US market was the most influential in the world and other markets followed it. Studies have also found that the chronological ordering of the markets is also important for the existence of volatility spillover. All studies on India have identified India as having been influenced by other markets than leading them. Volatility is observed to be spilling over to India from other markets while, there are some evidence of mean spillover from India to other markets.

2.3. Review of the Models Used

The present study mainly uses two types of methods to examine volatility spillover namely the Vector Auto Regression (VAR) model and the conditional volatility model as represented by the GARCH family of models. A brief review of the two methods follows.

2.3.1 Vector Auto Regression

Vector Auto Regression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach side steps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of the endogenous variables themselves in the system.

The mathematical representation of VAR is:

$$y_t = a_1 y_{t-1} + \dots + a_p y_{t-p} + b x_t + \varepsilon_t$$

where, y_t is a k vector of endogenous variables, x_t is a d vector of exogenous variables a_1 … a_p and b are matrices of coefficients to be estimated and ε_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and are uncorrelated with all of the right hand side variables.

This can be extended in to bivariate or multivariate VAR. A bivariate VAR equation will be as follows:

$$y_t = a_1 + a_2\, y_{t-1} + a_3\, y_{t-2} + a_4\, x_{t-1} + a_5\, x_{t-2} + u_{1t}$$

$$x_t = b_1 + b_2\, x_{t-1} + b_3\, x_{t-2} + b_4\, y_{t-1} + b_5\, y_{t-2} + u_{2t}$$

Since only lagged values of the endogenous variable appear on the right hand side of the equations, simultaneity is not an issue and ordinary least squares (OLS) yields consistent estimates. Moreover, even though the innovations ε_t may be contemporaneously correlated, OLS is efficient and equivalent to generalized least squares since all equations have identical regressors.

2.3.2 GARCH Model

It is well known fact that the variance of financial time series goes on changing from time to time. Due to this, the earlier methods of squared returns and range estimators of volatility proved to be inadequate for modeling purposes. Engle (1982) introduced the ARCH model to capture the changing volatility in financial series in which the conditional variance σ_t^2 was defined as a linear function of past squared errors. The simplest representation of this model is the ARCH (1) which has the form,

$$r_t = \tau + \mu\, r_{t-1} + \varepsilon_t, \text{ where, } \varepsilon_t \mid F_{t-1} \sim N\,(0,\sigma_t^2)$$

r_t is current return and r_{t-1} is previous return, ε_t is the error term and F_{t-1} is the information set up to t_{-1} and σ_t^2 is conditional variance.

and

$$\sigma_t^2 = \alpha + \beta\, \varepsilon^2_{t-1} \qquad \text{where a > 0 and c} \geq 0.$$

With the addition of a foreign market the mean equation changes to:

$$r_t = \tau + \mu\, r_{t-1} + \eta_i\, f_{it-1}\, \varepsilon_t, \ \text{ where, } \varepsilon_t \mid F_{t-1} \sim N\,(0,\sigma_t^2), \text{ where}$$

f_{it-1} is the foreign market return.

The conditional variance at time t, σ_t^2, here is defined as a positive function of the square of last period's error, ε^2_{t-1}. While the ARCH models do not allow the conditional variance at time t to have a stochastic component, the model can incorporate additional squared error terms from prior period.

Bollerslev (1986) generalized this model by allowing the conditional variance, σ_t^2 to be a function not only of last period's error squared, $\varepsilon^2_{\ t-1}$ but also of its conditional variance, σ^2_{t-1}. The GARCH (1, 1) model defines the conditional variance at time t to be of the form,

$$\sigma_t^2 = \alpha + \beta\, \sigma^2_{t-1} + \gamma\, \varepsilon^2_{t-1}$$

The model can be further enhanced by having additional explanatory variables in it. The equation will then look like,

$$\sigma_t^2 = \alpha + \beta\, \sigma^2_{t-1} + \gamma\, \varepsilon^2_{\ t-1} + \rho_i\, X_{it-1}$$

The present study has used the residual from the volatility equation of the foreign markets as additional explanatory variable in the equation for the domestic market. The residual is implied by the variable X in the above equation.

The GARCH formulation can also be extended to include additional squared errors and variances from past periods. But empirical studies revealed that equity prices responded with greater volatility to negative news than to a positive one. In order to account for this asymmetry in equity price behavior, Nelson (1991) introduced the asymmetric GARCH model called the Exponential GARCH or EGARCH. The variance equation of the model is of the following form.

$$\ln\ \sigma_t^2 = \alpha + \beta\ (\epsilon_{t-1}^2 / \sqrt{\sigma_{t-1}^2})\ + \gamma\ \left|\varepsilon_{t-1}^2 /\ \sigma_{t-1}^2\right| +\ \rho\ \ln\ \sigma_{t-1}^2$$

The new coefficient β in the above equation represents the asymmetric behavior. A negative sign to β will imply presence of asymmetry and then stock price volatility will increase to a greater extent as a result of a negative shock than to a positive one.

The present study uses an auto regressive equation of the first degree as the mean equation for the volatility model and also incorporates the return of the foreign market whenever necessary in the mean equation as an additional explanatory variable. The residual obtained from the volatility equation of the foreign market is used as the exogenous variable in the volatility equation of the domestic market as and when necessary to account for the volatility spill over. Present study uses AR (1) in the mean equation throughout the analysis as it is seen to be sufficient in capturing the behavior of equity markets and more complicated AR terms are known to make the model more complicated without making any fruitful contributions. This model has been widely used in studies like Sarma *et al* (2001) and Nath and Varma (2003). The equation with the foreign market is of the form:

$$\ln \sigma_t^2 = \alpha + \beta\,(\epsilon_{t-1}^2/\sqrt{\sigma_{t-1}^2}) + \gamma\,\left|\varepsilon_{t-1}^2/\,\sigma_{t-1}^2\right| + \rho\,\ln \sigma_{t-1}^2 + \lambda_i\, X_{it-1}$$

where, X_{it} is the residual obtained from the volatility equation of the foreign market.

The rational for using VAR is that it does away with the necessity for structural modeling as every endogenous variable in the system is explained as a function of the lagged values of the endogenous variables themselves, while that for using conditional volatility models is the nature of data that is being dealt with. Financial data is known for its volatility clustering which is accounted for by conditional volatility models. It also has provisions to account for asymmetry as well as fat tailness to a fair extent. As it models return volatility as a function of past and since, most of the market players use past as a useful way of projecting future in equity market, this model is closely linked to the practice followed in the industry as well.

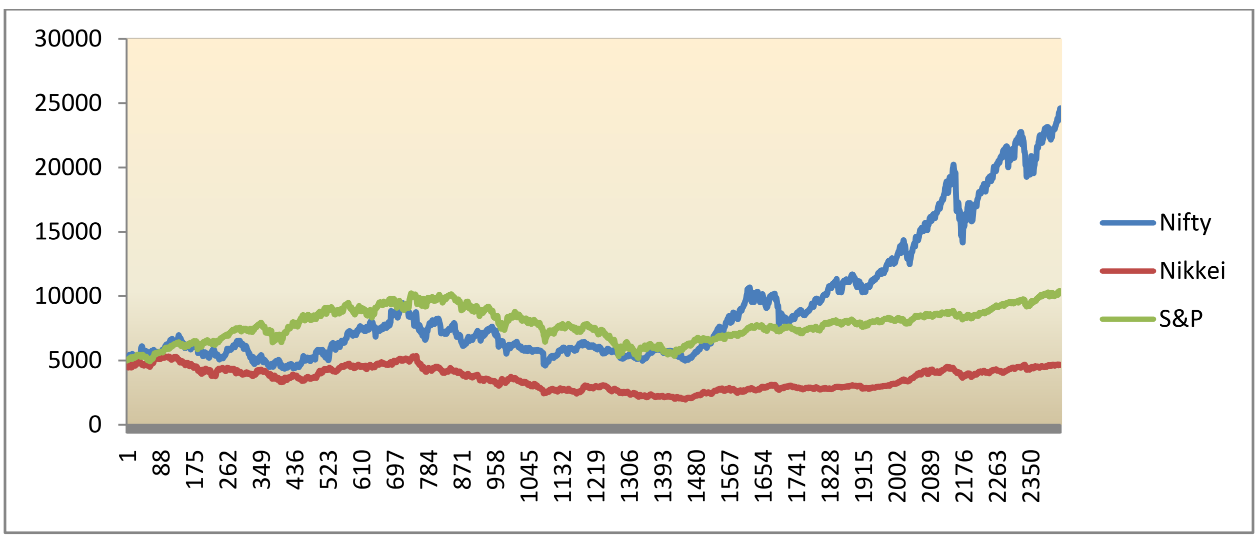
2.4 Data

Daily return is used in the study and the return was found out by taking the log of the difference of index closing prices on successive days and ranges from January 1 1997 to July 20 2007. Since there are three markets and all of them do not operate on the same day during the entire period, whenever a market was closed for trading for a particular day the return for all the markets for that day have been removed and hence the final number of observations is 2426 though the original number runs from 2547 for S&P 500 to 2642 for Nifty. All the returns are measured in the local currency. Nifty is a free floating index consisting of a well balanced portfolio of 50 common stocks of the most actively traded companies and are invariably the market leaders in their industry. For Nikkei and S&P 500 the number of scripts is 225 and 500 respectively. Data for Nifty return was collected from the official website of the National Stock Exchange of India and those for Nikkei and S&P 500 were collected from econstats.com.

2.5 Empirical Analysis

As a starting point of the discussion on the volatility spill over between Nikkei, Nifty and S&P 500, it would be prudent to have a feeling of the movement of the indices over the study period. It would give a primary idea about the response of each market to major market collapses overseas and also to sustained booms. The markets have been indexed to a base of 5000 for easy comparison.

Figure.2.1 Comparison of Nikkei, Nifty and S&P 500 performance



It is observed from the figure that Nikkei has remained at the same level throughout the period with occasional movements on either side. S&P 500 has showed more variation than Nikkei but is not substantial. Nifty on the other hand moved along with other markets till early 2003 and from there a spurt in activity is observed till the end of the period. A close observation of the figure reveals that most of the fluctuations in one market were followed by the other market as well. The patterns are clearly recognizable around 1700, 2150 and 2300, though the variations are substantially more pronounced for Nifty owing to its higher value. In terms of percentages, all the markets may be seen to be reacting in a very similar manner and magnitude.

2.5.1 Preliminary Discussion

Equity market data is different from the other economic data in that it follows its own rules and patterns. Econometric investigation requires the data to possess or not to possess certain characteristics for its smooth handling. So it is imperative to have an enquiry in to the characteristics of the data like its stationarity, distributional properties and other characteristics before we commit ourselves to dealing with it to unravel the complex interrelationships among different variables.

Table 2.1 Basic statistics

Parameters	**NKR**	**NR**	**SPR**
Mean	0.007721	0.079532	0.036720
Median	0.003201	0.137692	0.069166
Maximum	7.488904	10.91974	5.732732
Minimum	-7.394275	-15.59416	-6.865681
Standard Deviation	1.474644	1.694858	1.163450
Skewness	0.018850	-0.375880	0.000898
Kurtosis	4.668100	10.50497	5.856090
Jarque-Bera	281.4139	5750.605	824.5621

Note: NKR, NR and SPR stands for Nikkei, Nifty and S&P 500 return.

The table is self explanatory. Nifty has the highest mean followed by S&P 500 and Nikkei. Nifty also tops in standard deviation but the second spot is occupied by Nikkei followed by S&P 500. Thus, Nifty has the best average return while S&P 500 is seen to be the least risky market. The normality assumption is rejected for all the three markets conclusively as the Jarque-Bera statistics is quite high. Only Nifty among the three is negatively skewed while the other two has slightly longer right hand tails. Coefficient of Kurtosis shows that all the three markets are leptokurtic but Nifty is more pronounced among them with a value of 10.50. This indicates that the return distributions have leaner peaks and fatter tails than a normal distribution and it would be proper to go for a distribution like Student-t for modeling purposes.

2.5.2 Test of Stationarity

Another property that a time series needs to have to subject it to econometric investigation is stationarity. Broadly speaking, a stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Gujarati, D, 2004). Normally, financial data are non stationary at the level and stationary at the first difference. There are different techniques in econometrics to find if the time series is stationary or not. The present study uses the Augmented Dicky-Fuller (ADF) , Philips-Perron (PP) and KPSS tests to find if the three time series available are stationary or not.

Table 2.2 Test for Stationarity

Indices	ADF	Philips-Perron	KPSS
NKR	-50.3284 (-3.4328)	-50.5839 (-3.4328)	0.3219 (0.7390)
NR	-47.2539 (-3.4328)	-47.2154 (-3.4328)	0.2284 (0.7390)
SPR	-50.0039 (-3.4328)	-50.4042 (-3.4328)	0.2059 (0.7390)

Figures in the parentheses show t values at one percent level of significance

The result shown here is for the return series and all the three measures of stationarity confirm the stationary properties of the return data. Notice here that while the ADF and PP tests have non stationarity as the null hypothesis, KPSS test has stationarity as the null.

2.5.3 Correlation

Correlation is a common measure used to identify the relation existing between multiple variables. Since, the present study basically analyzes the interrelationship among the three markets, the measure may be useful as a starting point of the discussion on the co-movement of the markets.

Table 2.3 Correlation Matrix

Indices	Nikkei	Nifty	S&P 500
Nikkei	1	0.027027	0.316011
Nifty	0.027027	1	0.079530
S&P 500	0.316011	0.079530	1

The result shows that there is very little co-movement between the markets as the highest value is the 0.31 between Nikkei and S&P 500. Nifty seems not to be moving in tandem with Nikkei and S&P 500 as the correlation coefficients are at a paltry 0.02 and 0.07 respectively. But there are grave dangers in using the correlation as it basically examines the linear relationship existing among the markets. But the movement of the market in real world is not that simple and linear. Hence, better measures are called for as tools for analyzing the interrelationship among the markets.

2.5.4 Vector Auto Regression (VAR) Framework

An examination of the Vector Auto Regression model will help to have a preliminary idea about market dependence and the influence each market is having on the other. Lag length of the Vector Auto Regression was selected on the basis of Akaike-Schwarz information criteria. Result for the lag length test is given in the appendix A1. The result obtained for VAR is displayed below in tabular format.

Table 2.4 Estimation of VAR Model

Parameters	**NKR**	**NR**	**SPR**
NKR(-1)	-0.0989 (-4.7075*)	-0.0400 (-1.5895)	-0.0307 (-1.7521)
NKR(-2)	-0.0477 (-2.3765*)	0.0211 (0.8759)	-0.0038 (0.2276)
NR(-1)	0.0147 (0.8492)	0.0340 (1.6381)	0.0041 (0.2866)
NR(-2)	-0.0145 (-0.8456)	-0.0494 (-2.3924*)	0.0089 (0.6177)
SPR(-1)	0.4176 (16.8887*)	0.2572 (8.6779*)	-0.0094 (-0.4562)
SPR(-2)	0.0701 (2.6740*)	0.0282 (0.8969)	-0.0103 (-0.4703)
C	-0.0071 (-0.2530)	0.0697 (2.0527*)	0.0366 (1.5466)
R^2	0.1106	0.0340	0.0021
Adjusted R^2	0.1084	0.0316	-0.0003
F-Statistic	50.1270	14.2144	0.8706

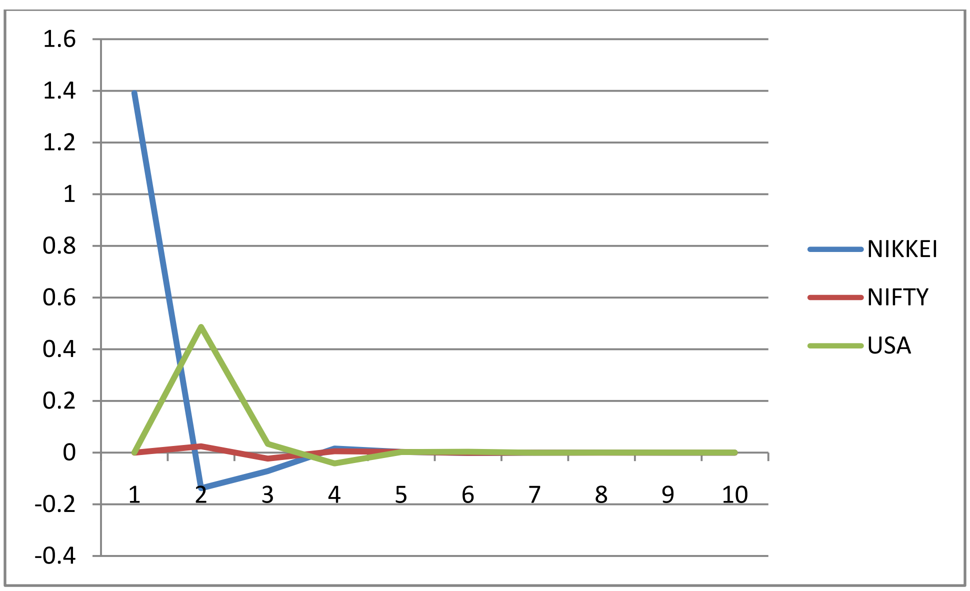
i) Note:NKR stands for Nikkei return, NR for Nifty return and SPR for S&P 500 return,(ii) t values are given in the parentheses

Only 6 of the 18 coefficients in the study turn out to be significant. Nikkei return is seen to be influenced by its own past return up to the second lag as well as the two lags of the S&P 500, while it is not being affected by the return on Nifty at all. The coefficients of S&P 500 are positively significant and are observed to be comparatively large while those of the lagged Nikkei returns are negative and negligible. In the case of Nifty only two coefficients are significant. The return of Nifty is being influenced by its own second lag and by the first lag of S&P 500. In this case also S&P 500 is seen to be having more influence in terms of the magnitude of its coefficient. None of the coefficients in the equation for S&P 500 are significant at 5% level but the first lag of Nikkei return is significant at 10% level. All these points to the dominant influence the US market is having on the other two markets. The lagged S&P 500 return is seen to be significant and large in the equations for both of the other markets while none of the other two markets' lagged returns are having any impact on the S&P 500 returns. This is in sync with a plethora of studies conducted on the issue.

2.5.4.1 Impulse Response Functions

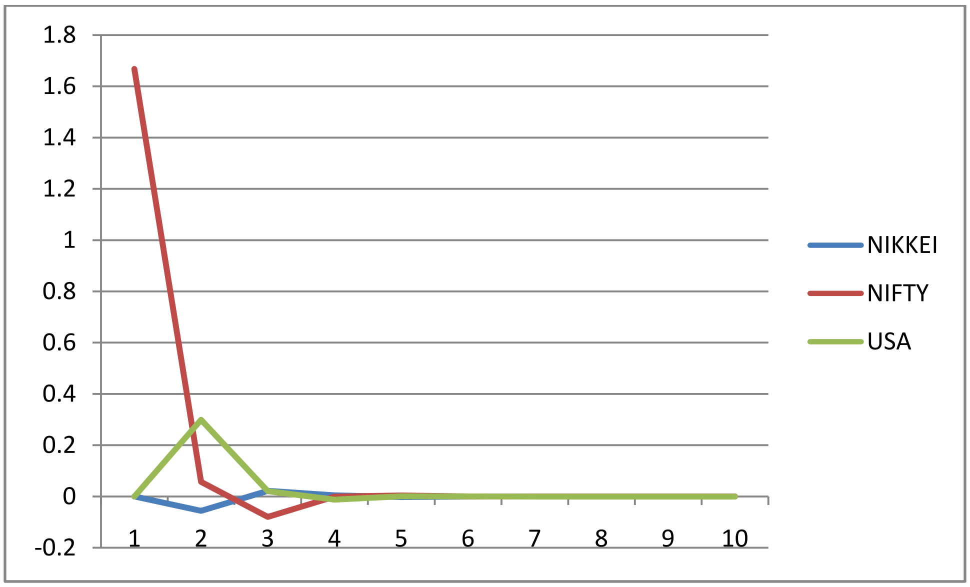
To obtain additional information in to the mechanism of international transmission of stock market movements, an examination of the pattern of dynamic responses of each market to a shock in one of the market was also conducted. Figures 2.2 to 2.4 provide normalized impulse responses of the three markets to a typical shock, defined as the positive residual of one standard deviation unit, in each of the other market.

Figure 2.2 Impulse Response of Nikkei



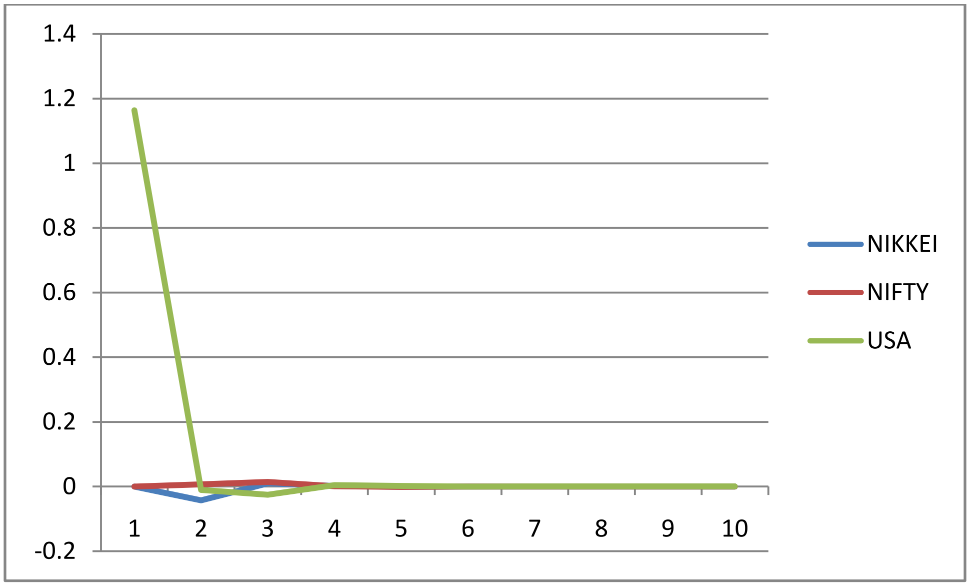
It is seen from the figure that, Nikkei is adjusting to shocks on its own return mostly by the second day, but the after effects continue well in to the fourth day. Nikkei responds rather haphazardly to a unit shock to the S&P500 return. It has spike in the second day followed by two days of erratic movement and settles down to the trend on the fifth day. The shock to Nifty return appears to be inconsequential in the case of Nikkei as it can hardly be separated from the trend.

Figure 2.3 Impulse Response of Nifty



The response pattern of Nifty is very similar to that of the Nikkei to a unit shock in the other market. While it is taking time to adjust to the shocks on its own return, it adjusts to the Nikkei shocks on the third day itself and as expected, the S&P 500 shock is greater compared to that of Nikkei and the market is accommodating it only on the 4th day.

Figure 2.4.Impulse Responses of S&P



The S&P 500 is observed to be susceptible to external shocks to a very low degree in that, a unit shock to the Nikkei is having a small impact on the second day and all the adjustments are over within three days. The examination of impulse response function underline the findings of Vector Auto Regression model of the dominance of US market and further it also throws light in to the market efficiency of the three markets studied. S&P 500 is quickly adjusting to all shocks and has the largest efficiency in processing information followed, surprisingly by Nifty. But there is hardly anything to choose between Nifty and Nikkei in this regard.

2.5.4.2 Variance Decomposition Analysis

Variance decomposition is a useful tool to analyze the influence that one market may be having on the other. It explains how much percentage of innovation in one market is explained by that market itself as also the respective percentages of the other markets.

Table 2.5 can thus be viewed as a summary that is useful in identifying the main channels of influence in the three market dynamic system.

Table 2.5 Variance Decomposition

Nikkei				Nifty				S&P 500			
SE	NKR	NR	SPR	SE	NKR	NR	SPR	SE	NKR	NR	SPR
1.39	100	0	0	1.66	4.3	95.69	0	1.16	3.16	0.22	96.6
1.47	89.37	0.1	10.52	1.69	4.3	92.81	3.01	1.16	3.3	0.22	96.46
1.47	89.33	0.12	10.54	1.69	4.17	92.81	3.02	1.16	3.3	0.24	96.45
1.47	89.26	0.12	10.61	1.69	4.16	92.8	3.02	1.16	3.3	0.24	96.45
1.47	89.26	0.12	10.61	1.69	4.16	92.8	3.02	1.16	3.3	0.24	96.45
1.47	89.26	0.12	10.61	1.69	4.16	92.8	3.02	1.16	3.3	0.24	96.45

Note: NKR stands for Nikkei return, NR for Nifty return, SPR for S&P 500 return and SE for Standard Error.

The results are presented only for a period of six days as the following days do not make any effective difference to the conclusion. The obtained result indicates that no national stock market is exogenous in that a market's innovations fully account for its variance. A good deal of interaction is found among the three markets. At a horizon of 6 days, Nifty and S&P account for 10.74 per cent error variance in Nikkei while Nikkei and S&P account for 7.2 per cent of error variance of Nifty in the same horizon. In this case also S&P 500 stands unique in that it accounts for 96.45 per cent of its own error variance even in to the 6th day or in other words, Nikkei and Nifty combined account for only 3.55 per cent of the error variance of S&P 500 up to the 6th day. S&P 500 contributes 3.02 per cent error variance of Nifty and 10.61 per cent error variance of Nikkei while Nikkei accounts for 3.3 per cent error variance of S&P 500 and 4.16 per cent error variance of

Nifty. Nifty is having the least impact on the other markets with it contributing to 0.12 per cent and 0.24 per cent error variance of Nikkei and S&P 500 respectively.

Examination of variance decomposition and impulse response function together with the basic Vector Auto Regression framework confirms the superiority of US market in terms of its impact on Nikkei and Nifty. This finding is in conformity with a similar study by Eun and Shim (1989) in which it was found that the US market acted as the leader of the major European and Asia-Pacific markets.

2.5.5 Volatility Spillover

Mean and volatility spillover has been studied using the AR (1) - GARCH (1, 1) model. The mean equation of each of the domestic market has the return of the other two markets individually as explanatory variables and the volatility equation has the residual from the volatility equation of the other two markets individually as explanatory variables. Further, the return and residuals of the foreign markets have been combined in the mean and volatility equation respectively of the domestic market to see if the addition of the second market imparts any additional explanatory power in the equation of the domestic market. An examination of the basic model of each of the markets may be handy for testing specification accuracy before we go in to the spillover models.

Table 2.6 Basic Model*

Parameters	Nikkei	Nifty	S&P 500
τ	0.0517 (2.0715)	0.1373 (5.3058)	0.0646 (3.5588)
μ	-0.0153 (-0.6907)	0.0790 (3.8498)	-0.0338 (-1.5399)
α	0.0252 (2.6275)	0.1159 (4.2189)	0.0090 (2.5344)
β	0.0728 (6.6673)	0.1185 (6.4798)	0.0648 (6.7390)
γ	0.9169 (74.0378)	0.8429 (39.7728)	0.9303 (93.3784)
Skewness	0.0163	-0.2834	-0.0204
Kurtosis	4.6864	10.4611	5.8597
Ljung-Box Q (6 lags)	9.3281	14.183	22.369
Ljung-Box Q (12 lags)	16.62	32.61	27.809

t values are given in the parentheses,*This model is based on equations given in pages 41 and 42.

Of all the three mean equations, only the auto regressive term of Nifty is significant at the conventional level. Coming in to the variance equations, we see high persistence of volatility as the combined values of β and γ is nearly one for all three equations. Further, it is also observed that the impact of recent news as shown by β is comparatively high for Nifty from the other markets. This shows the market's vigorous response to recent news flows. Testing the residuals for model misspecification, we find that, except for Nikkei, the other two markets have a slightly negatively skewed distribution. But the value of Skewness is so low as to be ignorable. The positive Skewness of Nikkei is also quite low. A slight concern is the high value of Kurtosis for Nifty which is at 10.46, which implies that the model has not fully accounted for the thin peaks and fat tails as one would expect it to. But the same for the other two markets are at allowable level. The Ljung-Box Q statistics is within the conventional level for both Nikkei and S&P but in this case too, Nifty has its own pattern. But it is still not at an alarming level. An examination of the basic volatility model has given satisfactory results in that the model appears to be well specified without any major flaws. Only the model for Nifty seems to be slightly out of line with expectations but is quite manageable.

If information flow from foreign market is crucial for the mean and volatility of the domestic market and assuming such flow to be continuous across the global markets, a particular market's return and volatility should be influenced more by the return and volatility characteristics of the market that closed just prior to the opening of the domestic market. For testing if this is so, a model with the mean equation of the domestic market, having the return of the immediately closed foreign market as explanatory variable, and volatility equation of the same market, having the residual obtained from the volatility equation of the foreign market that is just closed for trading as explanatory variable, is estimated for all the three markets. As per this logic, Nifty will be having the return and residuals of Nikkei as explanatory variable in the mean and variance equations, S&P 500 will be having the return and residuals of Nifty as explanatory variables in its mean and variance equations and Nikkei will be having the return and residuals of S&P 500 as explanatory variables in its mean and volatility equations respectively. The results are given in table 2.7.

Table 2.7 Spillover Model for the Near Market with GARCH*

Parameters	Nikkei	Nifty	S&P 500
τ	0.0334 (1.4390)	0.1388 (5.5940)	0.0543 (3.0188)
μ	-0.0635 (3.0735)	0.0703 (3.5322)	-0.0518 (-2.3183)
η	0.4334 (18.1339)	0.2356 (12.3574)	0.0657 (5.6892)
α	0.0113 (1.6329)	0.0803 (3.3726)	0.0059 (1.6238)
β	0.0623 (5.7845)	0.1168 (6.3997)	0.0650 (6.4926)
λ	0.9128 (71.3752)	0.8434 (41.1261)	0.9263 (87.9690)
ρ	0.0298 (3.7452)	0.0156 (2.1780)	0.0025 (2.3210)
Skewness	0.0174	-0.1902	0.0076
Kurtosis	4.7708	9.7257	5.9093
L-B (6 Lags)	10.152	13.487	25.15
L-B (12 Lags)	18.053	29.853	31.018

(i) t Values are given in the parenthesis, (ii) D &λ are respectively the mean and volatilit y spillover from foreign market,*This model is based on the equation given in pages 41 and 42.

The result supports the hypothesis that a particular market is likely to be influenced by the return and volatility of the market that closed just prior to the opening of the former. Model specification has improved for Nifty while it has worsened for S&P 500. Skewness and Kurtosis are at acceptable levels except for the Kurtosis of Nifty which is again observed at a comparatively high 9.7257. Auto regressive terms of all the markets are significant in the new model and are negative except for Nifty. Mean spill over is seen from S&P 500 to Nikkei, from Nikkei to Nifty and from Nifty to S&P 500. It is particularly strong from S&P 500 to Nikkei and from Nikkei to Nifty underlining the dominance of the two markets as compared to Nifty. Mean spill over from Nifty to S&P 500, though significant, is relatively weak. Variance equation of Nifty again shows that the market attaches high importance to recent information as compared to the other two markets. The coefficient of the residual of the variance equation of the foreign market as signified by ρ is significant for all the three markets. It shows that there is volatility spill over from S&P 500 to Nikkei, from Nikkei to Nifty and from Nifty to S&P 500. Exploring the values, we find that the influence of S&P 500 on Nikkei is again the strongest followed by that of Nikkei on Nifty and finally that of Nifty on S&P 500. This is similar to the findings that we had in the mean spill over.

The findings are in confirmation with other like studies by Eun and Shim (1989), Hamao (1999), Booth (1997), Kumar (2002), Baele (2004) and Gannon (2004). Though, only Kumar had included India in the above studies, the results of others found US market to be significantly influencing other markets whether they were in Europe or Asia. The present study also finds US market as the most important producer of information. As the next step, an analysis to check, whether the results are different when we have the variables of the farther market as the explanatory variables in the mean and volatility equation of the domestic market is done. As per our hypothesis, the results should not indicate any greater degree of spillover than the ones that we have already got. The result is given on table 2.8 followed by detailed explanation.

Table 2.8 Spillover Model for Far Market with GARCH*

Parameters	Nikkei	Nifty	S&P 500
τ	0.0139 (0.5872)	0.1338 (5.2662)	0.0594 (3.2937)
μ	-0.0229 (1.1547)	0.0653 (3.2234)	-0.0923 (4.1486)
η	0.0425 (3.2357)	0.2059 (8.8019)	0.1254 (8.8923)
α	0.8429 (4.7100)	0.1107 (4.0318)	0.0079 (2.1228)
β	0.1338 (4.4890)	0.1228 (6.4852)	0.0631 (6.5781)
λ	0.4567 (4.5849)	0.8360 (38.6729)	0.9292 (89.5699)
ρ	0.0104 (1.2699)	0.0079 (0.8840)	0.0017 (0.7430)
Skewness	0.0212	-0.2703	-0.0083
Kurtosis	4.6694	10.8033	6.0309
L-B (6 Lags)	9.9578	14.747	22.839
L-B (12 Lags)	16.896	33.485	27.9111

(i) t values are given in the parentheses, (ii) D &λ respectively are mean and volatility spillover from foreign market,* This model is based on equations given in pages 41 and 42.

The outcome of the model is again in line with expectations. There is still significant mean spillover effect from foreign to the domestic market and the relative strength of different countries is also similar to our first model. Nifty is seen to be attaching more importance again to recent news than other markets. The difference between the two models is in the volatility spillover space. Unlike the earlier model, which tested for volatility from recently closed to the next opening market, the present model not only fails to add more to the volatility spillover but all three volatility spillover parameters are seen to be small and insignificant. This attests to the strength of the model as also tells that volatility in one market is affected by volatility in the market that closed immediately prior to the opening of that market.

So far, an examination of the individual effects of each market on the other in terms of volatility and mean spillover was conducted. This fails to give the larger picture, where every market is put in comparison with both markets in the same model to see the separate as well as the combined effect of the two markets on the dependent market. This will also throw light if the combination of market can explain the spillover effect by a higher degree than on an individual basis.

Table 2.9 Spillover Model with GARCH*

Parameters	Nikkei	Nifty	S&P 500
τ	0.0294 (1.2641)	0.1354 (5.4987)	0.0529 (2.9394)
μ	-0.0667 (3.1118)	0.0619 (3.1250)	-0.0995 (-4.4380)
η_1	0.0228 (1.3935)(I)	0.2052 (10.3207)(J)	0.1125 (7.8198)(J)
η_2	0.4313 (17.8703)(U)	0.1258 (5.3277)(U)	0.0481 (4.1027)(I)
α	0.0102 (1.3522)	0.0858 (3.4316)	0.0058 (1.5808)
β	0.0646 (5.5939)	0.1202 (6.4077)	0.0630 (6.4373)
γ	0.9005 (63.7579)	0.8348 (39.5345)	0.9273 (86.3018)
ρ_1	0.0061 (2.2772)(I)	0.0223 (2.4634)(J)	0.0008 (0.3705)(J)
ρ_2	0.0309 (3.4832)(U)	0.0057 (0.6760)(U)	0.0020 (1.9295)(I)
Skewness	0.0196	-0.1991	0.0070
Kurtosis	4.7570	10.0100	6.0806
Ljung-B0x(6 Lags)	10.7	13.635	24.82
Ljung-B0x(12 Lags)	18.586	30.570	30.347

i) Letters in the parenthesis stand for different markets; J for Nikkei, I for Nifty and U for S&P 500 (ii) Figures in the parentheses show t values,*This model is based on equations in pages 41 and 42.

With the combination of the two foreign markets in the mean and volatility equation for the domestic market, there is no perceptible improvement in the model specification. Coefficients of Skewness, Kurtosis and Ljung-Box Q remain almost the same as in model1. Coefficient of mean spill over for all markets is significant and perceivable change is observed only in the case of S&P 500 where the coefficient of Nikkei return rises to 0.1156 from 0.0657. It is also observed that now, Nikkei is seen to have a greater influence on the return of S&P 500 as compared to Nifty. But major changes are observed in the volatility equation. The coefficient of Nifty residuals becomes significant in the volatility equation of Nikkei. This is surprising taking in to account the fact that Nikkei opens 14 hours after Nifty closes and that many other markets are in operation during the interim. It may be due to the pass through of European market volatility to Nikkei as those markets and Nifty are concurrently in operation for 3 hours daily. Another noticeable change is that, although the coefficient S&P 500 does not alter substantially, influence of other market on the volatility of S&P 500 becomes insignificant. It was found in model 1 that Nifty was able to exert an influence on S&P 500 volatility but this pales in to insignificance in the combined model and neither is Nikkei seen to have any effect on the S&P 500 volatility.

All this points to the major impact the US market has on the other two markets. The reason for the superiority of USA is still a matter of controversy. It may be due to the volume effect, high market capitalization of US market or due to the important role the US economy and its currency have been playing in international trade. Whatever the reason, though there is a mean spillover across all the markets studied, S&P stands unique in volatility spillover by not being influenced by the volatility of the other markets. Hence, it is logical to conclude that all information pertaining to market volatility are produced in the USA and from there it spills over in to other markets across the globe.

So far, the study was conducted on the naïve assumption that the equity markets respond to good news and bad news in similar fashion. But in real world this is hardly the case. It has been observed that market behaves asymmetrically to information in that it exhibits more volatility to bad news as compared to good news. Asymmetric behavior has been ascribed to leverage effect and feedback effect. The former refers to the case where the debt – equity ratio of the concerned stock rising and this leading to further fall in the price. The feedback hypothesis refers to the bilateral spillover of volatility between markets as a result of spurt in volatility in any of these markets. The asymmetric behavior has been succinctly summarized in Padhi (2005) as, 'foreign market turmoil raises the trader's expectation of volatility in the domestic market. The effect of such a volatility shock is often reflected in a trader's reluctance to buy and willingness to sell in anticipation of a volatile market. As a result stock prices have to drop to balance the buying and selling volume. Thus, an anticipated increase in volatility leads to immediate price drop, as predicted by the volatility feedback hypothesis. This drop in stock price raises the leverage ratio, which by the leverage hypothesis brings about a further increase in volatility and therefore a further drop in price'. This phenomenon was first observed by Mandelbrot (1963) and later Fama (1965) also found this and they used a stable Paretian process to define the return distribution. Later studies confirmed this asymmetry. Nelson (1991) modified the basic GARCH model to account for this asymmetric behavior of equity prices and proposed EGARCH. It has been documented by empirical research that EGARCH captures the asymmetry in the return distribution satisfactorily. In order to test if the inclusion of the asymmetric term in the present spill over models does anything to improve the information content of the study, an attempt was also made to estimate the same models with the presence of the asymmetric term. Tables containing the results are given in the appendices A 2 to A 5.

Examination of the result does not make any change to the information that we have already got by the interpretation of the naïve GARCH model. Whatever change is observed only helps to strengthen the existing result. There is no worsening or improvement in model specification. Observation of mean spillover parameter also tells that there is an across the board mean spillover among the markets investigated. As in the naïve GARCH model, there is volatility spillover from Nikkei to Nifty and from S&P 500 to Nikkei in the individual examination of the model. But Nifty volatility is seen not to be defining the volatility of S&P 500 even in the individual model as was in the case with the naïve GARCH. Thus, unlike the earlier model, examination of the problem with EGARCH model makes US market completely independent in terms of volatility spillover. Going in to the combined model, we see a similar result except for the fact that, Nifty which was seen to be spilling volatility in to the Nikkei is not observed to have any significant influence in the volatility of Nikkei. Thus, Nifty is a complete follower among the three markets in that its volatility is being affected by at least one of the other markets but it is not able to exert any significant influence on the volatility of either of the other two markets.

2.6 Concluding Remarks

The present study has attempted an investigation in to the volatility spillover among Nikkei, Nifty and S&P 500. The relation and the approximate influence of one market on the other was analyzed with the help of VAR model and then the volatility spillover from an individual foreign market to the domestic market and combined volatility spillover from the two foreign markets to the domestic market was also examined using the GARCH model. In order to account for the asymmetry present in the markets a similar investigation was made with the EGARCH model.

The coefficients of S&P 500 were found to be significant in the VAR equation for Nikkei and Nifty while none of the coefficients of these markets were significant in the equation of S&P 500. Nikkei and Nifty did not have any statistically significant coefficients in each other's equation. Impulse response function also showed that shocks to Nikkei and Nifty returns were not able to have perceivable effect on S&P 500 and it was able to make all adjustments in a matter of 3days. This attests to the high information processing capacity of S&P 500. Nikkei and Nifty returns responded perceptibly to the shocks on the returns of S&P 500 and it was observed that Nikkei was less efficient than Nifty in processing information as the former took more days than the latter to make full adjustments to the disturbances. Examination of the variance decomposition also underlined the dominance of S&P 500. Nikkei and Nifty were able to account for only 3.5 per cent of the error variance of S&P 500 while corresponding figure for S&P 500 was 10.6 and 3 respectively up to the 5th day. Nifty, in fact, explained little of the error variance of either Nikkei or S&P 500. It was, in short, a follower of its two big brothers.

Checking for volatility and spillover using the conditional volatility models, it was observed that there was across the board spillover of mean among the three markets, whether they were taken in the chronological order of functioning or as a group. The result did not change with EGARCH also. Most of the times mean spillover effect from foreign market was seen to be as great as to shadow its own effect on its mean through the autoregressive term. But there were significant findings in the volatility spillover study. It was found that volatility of domestic market was influenced by the volatility of foreign market that closed immediately prior to the opening of domestic market. But S&P 500 showed an exception in the EGARCH model by not being affected by the volatility in Nifty. Taking the other two markets together, it was seen that while Nikkei and Nifty followed the same pattern as in the individual models, S&P 500 differed from it in that the volatility of the market was not defined either by volatility of Nifty or Nikkei while it was actively spilling volatility in to Nikkei. The significant conclusion of the study is that the US market acts independently with respect to Nikkei and Nifty and is the most important producer of information that affects the mean and volatility of the other two markets. Between the other two markets, Nifty is observed to be less influential. It is seen to follow the other two markets.

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Chapter 3

An Empirical Analysis of Risk-Return Tradeoff in Indian Equity Market

3.1 Introduction

Rational investors as maximizers of their expected profit want greatest return from their investment. But simultaneously, they are constrained in this ambition by their aversion to risk and are restricted in the maximization motive by this factor. It has been laid down in almost every financial economics text book that risk and return are inversely related i.e. one has to bear additional risk to earn extra return on one's investment. Because an investor is concerned with the terminal value of his investment and this value depends to a large degree on the variance of return, a large variance puts lot of uncertainty on the expected return as far as the investors are concerned and hence, the obvious justification for the huge importance attached to variance or standard deviation as a measure of risk. Variation in the return of equities and bonds are laid down as classic examples for this; so are the offer of higher rates of returns by less credit worthy corporations as compared to national governments or more solid and financially secure corporations. In this background of risk return relations, stock market assumes a pivotal place as it is one of the most important wealth portfolio dealt in financial economics as well as in the investment strategies of individuals and institutions alike. Like all opinions in economics, this relation is also marred by controversies and by findings and counter findings over the years. Therefore, the question that the present study has posed is the relation between risk and return within equities. It analyzes whether they are related and if related to what extent they are related as also the kind of relation between them.

Formal study of risk-return relation started in financial economics in the 1950's with Markowitz's seminal work titled, 'Portfolio Selection'. Later this developed in to Capital Asset Pricing Model (CAPM) through Mean-Variance analysis. The established wisdom of the times was that, there need to be a tradeoff between risk and return and investors were assumed to balance their portfolio with a sufficiently mixed bag of financial instruments commanding specific risk and return. Since the present study highly resembles the CAPM in the case of broader markets, its desirable that a review of the foundation of risk-return relation as manifested through CAPM is done.

3.2 Capital Asset Pricing Model (CAPM)

CAPM is used to determine a theoretically appropriate rate of return of an asset, if that asset is to be added to an already well diversified portfolio, given that asset's non-diversified or systematic risk. The model takes in to account the asset's sensitivity to systematic risk, represented by the quantity β. The model has its foundations in Markowitz (1952) and later Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966) developed it in to maturity. The relation is defined as,

$$ER_i = R_F + (ER_M - R_F)\beta_i$$

The term β_i is a measure of systematic risk of asset *i*.

The above equation can be reformulated as,

$$R_i = \alpha_0 + \alpha_1 \beta_i + u_i$$

Where,

$\alpha_0 = R_F$ or return on risk free asset

$\alpha_1 = (ER_M - R_F)$,

R_i is the realized return on asset *i* over the sample period

And

u_i = the expectational error $R_i - ER_i$

β_i is the measure of risk as already pointed out and since it is not observable in the real world, sample estimates are used to find it.

CAPM as a method can be handy to find risk or 'beta' of an individual asset but is incapable of measuring risk of the market as a whole. So the practice is to substitute market risk estimate, standard deviation or variance, in place of beta and then run the regression on market return. This will help in identifying relation between risk and return for the market. Thus, a slight modification of the CAPM will help to unravel market risk-return relation.

3.3 Review of literature

The starting point of formal academic discussion on risk premium started with Markowitz (1952) which later developed in to the mean variance theory or what is still being called the modern portfolio theory. The basic postulates of the theory are, strategy of diversified investment pays better than a concentrated one, market rewards investors for taking extra risk, it does not reward for taking idiosyncratic risk and all investors hold risky and riskless assets in their portfolio. Individuals, as rational beings, are assumed to prefer lower variance at a given mean or a higher mean at given variance. All subsequent developments in the risk return literature broadly followed this trend.

Tobin (1958), improved up on the liquidity theory formulated by J M Keynes by incorporating expectations and diversification aspects in to investor behavior and simultaneously carried the Mean-Variance analysis forward with it. According to him, investors formed expectations of future movement in interest rate and hence there was no difference between actual and expected rates. The diversification approach pointed to the investor behavior in which they were assumed to diversify the asset allocation in accordance with their risk preferences. He further divided investors in to risk averters and risk lovers. The former, according to him preferred moderate return as they were not prepared to be subjected to the uncertainty involved in higher return and the latter included the category of investors who preferred greater returns and were disposed to take larger amounts of risk to obtain this. Thus, the analysis assumed a tradeoff between risk and return in the sense of higher return leading to greater risk and vice versa. This extra return that the risk lover gets may thus be called as a premium or reward for taking extra risk. Existence of the concept of risk premium was thus observable in the work.

The possibility of forming the best return portfolio available to the investor at least risk was examined by Sharpe (1964), in a paper titled, “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk” which was based on the mean – variance analysis. According to him, all assets entering efficient combination – one over which no improvement can be made in terms of expected return or variance - must have return and risk values lying on the security market line. Prices will adjust so that assets which are more responsive to changes in the return of a combination of assets will have a higher expected return than those which are less responsive. That part of an asset's risk which is due to its correlation with a combination of assets cannot be diversified away. Since this systematic risk cannot be diversified away it is to be directly related to the expected return. He assumes that this perfect correlation among the efficient combinations could be due to their common dependence on economic activity. Thus, diversification cannot help in managing this risk. Hence, only the responsiveness of an asset's rate of return to the level of economic activity is relevant in assessing this specific risk. Prices will adjust until there is a linear relationship between the magnitude of such responsiveness and expected return. It is, thus clear that he supports the hypothesis of a direct relation between risk and return.

Lintner (1965), in his study dealt with the selection of portfolio by individual investors. He did not deal with the risk – return tradeoff as such. According to him stocks whose expected return is less than the risk free rate will also be held long in the portfolio if they are negatively correlated with other stocks held long in the portfolio or positively correlated with other stocks held short in the portfolio. This is because the 'variance offsetting' characteristic of this stock may be greater than its low return characteristic. Positive correlations with other securities held short in the portfolio have a similar variance offsetting effect. He also found out that any stock with positive risk premium will be held short in the portfolio if it is positively correlated with the stocks held long in the portfolio or if it is negatively correlated with other stocks held short in the portfolio. Thus, he concluded that positive risk premium is neither a necessary nor a sufficient condition for a stock to be held long in a portfolio. So in effect, he found out the portfolio to have a positive risk premium but not to all the stocks.

Risk - return dynamics in an optimization framework involving intertemporal choice was studied by Merton (1973). He showed that all risk averse utility maximizers will attempt to hedge against an unfavorable shift in the investment opportunity set in the sense that if the marginal change in consumption to a change in investment opportunity set is less than zero i.e. consumption is relatively constant, then the consumers will demand more (less) of the i^{th} asset, the more negatively (positively) correlated its return is with the changes in investment opportunity set. Thus, if the ex-post opportunity set was less favorable than was anticipated, the investor will expect to be compensated by a higher level of wealth through the positive correlation of return from the i^{th} asset. Similarly, if the ex-post return was lower, he will expect a more favorable investment environment. This implies a sort of inter-temporal consumption smoothing behavior i.e. maintenance of a constant level of consumption. This can be defined as a negative relation between risk and return as the economic unit in question seeks to hedge the risk posed by the uncertainties on his return.

Merton (1976) ventured in to a relatively unchartered territory. Though there were methods to find the expected return of an individual asset previously, the literature was starved of models dealing with market return. The study was conducted with the notion that variance of the return along with interest rate – risk free asset – were capable of explaining expected return of equity market. This was strictly in line with the existing idea that equity price was the sum of the risk free rate and a premium for the risk attached to equities. One of the findings of the study was that, in estimating models of expected return of the market, non negativity condition of the expected excess return should be explicitly included as part of the specification. Estimates of expected return based on the assumption of constant variance produced drastically different results as compared to the least square estimates. Thus, it also suggested that the series of expected return should be adjusted for heteroscedasticity. The study found scope for further improvements by using more accurate variance estimating models using non-market data – due to the potential noise in market data – and lengthening the time period of estimates.

An examination whether the time varying risk premia on different term based debt instruments can be modeled as risk premia, where the risk is due to unanticipated interest rate movements and is measured by the conditional variance of one period holding yield was done by Engle *et al.* (1987) and the study also introduced the ARCH-M model which extended the basic ARCH model to allow the conditional variance to affect mean as a determinant of current risk premium. The model was applied to three different data sets – three, six and nine month treasury bills – of bond holding. ARCH effect was clearly visible in the forecast errors of bond holding yields indicating substantial variation in the dynamics of uncertainty over time. This measure of uncertainty was seen to be significant in explaining the expected returns in two out of the three data sets and was found to be significant only at slightly more than five per cent level for the third. In the short term bond case, the risk premia was found to be two third of the standard deviation of the return. The study asserted the existence of risk premium and concluded that risk premia are not time invariant but they vary systematically with agent's perception of underlying uncertainty.

Breen *et al.* (1989), examined whether the stochastic variation in stock index excess return was predictable with a fair degree of statistical and economic significance by analyzing the negative correlation between stock index returns and Treasury bill interest rate. The study made use of monthly data from April 1954 to December 1986 for equally weighted and value weighted indices of New York Stock Exchange (NYSE). The study constructed a forecasting model based on this negative relation and evaluated the forecasting ability of the model and concluded that treasury bill return can indeed forecast changes in the distribution of stock index excess return when the index was a value weighted portfolio. The predictability was found to be statistically significant on a standard significance test procedure and also economically significant as the forecasts of the value weighted excess return was on an annual basis worth two per cent of the value of the assets managed. However, the model failed to show any statistical or economic capability in predicting the return on the equally weighted index. The authors attributed this to the January seasonal effects and leptokurtosis which was pronouncedly higher for equally weighted index. It was also found that the excess return on stocks were relatively less volatile and more likely to be positive during up markets than during down markets.

The relation between mean and variance of US stock market for the period 1970 to 1987 using GARCH-M model was investigated by Baillie and DeGennaro (1990). The study found no significant relation between mean and variance and the coefficient of the variance term in the mean equation was found to be insignificant. Similar exercise was done using Student - t distribution and the results did not appear to be different. Substituting the variance of the return with standard deviation produced similar result and the study concluded saying that the old hypothesis of a positive relation between expected return and conditional variance was invalid. It also found the normal distribution to be incapable of accounting for excess kurtosis found in financial data. As a measure of checking robustness of the results, a similar analysis was conducted using monthly data for the same period. Variance of the excess return was used as the regressor and the monthly US Treasury Bill rate was used to calculate the excess return. The result obtained from using the monthly data also failed to validate any significant relation between first and second moments.

Haugen *et al.* (1990) studied volatility shifts and its impact on mean variance and its influence on risk premia for Dowjones daily return from 1897 to 1989. The study identified 205 events that led to an increase in variance and 197 events that caused a decline. It identified only 1/4th of the variance shifts to be associated with a major information arrival or news flow. The study found that, over the sample period, significant negative average returns and average excess returns were realized subsequent to volatility decreases and that the return behavior was more exaggerated in case of an increase in volatility. Analyzing the realized returns subsequent to stock adjustments to volatility shifts, the study found the annualized mean return to be 12.6 per cent following volatility increases and -0.36 per cent following volatility declines. This, according to the study, pointed to the time variation in risk premium as well as reinforced the hypothesis that stock price adjustments are induced by changes in volatility as opposed to changes in expected future cash flows. The study also found that volatility shifts were more frequent in the early phase of the sample. However, an important finding of the study was that the last two decades, 1970's and 1980's, broke the trend and gave exactly opposite results.

The then existing models treated positive and negative shocks as having same impact and thereby failed to account for the asymmetry that was rampant in financial data. Nelson (1991) attempted to plug those gaps in conditional volatility models. The study generated a new model, exponential GARCH or EGARCH, which responded differently to positive and negative shocks. It also examined the relation between the level of market risk and required return, the asymmetry between positive and negative returns on their effect on conditional variance, persistence of shocks to volatility, existence of fat tails in conditional distribution of returns and the contribution of non-trading days to volatility on an empirical basis for the US market daily return from July 1962 to December 1987. The estimated risk aversion parameter was found to be negative and significant using conditional variance as an explanatory variable in the auto regressive equation of excess returns. The asymmetric relation between return and changes in volatility was found to be substantial and highly significant. The study found the shocks to be persistent but results were not emphatic. The study also found evidence for the existence of fat tail as also observed that non-trading days contributed only as much as $1/5^{th}$ to the volatility as compared to trading days. The study, thus, negated the existence of a positive relation between expected return and conditional variance.

Backus and Gregory (1993) in an article examined whether dynamic theory can be used to deduce a relation between risk premium and conditional second moments that can be used in empirical studies. The study computed equilibrium values of risk premium and conditional second moments for excess return on equity and two period real bonds. In the theoretical model, a representative agent was assumed to consume endowment of a single good whose growth rate varied over different states – periods – of the economy at a particular pace. The study formulated four situations: ρ – auto correlation of any random variable adapted to a particular state of the economy – placed at -0.3 and 0.3, an economy with five states with growth rates equally spaced and having a uniform equilibrium distribution and finally an economy that alternates between the two states. The study found a positive relation between risk premium and conditional variance for bonds and equities for the first model whereas it was found to be negative for the second model with ρ assumed to be 0.3. The third model found no linear relation between the two variables and the result showed a 'U' shaped curve. A negative serial correlation was found within each regime in the fourth model but the regimes themselves were positively correlated. The study concluded that, theory can produce a variety of relations between risk premium and conditional variance. Depending on the parameters of the economy, the form of the relation, according to the study, could be increasing, decreasing, 'U' shaped or 'saw toothed'.

The relation between risk and return for US stock market monthly data from 1954 to 1988 was investigated by Glosten *et al.* (1993) using GARCH-M, Nelson's EGARCH and Campbell's instrumental variable models. The study also allowed the variance equation to have seasonal variation for the months of January and October as those two months showed excess volatility as compared to the other months. The study found a positive but insignificant relation between risk as defined by the conditional volatility of excess return and return using standard GARCH-M framework. Estimation of the model using Campbell's instrumental variables gave a negative relation between the two variables. When the model was modified to have positive and negative unanticipated returns to have different impacts on the conditional variance, a negative relation between conditional mean and conditional variance was again found. This negative relation became statistically stronger when conditional variance was allowed to have deterministic monthly seasonal and to depend on the nominal risk free interest rate. The study also found that the statistical properties of monthly and daily data varied significantly in that the persistence of volatility was seen to be quite weak in the former as also a positive shock to monthly return was found to have volatility smoothening effect, whereas in the daily data, positive and negative shocks led to a spurt in volatility though the impact of the positive shock was milder.

Campbell (1996) examined the risk return relation of the US stock market for monthly as well as annual data from 1952 to 1990 and from 1871 to 1990 respectively. The study made use of the multi-factor model as well as the vector auto regression framework for the purpose. The variables used were the real value weighted stock index, relative treasury bill rate – defined as treasury bill rate minus one year moving average – and the spread between long and short term government bonds for monthly data and gross national product, long term government bond yield and return on gold in addition to the return on stocks and dividend yield in the case of annual data. The study was intended as an improvement over the consumption capital asset pricing model. It found labor income growth and dividend yield as capable of forecasting the return on common stocks and other variables were found to have negligible role in determining excess stock return. The relation was rather obscure in the case of annual data. The study also found innovations to income to be much less volatile than that to stock returns thereby showing that estimation of market risk as depending solely on return may grossly over estimate it. Further, it was also found that future stock returns were highly volatile and that there existed a strong negative relation between future return and current return which can be interpreted as a negative relation between stock return and volatility.

The cyclical behavior of expected stock returns, their volatility and the risk and return relation in association with various holding intervals was explored by Harrison and Zhang (1999). Using a semi-parametric method and Monte Carlo integration, the expected return and conditional volatility of excess stock return for periods ranging from a month to two years were obtained. This method is superior to many other methods in that it did not impose any parametric restrictions on conditional mean or variance or on the relation between dependent and independent variables. Using proxies for the business conditions of the economy, the study found that both expected excess return and risk measured by conditional volatility are countercyclical over the period. The study could not account for any clear cut relation between risk and return over a month. However, a positive risk and return relation was found at longer periods such as a quarter and one and two years. Time invariant risk and return relation was also explicitly tested with the Sharpe ratio and it was found that the relation varied with business cycles.

Whitelaw (2000) modeled risk return behavior of US market for the period from January 1959 to December 1996 on a monthly basis. The model was estimated using monthly data on a real aggregated chain weighted consumption of non-durable goods and services. The study used regime shifting models and defined consumption equation as an auto regressive process with each regime shift implying a different auto regressive process. The two regime specifications adopted by the study were able to identify the expansionary and contractionary phases of the business cycles with National Bureau of Economic Research of USA (NBER) business cycle dating. Expected returns and conditional volatility in the study exhibited a complex non-linear relation. They were found to be negatively related over the long term and this relation varied substantially over time. The key feature of the specification was the regime parameters that implied different means of consumption growth across regimes. Starkly contrasting was the result using single regime model, which produced strongly positive and emphatically linear relation between expected return and volatility when calibrated to the same data.

An attempt to explain the risk-return tradeoff using a host of Macro Economic variables like consumption, labor income, wealth and population was made by Lettau and Ludvigson (2001). Three month Treasury Bill rate was used as the risk free rate to find excess return on equities. Result of the regression of consumption-wealth ratio on equity market volatility showed that it was both a statistically significant and economically important determinant of future stock market volatility. It also found that excess stock market return as well as the volatility of this return was forecastable with Macroeconomic variables like consumption-wealth ratio. Though the study found consumption-wealth ratio to be explaining both excess return and volatility, the coefficient of consumption wealth ratio in volatility equation was found to be negative and significant while that in excess return equation was found to be positive and significant. This signifies the existence of a negative relation between excess return and volatility implying low volatility in times of high risk premia and vice versa.

Pastor *et al.* (2004) analyzed the risk return tradeoff for the G-7 countries using the implied cost of capital as a proxy for the expected market return. Firm level implied cost of capital was averaged to find country level implied cost of capital. The study computed both equal weighted and value weighted implied cost of capital for each country. Expected excess return was defined by the study as the difference between implied cost of capital and long term government bond yield. Average of the squared daily market return was used as the measure of variance. Using the method, it found support for a positive relation between risk and return in both, the value weighted and equal weighted cases. This relation was found to be statistically significant for five out of seven countries in the case of value weighted index. A statistically significant positive relation between shocks to risk premia and shocks to volatility was found for Canada, France, Germany and USA. Similar results were found for value weighted average implied risk premium for four of the seven countries. The study also found positive inter-temporal risk return tradeoff at the global level. World market volatility and risk premia as well as individual country volatility to world market risk premia were also found to be positively related to each other.

Evidence for a positive and significant risk aversion parameter or price of risk for S&P 500 value weighted cash as well as futures indices and Centre for Research in Security Prices (CRSP) value weighted index was found by Bali and Peng (2005) in a paper titled, "Is there a Risk-Return Trade-off?; Evidence from High Frequency Data". Excess return was approximated by a linear function of the variance. The study used three types of variances: square of five minutes return, GARCH based variance estimation and implied volatility based variance. The last one is an indicator of market's expectation of future volatility. The study found a positive and significant relation between risk and return for all three types of variance for all markets examined thereby validating the existing hypothesis relating to risk return interaction. Robustness of the results was also checked using daily data as well as inserting Macroeconomic variables in to the equations. Daily data produced positive but insignificant results which imply that the positive coefficient of risk aversion was an outcome of the characteristics of the data earlier employed. The second test of robustness by including Macro economic variables, Federal Reserve rate and yield spread between BAA and AAA rated bonds, improved the significance level of the parameters with a negative sign. This, according to the authors, was due to the reduced noise in the data as a result of the inclusion of new variables.

3.3.1 Studies on Indian Market

In spite of the enormous amount of work done on the relation between risk and return, studies based on Indian markets are extremely scarce. Those that have been performed are very preliminary in scope in that they have just attempted to find risk premium by using annualized return and risk free rate. Since the present study is focused on the Indian context, it would be desirable to have a review of the works done on India.

Varma and Barua (2006) attempted to estimate the risk premium as BSE Sensex as the barometer for the period 1981 to 2005. Since data for the index was not available prior to 1985, the data for the first four years was created using available information of the stock prices of the largest cap stocks of the period and this index was used as benchmark till 1996 when regular monitoring of index composition started. Similar was the case with risk free rate – which was repressed during 1980s and early 1990s. The paper compensated for the repression using US interest rate – after accounting for exchange rate variation over the period - and Indian interest rate after financial liberalization as indicators of the repression period’s actual interest rate. Risk premium was defined as the excess return of the market over the risk free rate and the average return was computed using both geometric and arithmetic means. The study found that the risk premium was 8.75 per cent on a geometric mean basis and about 12.5 per cent on an arithmetic mean basis. There was found to be no significant differences between pre and post reform periods.

Mehra (2006) analyzed the risk premium of the Indian market along with some of the developed markets and found it to be 9.7 per cent in the post reform period in India. This was much higher than those found for the more developed economies. The study found enormous disparity between the return on equity and bond. Using standard theory to estimate risk adjusted return, the study found that the US stock market should only have around 1 per cent risk premium while the actual figure ranged from 4 per cent to 7.3 per cent. Doing the same exercise in the Indian case, the study found that the equity premium in India should be in the range 0.02 per cent to 0.16 per cent if the coefficient of risk aversion was varied from 2 to 10 i.e. all possible imaginable levels. This astonishing finding was termed by the author as the ‘equity premium puzzle’ and pointed out the incapability of financial models to perform well when confronted with real data.

Risk-return relation may be one of the most researched topics in financial economics and hence there is no paucity of literature on the issue, but an examination of the studies so far conducted reveals that there is no agreement over the relation between risk and return and that the risk aversion parameter or evidence of risk premium varies from studies to study not only in terms of magnitude but also in terms of significance and sign. This assertion stands whether we take studies with similar methods, time periods, markets or variables. Hence, researchers are still actively engaged in trying to unlock this mystery or “risk premium puzzle” as referred by Mehra (1985) though in a different context. The present study also attempts to make its own mark in the field by checking the existence of risk premium and the sign, significance and magnitude of the risk aversion parameter.

3.4 Review of Models Used

Present study uses simple regression framework to analyze the relation between risk and return with weekly return as dependent variable and standard deviation as independent variable. Variance is obtained using three methods: moving standard deviation, GARCH model and EGARCH model. Each of these methods is explained in detail.

3.4.1 Regression

Regression analysis refers to the technique of modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. A regression analysis helps us understand how the typical value of the dependent variable changes when the independent variable is changed. It in a sense shows conditional expectation of the dependent variable given the independent variables.

A simple regression equation assumes the following form,

$$y_i = \alpha_0 + \beta_0 x_i + e_i, \qquad i = 1, 2 \ldots. N,$$

where, y_i and x_i are respectively dependent and independent variables,

and 'e_i' is the error term.

A multiple regression can be represented as,

$$y_i = \alpha_0 + \beta_0 x_i + \gamma_0 z_i + e_i$$

where, x_i and z_i are independent variables having a bearing on y_i.

Present study has weekly return on selected indices as dependent variable and standard deviation of these returns as independent variable. Format of the equation changes into multiple one when, additional variables like the auto regressive term or macro economic variables are introduced into the equation.

3.4.2 Moving Standard Deviation

In probability theory and statistics, standard deviation is a measure of the variability or dispersion of a population. Hence, it is being used as a measure of risk by practitioners and academicians alike. A low standard deviation indicates that the data points tend to be very close to the mean value, while high standard deviation indicates that the data are spread out over a large range of values.

Present study has 694 weekly return observations and has to calculate standard deviation for the last 494 observations. Hence, it uses moving standard deviation under which the standard deviations of first 200 observations are computed and then the first observation is dropped and 201st added to get the next series of 200 observations. This process continues until standard deviation for the last observation is obtained.

3.4.3 GARCH Model

It is well known fact that the variance of financial time series goes on changing from time to time. Due to this, the earlier methods of squared daily returns and range estimators of volatility proved to be inadequate for modeling purposes. Engle (1982) introduced the ARCH model to capture the changing volatility in financial series in which the conditional variance σ_t^2 was defined as a linear function of past squared errors, ε^2_{t-1}. the simplest representation of this model is the ARCH(1) which has the form,

$$r_t = \tau + \mu\, r_{t-1} + \varepsilon_t, \ \text{where, } \varepsilon_t \mid F_{t-1} \sim N\,(0,\sigma_t^2)$$

r_t is current return and r_{t-1} is previous return, ε_t is the error term and F_{t-1} is the information set up to t_{-1} and σ_t^2 is conditional variance.

and

$$\sigma_t^2 = \alpha + \beta\, \varepsilon^2_{t-1} \qquad \text{where } a > 0 \text{ and } c \geq 0.$$

The conditional variance at time t is a positive function of the square of last period's error ε^2_{t-1}. While the ARCH models do not allow the conditional variance at time t to have a stochastic component, the model can incorporate additional squared error terms from prior period.

Bollerslev (1986) generalized this model by allowing the conditional variance σ_t^2 to be a function not only of last period's error squared, ε^2_{t-1} but also of its conditional variance σ^2_{t-1}. The GARCH (1, 1) model defines the conditional variance σ_t^2 at time t to be of the form,

$$\sigma_t^2 = \alpha + \beta\, \sigma^2_{t-1} + \gamma\, \varepsilon^2_{t-1}$$

The GARCH formulation can also be extended to include additional squared errors and variances from past periods. But empirical studies revealed that equity prices responded with greater volatility to negative news than to a positive one. In order to account for this asymmetry in equity price behavior, Nelson (1991) introduced the asymmetric GARCH model called the Exponential GARCH or EGARCH. The variance equation of the model is of the following form.

$$\ln(\sigma_t^2) = \alpha + \beta\ (\epsilon_{t-1}^2/\sqrt{\sigma_{t-1}^2})\ + \gamma\ \left|\varepsilon_{t-1}^2/\ \sigma_{t-1}^2\right| + \ \rho\ \ln(\sigma_{t-1}^2)$$

The new coefficient β in the above equation represents the asymmetric behavior. A negative sign to β will imply the presence of asymmetry and then the stock price volatility will increase to a greater extent as a result of a negative shock than to a positive one.

3.5 Data

The analysis is done for two of the major indices of National Stock Exchange of India viz. Nifty and Nifty Junior. Data for these two indices are collected from the official web site of the National Stock Exchange of India. Data used in the study is weekly returns on these two indices which are obtained by taking log differences of successive week closing prices of the indices. Excess return is defined as the difference between weekly returns and the risk free rate. Interest rate on the 91 day Treasury bill is used as risk free rate and is obtained from the official web site of the Reserve Bank of India. Equity data is for a period of 693 weeks from October 1995 to January 2009 and Treasury bill data from September 1998 to January 2009. This gap between the two series is due to the greater number of data points needed for equity series due to the necessity to calculate standard deviation over a fair length of time. This fair length of time is defined in the study as 200 observations i.e. approximately four years.

3.6 Empirical analysis

Financial data has its own idiosyncrasies as compared to other data and there are wide variations in behavior within different periods of the same data. It could be seen to have a particular behavior for high frequency while this may not be applicable to weekly or monthly data. Analysis of the nature of data at hand before beginning empirical work can help in specifying correct models.

Table 3.1 Preliminary Statistics

Parameters	**NR Weekly**	**NR Daily**	**NJR Weekly**	**NJR Weekly**
Mean	0.2120	0.0470	0.2800	0.0574
Median	0.4704	0.0976	0.5800	0.1257
Maximum	14.8173	10.4441	15.2740	8.6457
Minimum	-15.9497	-12.2377	19.9067	-12.3074
Standard Deviation	3.6255	1.7292	4.3689	1.9749
Skewness	-0.1354	-0.2415	-0.5398	-0.4409
Kurtosis	4.7153	7.0996	5.2370	6.6411
Jarque-Bera	87.0772	2392.036	178.1705	1970.285

Note: NR and NJR stands for Nifty and Nifty Junior returns

A glance at the preliminary statistics shows that the weekly data tends towards normality more than the daily data. It is more flat topped and its Jarque-Bera statistics is substantially lower but still rejects normality. It can also be observed that the series have a longer left tail and heavier tails in general as compared to a normal distribution. Hence, it would be prudent to use a heavy tail distribution such as a student t, while estimating variance along with normal distribution. The range as well as the standard deviation estimates shows that Nifty Junior is riskier than Nifty and also commands a premium in the sense of a higher return for this extra risk as its weekly and daily mean and median are higher than that of Nifty. Whether this can be taken as a validation of the existence of risk premium can be ascertained only after doing more rigorous analysis.

3.6.1 Test of Stationarity

A series is said to be stationary if the mean and variance of the series are constant over time. A model whose coefficients are non-stationary will exhibit the property that previous values of the error term will have a non-declining effect on the current value of the series as time progresses. Financial data are in ordinary course found to be non-stationary at the level and stationary at the first difference. This is especially so in the case of daily and intra-day data. Present study uses weekly data and hence the noise associated with daily data may not be present in this case as observed in the basic statistics where, it was found that weekly data do not have the extremes present in daily data. However, stationarity of the data is an important property for econometric application and hence the data is subjected to stationarity test first at the return level using three methods, Augmented Dicky-Fuller test (ADF), Philips-Perron (PP) test and Kwiatkowski, Philips, Schmidt and Shin (KPSS) Test.

Table 3.2 Test of Stationarity

Tests	NR	NJR
ADF	-24.3476 (3.4395)	-15.1033 (3.4395)
PP	-24.3434 (3.4395)	-23.7206 (3.4395)
KPSS	0.1135 (0.7390)	0.0866 (0.7390)

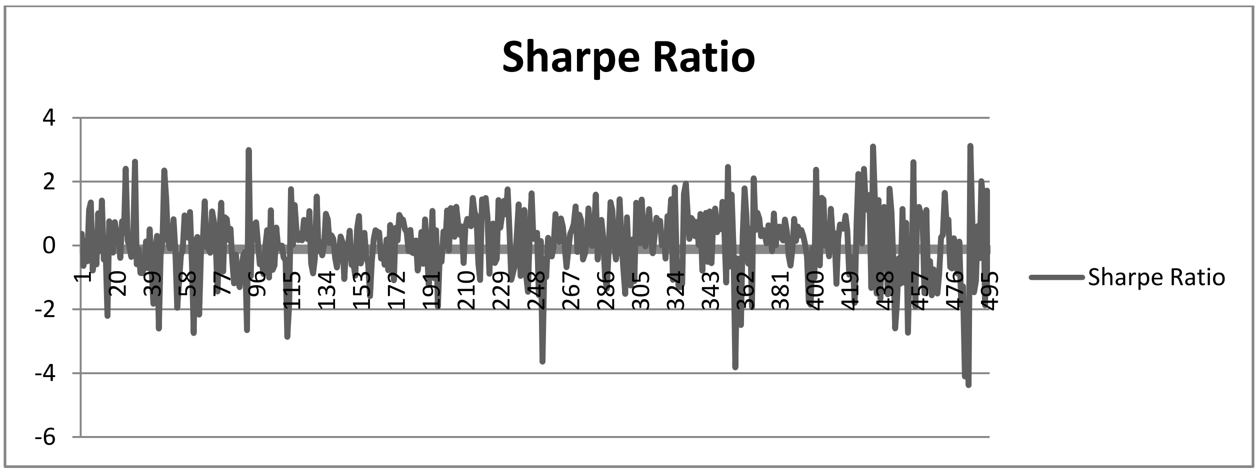
Note: NR and NJR stands for Nifty and Nifty Junior returns

Results of the stationarity test show that both series are stationary at the return level. Critical values of ADF and PP tests are well above the one per cent confidence level and hence the null hypothesis of non-stationarity is rejected and the critical value of the KPSS test is within the one per cent confidence level thereby accepting the null hypothesis of stationarity.

3.6.2 Sharpe Ratio

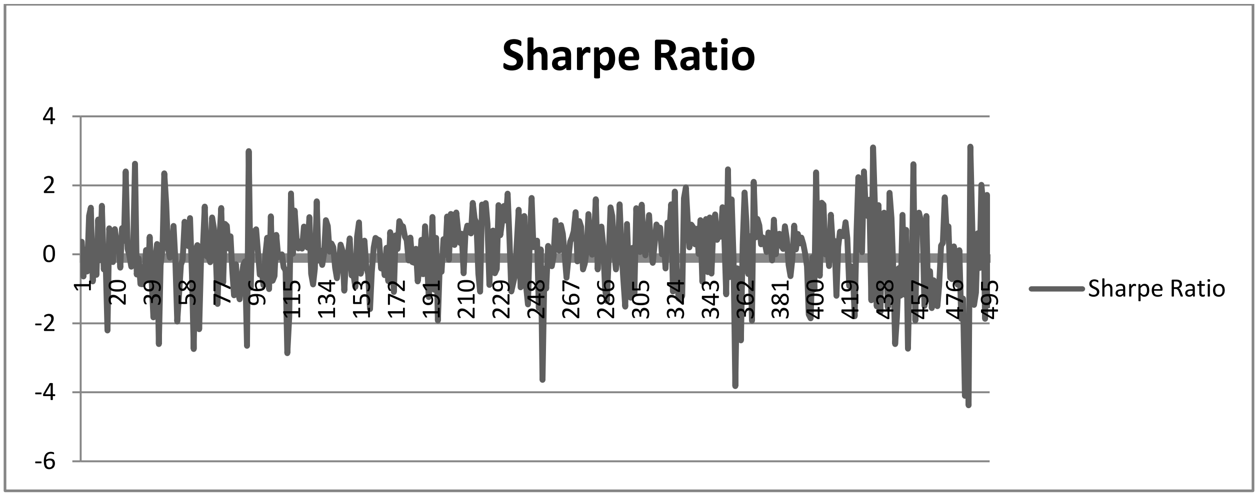
The basic question in this study is how the mean return per unit risk changes over time. This return per unit of risk is called the Sharpe ratio. It is the excess return from the stock market divided by the conditional standard deviation. Understanding the time series properties of the Sharpe ratio is crucial to the development of theoretical models capable of explaining observed patterns of stock market return and volatility. If the Sharpe ratio is constant throughout the period, it is an indication that there is a constant risk – return ratio and if it wildly fluctuates over time, it means that there is no clear relation between risk and return. It could also be taken as an indication that there exists no risk premium for if there were a premium, the ratio should not be fluctuating over time as a higher standard deviation would be consistent with a higher return. It is also an indicator of time varying relation existing between risk and return. A graphical representation can be a useful tool to analyze Sharpe ratio.

Figure 3.1 Sharpe Ratio for Nifty



Most of the observations of Sharpe ratio come in the positive territory; however, there are frequent negative ones which appear to be substantial in magnitude. Observation of the trend of the ratio shows that it has been anything but constant. There are wide variations in the value of Sharpe ratio rejecting the existence of a time invariant risk premium. The wide variations also show that there is no definite relation between risk and return as maintained by the Capital Asset Pricing Models. An increase in risk as measured by standard deviation is not associated with an increase in return and vice versa. A similar exercise is done for Nifty Junior.

Figure 3.2 Sharpe Ratio for Nifty Junior



Both figures look very similar and there is hardly anything that can be added to what has already been said. After analyzing the Sharpe ratio it has been established in a preliminary manner that risk-return relation is time variant and there is no constant, well defined relation between both these variables. This goes against many of the theories of financial economics but is certainly not without peers. Lettau and Ludvigson (2002) found similar results in a study as did Engle *et al.* (1987) and a host of other researchers.

3.6.3 Risk-Return Tradeoff

The tradeoff involving risk and return is analyzed in the present study using regression framework with excess return as the dependent variable and variance as the independent variable. Since, risk and return are commonly known to be moving in the opposite direction the study hope to find a positive relation between the two i.e. a higher variance to be followed by a higher return. The coefficient of risk as implied by standard deviation is expected to be positive and significant which would mean that there is a tradeoff between the two. Regression results with variance as found using moving standard deviation will be followed by the ones calculated using naïve GARCH and EGARCH.

Table 3.3 Risk-Return Tradeoff with Moving Standard Deviation

Parameters	**NR**	**NJR**
Constant	2.7524 (1.0372)	2.3008 (1.6877)
Standard Deviation	-0.7524 (-1.8874)	-0.4891 (-1.5162)
R^2	0.0077	0.0046
Adjusted R^2	0.0051	0.0026
D-W Statistic	1.8918	1.7787

Note (i) NR and NJR denote Nifty and Nifty Junior returns(ii) Values in parenthesis are‘t’ statistics

Regression equation with standard deviation as the sole independent variable shows good model specification. However, result produces surprising elements. None of the regressors are significant at five percent level. The coefficient of standard deviation is -0.75 with a t value of -1.88. This shows a negative relation between risk and return i.e. expected excess return goes down as risk increases. Similar is the case with Nifty Junior where the coefficient of standard deviation is significant only at 15 per cent level and the value is negative though lower as compared to Nifty. Negative value of the risk aversion parameter implies that taking extra risk do not guarantee extra return or in other words that risk premium is inexistent. The same analysis with auto regressive term of the dependent variable is also done as it will help in reducing the potential noise present in the weekly data.

Table 3.4 Risk-Return Tradeoff with Moving Standard Deviation and AR Term

Parameters	NR	NJR
Constant	2.6363 (1.9391)	1.9969 (1.4678)
AR(-1)	0.0504 (1.1166)	0.1053 (2.3447)
Standard Deviation	-0.7223 (1.8014)	-0.4264 (1.3255)
R^2	0.0098	0.0154
Adjusted R^2	0.0058	0.0114
D-WStatistic	1.9987	2.0242

Note (i) NR and NJR denote Nifty and Nifty Junior returns(ii) Values in parenthesis are‘t’ statistics

Results do not show any improvement with the inclusion of auto regressive term. Model specification slightly improves for the equation. Sign of the risk aversion parameter is still negative and insignificant for Nifty as well as Nifty Junior. Neither is there any appreciable change in the magnitude of the two parameters. Auto regressive term for Nifty is insignificant which means there is no effect of past week on the return of Nifty for the present week. However, it is significant for Nifty Junior. The main outcome of the model substantiates the finding of the first model of the absence of risk premia for Nifty and Nifty Junior

Table 3.5 Risk-Return Tradeoff with GARCH Standard Deviation

Parameters	Normal		Student - t	
	NR	NJR	NR	NJR
Constant	0.9543 (1.8309)	1.2673 (2.1472)	0.9722 (1.8180)	1.4162 (2.2252)
Standard Deviation	-0.2103 (-1.4738)	-0.2390 (-1.8465)	-0.2134 (-1.4679)	-0.2775 (-1.9432)
R^2	0.0044	0.0068	0.0043	0.0076
Adjusted R^2	0.0023	0.0048	0.0023	0.0056
D-W Statistic	1.9080	1.8187	1.9118	1.8198

Note (i) NR and NJR denote Nifty and Nifty Junior returns(ii) Values in parenthesis are‘t’ statistics

However, due to the specific characteristics of financial data, ordinary methods often fail to do justice to the behavior of its moments. Especially, volatility clustering and fat tails are difficult to capture using moving standard deviation. GARCH family of models does a very good job in this respect. Hence, they are employed to find standard deviation and the standard deviation as obtained from GARCH model with normal and student-t assumptions of the error distribution are used as dependent variable in the model. Examination of the result shows that none of the risk aversion parameter for either of the markets is significant at conventional levels. As with the models earlier examined, sign of the risk aversion parameter for all of these models are again negative implying no tradeoff between risk and return. Result for a same exercise with addition of the auto regressive term is presented in the table below.

Table 3.6 Risk-Return Tradeoff with GARCH Standard Deviation and AR Term

Parameters	Normal		Student - t	
	NR	NJR	NR	NJR
Constant	0.8468 (1.5924)	0.9331 (1.5322)	0.8531 (1.5567)	1.0650 (1.6232)
AR(-1)	0.0477 (1.0394)	0.0958 (2.0629)	0.0467 (1.0129)	0.0949 (2.0451)
Standard Deviation	-0.1828 (-1.258)	-0.1683 (-1.262)	-0.1828 (-1.229)	-0.2018 (-1.372)
R^2	0.0066	0.0153	0.0064	0.0159
Adjusted R^2	0.0025	0.0113	0.0023	0.0119
Durbin-Watson Statistic	2.0063	2.0291	2.0071	2.0288

Note (i) NR and NJR denote Nifty and Nifty Junior returns (ii) Values in parenthesis are‘t’ statistics

Again all the parameters including the auto regressive terms for Nifty and Nifty Junior are negative and an examination of the risk aversion parameter confirms earlier finding of the inexistence of risk premium. Not only are risk aversion parameters insignificant, they are also found to be negative in value. Auto regressive term of Nifty again is insignificant and that for Nifty Junior Significant. All these results contradicts the capital asset pricing models and goes with the more recent findings that there is no tradeoff between risk and return and additional risk bearing is no guarantee for additional return.

However, there is still scope for improvement of the model. Equity prices are notorious for their asymmetric behavior. They are found to be reacting much more violently to a negative shock than to a positive one and the ordinary GARCH model or the moving standard deviation fails to take this in to account. It was Nelson (1991) who formulated the exponential GARCH or the EGARCH model that took asymmetric behavior of equity prices in to consideration while modeling standard deviation. Result of a third type of model with standard deviation as predicted using EGARCH is given in table 3.7.

Table 3.7 Risk-Return Tradeoff with EGARCH Standard Deviation

Parameter	**Normal**		**Student - t**	
	NR	NJR	NR	NJR
Constant	1.3847 (2.7960)	1.0920 (1.8473)	1.6044 (3.0647)	1.8480 (2.9013)
Standard Deviation	-0.3397 (-2.476)	-0.2006 (-1.527)	-0.4031 (-2.768)	-0.3816 (-2.656)
R^2	0.0123	0.0047	0.0153	0.0141
Adjusted R^2	0.0103	0.0027	0.0133	0.0121
Durbin-Watson Statistic	1.9915	1.8406	1.9938	1.8766

Note (i) NR and NJR denote Nifty and Nifty Junior returns (ii) Values in parenthesis are‘t’ statistics

Result of the model is quite different from the earlier ones. Though, the sign of the risk aversion parameter remains negative, their statistical significance improves perceptibly and move in to the significance territory while magnitude of the parameters comes down. This not only shows that there is no risk premium but also that investors discount their expectations of future returns based on the available information on volatility at present. This result is against the theoretical assertion which has been in existence from the early 1950’s that there is a positive relation between risk and return. Same exercise is done with the inclusion of auto regressive term to reduce noise in the data and is given in the table below.

Table 3.8 Risk-Return Tradeoff with EGARCH Standard Deviation and AR Term

Parameters	Normal		Student - t	
	NR	NJR	NR	NJR
Constant	1.3270 (2.4103)	0.5418 (0.8361)	1.5597 (2.7168)	1.4075 (2.0240)
AR(-1)	0.0122 (0.2443)	0.0993 (2.0035)	0.0094 (0.1922)	0.0748 (1.5234)
Standard Deviation	-0.3239 (-2.122)	-0.0780 (-0.540)	-0.3909 (-2.449)	-0.2830 (-1.802)
R^2	0.0124	0.0127	0.0154	0.0187
Adjusted R^2	0.0084	0.0087	0.0114	0.0146
Durbin-Watson Statistic	2.0117	2.0316	2.0098	2.0260

Note (i) NR and NJR denote Nifty and Nifty Junior returns (ii) Values in parenthesis are‘t’ statistics

Result does not differ much when the auto regressive term is added to the equation except that both of the risk aversion parameters of Nifty Junior become insignificant. Signs and magnitude of parameters for Nifty remain same while sign remain same for Nifty Junior and magnitude falls considerably.

All the above results invalidate the risk-return tradeoff assertion and add meat to the findings of Baillie and DeGennaro (1990), Nelson (1991), Glosten *et al.* (1993), Campbell (1996), Lettau and Ludvigson (2001) and a number of other studies including one by the present author (2008) where it was found that the positive relation between risk and return in the daily data for the Indian market was insignificant. A robustness check for these results is also carried and the results are presented in the appendices A 6 to A 11. 91 day Treasury Bill rate is used as the controlling variable in the equation and it failed to produce any surprising result from the one that is already been obtained. Risk aversion parameters become significant whenever the EGARCH models are employed and the signs of all coefficients of risk aversion for all markets are found to be negative. Thus it can clearly be concluded that empirical evidence does not support the existence of a premium for risk in Indian market for weekly data.

3.7 Concluding Remarks

Present study has investigated for the existence of risk premium in the Indian equity market using 14 year weekly data of Nifty and Nifty Junior along with that of 91 day Treasury Bills. Standard deviation of weekly return was regressed on weekly excess return. The model was estimated with an auto-regressive term as well as without one. Weekly excess return was defined as the difference between weekly return and the return on the 91 day Treasury bill. Three types of models were used to calculate variance: moving standard deviation, Naïve GARCH and EGARCH. A check of robustness was also done with the addition of return on the Treasury bill as a dependent variable.

The study produced strikingly different results from the conventional wisdom. Existing notions on the risk-return relation varies widely. There was assumed to be a tradeoff in the relation in the early years. However, differences in opinion began to emerge towards the later years and at present both sides are balanced in terms of empirical evidence. Findings of the present study add strength to the opinion that there is no tradeoff between risk and return and that there is no assurance of a higher return on a high risk investment in the Indian equities. Three models were tested and all of them produced negative coefficients for the risk aversion parameter. But, these parameters were mostly insignificant except those for the standard deviations estimated using exponential GARCH model. This indicates the better ability of asymmetric models to capture market behavior as well. Same classes of models were estimated with the addition of an auto regressive term in the regression equation and that produced similar result. Adding a macroeconomic variable, 91 day Treasury bill rate, to the same equations as a means of checking robustness of the results was also done. This did not bring any substantial changes to the result in terms of sign, magnitude or statistical significance. All these point to the negation of a tradeoff between risk and return.

A comparison of the statistical properties of daily and weekly data showed no breakaway differences between the two in terms of tail behavior or normality, though weekly data appeared to have a flatter head than daily data. Auto regressive term in the regression equation was found to be insignificant in majority of cases leading to the conclusion that previous week has a negligible effect on the returns of present week. In case of daily data, auto regressive terms are always seen to be significant and more often than not are the most important explanatory variable for the next day returns.

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Chapter 4

Different Approaches to Measuring Value-at-Risk

4.1 Introduction

There are different approaches to measuring Value-at-Risk. All these approaches give a possible outcome based on a certain confidence level over a period of time. This single figure represents the entire quantifiable risk that the portfolio is subject to. Different methods may give different results but all these converge to a value in the broader sense. These methods can be segregated in to parametric and non-parametric. Former includes methods like the GARCH, Monte Carlo simulation models and Delta-Normal method while the latter includes models without any distributional assumptions. Historical simulation and Hybrid approach come under the second category. The first priority of a risk manager is to decide the method that has to be adopted for identification and containment of risk. An appraisal of the most popular existing models for measuring value at risk will help in understanding the level of development of risk management as also the complexity and computational requirements involved in each of these models. It can also benefit a researcher by helping him to concentrate on a few models for empirical testing by narrowing down the selection by dropping very similar models from the analysis. This will avoid redundancy and will make the study a more focused one. Taking all these points in to consideration, a brief review of the major models used in risk management industry for the calculation of Value-at-Risk is explained.

4.2 Delta - Normal Method

It is one of the parametric approaches to measuring risk. It assumes the individual asset returns of a portfolio to be normally distributed. Since, the portfolio return is a linear combination of the individual assets it is also assumed to be normally distributed. The portfolio return can then be represented as

$$R_{p,t+1} = \sum_{i=1}^{N} w_{i,t} \, R_{i,t+1}$$

Where the weights w i and t are indexed by time to recognize the dynamic nature of funding position.

Risk is thus a combination of exposures to assets whose returns are assumed to be normally distributed and by the forecast of the covariance matrix $\sum_{t+1}$. Covariance matrix can be generated using historical data or by applying risk measures from options or by a combination of both.

Delta-Normal approach is superior to the other methods in that it is very simple to interpret and can be computed much faster. It can also incorporate a larger number of assets. Further, the assumptions of normally distributed asset returns approximate to reality as the market tend to be more efficient. But it is beset with many problems as well. Though the option implied risk measure is much better than the one with historical data, it will not be available for all asset positions. The normal distribution based historical data is incapable of capturing infrequent and extreme events. Thus the method fails when event risks are present. The assumption of normal distribution is itself unrealistic as financial data is observed to be more fat tailed. This causes under estimation of the true

Value-at-Risk. Delta-Normal method can also not measure risk when non-linear instruments like options are present in the portfolio, whose deltas become unstable as it approaches expiration.

4.3 Monte Carlo Method

The name Monte Carlo is very general. It has been derived from the chance games played in famous casinos in Monte Carlo. They are essentially games with a random outcome. Monte Carlo methods are stochastic techniques meaning they are based on the use of random numbers and probability statistics to investigate problems (Woller, 1996). It is a non-parametric method as no distributional assumption is made. The first step in it is to identify the important market factors. Next involves the building of a joint distribution of factors based on one of the following; historical data, data implied by observed prices, and data based on specific economic scenarios. Finally, simulation is performed typically with a large number of scenarios. Then, the profit and loss is determined at each quantile. To formulate the problem precisely, let,

R = risk factors

Δt = time period

Δs = change in risk factors over Δt

V = loss in portfolio value

V depends on ΔR and given the magnitude of ΔR, v will have certain distribut ional characteristics. There are two closely related problems with the distributional assumptions of v. The first is the problem of estimating a loss probability p (v>x), given a loss threshold x. Second is the inverse problem of finding quantity x_p for which, p $(v>x_p)$ = p, gives a probability, p. Estimation of Value-at-Risk is an instance of the second problem, typically with p = 1% or 5% (Glasserman *et al*, 2000).

Focusing on the first problem, the main steps in a basic Monte Carlo approach to estimating loss probabilities may be laid down as follows.

Create N scenarios by sampling deviations in risk factors ΔR_1 …. ΔR_N over Δt.

Calculate portfolio value at the end of each Δt as $R + \Delta R_1 + \ldots. + \Delta R_N$

Find out the losses, v, as, $R – (R + \Delta R_1) + \ldots. + R – (R + \Delta R_N)$

Calculate the percentage of scenarios in which the losses exceed x: N-1 $\sum_{i=1}^{N}$ I (Vi > x) where, I (Vi > x) = 1 if N-1 > x and 0 otherwise.

Different paths followed by the risk factors can be generated using a number of methods. Using historical data is one among them. Though the process may look similar to historical simulation, it is essentially different in that historical simulation uses real observed changes in market place over the last x periods to generate y hypothetical portfolio paths or losses whereas in the Monte Carlo method, a random number generator is used to produce tens of thousands of hypothetical changes in the market (Bohdalova, 2007). The risk factors can be assumed to be distributed with conditional normality and a covariance matrix can be found out from it using EWMA or GARCH. Another commonly used method for simulating the path of a risk factor is the Geometric Brownian Motion, which is the basis for the theory of option pricing. It assumes that innovations in the asset prices - risk factors - are randomly generated over time and that small movements can be generated by

$$D_{st} = \mu_t\, s_t\, d_t + \sigma_t\, s_t\, d_z$$

This method has many advantages, one among them being that no distributional assumption is made with regard to the returns. Accuracy of predictions is capable of being raised by generating more scenarios. Another important advantage is that it can account for non-linearity thereby making it possible to accommodate options as well. But it is very expensive to compute as the time required for prediction is usually very high. The standard deviation of Value-at-Risk forecasts also tends to be very high leaving it incapable of using for risk measurement and containment. Apart from this, it is only moderately useful in case of a financial institution with a large number of dealers or an internet brokerage establishment with a large number of day traders. In each of these cases, the universe of traded products stays fixed in a day, and a large number of Value-at-Risk computations are required intra-day in doing risk measurement.

4.4 Extreme Value Theory

Some Value-at-Risk measures focus on the tail behavior of financial return series. For instance, economic capital is often estimated at an extremely high percentile, such as 99.97% for a AA company. For another example, when conducting stress tests, the possible behavior of portfolio returns is pushed to an extreme limit. Extreme value distribution as their name suggest, examines the distribution of the extreme value of a random variable, which is typically assumed to be independently and identically distributed. These extreme returns or exceptional losses are extracted from the data and an extreme value distribution may be fitted to these values Alexander and Sheedy (2004). The extreme value theorem states that given $X_1, X_2, \ldots$ Xn and two parameters ($\alpha_n>0$) and β_n (n=1,2,…), a random variable Y_n can be found out which depends on another parameter τ and is distributed as a general Pareto distribution.

The random variable Y_n = maximum $(X_1, X_2, \ldots X_n) - \beta_n / \alpha_n$

This will be a non-zero value. The numbers α_n, β_n, and τ are interpreted respectively as a dispersion parameter, a location parameter and a tail parameter. $\tau < 0$ corresponds to X_i values with a fat tail distribution, $\tau = 0$ has a thin tail distribution $\tau > 0$ has a no tail distribution.

4.4.1 Estimation of Parameter

N periods of each of a duration n of X_n will give N values for the loss variable (Y_n) in question. We express the successive observations of the variation in value variable as $X_1, X_2, \ldots x_{nn}$ and the extreme value observed for the ith section of observation as $\hat{y}_{i.n}$, (i=1,2,….N). Arrange these values in increasing magnitude such that,

$$Y'_1 \leq Y'_2 \leq \ldots . Y'_N$$

It is possible to demonstrate that if the extremes observed are in fact a representative sample of the law of probability given by extreme value theory, we have,

$$F_y = Y'I - \beta_n / \alpha_n = i / N + 1 + u_i \text{ , } i=1,2,\ldots .N$$

Where, u_i values correspond to a normal zero expectation law. Taking the iterated log for the two expressions,

$$-l_n\,[-l_n\,(i / N+1)] = 1 / \tau\,\{l_n\,\alpha_n - l_n\,[\,\alpha_n - \tau\,(Y'I - \beta_n)]\} + \varepsilon_i$$

This relation constitutes a non-linear regression equation for the three parameters α_n, β_n and τ.

4.4.2 Estimating Parameters Using Semi-Parametric Method

The method involves the calculation of an intermediate parameter. The i^{th} observation is termed x(i) after the observations are arranged in increasing order. The first stage consist of setting a limit M so that only the M highest observations from the sample will be of interest in shaping the tail distribution(Gallatti,2003) . It can be shown that an estimation of the tail parameter can be given by,

$$\bar{T} = 1 / M \sum_{k=1}^{M} L_N\ X_{(n-k+1)} - L_N\ X_{(N-m)}$$

The optimal choice of M can be made using a graphic method (Mcneil, 1996) or the bootstrap method (Danielsson and DeVries, 1997).

4.4.3 Calculation of Value-at-Risk

The future value of the risk is estimated in exactly the same way as for the historical simulation.

$$X(t)\,(1) = x\,(0) + \Delta\,(t)\,.\,X\,(0),\ t = -T + 1\ldots -1, 0.$$

The adjustment for the left tail of the distribution is made by,

$$\bar{F}Y(Y) = M/n\,(x(M+1)/y)1/\hat{\tau}$$

The distribution tail is simulated by taking a number of values at random from the re-evaluated distribution of the $Y_{(t)}$ (1) values and by replacing each x value lower than x (M+1) by the corresponding value obtained from the distribution of the extremes.

The extreme value theory is useful for capturing the extreme events as it is based on tail modeling. It is also useful when high percentiles are used. One of the main drawbacks of the model is the substantial data requirements as a large amount of observations are needed in the tails for efficient capturing of extreme events. Secondly, the assumption of the independently and identically distributed observations may not really be applicable in financial markets.

4.5 Risk Metrics

The work on Risk Metrics was started in 1980's by JP Morgan, now known as JP Morgan Chase. Then, it was only a firm-wide value at risk system. Each day the deltas of the positions were aggregated to express the combined value of the portfolio as a linear polynomial of risk factors. This data set was used to calculate standard deviation. In 1994 they officially published the Risk Metrics system which was made freely available to all. Risk Metrics is a parametric method in that it assumes a normal distribution of returns.

The Risk Metrics system envisaged the forecast of variance for time, t as a weighted average of the previous forecast and of the latest squared innovation. The weights used were λ and $(1- \lambda)$ respectively. Thus, it was an exponentially weighted moving average model.

$$h_t = \lambda\, h_{t-1} + (1- \lambda)\, r_{2\,(t-1)}$$

The only parameter λ is the decay factor and must be less than one.

By recursively replacing ht-1 in the equation we can obtain,

$$h_t = (1- \lambda) (r_{2t-1} + \lambda r_{2t-2} + \lambda_2 r_{2t-3} + \ldots)$$

The model is a special case of GARCH model in which α_0 is set equal to zero and the sum of α_1 and β set as 1. Thus, it does not allow mean reversion and the monthly and daily volatilities become equal. Risk Metrics uses 0.94 as the decay factor for daily data and 0.97 as the decay factor for the monthly data. A month is defined by Risk Metrics as consisting of 25 days.

This model is particularly easy to implement as only one parameter is used making it robust to estimation errors. Like the GARCH model, estimation is recursive; the forecast is based on the previous forecast and the latest innovation. The whole history is summed up in h_{t-1}. One important thing to be mentioned about the model is that the number of effective observations will be considerably smaller than the actual ones because of the declining weights. It decays so fast that the weights become as small as 0.00012 from data more than 100 days old, assuming daily data. Further, it is highly parametric, which is an unrealistic assumption as financial data series exhibit fat-tails, skewness and unstable correlations. The accuracy of this method becomes weaker when the portfolios exhibit asset concentration. It cannot also effectively deal with situations where the portfolio consists of non-linear positions like options.

4.6 Hybrid Approach

The biggest challenge in selecting a proper method for predicting Value-at-Risk is to have a single and easily implementable approach that provides a reasonable degree of accuracy. As the name implies, hybrid approach is the product of mixing two existing models in the risk management field.

Two of the most popular methods to Value-at-Risk estimation are the Exponentially Weighted Moving Average or Risk Metrics and the Historical Simulation. The former attaches exponentially declining weights to the past returns with the more recent ones getting maximum weightage. These declining weights help to capture the cyclical nature of returns. Historical Simulation on the other hand rests on the assumption that past repeats itself. This method arranges the data in ascending order and finds out the cut-off corresponding to the confidence level selected and that figure is considered to be the Value-at-Risk for the next day. Thus, hybrid approach combines the methodology of two existing approaches to come up with an easy to implement procedure which inherits many of the advantages of these two approaches (Boudoukh *et al*, 1997)

This method is implemented in three steps;

Step 1: Denote by $R_{(t),}$ the realized return from t-1 to t. To each of these most recent k returns, $R_{(t),}$ $R_{(t-1),}$ … , $R_{(t-k+1),}$ assign a weight, [(1-λ) / (1-λ)k], [(1-λ) / (1-λ)k] λ, …., [(1-λ) / (1-λ)k] λk-1 respectively. The constant, [(1-λ) / (1-λ)k], ensures that the weights sum to 1.

Step 2: Order the above weighted returns in ascending order of their magnitude.

Step 3: In order to obtain x per cent Value-at-Risk of the portfolio, start from the lowest return and keep accumulating the weights until x per cent is reached. Linear interpolation is used between adjacent points to achieve exactly x per cent of the distribution when two accumulated weights lie at either side of the confidence level.

This method has the advantage that it is easy to implement and computationally cheaper. It combines some of the benefits of both of its component methods for Value-at-Risk estimation, such as giving less weight to distant observations and accounts for the empirical tail skewness and other properties of the observed data series. But in some aspects, the component methods demand different treatments. A case in point is the number of data points to be used; while Risk Metrics works better with shorter horizon like one year, historical simulation requires larger data series, sometimes stretching even to five years and more.

4.7 NSE Method

A perceptible rise in return volatility due to various domestic and international factors led regulators and other market players in India to think seriously about their exposure to risk and the ways to manage it. As a result a committee under Professor Jayant R Varma was constituted by the National Stock Exchange of India to make recommendations on the risk management strategies to be adopted. In the study, Professor Varma found out the GARCH model with Generalized Error Distribution assumption to be most efficient in tracking risk. But due to the simplicity and speed of calculation he recommended the Exponentially Weighted Moving Average method which was finally adopted by NSE. This method closely follows on the Risk Metrics system developed by JP Morgan Chase.

Calculation of Value-at-Risk as per the method adopted by NSE involves the following steps.

Step 1: Obtain the daily closing prices of the security/index over a period of time and calculate the log return with respect to the previous closing price.

For securities, $R_n = \log [P_n / P_{n-1}]$

And for indices, $R_n = \log [v_n / v_{n-1}]$

Where, R_n= return on the security, V_n = Value of the index, P = price and n = time

Step 2: compute the initial volatility by calculating the initial standard deviation of returns for the one year period using the formula,

$$\sigma_0 = \sqrt{\sum_{i=1}^{n}(Rm - Ri)^2/n}$$

R_m is the mean return for the reference period.

Step 3: Calculate daily volatility for subsequent days.

For the next day, the volatility will be,

$$\sigma_1 = \sqrt{\lambda\sigma^2 + (1-\lambda)R_1}2$$

Where, $\lambda = 0.94$ is a parameter which indicates how rapidly volatility estimate changes.

Step 4: Calculate Value-at-Risk for the security at 3.5σ level and for the index at 3σ level. A higher σ level is used for the security because an individual security is expected to have a higher volatility as compared to the index, which is a portfolio.

Step 5: Calculate Value-at-Risk for a security or index for a particular day using the σ for both long and short positions.

For security;

Value-at-Risk for short position = Exp (3.5σ) – 1

Value-at-Risk for long position = 1- Exp (-3.5σ)

For index;

Value-at-Risk for short position = Exp (3σ) – 1

Value-at-Risk for long position = 1- Exp (-3.σ)

To ensure that risk for all possible situations are covered, long Value-at-Risk or short Value-at-Risk, whichever is higher, is considered for the script or index as the case may be (Das A, *et.al*, 2008)

4.8 The GARCH Models

The Generalized Autoregressive Conditional Heteroscedastic (GARCH) models are used to describe and predict conditional variance of a given series. These types of models assume present variance to be dependent on the previous variance and the square of the previous error term. The basis for these models was laid by Engle (1982) through his path breaking analysis of Auto Regressive Conditional Heteroscedastic model (ARCH). In traditional econometrics, the variance of the error term was assumed to be constant. Later empirical works rejected this idea. An asset holder is actually interested to know the conditional variance rather than the unconditional variance of the return of the asset that he is holding, hence, the importance of modeling variance from past information. The earlier method of modeling variance was faulty as the selection of the dependent variable was often arbitrary. Instead of using ad hoc variable choices, Engle (1982) showed that it was possible simultaneously to model mean and variance of a series. He modeled conditional variance as a function of the squares of the estimated residuals,

$$r_t = \tau + \mu r_{t-1} + \varepsilon_t, \text{ where, } \varepsilon_t \mid F_{t-1} \sim N(0,\sigma_t^2)$$

r_t is current return and r_{t-1} is previous return, ε_t is the error term and F_{t-1} is the information set up to t_{-1} and σ_t^2 is conditional variance.

and

$$\sigma_t^2 = \alpha + \beta\, \varepsilon^2_{t-1} \qquad \text{where } a > 0 \text{ and } c \geq 0.$$

This is called the ARCH model and where, ε_{t-i}^2 is the square of previous period's error term. Later, Bollerslev (1986) modified the basic ARCH model by including the moving average term with the auto-regressive term. Hence, variance became a function of the past variance, σ_{t-1}^2 and the square of the residual of the previous period, ε_{t-1}^2.

$$\sigma_t^2 = \alpha + \beta\, \sigma^2_{t-1} + \gamma\, \varepsilon^2_{t-1}$$

This model can be used to predict the next day variance as well.

$$\sigma^2_{t+1} = \alpha + \beta\, \sigma^2_t + \gamma\, \varepsilon^2_t$$

Once the variance is predicted, it has to be multiplied with the value of the respective distribution corresponding to the confidence level selected.

GARCH model was decisive breakthrough in modeling volatility. It is atheoretical and hence does away with the problem of defining proper explanatory variables for modeling variance. Secondly, it is observed in financial data that volatility appears in clusters rather than in an isolated fashion. GARCH models can sufficiently account for this volatility clustering. Thirdly, it is superior to its predecessor, the ARCH model, in that no non-negativity constraints are needed to be imposed on its coefficients.

4.8.1 Variations of the Basic GARCH Model

Inspite of all advantages, GARCH model suffers from serious inadequacies. It has been empirically proven that volatility reacts differently under different circumstances. It has been observed that a bad news creates greater volatility than good news. This phenomenon is ascribed to two factors, viz. leverage effect and volatility feedback effect. The former refers to the increased leverage of the firm as a result of a rise in its debt-equity ratio due to a fall in its equity value. According to the latter hypothesis, if expected returns increase when stock price volatility increases, the stock price should fall when the volatility increases (Brooks, 2002).

Two popular models that take in to account this asymmetry in stock price behavior are the exponential GARCH and the GJR model.

4.8.1.1 Exponential GARCH (EGARCH)

This model was proposed by Nelson (1991). Of the various ways to express conditional variance in this model, the most popular one is,

$$\ln(\sigma_t^2) = \alpha + \beta\ (\epsilon_{t-1}^2/\sqrt{\sigma_{t-1}^2})\ + \gamma\ \left|\varepsilon_{t-1}^2/\ \sigma_{t-1}^2\right| +\ \rho\ \ln(\sigma_{t-1}^2)$$

The new coefficient β in the above equation represents the asymmetric behavior. A negative sign to β will imply the presence of asymmetry and then the stock price volatility will increase to a greater extent as a result of a negative shock than to a positive one.

An advantage of this model is that there is no need for imposing non-negativity constraints. Second advantage is, obviously, that it allows for asymmetry. Thirdly, instead of using the value of u_{2t-1}, the EGARCH model uses the level of standard value u_{t-1}. According to Nelson, this allows for more natural interpretation of the size and persistence, of shocks as u_{t-1} is a unit free measurement.

4.8.1.2 TARCH or GJR Model

Glosten *et al.* (1993), showed how to allow the effects of good and bad news to have different effects on volatility. The conditional variance here is given by,

$$\sigma_t^2 = \alpha + \alpha_1 \varepsilon_{t-1}^2 + \beta\, d_{t-1}\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2$$

Where, $d_{t-1} = 1$, if $\varepsilon_{t-1}^2 < 0$

= 0 otherwise.

σ_t^2 current day variance and σ_{t-1}^2 and ε_{t-1}^2 are previous day's variance and previous day's error squared.

If $\gamma > 0$, it is safe to assume that there is asymmetry in equity return behavior.

4.9 Historical Simulation

It is one of the simplest and most effective methods of Value-at-Risk estimation. While, other models are beset with problems like distributional assumptions, substantial data requirements etc., this proves an effective one for practical considerations. This method only requires at least 250 observations. Since, the estimated Value-at-Risk under this method is based on the empirical distribution of historical return of each risk factor, it reflects a more realistic picture of the portfolio's past risk. The first step under this method is to collect the return series of the portfolio for which Value-at-Risk is to be calculated. The series has then to be arranged in the ascending order of its magnitude. Then, find out the value corresponding to the α per cent on the series starting from the lowest value and the value corresponding to the $\alpha+1$ is taken as the expected maximum loss of the portfolio for the next day.

4.9.1 Historical Simulation with Boot Strapping

This is popularly used variation of historical simulation. The data set is the actual returns observed in the real portfolio for which Value-at-Risk is being calculated. Out of a data set of historical returns, R, an element r_i is selected such as $r_i \in R$.

Where, i = 1,2,… T, refers to past days.

The price of asset Y is formed in a simulated way as,

$$Y^*_{t+1} = Y_T + Y^*_T \, r_T$$

The above process is repeated and the simulated price series Y* is recursively updated up to the last day of the value at risk horizon. These simulated prices for days, T+1, T+2, … , T+N forms a pathway or scenario for the risk factor or asset return Y.

Historical simulation has many advantages over the other methods. It is the easiest and simplest method available to calculate Value-at-Risk. Secondly; its data set is drawn from a real distribution and hence does not suffer from the distributional deficiencies often pointed out in the other models. It also does away with the necessity of computing a covariance matrix. However, it requires independently and identically distributed return series under which condition the inferences made about potential portfolio losses remain unchanged over time.

4.10 Conditional Autoregressive Value-at-Risk

Conditional auto regressive Value-at-Risk or CaViar is based on the existence of auto correlation in stock market return. The method seeks to model the quantile of the return distribution. According to this model, Value-at-Risk which is strictly linked to standard deviation should follow it in a strict fashion. It has been empirically proven that standard deviation or volatility of stock market return tend to be clustered over time. This phenomenon is statistically expressed as auto correlation in returns. This characteristic of stock return can be formalized by the use of auto regressive types of models.

A general form of CaViar is,

Value-at-Risk$_t$ = f (x_t,β_θ)

$$\beta_0 + \sum_{i=1}^{p} \beta_i VaR_{t-1} + l(\beta_{p+1,} \ldots \beta_{p+q,} \mu_{t-1})$$

Where, μ_{t-1}, is the information set available at time t.

The above formulation can be reduced in to,

Value-at-Risk$_t$ =

$$\beta_0 + \beta_1 \text{ var}_{t-1} + l\ (\beta_2,\ y_{t-1},\ \text{var}_{t-1})$$

The auto regressive term β_1 Value-at-Risk$_{t-1}$ ensures that the Value-at-Risk changes smoothly over time. The role of $l(\beta_{p+1,} \ldots\ \beta_{p+q,}\ \mu_{t-1},)$ is that of linking the level of Value-at-Risk to the level of y_{t-1}. It thus, measures how much the Value-at-Risk should change based on new information in y. Value-at-Risk is expected to increase as y_{t-1} becomes very negative as one bad day makes probability of next somewhat greater and to fall marginally as it becomes positive.

4.11 Principal Component Analysis

Principal component analysis is a statistical technique in which the original variables are replaced by a smaller number of artificial variables that preserves as much as possible of the variability of the original variables. This is done for two purposes: (i) to reduce the number of variables and (ii) to detect a structure in the relationship between variables. The key idea of principal component analysis is to perform a linear transformation of the original data to a new orthogonal co-ordinate system such that the axes are ordered in terms of the amount of variance in data set. In other words, the greatest variance by any projection of the original data set comes to lay on the first axis, called the first principal component, the second greatest variance on the second axis and so on.

Consider a set of n variables $x_1 \ldots x_n$ as a random vector X with zero empirical mean and non-singular covariance matrix **Σ**

E (X) = 0

Cov (X) = **Σ** ≥0

4.11.1 The First Principal Component

The objective is to find the linear combination of random variables $x_1 \ldots x_n$ that captures as much of the variability of the random variables $x_1 \ldots x_n$ as possible. In other words, for a linear combination,

$$\beta_{tx} = \sum_{i=1}^{n} \beta_i \, x_i$$

Maximize its variance,

D2 (β_{tx}) subject to

$$\|\beta\|^2 = \beta^2 \beta = 1$$

Where, β is a weight vector that tells us by what vector each of the variables x_j affect the variance of the linear combination β_{tx}. The condition, $\|\beta\|^2 = \beta^2 \beta = 1$ is a norming condition.

4.11.2 The Second Principal Component

The next step is to find the linear combination of random variables $x_1 \ldots x_n$ that is uncorrelated with first principal component and contains as much of the variability in random variables, $x_1 \ldots x_n$ as possible.

$\beta_{tx} = \sum_{i=1}^{n} \beta_i \, x_i$

Maximize its variance

D^2 (β_{tx}) subject to

$\|\beta\|^2 = \beta^T \beta = 1$

And

Cov (y1, β_{tx}) = 0.

4.11.3 Remaining Principal Components

Continuing in the same way produces all n linear combinations of X with the following properties.

1. Variance of the linear combination is the largest possible
2. The linear combination is uncorrelated with the previously identified linear combination.
3. These linear combinations form the principal component of random variable X

4.11.4 Choosing the Number of Principal Components

One of the basic rules for the selection of a principal component is the threshold criterion which guides to select as many principal components as necessary for the cumulative explanatory degree to exceed certain percentages such as 90 per cent. Another criterion is to sort the Eigen values in order of magnitude and select the largest among those.

4.11.5 Variance of a Portfolio

The variance of a portfolio, z is given by the sum of the squared exposures times the variance of each principal components. This is a remarkable simplification compared to the variance calculated with the original variables because instead of requiring all of the variances and co-variances of the original variables, it is enough to use a few variables.

4.12 Concluding Remarks

The chapter has dealt with the major models currently used for the calculation of Value-at-Risk. It consists of the most popular ten models. They include parametric, non-parametric as well as semi-parametric models. The analysis has thrown light on the methodology followed by each model as well as tried to uncover the major strengths and weaknesses of each of the models. But as a mere theoretical appraisal would be inadequate to test the effectiveness of the models in real world, the following chapter deals in detail with their forecasting ability. This chapter, thus, acts as an appetizer for that.

Chapter 5

Selection of Value-at-Risk Model

5.1. Introduction

Variance as a measure of risk was first proposed by Markowitz (1952) and due to its intuitiveness and simplicity it is being used in the industry till date as a valid and efficient method of assessing risk of a security or a portfolio though recently volatility is assuming its place. Emergence of large investment banks and unprecedented increase in the turnover in financial markets has raised competition among financial institutions to a higher level and this has prompted them to go beyond the frontiers and seek profits at levels of risk that could not have been dreamt of previously. This has many pitfalls and the stories of Orange Country, Long Term Capital Management (LTCM) and more recently Lehman Brothers testifies to this fact. The tendency to assume excess risk has necessitated risk mapping of these institutions to a level never seen before from the part of both the management and the regulators. It was in response to this need of the industry and regulators that various models came out both from the industry itself as well as academics. Proliferation of risk measurement models has put the management in difficult waters as selection of a model capable of accounting for the institution's risk is an arduous and tricky task. Many studies have thus attempted to find an answer to this question by testing the existing risk measurement models at empirical level. Variance is at the centre stage of all these models and yet there are models that have gone beyond variance and parametric assumptions as variance alone may not be an appropriate proxy for risk. Hence, a healthy mix of models involving variance and parametric assumptions as well as non-parametric assumptions is necessary if a study on Value-at-Risk model selection has to be comprehensive. This chapter concentrates on testing some of the most popularly used Value-at-Risk forecasting models on an empirical basis. The models include naïve GARCH, EGARCH, GJR GARCH, Historical Simulation, Monte Carlo Simulation, Exponentially Weighted Moving Average (EWMA) model currently used by National Stock Exchange of India (NSE) and the Hybrid approach which was developed as a mix of Historical Simulation and EWMA. The chapter also undertakes back testing of the results using the technique developed by Christoffersen (1998) to find whether any model can be found out as one with universal application. A model will be called a successful one if it can pass all the three back testing in three markets at two different levels of confidence i.e. 95 and 99 per cent.

5.2 Review of Past Studies

A review of the past studies will not only give an idea of the trend of studies held in the past but also an insight in to the gaps that other authors have left in the literature. It will also sharpen focus on the area of study as also the methodology that is to be used.

Engle (1982) in his path breaking paper titled, ‘Auto Regressive Conditional Heteroscedasticity with Estimates of the Variance of United kingdom Inflation’, formulated a new method for modeling variance. These types of models dominated the study on finance in the next two and half decades. Traditional econometric models assumed a constant one period forecast variance. The break through achieved by the paper was the introduction of Auto Regressive Conditional Heteroscedastic (ARCH) process to generalize the rather unrealistic assumption of constant one-period forecast variance. These processes were mean zero and serially uncorrelated with non-constant variances conditional on the past but had the unconditional variance remaining constant. A regression model was then introduced with the disturbances following an ARCH process. Maximum likelihood estimators were described and a simple scoring iteration formulated. According to him, though ordinary least squares method maintained its optimality properties in the set up, maximum likelihood were found to be more efficient. To test whether the disturbances followed an ARCH process, the Lagrange Multiplier procedure was employed. The test was based simply on the auto correlation of the residuals. This model was then used to estimate the mean and variance of the inflation in United Kingdom. ARCH effect was found to be significant and the estimated variances were found to be increasing substantially during the 1970s.

Engle and Susmel (1993) studied the relation between news and volatility by defining the news impact curve which measured how new information was incorporated in to volatility estimates. The study introduced and contrasted several models that allowed different types of asymmetry in the impact of news on volatility. These models were fitted to daily Japanese stock returns from 1980 to 1988. All the models found that negative shocks led to more volatility than positive shocks and this was particularly apparent for larger shocks. The diagnostic technique, however, found the modeled asymmetry to be inadequate. The GJR model was found to the best. The partially non-parametric ARCH model confirmed this behavior. The difference between the former and EGARCH and GJR were manageable under normal conditions but differed widely during extreme shocks. EGARCH was found to be least effective as its estimated conditional variance was seen to be higher than its squared residuals. The results were similar, although less dramatic, when the same analysis was conducted excluding the October 1987 crash. Over all, the results showed a greater impact on volatility for negative return shocks. The results indicated that the GJR model was best at parsimoniously capturing the asymmetric effect.

In a study of the Danish Mortgage Backed Securities (MBS) market, Jakobson (1995) followed the Risk Metrics as much as possible to make the study comparable to the other studies while maintaining uniqueness by keeping the study slightly different from the traditional Risk Metrics approach. The study found that it was possible to include even large portfolios of MBS in to the overall estimates of daily Value-at-Risk. However, it was also found that delta equivalent valuation technique was better than the more recent Monte Carlo simulation approach suggested by Risk Metrics document to obtain ex-ante estimates of Value-at-Risk. The empirical test was performed for one day horizon for the period January 4, 1993 to March 29, 1995 with a total of 566 days on bullet and serial bonds as well as MBS. While the model did well in the case of bullet bonds, its predictability declined considerably coming to the serial bonds and was almost ineffective in the case of MBS. The study attributed this mass failure to the inadequacy of the MBS model. It also pointed an accusing finger at the way correlation structure was calculated.

Bedar (1995) analyzed the pitfalls that one may face while using Value-at-Risk. According to the study the results of Value-at-Risk may vary for the same portfolio of instruments depending on the assumptions, methodology and parameters. The study calculated Value-at-Risk for three hypothetical portfolios using eight types of methodologies. The methods used were HS, Monte Carlo Simulation, both with one day as well as with two weeks horizon with historical correlations provided by Risk Metrics and those provided by Basel Committee. The study found wide variations in results with the Value-at-Risk ranging between one to fourteen times depending on the different assumptions and parameters used. The magnitude of variation, however, did not follow any clear rule of thumb. According to the study, Value-at-Risk did not provide certainty or confidence of outcomes but rather an expectation of outcomes based on a specific set of assumptions. Furthermore, many risk variables such as political risk, liquidity risk, personal risk, regulatory risk, phantom liquidity risk and others could not be captured through the quantitative techniques employed by Value-at-Risk. Therefore, the study recommended supplementing Value-at-Risk not only with stress testing but also with prudent checks and balances, procedures, policies, controls, limits, random audits and appropriate reserves.

The performance of equally weighted and HS Value-at-Risk methods with 50, 125, 250, 500 and 1250 numbers of daily samples as also the EWMA with λ being assigned values of 0.94, 0.97 and 0.99 was analyzed by Hendricks (1996). The study found that all the approaches covered risk adequately and the Value-at-Risk figures did not substantially deviate from one another though small amount of variability was found which was more pronounced for shorter window sizes. 95^{th} percentile was seen to be doing better that the 99^{th} percentile. The outcomes that were not covered by the risk estimates were found to be much higher than the confidence bands. This shows the inability of the models to account for the extreme values present in the return series. In terms of overall performance, the EWMA method was found to be superior. Thus, the study concluded saying that extreme outcomes occurred more often and were larger than predicted by normal distribution and that the size of the market movement was not constant over time.

In an attempt to plug the loopholes in EWMA and historical simulation, Boudoukh *et al.* (1997) developed a new model named hybrid model in which was clubbed the advantages of EWMA and historical simulation. The method attached more weight to the recent observations and also accounted for the fat tails and asymmetry by sampling from the historical series. The study also did an empirical analysis by taking 6 years data from January 1, 1991 to December 5, 1997 for Deutche Mark, oil, S&P 500 and Brady bond index. The study also reported results for equally weighted portfolio of the four return series and for tail events across the four series. 250 days was used as the window size for all models viz. historical simulation, EWMA and hybrid. The results showed a preference towards the non-parametric method with historical simulation and hybrid scoring better than EWMA and between them hybrid was found to be doing better than historical simulation. An examination of the auto correlation structure revealed that the average series had the least auto correlation followed by Brady bond index and oil, showing that the hybrid method is well suited for fat tailed and skewed series. Thus, the study concluded saying that the hybrid method had significant statistical advantages over historical simulation and EWMA especially in cases where fat tails and skewness were present.

Most of the literature on interval forecasts implicitly assumes homoskedastic errors when the results are violated and proceed merely by testing for correct unconditional coverage which in fact, is not very different from nominal coverage. It was Christoffersen (1998) who set out to build a consistent framework for conditional interval forecast evaluation which is crucial when higher order moments are present. The study suggested a likelihood ratio test of conditional coverage which was decomposed in to sub sets of independence and unconditional coverage tests. Extension of the basic set up to include general information sets, asymmetric intervals and multivariate time series were also provided. Using empirical analysis, the study proved that Risk Metrics passed most of the coverage tests but failed in many others. However, GARCH with Student – t distributional assumption passed more number of coverage tests both in terms of getting the dynamics as well as nominal coverage right. It was also observed by the study that both dynamic and parametric forecasts were often rejected in favor of static interval forecast when the desired coverage was high. Risk Metrics did better than GARCH in this regard. The study recommended combining a simply dynamic variance specification with a non-parametric distribution as a favorable alternative.

Theoretical and empirical limitations of Value-at-Risk measures were analyzed by Danielsson and De Vries (2001). According to the study, most existing risk models broke down in times of crisis because the stochastic process of market prices was endogenous to the actions of the market participants and once the risk process is made the target of controls, it changed its dynamics making risk forecasting unreliable. This was, according to the study, prevalent more during times of crises. The current risk forecasting using empirical methods on historical data was lacking in robustness of forecast as it produced excessively volatile forecasts. The study recommended the use of risk models which incorporated insights from economic and financial theory in conjunction with financial data during crisis, which would have the potential to provide much more accurate answers as it would be able to address issues such as liquidity dynamics more directly. It pointed at the simplicity of Value-at-Risk model itself as it curse as chances of manipulation are more due to its simplicity.

Holton (2002) reviewed the history of the development of Value-at-Risk from the start of the last century. According to the study, Value-at-Risk developed on two fronts .viz. portfolio theories and capital adequacy theories. The paper particularly concentrated on the capital adequacy part as the portfolio part had already been analyzed previously. The discussion on the concept started in the 1920's in a non-mathematical manner and the first quantitative assessment had to wait till 1945. Though, development of the concept was subdued during the 1950's and 1960's due to limited processing power, the period saw vital academic contributions from the works of Markowitz, Tobin and Lintner. Unprecedented increase in trading activities in the 1970's and following years exposed, according to the study, the financial institutions to greater risk and it enhanced the importance of Value-at-Risk. This was followed by the establishment of the Basel Committee on banking supervision and its subsequent stipulations on regulatory capital requirements for banks. The G-30 published a report in 1993 which emphasized on risk management relating to derivatives and used the term Value-at-Risk for the first time. But the real boom, according to the review, came only after the introduction of the Risk Metrics by J P Morgan Chase in 1993.

Giorgi (2002) attempted a study on the portfolio selection problem following the mean-risk approach. The study took three forms of deviations or risks viz. standard deviation, Value-at-Risk and the expected short fall. It showed that under the assumption of multivariate Gaussian distributional assumption, the set of efficient portfolios under

Value-at-Risk and expected short fall was a sub set of the set of efficient portfolios under standard deviation. Portfolio selection could be inefficient under Value-at-Risk or expected short fall, but the opposite was never found to occur. Moreover, the set of efficient portfolios under Value-at-Risk was found to be a proper sub set of efficient frontiers under expected short fall. It was also found by the study that a combination of parameters with means and Value-at-Risk and mean and expected short fall at particular levels of α could be empty for value of α greater than a given level. This pointed at the importance of selecting level of α. In the presence of a risk free asset, the set of efficient portfolios under various risk measures were identical unless one of the spaces of the risk measures was empty. Using a general procedure for portfolio selection under expected short fall, the study tried to find an optimum portfolio for a data set from the Swiss market index and obtained an asset allocation similar to the mean-variance allocation.

A comprehensive analysis of the forecasting ability of GARCH models as a tool of analysis for Value-at-Risk calculation was done by Angelidis *et al.* (2004). The study used the unconditional and conditional tests developed by Christoffersen (1998) to bring out the statistical significance of GARCH, EGARCH and TARCH models under different autoregressive (AR) and moving average (MA) terms as well as different p and q orders. The study was conducted on S&P 500, DAX, CAC 40, FTSE 100 and Nikkei to have robustness in results. However, the results produced no uniform conclusion. Nikkei was found to be performing better than all the other markets in most of the models tested. Further, sample size was found to be crucial in producing results as the same model with different sample sizes were found to be producing contrary results. Among distributions, Student – t was found to be delivering better results as compared to either normal or generalized error distribution (GED) and the latter was found to be doing slightly better than normal distribution for the 99 per cent confidence level. There was substantial difference in the results for 95 and 99 per cent confidence levels with the latter giving extremely poor results in most cases. Here also, Nikkei stayed unique by giving close to 1 per cent exceptions. Though shorter sample periods produced better forecasting ability, S&P 500 was found to be an exception as large sample produced better result in this case. Turning now to the models, TARCH was found to be doing better in all cases except under GED and the simpler versions of the volatility models were found to be capturing Value-at-Risk better than the others.

The predictive performance of various classes of Value-at-Risk models in their different varieties like unfiltered and filtered models, parametric and non-parametric distributions, conventional and extreme value distributions and quantile regression and inverted conditional distribution function was undertaken by Bao *et al*. (2004). Making use of the reality check test of White, the study compared the predictive power of alternative Value-at-Risk models in terms of empirical coverage probability and the predictive quantile loss for the stock markets of five Asian economies viz. Indonesia, Korea, Malaysia, Taiwan, Thailand, that underwent the financial crisis of 1997-98. The study was conducted for the period starting from July 1 1988 till December 31 1999. The study found Risk Metrics to be performing well before and after the crisis, while Extreme Value Models were found to be doing better during the crisis. Usefulness of filtering was found to be mixed while forecastability was found to be varying with the confidence level selected. The study concluded saying that prediction of market conditions during crisis was more difficult and yielded poorer results than during tranquil periods and that most Value-at-Risk models generally behaved similarly before and after the crisis but differently during the crisis. The study thus recommended the use of a regime shifting models.

An examination the forecasting performance of three Value-at-Risk models viz. RiskMetrics, normal APARCH and Student APARCH for TAIFEX and SGX-DT, Taiwanese indices, for the period May 7, 1998 to January 31, 2002 and January 21, 1998 to January 31, 2002 respectively was undertaken by Huang and Bor-Jing (2004). All models were tested with a Value-at-Risk level α, which ranged from 5 per cent to 0.01 per cent using a moving window with 500 days data. Generally the Risk Metrics method was found to have the highest failure as it did not pass the unconditional coverage test at 99 per cent level. The Student APACRH model yielded the highest Value-at-Risk estimate and the lowest failure rate. However, it failed the conditional and unconditional tests for the SGX-DT futures. Normal APARCH model generated more accurate Value-at-Risk forecasts as it passed the conditional and unconditional coverage tests for both confidence level and for both markets. Moving to the higher confidence levels, it was observed that the Student APARCH model outperformed the other two not only in terms of coverage but also in terms of giving the least unexpected loss, the credit for which went to the normal APARCH model at more liberal confidence levels. RiskMetrics and normal APARCH models under predicted risk and the former was found to be the least efficient.

A comparison of stochastic volatility and GARCH models using a Markov chain Monte Carlo and importance sampling technique for volatility estimation, model misspecification testing and comparisons for general volatility models, including GARCH and stochastic volatility formations was presented by Gerlach and Frank (2005).

Integrated model likelihood ratios were estimated and employed to compare among competing classes of volatility models. The performance of some GARCH and stochastic volatility models, incorporating fat tailed errors and Markov switching, was computed for the S&P 500 daily return index and the US/Canadian Dollar exchange rates. The comparison as already mentioned was made using integrated likelihoods and residuals, incorporating parameter uncertainty and some model uncertainty. Simulation studies were carried out to confirm that the Bayesian approach was reliable for these models. This general approach presented for carrying out inference, model comparison and misspecification testing in Markov switching stochastic volatility and GARCH models was Bayesian in nature and consisted of parameters and state estimation and model comparison by marginal likelihood and residual tests for model adequacy. For the two real sets of financial data sets analyzed by the study, the simple GARCH model with student t-errors did best in terms of likelihood performance.

2.1 Studies on India

Varma (1999) tested EWMA-GED and GARCH-GED for Nifty index of NSE for the period July 1, 1990 and June 30, 1998. The study took logarithmic return of the index for the mentioned period. It was found by the study that the actual number of Value-at-Risk violation was greater than the expected number for both models under different scenarios, but the difference was not statistically significant in most cases. GARCH-GED was found to be performing better than EWMA-GED as the number of violations in the former was lower than those in the latter. However, the study recommended the use of EWMA-GED over GARCH-GED due to various reasons: EWMA was found to be simpler and easier to understand and was not much different from the moving average which was already familiar to most market participants. EWMA was also found to be more tractable whereas GARCH was found to be more complex and computationally demanding. EWMA model was also found to be more robust under regime shifts as it did not involve any notion of long run volatility whereas GARCH essentially involve such a notion. The study also found the returns to be non-normally distributed as it was having thinner head and fatter tail.

Forecastability of seven models viz. EWMA, GARCH (1, 1), GARCH (2, 2), GARCH (5, 5), EGARCH (1, 1), EGARCH (2, 2) and GJR (1, 1) for different indices of NSE and Bombay Stock Exchange (BSE) using data for the period January 2, 2006 to November 5, 2007 and used the subsequent 22 days to test the efficiency of the models in forecasting the worst case scenarios was done by Das *et al*. (1998). EWMA model tested was the one currently used by NSE. The results showed that all the GARCH models and its variations did better than EWMA model for all the indices. All the EWMA models were found to be in the red light zone while various GARCH models were found to be in yellow or green light zones. The test was repeated with the distributional assumption changing to Student – t, but the results were not the least different. GARCH (1, 1) was found to be giving best forecasting results followed by GARCH (5, 5). Thus, the study concluded by saying that the EWMA model currently used by NSE and which was actually recommended for use by a study of Varma (1997) fared worse as compared to more conventional heteroskedasticity models.

Sarma *et al.* (2001) examined how a Value-at-Risk model should be selected, setting statistical accuracy as an important model selection criteria. The study forecasted Value-at-Risk using historical simulation, Risk Metrics, GARCH and EWMA and subjected these models to conditional coverage tests developed by Christoffersen as also loss function developed by Lopez (1998) and regression based tests for finding higher order dependence among exceptions. Generally, sample sizes of 50, 125, 250, 500 1250 were used and for Risk Metrics the value of λ selected were 0.90, 0.94, 0.96 and 0.99. The study found historical simulation to be doing poorly in terms of Value-at-Risk prediction as very few models passed the preliminary tests. Same was the case with GARCH model but it did better than historical simulation and EWMA in terms of surviving the regression based tests and moving in to the loss function. Though many of the EWMA based models passed the initial tests, none of them survived regression test. Only Risk Metrics with λ = 0.90 passed all the tests and that too only from the firm's side. Shorter sample sizes were found to be doing better and in terms of confidence level 95 per cent did better on aggregate though none of the models passed all the tests. S&P 500 could get no models passed at the 99 per cent level and over all Nifty results were seen to be giving better forecasts.

The limitations of conventional Value-at-Risk evaluation methods were brought to light by Darbha (2001). It was not possible to measure the intensity of the loss; neither could the tail be properly captured as it was highly volatile. Further, introduction of a new model necessitated recalculation of Value-at-Risk for the entire portfolio. The study formulated the Hybrid approach as a combination of HS and extreme value theory (EVT) to find Value-at-Risk for a portfolio of 18 fixed income securities. The study used an in sample data length of 850 days and 250 day's data was used for back testing purposes. The confidence level used was 99 per cent. The data was found to have excess kurtosis as well as negative skewness underlining the non-normality. None of the models, HS, normal or EVT, outperformed the other at one day horizon. Failures of all the models were higher than expected but within the confidence bands. EVT was found to have least amount of Value-at-Risk. HS and normal methods produced no failures at ten day and one month horizons while EVT produced failures close to the theoretical levels and the amount of Value-at-Risk was much less in this case and the tendency got magnified as a move was made from 10 day to one month. The paper concluded that the adoption of EVT should not be based on empirical evidence but from its theoretical soundness. It also suggested use of 10 day Value-at-Risk with a smaller multiplication factor.

Nath and Varma (2003) in a paper discussed issues relating to the implementation of Value-at-Risk models for the portfolios of Government of India (GOI) securities held by banks and primary dealers. The study analyzed the performance of three models viz. normal-variance-covariance, HS and EVT using Hill's estimator. The study used the simple nominal coverage with realized returns as compared to capital charges as the back testing strategy and took 290 days as window size which amounts to a year in bond market. The study used GOI bonds outstanding as on June 23rd 2003 for the analysis. The study found that Value-at-Risk models under normality assumption for rolling samples as well as the Risk Metrics approach performed poorly as the number of Value-at-Risk violations were found to be much higher than expected. In the case of full sample homoscedastic normality and also for HS approach, the number of failures was closer to expectations. The Hill's tail index based Value-at-Risk was found to be the best by giving better coverage as it produced larger Value-at-Risk figures. The detailed back testing results for selected GOI bonds also revealed similar findings. Number of failures in the case of Hill's tail index based Value-at-Risk model never exceeded the theoretical number. For HS method, estimates exceeded the theoretical levels in a few cases. The performance of normal based Value-at-Risk models generally and Risk Metrics in particular was found to be worse.

Due to the huge data requirements imposed by the conventional HS method, Dutta and Bhattacharya (2008) used a bootstrapped methodology of Historical Simulation (HS) to calculate Value-at-Risk for Nifty. The study analyzed the relative performance of various types of Value-at-Risk techniques. 95 per cent level was selected as the confidence level and 5 days as the forecast horizon. The data analyzed was from April 1st 2000 to March 31st 2007. The study found the returns to have fatter tails than a normal distribution using the Q-Q plot and rejected parametric methods and especially normal distribution as unrealistic. It found the 5 day Value-at-Risk to be 49.935 for HS and 92.5742 for expected short fall. Using the bootstrapped method of HS, the study found Value-at-Risk to be 51.2312. Since, HS accounted for the non-linearity present in the data set because of its association with volatilities and correlations present in the historical data, the study recommended the use of HS with boot strapped methodology as HS alone might not have all the stressed scenarios.

Review of the literature over the years available on the problem shows that there has been very few studies on the Indian equity market and that whatever studies that have taken place have attempted only a preliminary analysis. They have been limited in terms of number of models, window sizes, types of distributions and the kind of markets studied. This can be seen at the international level also. This points at the importance of a comprehensive study aimed at touching every aspect of model selection as far as possible, hence, the importance of the study that is being contemplated.

5.3 Methodology

The study seeks to find the best model from a variety of Value-at-Risk models available in the literature through a careful empirical analysis. As such, it deals with a number of models popularly used in the industry to obtain Value-at-Risk figures. The study uses seven such models, naïve GARCH, EGARCH, GJR GARCH, Historical Simulation, Monte Carlo Simulation, EWMA used by NSE and the Hybrid approach for window sizes of 250, 500, 1000 and 1500. 1000 one day ahead Value-at-Risk figures are predicted for facilitating back testing. Detailed procedures for all of the above models are given in Chapter 4 and hence are dropped here for the sake of avoiding redundancy. However, it would be prudent to give a roundup of the basic procedure involved in each model.

5.3.1 Conditional Volatility Models

The GARCH family of models pioneered by Engle (1982) and later developed by Bollerslev (1986) estimate conditional volatility. The simple AR (1) - GARCH (1, 1) model is as follows;

$$r_t = \tau + \mu\, r_{t-1} + \varepsilon_t, \text{ where, } \varepsilon_t \mid F_{t-1} \sim N(0,\sigma_t^2)$$

r_t is current return and r_{t-1} is previous return, ε_t is the error term and F_{t-1} is the information set up to t_{-1} and σ_t^2 is conditional variance.

$$\sigma_t^2 = \alpha + \beta\, \sigma^2_{t-1} + \gamma\, \varepsilon^2_{t-1}$$

Here, the first equation captures the error term and the second equation estimate the standard deviation (SD) as a function of previous period's error term, ε_{t-1}^2 and previous period's SD, σ^2_{t-1}. After obtaining the conditional SD, Value-at-Risk is found out under the assumption of normal and Student – t distribution by multiplying the resultant SD with the value of the confidence level for the respective distributions assumed.

The naïve GARCH model discussed above has the empirical limitation that it fails to capture asymmetry reflected in stock movement as a function of the nature of information, i.e. the tendency of volatility to increase more as a result of a negative news (ε_t <0) than to a positive news (ε_t >0). As this is an important observed phenomenon, the paper also proposes to use the asymmetric GARCH, which is called Exponential GARCH or EGARCH expounded by Nelson (1991), which is a widely used model to capture asymmetry in the return distribution.

$$\ln(\sigma_t^2) = \alpha + \beta\ (\epsilon_{t-1}^2/\sqrt{\sigma_{t-1}^2})\ + \gamma\ \left|\varepsilon_{t-1}^2/\ \sigma_{t-1}^2\right| +\ \rho\ \ln(\sigma_{t-1}^2)$$

The new coefficient β in the above equation represents the asymmetric behavior. A negative sign to β will imply the presence of asymmetry and then the stock price volatility will increase to a greater extent as a result of a negative shock than to a positive one.

An advantage of this model is that there is no need for imposing non-negativity constraints. Second advantage is, obviously, that it allows for asymmetry. Thirdly, instead of using the value of u_{2t-1}, the EGARCH model uses the level of standard value u_{t-1}. According to Nelson, this allows for more natural interpretation of the size and persistence, of shocks as u_{t-1} is a unit free measurement.

Glosten *et al.* (1993), in a different way showed how to allow the effects of good and bad news to have different effects on volatility. The conditional variance here is given by,

$$\sigma_t^2 = \alpha_0 + \alpha_1\, \varepsilon_{t-1}^2 + \beta\, d_{t-1}\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2$$

Where, $d_{t-1} = 1$, if $\varepsilon_{t-1}^2 < 0$

$= 0$ otherwise.

σ_t^2 current day variance and σ_{t-1}^2 and ε_{t-1}^2 are previous day's variance and previous day's error squared.

If $\gamma > 0$, it is safe to assume that there is asymmetry in equity return behavior.

After obtaining the conditional SD, Value-at-Risk is found out for normal and Student - t distribution as done above for the naïve GARCH model. For all the above models a 5 and 1 per cent levels of confidence are used. The conditional SD is obtained using as many data points as necessary and in this process we move forward one day at a time.

Eg: For a model of 1500 observations, 1501st day's Value-at-Risk forecast is made using the first 1500 observations. For the 1502nd day's Value-at-Risk forecast, first day is dropped and return from 2nd to 1501 are used and this process goes on until we have sufficient number results - the study uses 1000 such one step ahead forecasts - for back testing purposes.

5.3.2 Historical Simulation

The foundation of historical simulation is in the theory that history repeats itself even in financial markets. In the context of the present study, for each window size, respective number of observations is taken and they are then arranged in ascending order of their magnitude to find the lower 5 per cent plus one value and one per cent plus one value to find Value-at-Risk at five and one per cents respectively. Window is then rolled over to find the next day's Value-at-Risk.

5.3.3 Monte Carlo Simulation

First thing to be done under this method is to define parameters viz. mean and variance of each of the samples taken under all the window sizes. A simulation is done followed by this which will give 1000 observations having the defined characteristics and the lower five and one per cent values are separated to take the next value which is defined as the Value-at-Risk for the next day. Window size is then rolled over by dropping the first day return and extending in to the n+1th day and the same procedure is repeated till 1000 results are obtained.

5.3.4 EWMA used by NSE

The method involves finding the log return on the respective index and then finding the standard deviation using the first equation given in section 4.7. The next step involves the prediction of next day's standard deviation using the next equation given in section 4.7. A weight of 0.94 is given to the current day's standard deviation while predicting next day's standard deviation which shows how rapidly volatility estimates change. The observed standard deviation is then multiplied by three to get the Value-at-Risk figure for next day.

5.3.5 Hybrid Approach

As the name implies this is a combination of two methods viz. EWMA and historical simulation. Under this method, realized returns from t-1 to t are given weightages of [(1-λ) / (1-λ)k], [(1-λ) / (1-λ)k] λ, …., [(1-λ) / (1-λ)k] λk-1 respectively. The constant, [(1-λ)

/ (1-λ) k], ensures that the weights sum to 1. These weighted returns are then ordered in the ascending order of their magnitude and to obtain Value-at-Risk at x per cent weightages are accumulated until x per cent is reached and the value corresponding to x percentage is denoted as next day's Value-at-Risk. Linear interpolation is used between adjacent points to achieve exactly x per cent of the distribution when two accumulated weights lie at either side of the confidence level.

5.3.6 Back Testing

Back testing of estimated Value-at-Risk figures is done on the basis of the philosophy that the correctly specified Value-at-Risk model failures should not exceed the pre-specified failure rate. For this purpose Peter F Christoffersen (1998), has developed three tests, viz.

1. Test of correct unconditional coverage
2. Test of independence
3. Test of correct conditional coverage

These tests as well as the loss function which is to follow were extensively used by Sarma *et al.* (2001) and Angelidis *et al*. (2004) in their papers.

For back testing Christoffersen defines failure rate It as;

I_t = {1 if $r_t < v_t$

{0 otherwise

v_t is the forecast value of Value at Risk. The tests are carried out in the Likelihood Ratio (LR) framework.

5.3.6.1 Correct Unconditional Coverage Test

Here the null hypothesis is that the failure probability is p.

$$LR_{uc} = -2 \log [p^{n1}(1-p)^{n0} \diagup \pi^{n1}(1-\pi)^{n0} \sim \chi 2 \ (1)$$

P: confidence level

n1: number of failures, i.e. Value at Risk exceedences

n0: number of successes

π: $n_1 \diagup n_0 + n_{1,}$ the MLE of p.

5.3.6.2 Test of Independence

In the test for independence, the hypothesis of an independently distributed failure process is tested against the alternative of a Markov first order failure process.

$$LR_{ind} = -2 \log (1-\pi_2)^{(n00+n10)} \ \pi_2^{(n01 + n11)} \diagup (1-\pi_{01})^{n00} \pi_{01}^{n01}(1-\pi_{11})^{n10}\pi_{11}^{n11} \sim \chi^2$$

(1)

Where,

n_{ij} = number of i_s followed by number of j_s

$\pi_{ij} = \Pr \{I_t = i/I_{t-1} = j\}$ (i,j=0)

$\pi_{01} = n_{01} \diagup n_{00} + n_{01}$

$$\pi_{11} = n_{11} \Big/ n_{10} + n_{11}$$

$$\pi_2 = n_{01} + n_{11} \Big/ n_{00} + n_{01} + n_{10} + n_{11}$$

5.3.6.3 Test of Correct Conditional Coverage

In the correct conditional coverage, the null hypothesis of an independent failure process with failure probability p is tested against the alternative hypothesis of first order Markov process with a failure process different from p.

$$LR_{cc} = -2 \log (1-p)^{no} p^{n1} \Big/ (1-\pi_{01})^{n00} \pi_{01}^{n01}(1-\pi_{11})^{n10} \pi_{11}^{n11} \sim \chi2 \ (2)$$

The values in the brackets in the equations signify the degrees of freedom of the LR estimates that are defined to be distributed as Chi-Square.

5.4 Data

The study uses three indices viz. Nifty, Nifty Junior and Nikkei, to find Value-at-Risk and for subsequent analyses. The data for Nifty and Nifty Junior are collected from the official web site of the National Stock Exchange of India and that for Nikkei from Econstats web site. They are daily returns ranging from 1st January 1997 to 20th July 2007. Nifty and Nifty Junior have a total of 2641 observations while Nikkei has 2588.

5.5 Empirical Analysis

Available data should have some desirable properties if it has to be subjected to econometric investigation. Hence, it is advisable to have an idea of the basic characteristics of the data before a thorough empirical investigation is conducted on it. This will help to channel the investigation in to more realistic avenues. It may also help in the interpretation of the results once they are available.

5.5.1 Basic Statistics

Table 5.1 Basic Data Analysis

Parameters	NJR	NKR	NR
Mean	0.00985	7.94E-05	0.000732
Median	0.001868	5.00E-05	0.001374
Standard Deviation	0.018825	0.014446	0.015985
Skewness	-0.51277	0.0333	-0.27247
Kurtosis	6.764256	4.881921	7.65799
Jarque-Bera	1674.981	382.236	2420.237

NJR, NKR and NR denote returns on Nifty Junior, Nikkei and Nifty

Observation of the table on basic statistics shows that Nifty Junior has the highest mean and median followed by its senior counterpart Nifty. It is the same in the case of standard deviation also thus intuitively showing that Nifty Junior is the riskiest of the three. Indian markets are seen to be negatively skewed while the Japanese market is slightly positively skewed. High values for kurtosis indicates the fat tailed nature of the data necessitating a fat tailed distribution in the study which is done by having a Student – t distributional assumption. This tendency is further confirmed by the high Jarque-Bera values for the three markets thereby rejecting the possibility of the data having normal distribution.

5.5.2 Test for Stationarity

Data need to be stationary at the level at which it is being econometrically examined. Normally data on financial variables are non-stationary at the level and stationary only at first difference. The study uses daily return and hence the data is expected to be stationary. However, it is imperative in this type of studies to confirm it before conclusions are drawn.

Table 5.2 Test of stationarity

Indices	ADF	PP	KPSS
NR	-37.4094 (-3.4326)	-48.4473 (-3.4326)	0.2335 (0.739)
NJR	-35.8463 (-3.4326)	-44.6575 (-3.4326)	0.1677 (0.739)
NKR	-38.9457 (-3.4326)	-53.059 (-3.4326)	0.3180 (0.739)

(i) Figures in parenthesis are‘t’ values at one per cent level of significance (ii) NR, NJR and NKR denote Nifty, Nifty Junior and Nikkei returns

The table is self explanatory and all variables are seen to be stationary at one per cent level itself with all the three tests. Hence, the three data series can be used to do econometric investigation without the possibility of the results having less validity.

5.5.3 Why Student – t Distribution?

Examination of the basic statistics for all the three indices shows that the return distribution is not normally distributed but possesses thinner heads and fatter tails than a normal distribution thus approximating them to a Student – t distribution. The distribution was published by Gosset (1908) and has a probability distribution of the ratio,

$$\frac{z}{\sqrt{\frac{v}{\vartheta}}} = \mathrm{z}\sqrt{\frac{\vartheta}{v}}$$

Where, z is normally distributed with expected value zero and variance 1,

V has a Chi-square distribution with v degrees of freedom

And Z and V are independent

And it has a probability density function which can be defined as,

$$f(t) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi}\,\Gamma(\frac{\nu}{2})}\left(1+\frac{t^2}{\nu}\right)^{-(\nu+1)/2},$$

Where v is the number of degrees of freedom and Ѓ is the Gamma function.

Thus, the study also uses Student – t distribution along with the normal one in running models in which parametric assumption is involved like conditional heteroskedasticity and Monte Carlo simulation models. This is expected to account for the fat tails of returns on the indices as found in the investigation of basic statistics.

5.5.4 Back Testing Results

This section deals in detail with the back testing results for the models that are used to find out Value-at-Risk of the three indices. Tables are arranged in such a way that a model with a particular distribution is followed by the same model with another distribution for one of the markets. This will be followed by the other two markets and in this way the results for the entire models used in the study will be reviewed. The section starts with the analysis of EGARCH model with normal distribution for Nifty. The 95 and 99 values signify the respective confidence level while *uc*, *ind* and *cc* signify unconditional coverage, independence and conditional coverage respectively for all the tables.

5.5.5 Conditional Volatility Models

Empirical analysis will start with the conventional conditional heteroscedasticity models themselves.

Table 5.3 EGARCH (1, 1) for Nifty with Normal Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.8	0.0832	0.0343	0.2243	97.8	10.8382*	0.3507	11.3262*
		500	94.8	0.0832	0.6082	0.7983	97.7	12.4853*	0.4435	12.8825*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(2,0)		250	94.7	0.1860	0.0138	0.3081	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	1.0696	1.9157	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141*
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(0,1)		250	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758*
		500	94.8	0.0832	0.6082	0.7983	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141*
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(0,2)		250	94.7	0.1860	0.0138	0.3087	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	1.0696	1.9157	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.2	5.2251**	0.9535	6.2150**
		1500	95.7	1.0807	2.1004	3.2691	98.4	3.0766	1.3076	4.4165
(1,1)		250	94.6	0.3287	0.0025	0.4422	97.9	9.2840	0.5493	9.8758*
		500	94.4	0.7308	1.0696	1.9157	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141*
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(1,2)		250	94.7	0.1860	0.0138	0.3087	97.9	9.2840*	0.5493	9.8758*
		500	94.3	0.9889	0.9238	2.0301	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141*
		1500	95.7	1.0807	2.1004	3.2691	98.4	3.0766	1.3076	4.4165
(2,1)		250	94.6	0.3287	0.0025	0.4422	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.9238	2.0301	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141*
		1500	95.7	1.0807	2.1004	3.2691	98.4	3.0766	1.3076	4.4165
(2,2)		250	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758*
		500	94.3	0.9889	0.1816	1.2880	97.7	12.4853*	0.3507	12.8825*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464

The model passes all the three tests, viz. unconditional coverage, independence and conditional coverage tests, with 95 per cent confidence level comfortably. But the results are found to be drastically different when it comes to the 99 per cent confidence level. Only ARMA (0, 2), (1, 2) and (2, 1) with 1500 observations are found to clear all the three tests. All the models pass the independence test. But as the models are required to clear all the three tests simultaneously, only the above mentioned three models can be said to be passing the coverage tests.

Table 5.4 EGARCH (1, 2) for Nifty with Normal Distribution

			95				99			
ARMA	EGARCH	Observations	coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,2)	250	94.8	0.0832	4.7724**	5.2121	97.8	10.8382*	0.8032	7.3141**
		500	94.8	0.0832	3.1440	3.4390	97.7	12.4853*	0.6688	8.5365**
		1000	95	0	0.6657	1.8344	98.1	6.4725*	1.1211	5.2464
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(2,0)		250	94.4	0.7308	0.0138	4.9468	98.2	5.2251**	0.9535	6.2150**
		500	94.6	0.3287	1.0696	3.3141	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	0.9956	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(0,1)		250	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		500	94.7	0.1860	3.1440	3.4390	98	7.8272*	0.6688	8.5365**
		1000	95.6	0.7885	0.5531	1.4316	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(0,2)		250	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		500	94.6	0.3287	2.8744	3.3141	98.1	6.4725	0.8032	7.3141**
		1000	95.1	0.0212	2.2913	3.4390	98.2	5.2251**	1.1211	5.2464
		1500	95.7	10.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(1,1)		250	94.7	0.1860	3.1440	3.4390	98	7.8272*	0.6688	8.5365**
		500	94.7	0.1860	3.1440	3.4390	98	7.8272*	0.6688	8.5365**
		1000	95.5	0.5438	0.4517	1.0877	98.3	4.0910**	1.1211	5.2464
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(1,2)		250	94.9	0.0209	3.7266	3.8523	98.2	5.2251**	0.9535	6.2150**
		500	94.6	0.3287	2.8744	3.3141	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(2,1)		250	94.6	0.3287	2.8744	3.3141	98.2	5.2251**	0.9535	6.2150**
		500	94.6	0.3287	2.8744	3.3141	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(2,2)		250	95.2	0.0853	4.7150	4.8987	98	7.8272*	0.6688	8.5365**
		500	94.5	0.5105	2.6187	3.2424	97.9	9.2840	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	1.8835	2.7620	98.5	2.1892	1.5151	3.7346

This model is more complicated than the earlier one as shown by the ordering of the conditional Heteroscedasticity term. Like the earlier one all except one of the different variations of this model clears the three tests under than 95 per cent level of confidence. Rate of success falls even more when it comes to 99 per cent level of confidence as only ARMA (2, 2) with 1500 observation clears all the three tests. Independence criteria is cleared both in the 95 and 99 per cent levels by all except one model. But results are unimpressive when it comes to the issue of simultaneity.

Table 5.5 EGARCH (2, 1) for Nifty with Normal Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	Lruc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	94.7	0.1860	0.5016	0.7966	97.7	12.4853*	0.4435	11.3262*
		500	94.5	0.5105	1.2272	1.8509	97.7	12.4853	0.3507	12.8825*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.8835	2.7620	98.2	5.2251**	0.9535	6.2150**
(2,0)		250	95.3	0.1932	2.9447	3.2342	97.6	14.2244*	5.5746**	19.8446*
		500	94.3	0.9889	2.1478	3.2542	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.2	5.2251**	0.9535	6.2150**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(0,1)		250	94.7	0.1860	0.5016	0.7306	98	7.8272*	0.6688	8.5365**
		500	94.5	0.5105	1.2272	1.8509	97.7	12.4853	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(0,2)		250	94.8	0.0832	0.0343	0.2243	98	7.8272*	0.6688	8.5365**
		500	94.2	1.2843	1.9320	3.3358	97.7	12.4853	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.2	5.2251**	0.9535	6.2150**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(1,1)		250	94.7	0.1860	0.0142	0.2002	98	7.8272*	0.6701	8.4973**
		500	94.4	0.7308	1.0696	1.9157	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.8835	2.7620	98.2	5.2251**	0.9535	6.2150**
(1,2)		250	94.7	0.1860	0.0142	0.2002	97.9	9.2840*	0.5504	8.4973**
		500	94.1	1.6162	1.7346	3.3508	97.7	12.4853*	0.3517	12.8825*
		1000	95.1	0.0212	0.9991	1.0203	98.1	6.4725*	0.8045	7.3141**
		1500	95.6	0.7885	1.8880	2.6764	98.3	4.0910**	1.1226	5.2464
(2,1)		250	94.6	0.3287	0.0027	0.3313	98	7.8272*	0.6701	8.4973**
		500	94.1	1.6162	1.8829	3.4668	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.7289	2.7620	98.3	4.0910**	1.1211	6.2150**
(2,2)		250	94.9	0.0209	0.0651	0.0860	98.1	6.4725*	0.8045	7.2770**
		500	94.2	1.2843	0.1272	1.5310	97.7	12.4853*	0.3507	12.8825*
		1000	95.3	0.1932	1.3128	1.6023	98	7.8272*	0.6688	8.5365**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464

Back testing result for this model looks more interesting. While the 95 per cent level model passes all the three tests of coverage like the earlier two models it follows the other two models in a more dramatic fashion when it comes to the 99 per cent level of confidence. While at least one of the different specifications of the earlier models were found to be clearing all the tests, none of the models under 99 per cent level of confidence under EGARCH (2, 1) is seen to be simultaneously passing all of the three tests. It thus automatically leads to the conclusion that EGARCH (2, 1) does not help in predicting Value-at-Risk figure at an acceptable level of confidence.

Table 5.6 EGARCH (2, 2) for Nifty with Normal Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,2)	250	95	0	0.8550	0.9576	97.8	10.8382*	0.4435	11.3262*
		500	94.3	0.9889	0.9238	2.0301	97.9	9.2840*	0.5493	9.8758*
		1000	95.2	0.0853	1.1481	1.3318	98	7.8272*	0.6688	8.5365**
		1500	95.7	1.0807	2.1004	3.2691	98.1	6.4725*	0.8032	7.3141**
(2,0)		250	94.8	0.0832	1.8835	2.7620	97.9	9.2840*	0.9535	6.2150**
		500	94.7	0.1860	0.5016	0.7966	97.9	9.2840*	0.5493	9.9758*
		1000	95.2	0.0853	1.7731	1.9631	98	7.8272*	0.5493	9.8758*
		1500	95.6	0.7885	1.1481	1.3318	98.2	5.2251**	0.6688	8.5365**
(0,1)		250	95	0	0.8550	0.9576	97.8	10.8382*	0.4435	11.3262*
		500	94.3	0.9889	0.5474	2.0301	97.9	9.2840*	2.2896	2.6935
		1000	95.3	0.1932	1.3128	1.3318	98	7.8272*	0.6608	8.5365**
		1500	95.7	1.0807	2.1004	3.2691	98.1	6.4725*	0.8032	7.3141**
(0,2)		250	94.8	0.0832	1.7731	1.9631	97.7	12.4853*	2.5738	15.1056*
		500	96.7	6.8784*	5.0305**	12.0827*	98.7	0.8306	2.0028	2.8596
		1000	95.2	0.0853	1.1481	1.3318	98	7.8272*	0.6688	8.5365**
		1500	95.6	0.7885	1.8835	2.7620	98.2	5.2251**	0.9535	6.2150**
(1,1)		250	94.8	0.0853	0.6082	0.7983	97.9	9.2840*	0.5493	9.8758*
		500	94.2	1.2843	0.7894	2.1932	97.8	10.8382*	0.4435	11.3262*
		1000	95.2	0.0853	1.1481	1.3318	98	7.8272*	0.6688	8.5365**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(1,2)		250	94.8	0.0832	1.7731	1.9631	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.9238	2.0301	97.8	10.8382*	0.4435	11.3262*
		1000	95.2	0.0853	1.1481	1.3318	98	7.8272*	0.6688	8.5365**
		1500	95.7	1.0807	2.1004	3.2691	98.4	3.0766	1.3076	4.4165
(2,1)		250	94.7	0.1860	1.5787	1.8737	97.5	16.0430*	2.0598	18.1535*
		500	96.9	8.7393*	0.9254	9.7277*	98.8	0.3798	2.2896	2.6935
		1000	95.7	1.0807	1.3128	1.6023	98	7.8272*	0.6688	8.5365**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(2,2)		250	95.1	0.0212	2.4347	2.5564	97.7	12.4853*	2.5738	15.1056*
		500	94.6	0.3287	1.3968	1.8366	97.6	14.2244*	0.2700	14.5401*
		1000	95.2	0.0853	1.1481	1.3318	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464

EGARCH (2, 2) with various ARMA orders are tested and found to be not very different from other models. All except two models, viz. ARMA (0, 2) with 500 observations and ARMA (2, 1) with the same number, pass the three tests under 95 per cent confidence levels. All the models pass independence test under 95 per cent as well as 99 per cent confidence levels. But only ARMA (1, 2) with 1500 observations is seen to pass unconditional and conditional coverage tests as also the test of independence. All the models tested for Nifty with EGARCH-Normal distribution have been reviewed and those of Nifty Junior are next in turn.

Table 5.7 EGARCH (1, 1) for Nifty Junior with Normal Distribution

			95				99			
ARMA Order	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.1%	1.6162	3.4353	3.5185	97.8%	10.8382*	1.2838	8.4973**
		500	94.3%	0.9889	2.1478	3.2542	98%	7.8272*	0.6688	8.5365**
		1000	95.5%	0.5438	1.6801	2.3161	98.1%	6.4725*	0.8032	7.3141**
		1500	95.6%	0.7885	1.8835	2.7620	98%	7.8272*	3.5057	11.3734*
(2,0)		250	94.8%	0.0832	3.4353	3.5185	98%	7.8272*	0.6701	8.4973**
		500	94.2%	1.2843	3.4887	4.8925	98.1%	6.4725*	0.8032	7.3141*
		1000	95.4%	0.3457	1.4900	1.9300	98.1%	6.4725*	0.8032	7.3141**
		1500	95.6%	0.7885	1.8835	2.7620	98.1%	6.4725	3.8666**	10.3775*
(0,1)		250	94.6%	0.3287	4.7724**	5.2121	98.2%	5.2251**	0.6606	5.9221
		500	94.3%	0.9889	3.7874	4.8938	98%	7.8272*	0.6688	8.5365*
		1000	95.4%	0.3457	1.4900	1.9300	98.1%	6.4725*	0.8032	7.3141**
		1500	95.6%	0.7885	1.8835	2.7620	98%	7.8272*	3.5057	11.3734*
(0,2)		250	94.9%	0.0209	3.7266	3.8523	98%	7.8272*	0.6688	8.5365**
		500	94.4%	0.7308	4.1007**	4.9468	98%	7.8272*	0.6688	8.5365**
		1000	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	0.6688	8.5365**
		1500	95.5%	0.5438	1.6801	2.3161	98.1%	6.4725%	0.6688	7.3141**
(1,1)		250	94.8%	0.0832	3.4280	3.6180	98.2%	5.2251**	0.6606	5.9221
		500	94.3%	0.9889	3.7874	4.8938	98%	7.8272*	0.6688	8.5365**
		1000	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	0.6688	8.5365**
		1500	95.6%	0.7885	1.8835	2.7620	98.1%	6.4725*	0.8032	7.3141**
(1,2)		250	94.7%	0.1860	3.1440	3.4390	98%	7.8272*	0.6688	8.5365**
		500	94.2%	1.2843	1.9320	3.3358	98.2%	5.2251**	0.6606	5.9221
		1000	95.4%	0.3457	1.4900	1.9300	98.1%	6.4725*	0.7368	7.2477**
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(2,1)		250	94.9%	0.0209	3.7266	3.8523	98%	7.8272*	0.6688	8.5365**
		500	94.2%	1.2843	3.4887	4.8925	98.1%	6.4725*	0.7368	7.2477**
		1000	95.4%	0.3457	1.4900	1.9300	98.1%	6.4725*	0.7368	7.2477**
		1500	95.5%	0.5438	1.6801	2.3161	98.1%	6.4725*	0.7368	7.2477**
(2,2)		250	94.6%	0.3287	4.7724**	5.2121	97.9%	10.8382*	0.5493	9.8758*
		500	94.3%	0.9889	2.1478	3.2542	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.4942	1.8399	98%	7.8272*	0.8164	8.6436**
		1500	95.8%	1.4215	2.3315	3.8389	98.2%	5.2251**	0.9535	6.2150**

An examination of the results of back testing for Nifty Junior with EGARCH (1, 1) and normal distribution shows that all except three varieties, viz. ARMA (0, 1), (0, 2) and (2, 2) with 250, 500 and 250 observations respectively, pass all the three tests used under 95 per cent level of confidence. But as already found for Nifty, the results are substantially different when it comes to the 95 per cent level of confidence. Though all expect one model pass the independence test only one model, ARMA (2, 0) with 1500 observations, pass the unconditional coverage test and only four models, ARMA (0, 1), (1, 1), (1, 2) and (2, 2) with 250, 250, 500 and 500 observations respectively pass conditional coverage test. But none of the models pass all the tests simultaneously.

Table 5.8 EGARCH (1, 2) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	94.1%	1.6162	2.3766	3.2227	97.8%	10.8382*	2.3071	16.5771*
		500	94.3%	0.9889	0.4059	0.8456	98%	7.8272*	2.5738	15.1056*
		1000	95.5%	0.5438	1.8835	2.7620	98.1%	6.4725*	0.9535	6.2150**
		1500	95.6%	0.7885	1.4900	1.9300	98%	7.8272*	0.6606	5.9221
(2,0)		250	94.4%	0.7308	3.4353	3.2227	97.6%	14.2244*	0.2700	14.5401*
		500	94.4%	0.7308	3.4887	1.9157	97.8%	10.8382*	2.8613	13.7440*
		1000	95.6%	0.7885	1.4900	2.7620	98.3%	4.0910**	0.5886	4.7139
		1500	95.5%	0.5438	1.8835	2.3161	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	94.5%	0.5105	2.6187	3.2424	97.7%	12.4853*	2.5738	15.1056*
		500	94.5%	0.5105	0.3208	0.9444	97.7%	12.4853*	2.5738	15.1056*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.4	0.7308	2.3766	3.2227	97.4	17.9466*	1.8308	19.8301*
		500	94.4	0.7308	1.0696	1.9157	97.8	10.8382*	2.8613	13.7440*
		1000	95.5	0.5438	1.6801	2.3161	98.3	4.0910**	0.5886	4.7139
		1500	95.5	0.5438	1.6801	2.3161	98.4	3.0766	0.5209	3.6297
(1,1)		250	94.3%	0.9889	3.7874	4.8938	97.6%	14.2244*	2.3071	16.5771*
		500	94.1%	1.6162	0.6662	2.4042	97.8%	10.8382*	2.8613	13.7440*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.5%	0.5438*	1.6801	2.3161	98.3%	4.0910	0.5886	4.7139
(1,2)		250	94.6%	0.3287	1.3968	1.8366	97.6%	14.2244*	2.3071	16.5771*
		500	94%	1.9842	1.5542	2.6622	97.6%	14.2244*	2.3071	16.5771*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,1)		250	94.6%	0.3287	1.3968	1.8363	97.6%	14.2244*	1.8308	19.8301*
		500	94.3%	0.9889	0.9238	2.0301	97.8%	10.8382*	2.8613	13.7440*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.3%	4.0910**	0.5886	4.7139
(2,2)		250	94.7%	0.1860	3.1440	3.4390	97.4%	17.9466*	1.8308	19.8301*
		500	94.2%	1.2843	0.1272	1.5310	97.9%	9.2840*	3.1714	12.4979*
		1000	95.7%	1.0807	2.1004	3.2691	98.2%	5.2251**	0.6606	5.9221
		1500	95.4%	0.3457	1.4900	1.9300	98.5%	2.1892	0.4573	2.6768

Nominal coverage at the 95 per cent level of confidence varies between a small range of 94.1 to 95.7 per cent and hence conditional and unconditional coverage tests are passed without any frill in this case. Since, the failures are not clustered together and are not dependent, test of independence is also passed comfortably at the 95 per cent level. However, things change enormously at the 99 per cent level. Only five, ARMA (0, 1), (0, 2), (1, 1), (1, 2) and (2, 2), of the 32 models are seen to pass all the three tests simultaneously. Although this is a more complicated model than the simple EGARCH (1, 1), this one fares better than the other as five are selected from this instead of none from the earlier one.

Table 5.9 EGARCH (2, 1) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	94.2%	1.2843	1.9320	3.3358	98%	7.8272*	0.6688	8.5365**
		500	94.7%	0.1860	3.1440	3.4390	97.8%	10.8382*	0.4435	11.3262*
		1000	95.3%	0.1932	1.3128	1.6023	98.2%	5.2251**	0.6606	5.9221
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(2,0)		250	93.9%	2.3877	2.6764	5.1900	97.9%	9.2840*	0.5493	9.8758*
		500	94.8%	0.0832	3.4280	3.6180	97.6%	14.2244*	2.3071	16.5771*
		1000	95.5%	0.5438	0.4517	1.0877	98.2%	5.2252**	0.6606	5.9221
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	93.9%	2.3877	1.3597	3.8733	98.1%	6.4725*	0.8032	7.3141**
		500	94.8%	0.0832	3.4280	3.6180	97.8%	10.8382*	0.4435	11.3262*
		1000	95.5%	0.5438	0.4517	1.0877	98.2%	5.2251**	0.6606	5.9221
		1500	95.3%	0.1932	1.3128	1.6023	98.2%	5.2251**	0.6606	5.9221
(0,2)		250	93.9%	2.3877	2.6764	5.1900	97.9%	9.2840*	0.5493	9.8758*
		500	94.7%	0.1860	3.1440	3.4390	97.7%	12.4853*	0.3507	12.8825*
		1000	95.5%	0.5438	0.4517	1.0877	98.2%	5.2251**	0.6606	5.9221
		1500	95.5%	0.5438	1.6801	2.3161	98.2%	5.2251**	0.6606	5.9221
(1,1)		250	93.8%	2.8260	4.0337**	6.9878**	98%	7.8272*	0.6688	8.5365**
		500	94.3%	0.9889	2.1478	3.2542	97.6%	14.2244*	2.3071	16.5771*
		1000	95.5%	0.5438	0.4517	1.0877	98.3%	4.0910**	0.5886	4.7139
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	93.8%	2.8260	4.0431	6.8692**	97.9%	9.2840*	0.5504	9.8345*
		500	94.3%	0.9889	2.1540	3.1429	97.6%	14.2244*	2.3101	16.5315*
		1000	95.5%	0.5438	0.4539	0.9977	98.3%	4.0910**	0.5880	4.6790
		1500	95.3%	0.1932	1.3167	1.5099	98.3%	4.0910**	0.5880	4.6790
(2,1)		250	94%	1.9842	4.7031**	6.6873**	97.9%	9.2840*	0.5504	9.8345*
		500	94.7%	0.1860	3.1440	3.4390	97.6%	14.2244*	2.3071	16.5771*
		1000	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.6606	5.9221
		1500	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.6606	5.9221
(2,2)		250	94%	1.9842	1.5436	3.5279	97.8%	10.8382*	0.4446	11.2827*
		500	94.7%	0.1860	0.5015	0.7966	97.7%	12.4853*	2.5738	15.1056*
		1000	95.4%	0.3457	0.3613	0.8012	98.2%	5.2251**	0.7368	7.2477**
		1500	95.6%	0.7885	1.8835	2.7620	98.3%	4.0910**	0.5886	4.7139

As with all other models reviewed so far, for EGARCH (2, 1) for Nifty Junior with Normal distribution also gives good predictability at 95 per cent level of confidence. Only three of the twenty four models fail to give statistically significant predictability. However, the results take a ‘U’ turn once the focus is shifted to the 99 per cent level of confidence. Though all the models pass the test of independence, they fail to give good result simultaneously as they fail either in the unconditional coverage or conditional coverage tests. Hence, none of the specifications from this model are found to be efficient predictors of risk

Table 5.10 EGARCH (2, 2) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	94.5%	0.5105	1.2272	1.8509	97.4%	17.9466*	1.8308	19.8301*
		500	94.8%	0.0832	1.7731	1.9631	97.3%	19.9292*	4.3513**	24.3352*
		1000	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	7.6135*	15.4812*
		1500	95.3%	0.1932	1.3128	1.6023	98.2%	5.2251**	0.6606	5.9221
(2,0)		250	94.5%	0.5105	0.3208	0.9444	97.6%	14.2244*	2.3071	16.5771*
		500	94.6%	0.3287	1.3968	1.8366	97.5%	16.0430*	5.1413**	21.2349*
		1000	95.2%	0.0853	2.6826	2.8663	98.1%	6.4725*	0.8032	7.3141**
		1500	95.3%	0.1932	1.3128	1.6023	98.2%	5.2251**	0.6606	5.2464
(0,1)		250	94.4%	0.7308	1.0696	1.9157	97.4%	17.9466*	1.8308	19.8301*
		500	94.5%	0.5105	1.2272	1.8509	97.5%	16.0430*	5.1413**	21.2349*
		1000	95.1%	0.0212	2.4347	2.5564	98%	78272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.6606	5.9221
(0,2)		250	94.5%	0.5105	0.3208	0.9444	97.5%	16.0430*	2.0598	18.1535*
		500	94.5%	0.5105	1.2272	1.8509	97.4%	17.9466*	4.7341**	22.7334*
		1000	95.1%	0.0212	2.4347	2.5564	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.6606	5.9221
(1,1)		250	94.1%	1.6162	1.7280	3.4668	97.4%	17.9466*	4.7341**	22.7334*
		500	94.6%	0.3287	0.4059	0.8456	97.6%	14.2244*	2.3071	16.5771*
		1000	95.2%	0.0853	1.1481	1.3318	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.6606	5.9221
(1,2)		250	94.2%	1.2543	1.9320	3.3358	97.4%	17.9466*	4.7341**	22.7334*
		500	94.2%	1.2843	1.9320	3.3358	98.2%	5.2252**	0.6606	5.9221
		1000	94.8%	0.0832	1.7731	1.9631	98.2%	5.2251**	0.9535	6.2150**
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(2,1)		250	94.1%	1.6162	1.4900	1.9300	97.2%	21.9880*	0.6606	5.9221
		500	94.5%	0.5105	3.2041	4.9421	97.7%	12.4853*	3.9913**	26.0361*
		1000	95%	0	0.0138	0.3087	98%	7.8272*	0.8172	8.6849**
		1500	95.4%	0.3457	2.2008	2.3034	98.2%	5.2251**	3.5057	11.3734*
(2,2)		250	93.9%	2.3877	4.3561**	6.8697**	97.3%	19.9292*	4.3513**	24.3352*
		500	95%	0	2.2008	2.3034	97.4%	17.9466*	4.7341**	22.7334*
		1000	95.2%	0.0853	1.1481	1.3318	97.9%	9.2840*	3.1714	12.4979*
		1500	95.1%	0.0212	0.9956	1.1173	98.3%	4.0910**	0.5886	4.7139

The case is very similar for EGARCH (2, 2) with normal distribution for Nifty Junior. Though the 95 per cent level does well for all models except one, there are no models in the 99 per cent basket that passes all the three tests. Hence, EGARCH (2, 2) is found inadequate for Value-at-Risk prediction. Tables next in line are the ones for Nikkei, the Japanese stock index.

Table 5.11 EGARCH (1, 1) for Nikkei with Normal Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.8%	0.0832	0.0343	0.2243	98.7%	0.8306	0.3428	1.1996
		500	95.4%	0.3457	0.3613	0.8012	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0003	0.6364	99%	0	0.2022	0.2223
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.2449	0.3649
(2,0)		250	94.9%	0.0209	0.1676	0.2933	98.6%	1.4374	0.3980	1.8636
		500	95.4%	0.3457	0.3613	0.8012	99%	0	0.2022	0.2223
		1000	95.2%	0.0853	0.0468	0.2305	99%	0	0.2022	0.2223
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.2449	0.3649
(0,1)		250	94.8%	0.0832	0.0343	0.2243	98.8%	0.3798	0.2918	0.6957
		500	95.4%	0.3457	0.3613	0.8012	99%	0	0.2022	0.2223
		1000	95.4%	0.3457	0.0074	0.4473	99%	0	0.2022	0.2223
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.2449	0.3649
(0,2)		250	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
		500	95.4%	0.3457	0.3613	0.8012	99%	0	0.2022	0.2223
		1000	95.2%	0.0853	0.0468	0.2305	99%	0	0.2022	0.2223
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.2449	0.3649
(1,1)		250	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		500	95.3%	0.1932	0.2815	0.5710	98.9%	0.0978	0.2449	0.3649
		1000	95.5%	0.5438	0.0003	0.6364	98.9%	0.0978	0.2449	0.3649
		1500	94.6%	0.3287	0.0025	0.4422	98.9%	0.0978	0.2449	0.3649
(1,2)		250	94.8%	0.0832	0.0343	0.2243	98.7%	0.8306	0.3428	1.1996
		500	95.3%	0.1932	0.2815	0.5710	99%	0	0.2022	0.2223
		1000	95.3%	0.1932	0.0229	0.3124	99%	0	0.2022	0.2223
		1500	94.6%	0.3287	0.0025	0.4422	98.9%	0.0978	0.2449	0.3649
(2,1)		250	94.7%	0.1860	0.0138	0.3087	98.5%	2.1892	0.4573	2.6768
		500	95.3%	0.1932	0.2815	0.5710	99%	0	0.2022	0.2223
		1000	95.3%	0.1932	0.0229	0.3124	99%	0	0.2022	0.2223
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.2449	0.3649
(2,2)		250	94.6%	0.3287	0.0025	0.4422	98.4%	3.0766	0.5209	3.6297
		500	95.5%	0.5438	0.4517	1.0877	99%	0	0.2022	0.2223
		1000	95.2%	0.0853	0.0468	0.2305	98.9%	0.0978	0.2449	0.3649
		1500	94.6%	0.3287	0.0025	0.4422	98.9%	0.0978	0.2449	0.3649

Results for Nikkei appear to be quite strong. Good result for Nifty and Nifty Junior in the 95 per cent bracket was quite the norm, however, they regularly faltered at the 99 per cent level. In the case of Nikkei, results are strong not only for the 95 per cent level, but they are cent per cent accurate in the case of 99 per cent level as well. No exceptions occur either at 95 or 99 per cent level.

Table 5.12 EGARCH (1, 2) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	94.8%	0.0832	0.0074	0.4473	98.7%	0.8306	0.3980	1.8636
		500	95.4%	0.3457	1.9803	2.1060	99%	0	0.2918	0.6957
		1000	95.5%	0.5438	0.0229	0.3124	99%	0	0.5886	4.7139
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.5886	4.7139
(2,0)		250	94.9%	0.0209	0.1676	0.1899	98.4%	3.0766	0.5209	3.6297
		500	94.7%	0.1860	0.3613	1.8737	98.8%	0.3798	0.2918	0.6957
		1000	95.3%	0.1932	0.0468	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.8%	0.0832	0.0138	0.2243	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	95.3%	0.1932	0.0229	0.3124	98.6%	1.4374	0.3980	1.8636
		500	94.8%	0.0832	1.7731	1.9631	98.8%	0.3798	0.2918	0.6957
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.7%	0.1860	0.0138	0.3087	98.3%	4.0910**	0.5886	4.7139
(0,2)		250	95%	0	0.1037	0.2063	98.5%	2.1892	0.4573	2.6768
		500	94.7%	0.1860	1.5787	1.8737	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.8%	0.0832	0.0343	0.2243	98.3%	4.0910**	0.5886	4.7139
(1,1)		250	95.1%	0.0212	0.0790	0.2007	98.4%	3.0766	0.5209	3.6297
		500	94.8%	0.0832	1.7731	1.9361	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		1500	94.8%	0.0832	0.0343	0.2243	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	94.9%	0.0209	0.0642	0.1899	98.4%	3.0766	0.5209	3.6297
		500	94.7%	0.1860	1.5787	1.8737	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		1500	94.8%	0.0832	0.0343	0.2243	98.3%	4.0910**	0.5886	4.7139
(2,1)		250	94.9%	0.0212	0.0642	0.1899	98.3%	4.0910**	0.5886	4.7139
		500	94.6%	0.3287	1.3968	1.8366	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0224	0.2156	98.4%	3.0766	0.5203	3.5960
		1500	94.8%	0.0832	0.0342	0.1181	98.3%	4.0910**	0.5880	4.6790
(2,2)		250	95%	0	0.1037	0.2063	98.3%	4.0910**	0.5886	4.7139
		500	94.6%	0.3287	1.4864	7.6705	98.5%	2.1892	1.6294	12.2853*
		1000	95.4%	0.3457	0.0074	0.4473	98.4%	3.0766	0.5209	3.6297
		1500	94.6%	0.3287	0.0025	0.4422	98.3%	4.0910**	0.5886	4.7139

Nikkei does comparatively better than either Nifty or Nifty Junior in being predictable using the EGARCH (1, 2). It has a 100 per cent success in back testing at 95 per cent level of confidence and only 13 out of the 32 models have statistically unacceptable prediction at 99 per cent level of confidence. Hence, the model is giving better result as compared to the Indian market but does not have as much accurate predictability as with using the simpler EGARCH (1, 1).

Table 5.13 EGARCH (2, 1) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95.3%	0.1932	1.1328	1.6023	98.9%	0.0978	0.2449	0.3649
		500	95.3%	0.1932	0.2815	0.5710	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.9019	1.1914	98.6%	1.4374	0.3980	1.8636
		1500	94.6%	0.3287	0.0025	0.4422	98.5%	2.1892	0.4573	2.6768
(2,0)		250	94.6%	0.3287	1.4015	1.7302	98.9%	0.0978	0.2447	0.3425
		500	95.1%	0.0212	0.9956	1.1173	98.8%	0.3798	0.2918	0.6957
		1000	95.4%	0.3457	0.7931	1.2330	98.6%	1.4374	0.3980	1.8636
		1500	94.7%	0.1860	0.0138	0.3087	98.5%	2.1892	0.4573	2.6768
(0,1)		250	94.8%	0.0832	0.6082	0.7983	98.7%	0.8306	0.3428	1.1996
		500	95.3%	0.1932	0.2815	0.5710	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.9019	1.1914	98.6%	1.4374	0.3980	1.8636
		1500	94.5%	0.5105	0.0002	0.6240	98.5%	2.1892	0.4573	2.6768
(0,2)		250	95.5%	0.5438	1.6801	2.3161	97.7%	12.485*	6.036*	18.567*
		500	95.2%	0.0853	10.030*	10.246*	97.7%	12.485*	10.3*	22.911*
		1000	95.1%	0.0212	16.008*	16.129*	98%	7.827*	7.613*	15.481*
		1500	94.7%	0.1860	13.221*	13.5163*	97.9%	9.2840*	7.0527*	16.3792*
(1,1)		250	94.9%	0.0209	0.7290	0.7499	98.8%	0.3798	0.2915	0.6713
		500	95.2%	0.0853	1.1481	1.3318	99%	0	0.2022	0.2223
		1000	95.3%	0..1932	0.9019	1.1914	98.6%	1.4374	0.3980	1.8636
		1500	94.6%	0.3287	0.0025	0.4422	98.5%	2.1892	0.4573	2.6768
(1,2)		250	94.8%	0.0832	1.7782	1.8614	98.9%	0.0978	0.2447	0.2020
		500	95.2%	0.0853	1.1518	1.2371	98.9%	0.0978	0.2447	0.3425
		1000	95.2%	0.0853	1.0143	1.0966	98.7%	0.8306	0.3425	1.1730
		1500	94.5%	0.5105	0.0002	0.5107	98.5%	2.1892	0.4569	2.6768
(2,1)		250	94.6%	0.3287	1.4015	1.7302	99%	0	0.2020	0.6713
		500	95.2%	0.0853	1.1518	1.2371	98.9%	0.0978	0.2447	0.2223
		1000	95.2%	0.0853	1.0143	1.0996	98.7%	0.8306	0.3425	1.8636
		1500	94.5%	0.5105	0.0002	0.6240	98.5%	2.1892	0.4573	2.6768
(2,2)		250	94.6%	0.3287	1.4015	1.7302	98.3%	4.0910**	0.5880	4.6790
		500	95.1%	0.0212	0.9956	1.1173	99%	0	0.2022	0.2223
		1000	95.4%	0.3457	0.7931	1.2330	98.7%	0.8306	0.3428	1.1996
		1500	94.6%	0.3287	0.0025	0.4422	98.5%	2.1892	0.4573	2.6768

The predictability of EGARCH (2, 1) with normal distribution as measured by unconditional, independent and conditional coverage tests appears to be a lot better than that using the EGARCH (1, 2) model with similar distributional assumption. Only 5 out of 32 models give predictability that is not statistically acceptable.

Table 5.14 EGARCH (2, 2) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.1%	0.0212	0.1529	0.2746	98.4%	3.0766	0.5209	3.6297
		500	94.7%	0.1860	3.1440	3.4390	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		1500	94.4%	0.7308	0.2461	1.0922	98.3%	4.0910**	0.5886	4.7139
(2,0)		250	94.7%	0.1860	0.0138	0.3087	98.3%	4.0910**	0.5886	4.7139
		500	94.8%	0.0832	1.7731	1.9631	98.8%	0.3798	0.2918	0.6957
		1000	95.4%	0.3457	0.0074	0.4473	98.4%	3.0766	0.5209	3.6297
		1500	94.3%	0.9889	0.1816	1.2880	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		500	94.7%	0.1860	3.1440	3.4390	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		1500	94.4%	0.7308	0.2461	1.0922	98.3%	4.0910**	0.5886	4.7139
(0,2)		250	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		500	94.9%	0.0209	1.9803	2.1060	98.8%	0.3798	0.2918	0.6957
		1000	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		1500	94.3%	0.9889	0.1816	1.2880	98.3%	4.0910**	0.5886	4.7139
(1,1)		250	94.7%	0.1860	0.2878	0.5827	97.9%	9.2840*	0.9019	10.2284*
		500	94.8%	0.0832	1.7731	1.9631	98.6%	1.4374	0.3980	1.8636
		1000	95.3%	0.1932	0.0229	0.3124	98.5%	2.1892	0.4573	2.6768
		1500	94.3%	0.9889	0.1816	1.2880	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	94.6%	0.3287	0.3594	0.7991	98.2%	5.2251**	0.6606	5.9221
		500	94.8%	0.0832	0.6082	0.7983	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.5%	2.1892	0.4573	2.6768
		1500	94.2%	1.2843	0.7894	2.1932	98.3%	4.0910**	0.5886	4.7139
(2,1)		250	94.7%	0.1860	1.0696	1.9157	98%	7.8272*	0.5886	4.7139
		500	94.8%	0.0832	1.7731	1.9361	98.6%	1.4374	0.3980	1.8636
		1000	94.8%	0.0832	2.6187	3.2424	98.6%	1.4374	2.5738	15.1056*
		1500	94.4%	0.7308	1.7731	1.9361	98.3%	4.0910**	0.3980	1.8636
(2,2)		250	94.2%	1.2843	0.1272	1.5310	97.7%	12.4853*	0.3507	12.8825*
		500	94.8%	0.0832	1.7731	1.9631	98.6%	1.4374	0.3980	1.8636
		1000	95.3%	0.1932	0.0229	0.3124	98.5%	2.1892	0.4573	2.6768
		1500	94.4%	0.7308	1.0696	1.9157	98.3%	4.0910**	0.5886	4.7139

Though predictability does not improve for Nikkei with the application of EGARCH (2, 2) with normal distributional assumption, it still manages a fair amount of accuracy. 17 out of 32 models tested simultaneously clears all the three tests thereby placing the market above the two Indian markets in terms of having a better predictability of risk.

Thus an analysis of the EGARCH model with normal distributional assumption has given a handful of models that pass all the criteria of a good back testing from three markets. Since only those models that pass all the three tests in the three markets can be said to be accurate predictors of risk, only those models can be thought of as successful ones.

However, a close observation of the result shows that, none of the models pass all the tests simultaneously in the same market as well as giving accurate result for all the other markets. Hence, it can be concluded that EGARCH models with normal distributional assumption fails in giving accurate prediction of one day ahead Value-at-Risk.

Normal distribution only approximates reality and it is a well known fact that distributions of financial series often have a fatter tail than normal distribution. Hence, theoretically a Student – t distribution approximates reality better. Therefore, the results of the same model with Student – t distribution are also worth observing.

Table 5.15 EGARCH (1, 1) for Nifty with Student – Distribution.

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.8	0.0832	0.0343	0.2243	98	7.8272*	0.6688	8.5365**
		500	94.8	0.0832	0.6082	0.7983	97.7	12.4853*	0.3507	12.8825*
		1000	94.9	0.0209	0.7259	0.8516	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(2,0)		250	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758*
		500	94.5	0.5105	0.3208	0.9444	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(0,1)		250	94.7	0.1860	0.0138	0.3087	98	7.8272*	0.6688	8.5365*
		500	94.6	0.3287	0.4059	0.8456	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.6	0.7885	1.8835	2.7620	98.3	4.0910**	1.1211	5.2464
(0,2)		250	94.8	0.0832	0.0343	1.9300	98	7.8272*	0.6688	8.5365**
		500	94.5	0.5105	0.3208	3.2691	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(1,1)		250	94.8	0.0832	0.0343	0.2243	98.1	6.4725*	0.6688	8.5365**
		500	94.4	0.7308	0.2461	1.0922	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(1,2)		250	94.7	0.1860	0.0138	0.3087	98	7.8272*	0.8032	8.5365**
		500	94.2	1.2843	0.1272	1.5310	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2464
(2,1)		250	94.8	0.0832	0.0343	0.2243	98.1	6.4725*	0.8032	7.3141**
		500	94.2	1.2843	0.1272	1.5310	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.7	1.0807	2.1004	3.2691	98.3	4.0910**	1.1211	5.2462
(2,2)		250	94.6	0.3287	0.0025	0.4422	97.9	9.2840*	0.5493	9.8758*
		500	94.2	1.2843	0.1272	1.5310	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	2.3315	3.8389	98.3	4.0910**	1.1211	5.2464

All the models, again, do exceedingly well at the 95 per cent level of confidence. None of the models move substantially away from the criteria of being accurate in predicting Value-at-Risk figure. However, the results for the 99 per cent level are exactly the opposite. Though some models pass one or two of the coverage tests, none of them are seen to be simultaneously passing all the three tests. Thus, EGARCH (1, 1) with‘t’ distribution fails in giving at least one model capable giving accurate prediction of one day ahead Value-at-Risk for Nifty.

Table 5.16 EGARCH (1, 2) for Nifty with Student – t Distribution.

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,2)	250	94.6	0.3287	2.8744	3.3141	98.1	6.4725*	0.8032	7.3141**
		500	94.8	0.0832	3.4280	3.6180	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.7	1.0807	0.6657	1.8344	98.4	3.0766	1.3076	4.4165
(2,0)		250	94.8	0.0832	1.7731	1.9631	98.2	5.2251**	0.9535	6.2150**
		500	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	0.5531	1.4316	98.4	3.0766	1.3076	4.4165
(0,1)		250	94.6	0.3287	1.3968	1.8366	98.1	6.4725*	0.8032	7.3141**
		500	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		1000	95.5	0.5438	0.4517	1.0877	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	0.5531	1.4316	98.3	4.0910**	1.1211	5.2464
(0,2)		250	94.9	0.0209	1.9803	2.1060	98.2	5.2251**	0.9535	6.2150**
		500	94.7	0.1860	3.1440	3.4390	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	0.5531	1.4316	98.4	3.0766	1.3076	4.4165
(1,1)		250	94.6	0.3287	1.3968	1.8366	98	7.8272*	0.6688	8.5365**
		500	94.7	0.1860	3.1440	3.4390	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	0.5531	1.4316	98.4	3.0766	1.3076	4.4165
(1,2)		250	95.1	0.0212	4.3697**	4.4914	98.1	6.4725*	0.8032	7.3141**
		500	94.7	0.1860	3.1440	3.4390	98	7.8272*	0.6688	8.5365**
		1000	95.3	0.1932	1.3128	1.6023	98.3	4.0910**	0.8032	7.3141**
		1500	95.5	0.5438	0.4517	1.0877	98.3	4.0910**	1.1211	5.2464
(2,1)		250	94.8	0.0832	3.4280	3.6180	98.1	6.4725*	0.8032	7.3141**
		500	94.6	0.3287	2.8744	3.3141	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	0.3613	0.8012	98.3	4.0910**	1.1211	5.2464
		1500	95.6	0.7885	0.5531	1.4316	98.4	3.0766	1.3076	4.4165
(2,2)		250	94.7	0.1860	0.0025	3.4390	97.9	9.2840*	0.5493	9.8758*
		500	94.6	0.3287	0.1272	3.3141	98.1	6.4725*	0.8032	7.3141**
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95	0	2.3315	1.4316	99	0	0.0181	6.8496**

In a very similar case to the earlier ones analyzed, EGARCH (1, 2) with Student – t distribution also produces good predictability at the 95 per cent level. Except for the ARMA(1, 2) model with 250 observations, all the other ones pass all the three tests and the above mentioned one fails only in not being independent. The results are different for the 99 per cent level of confidence. Only five models, ARMA (1, 0), (2, 0), (0, 2), (1, 1) and (2, 1) all with 1500 observations, clear all the three tests simultaneously. Hence, the rate of model selection is less than 20 per cent. Though much better than the earlier one, there is not much to hope for in this model as a majority fails to give accurate forecasts.

Table 5.17 EGARCH (2, 1) for Nifty with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	94.8	0.0832	0.0343	0.2243	97.7	12.4853*	0.3507	12.8825*
		500	94.6	0.3287	1.3968	1.8366	97.7	12.4853*	0.3507	12.8825*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(2,0)		250	94.9	0.0209	0.0642	0.1899	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	1.0696	1.9157	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(0,1)		250	94.8	0.0832	0.0343	0.2243	97.8	10.8382*	0.4435	11.3262*
		500	94.4	0.7308	1.0696	1.9157	97.7	12.4853*	0.3507	12.8825*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(0,2)		250	94.9	0.0209	0.0642	0.1899	98.1	6.4725*	0.8032	7.3141**
		500	94.4	07308	1.0696	1.9157	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(1,1)		250	94.9	0.0209	0.0642	0.1899	98.1	6.4725*	0.8032	7.3141**
		500	94.4	0.7308	1.0696	1.9157	97.7	12.4853*	0.3507	12.8825*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(1,2)		250	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758**
		500	94.3	0.9889	1.6801	2.0301	97.8	10.8382*	0.4435	11.3262*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150**
(2,1)		250	94.8	0.0832	0.0343	0.2243	98.1	6.4725*	0.8032	7.3141**
		500	94.3	0.9889	0.9238	2.0301	97.8	10.8382*	0.4435	11.3262*
		1000	95	0	0.8550	0.9576	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6..2150**
(2,2)		250	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758*
		500	94.3	0.9889	0.1816	1.2880	97.8	10.8382*	0.4435	11.3262*
		1000	95.1	0.0212	0.9956	1.1173	98	7.8272*	0.6688	8.5365**
		1500	95.8	1.4215	2.3315	3.8389	98.3	4.0910**	1.1211	5.2464

Nominal coverage of EGARCH (2, 1) for Nifty with Student – t distribution varies in a tight range of 94.4 to 95.8 per cent for the 95 per cent confidence level. Hence, all the models clear the three tests of coverage comfortably for this level of confidence. But like all other models, problem comes when the confidence band is brought down to the level which is normally used by the industry and regulators. It is easily observable that, though all the models with 99 per cent level of confidence pass the independence test, none of them could pass unconditional and conditional coverage tests simultaneously. In fact, none of them passed either of the tests individually too.

Table 5.18 EGARCH (2, 2) for Nifty with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,2)	250	94.9	0.0209	1.9803	2.1060	97.8	10.8382*	0.4435	11.3262*
		500	94.7	0.1860	13.2213*	13.536*	97.7	12.4853*	6.0360**	18.5679*
		1000	95.2	0.0853	1.1481	1.3318	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	1.6801	2.3161	98.1	6.4725*	0.8032	7.3141**
(2,0)		250	94.6	0.3287	1.3968	1.8366	97.7	12.4853*	2.5738	15.1056*
		500	94.3	0.9889	0.9238	2.0301	97.7	12.4853*	0.3507	12.8825*
		1000	95.2	0.0853	1.1481	1.3318	98	7.8272*	0.6688	8.5365**
		1500	95.4	0.3457	1.4900	1.9300	98.4	3.0766	1.3076	4.4165
(0,1)		250	94.7	0.1860	1.5787	1.8737	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	1.0696	1.9157	97.6	14.224*	0.2700	14.5401*
		1000	95.2	0.0853	1.1481	1.3318	98.1	6.4725*	0.8032	7.3141**
		1500	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
(0,2)		250	94.7	0.1860	1.5787	1.8737	97.8	10.8382*	0.4435	11.3262*
		500	94.4	0.7308	1.0696	1.9157	97.6	14.2244*	0.2700	14.5401*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.4	0.3457	1.4900	1.9300	98.3	4.0910**	1.1211	5.2464
(1,1)		250	94.8	0.0832	1.7731	1.9631	97.9	9.2840*	3.1714	12.4979*
		500	97.2	12.0358*	1.4233	13.5159*	99	0	2.9710	2.9931
		1000	95.4	0.3457	1.3128	1.6023	98.3	4.0910**	0.8032	7.3141**
		1500	95.5	0.5438	0.4517	1.0877	98.3	4.0910**	1.1211	5.2464
(1,2)		250	94.7	0.1860	3.1440	3.4390	97.5	16.0430*	0.2010	16.2946*
		500	95	0	2.2008	2.3034	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.4	0.3457	1.4900	1.9300	98.3	4.0910**	1.1211	5.2464
(2,1)		250	94.8	0.0832	1.7731	1.9631	97.7	12.4853*	0.3507	12.4979*
		500	94.5	0.5105	1.2272	1.8509	97.8	10.8382*	0.4435	2.9931
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.5	0.5438	0.4517	1.0877	98.3	4.0910**	1.1211	5.2464
(2,2)		250	94.8	0.0832	1.7731	1.9631	97.7	12.4853	0.3507	12.8825*
		500	94.1	1.6162	0.6662	2.4042	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98	7.8272*	0.6688	8.5365**
		1500	95.4	0.3457	1.4900	1.9300	98.3	4.0910**	1.1211	5.2464

Only two models, ARMA (1, 0) and ARMA (1, 1) with 500 observations each, fail at the 95 per cent level of confidence. Coming to the 99 per cent level of confidence, it is observable that only ARMA (2, 0) with 1500 observation could stand the rigors of back testing. All other models fail either in unconditional or in conditional coverage tests while only ARMA (1, 0) with 500 observations fail in the test for independence. Hence, there is not much to take away from this model either.

Table 5.19 EGARCH (1, 1) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	EGARCH	bservations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.8%	0.0832	3.4280	3.6180	97.9%	9.2840*	0.5493	9.8758*
		500	94.4%	0.7308	1.0696	1.9157	98%	7.8272*	3.5057	11.3734*
		1000	95.2%	0.0853	1.1481	1.1338	98.2%	5.2251**	0.9535	6.2150**
		1500	95.5%	0.5438	1.6801	2.3161	98%	7.8272*	0.6688	8.5365**
(2,0)		250	94.7%	0.1860	3.1440	3.4390	98.1%	6.4725*	0.8032	7.3141**
		500	94%	1.9842	2.9335	5.0415	98.1%	6.4725*	3.8666**	10.3775*
		1000	95.3%	0.1932	1.3128	1.6023	98.2%	5.2251**	0.9535	6.2150**
		1500	95.6%	0.7885	1.8835	2.7620	98.1%	6.4725*	0.8032	7.3141**
(0,1)		250	94.8%	0.0832	3.4280	3.6180	98.2%	5.2251**	0.9535	6.2150**
		500	94.3%	0.9889	0.9238	2.0301	98%	7.8272*	3.5057	11.3734*
		1000	95.3%	0.1932	1.3128	1.6023	98.2%	5.2252**	0.9535	6.2150**
		1500	95.5%	0.5438	1.6801	2.3161	98.1%	6.4725*	0.8032	7.3141**
(0,2)		250	94.6%	0.3287	2.8744	3.3141	98%	7.8272*	0.6688	8.5365**
		500	94.2%	1.2843	3.4887	4.8925	98%	7.8272*	3.5057	11.3734*
		1000	95.4%	0.3457	1.4900	1.9300	98.1%	6.4725*	0.8032	7.3141**
		1500	95.7%	1.0807	2.1004	3.2691	98.1%	6.4725*	0.8032	7.3141**
(1,1)		250	94.9%	0.0209	2.3766	3.2227	98.1%	6.4725*	0.8032	7.3141**
		500	94.1%	1.6162	2.1478	3.2542	98.1%	6.4725*	0.8032	7.3141**
		1000	95.4%	0.3457	1.4900	1.9300	98.1%	6.4725*	0.8032	7.3141**
		1500	95.6%	0.7885	2.1004	3.2691	98.2%	5.2251**	0.9535	6.2150**
(1,2)		250	94.6%	0.3287	3.7266	3.8523	97.9%	9.2840*	0.5493	7.3141**
		500	94.2%	1.2843	1.7289	3.4668	98%	7.8272*	3.5057	7.3141**
		1000	95.3%	0.1932	1.4900	1.9300	98.1%	6.4725*	0.8032	7.3141**
		1500	95.5%	0.5438	1.8835	2.7620	98.2%	5.2251**	0.9535	6.2150**
(2,1)		250	94.4%	0.7308	2.8744	3.3141	98%	7.8272*	0.6688	9.8758*
		500	94.3%	0.9889	3.4887	4.8925	98%	7.8272*	3.5057	11.3734*
		1000	95.4%	0.3457	1.3128	1.6023	98.1%	6.4725*	0.8032	7.3141**
		1500	95.7%	1.0807	1.6801	2.3161	98.1%	6.4725*	0.8032	6.2150**
(2,2)		250	94.6%	0.3287	2.8744	3.3141	98.2%	5.2251**	0.9535	6.2150**
		500	94%	1.9842	2.9335	5.0415	98.1%	6.4725*	0.8032	7.3141**
		1000	95.3%	0.1932	1.3128	1.6023	98.2%	5.2251**	0.9535	6.2150**
		1500	95.6%	0.7885	1.8835	2.7620	98.2%	5.2251**	0.9535	6.2150**

Subjecting Nifty Junior Value-at-Risk predictions to back testing with a 95 per cent level of confidence, it was found that all the models passed the three tests quite comfortably. Nominal coverage ranged between 94 per cent and 95.7 per cent. Though there were a few borderline cases, ultimately all the models qualified to be called good predictors of risk. However, like all the other models so far tested, all the predictability found at the 95 per cent level completely breaks down when it comes to the 99 per cent level. Though all except one model succeeds in the test for independence, none of them could make the cut off at the stricter 99 per cent level of confidence, leaving the model without any specimen progressing in to the next round.

Table 5.20 EGARCH (1, 2) for Nifty Junior with Student– t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	94.7%	0.1860	3.1440	3.4390	97.9%	10.8382*	0.5493	9.8758*
		500	94.3%	0.9889	0.9238	2.0301	98.1%	6.4725*	0.8032	7.3141**
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	1.1211	5.2464
		1500	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	0.5886	4.7139
(2,0)		250	94.5%	0.5105	2.6187	3.2424	98%	7.8272*	0.8172	8.6849**
		500	94.4%	0.7308	1.0696	1.9157	98.1%	6.4725*	0.8032	7.3141**
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
		1500	95.4%	0.3457	1.4900	1.9300	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	94.6%	0.3287	2.8744	3.3141	98%	7.8272*	0.6688	8.5365**
		500	94.3%	0.9889	0.9238	2.0301	98.2%	5.2251**	0.9535	6.2150**
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
		1500	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	0.5886	4.7139
(0,2)		250	94.6%	0.3287	2.8744	3.3141	97.9%	9.2840*	0.9019	10.2284*
		500	94.4%	0.7308	1.0696	1.9157	98.1%	6.4725*	0.8032	7.3141**
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
		1500	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	0.5886	4.7139
(1,1)		250	94.5%	0.5105	2.6187	3.2424	97.9%	9.2840*	0.9019	10.2284*
		500	94.3%	0.9889	0.9238	2.0301	98.1%	6.4725*	0.8032	7.3141**
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
		1500	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	94.5%	0.5105	2.6187	3.2424	97.8%	10.8382*	0.9909	11.8736*
		500	94.2%	1.2843	3.4887	4.8925	97.5%	16.0430*	0.2010	16.2946*
		1000	95.3%	0.1932	2.9447	3.2342	97.8%	10.8382*	6.5279*	17.4105
		1500	95.8%	1.4215	2.3315	3.8389	98.1%	6.4725*	0.8032	7.3141**
(2,1)		250	94.6%	0.3287	4.7724**	5.2121	97.6%	14.2244*	1.1817	15.4517*
		500	94.2%	1.2843	0.7894	2.1932	98%	7.8272*	0.6688	8.5365**
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
		1500	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	0.5886	4.7139
(2,2)		250	94.7%	0.1860	2.8744	3.4390	97.5%	16.0430*	0.2010	16.2946*
		500	94.3%	0.9889	2.9335	2.0301	98%	7.8272*	0.6688	8.5365**
		1000	95.4%	0.3457	1.3128	0.8012	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.8835	1.9300	98.3%	4.0910**	0.5886	4.7139

Result for this model looks very similar to the same model for Nifty. There is only one failure for the model at the 95 per cent level of confidence and the sole bunker is ARMA (2, 1) with 250 observations and it fails in clearing the test for independence. All the other models do pretty well at the 95 per cent level. However, the situation again become like that for its senior counterpart when it comes to the 99 per cent level of confidence. Only a handful of models, ie. 5, pass all the three tests. ARMA (2, 0), (0, 1), (0, 2), (1, 1) and (2, 1) clears all the tests to be qualified to be matched with the same class of models from the other two markets and all of them is found to have 1000 observations as the input used.

Table 5.21 EGARCH (2, 1) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	94.5%	0.3457	2.6187	3.2424	98%	7.8272*	0.8172	8.6849**
		500	94.3%	0.9889	2.1478	3.2542	97.9%	9.2840*	0.5493	9.8758*
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(2,0)		250	94.5%	0.3457	4.4189**	5.0526	98.1%	6.4725*	0.7368	7.2477**
		500	94.6%	0.3287	1.3968	1.8366	97.8%	10.8382*	2.8613	13.7440*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	94.3%	0.9889	2.1478	3.2542	98.1%	6.4725*	0.7368	7.2477**
		500	94.5%	0.3457	1.2272	1.8509	97.8%	10.8382*	2.8613	13.7440*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.3%	0.9889	3.7874	4.8938	98.1%	6.4725*	0.7368	7.2477**
		500	94.4%	0.7308	1.0696	1.9157	97.8%	10.8382*	2.8613	13.7440*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.3%	4.0910**	0.5886	4.7139
(1,1)		250	94.2%	1.2843	1.9320	3.3358	98.1%	6.4725*	0.7368	7.2477**
		500	94.5%	0.3457	1.2272	1.8509	97.9%	9.2840*	0.5493	9.8758*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	94.3%	0.9889	3.7874	4.8938	98.1%	6.4725*	0.7368	7.2477**
		500	94.4%	0.7308	1.0696	1.9157	97.9%	9.2840*	0.5493	9.8758*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,1)		250	94.4%	0.7308	2.3766	3.2227	98.3%	4.0910**	0.5886	4.7139
		500	94.5%	0.3457	1.2272	1.8509	97.8%	10.8382*	0.4435	11.3262*
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,2)		250	96.3%	3.8953**	1.5962	5.5669	99%	0	2.9730	2.9931
		500	94.5%	0.3457	1.2272	1.8509	97.6%	14.2244*	2.3071	16.5771*
		1000	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	0.5886	4.7139
		1500	95.7%	1.0807	2.1004	3.2691	98.5%	2.1892	0.4573	2.6768

Only two models in the EGARCH (2, 1) category with Student – t distribution fails to make the cut at the 95 per cent confidence level. ARMA (2, 0) fails in the test for independence and ARMA (2, 2) fails in the test for unconditional coverage. Nominal coverage range increases slightly to 96. 3 per cent on the upper side while remaining at 94.4 per cent on the lower side. But there are found to be only five survivors at the 99 per cent level of confidence and they are, ARMA (1, 0), (0, 1), (1, 2), (2, 1) and (2, 2), all from 1500 number of observations.

Table 5.22 EGARCH (2, 2) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	94.3%	0.9889	0.9238	2.0301	97.2%	21.9880*	1.4233	23.4681*
		500	93.8%	2.8260	1.1932	4.1473	97.4%	17.9466*	0.1429	18.1422*
		1000	95.5%	0.5438	1.6801	2.3161	97.9%	9.2840*	7.0527*	16.3792*
		1500	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.9535	6.2150**
(2,0)		250	94.2%	1.2843	1.9320	3.3358	97.3%	19.9292*	0.0953	20.0792*
		500	94.1%	1.6162	3.2041	4.9421	97.8%	10.8382*	0.4435	11.3262*
		1000	95.3%	0.1932	5.0767**	5.3662	97.9%	9.2840*	7.0527*	16.3792*
		1500	95.7%	1.0807	2.1004	3.2691	98.2%	5.2251**	0.9535	6.2150**
(0,1)		250	94.3%	0.9889	0.9238	2.0301	97.4%	17.9466*	1.8308	19.8301*
		500	93.9%	2.3877	1.3597	3.8733	97.4%	17.9466*	0.1429	18.1422*
		1000	95.4%	0.3457	3.2216	3.6615	97.9%	9.2840*	7.0527*	16.3792*
		1500	95.7%	1.0807	2.1004	3.2691	98.2%	5.2251**	0.9535	6.2150**
(0,2)		250	94.4%	0.7308	0.2461	1.0922	97.5%	16.0430*	0.2010	16.2946*
		500	94%	1.9842	4.6932**	6.8012**	97.7%	12.4853*	1.0841	13.6160*
		1000	95.3%	0.1932	5.0767**	5.3662	97.9%	9.2840*	7.0527*	16.3792*
		1500	95.7%	1.0807	2.1004	3.2691	98.3%	4.0910**	1.1211	5.2464
(1,1)		250	94.1%	1.6162	1.7289	3.4668	97.5%	16.0430*	0.2010	16.2946*
		500	94.2%	1.2843	3.4887	4.8925	97.5%	16.0430*	0.2010	16.2946*
		1000	95.3%	0.1932	2.9447	3.2342	97.8%	10.8382*	6.5279*	17.4105*
		1500	95.8%	1.4215	2.3315	3.8389	98.1%	6.4725*	0.8032	7.3141**
(1,2)		250	93.9%	2.3877	0.4530	2.9666	97.4%	17.9466*	0.1429	18.1422*
		500	93.8%	2.8260	4.0337**	6.9878**	97.9%	9.2840*	0.9019	10.2284*
		1000	95.4%	0.3457	3.2216	3.6615	97.8%	10.8382*	6.5279*	17.4105*
		1500	95.6%	0.7885	1.8835	2.7620	98.1%	6.4725*	0.8032	7.3141**
(2,1)		250	94.1%	1.6162	1.7289	3.4668	97.6%	14.2244*	0.2700	14.5401*
		500	93.9%	2.3877	2.6764	5.1900	97.8%	10.8382*	0.9909	11.8736*
		1000	95.4%	0.3457	3.2216	3.6615	97.8%	10.8382*	6.5279*	17.4105*
		1500	95.6%	0.7885	1.8835	2.7620	98.2%	5.2251**	0.9535	6.2150**
(2,2)		250	94.2%	1.2843	1.9320	3.3358	97.7%	12.4853*	2.5738	15.1056*
		500	94%	1.9842	2.9335	5.0415	97.6%	14.2244*	0.2700	14.5401*
		1000	95.3%	0.1932	2.9447	3.2342	97.8%	10.8382*	6.5279*	17.4105*
		1500	95.9%	1.8120	2.5771	4.4729	98.4%	3.0766	0.5209	3.6297

There are a few more failures even at the 95 per cent level of confidence for the EGARCH (2, 2) model for Nifty Junior with Student – t distribution at 95 per cent level of confidence. ARMA (2, 0), (0, 2) and (1, 2) fails at 1000 and 500 observations and there are two failure in the (0, 2) model; one each at 500 and 1000 observations. All of the failures come in the test for independence while two of them are clubbed with conditional coverage failures. Magnitude of failures climbs as a move is made from the 95 per cent level to the 99 per cent level. Only one model is found to be successfully predicting Value-at-Risk figures and is found to be ARMA (2, 2) with 1500 observations.

Table 5.23 EGARCH (1, 1) for Nikkei with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	95.4%	0.3457	0.3613	0.8012	98.6%	1.4374	0.3980	1.8636
		500	95.9%	1.8120	0.0616	1.9574	99.4%	1.8862	0.0725	1.9708
		1000	95.5%	0.5438	3.9676e-004	0.6364	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.0343	0.2243	98.9%	0.0978	0.2449	0.3649
(2,0)		250	95.1%	0.0212	0.1529	0.2746	98.7%	0.8306	0.3428	1.1996
		500	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1000	95.3%	0.1932	0.0229	0.3124	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.0343	0.2243	98.9%	0.0978	0.2449	0.3649
(0,1)		250	95.1%	0.0212	0.9956	1.1173	98.6%	1.4374	1.7458	3.2114
		500	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1000	95.5%	0.5438	3.9676e-004	0.6364	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.0343	0.2243	99.1%	0.1045	0.2449	0.3649
(0,2)		250	95.3%	0.1932	1.3128	1.6023	98.6%	1.4374	0.3980	1.8636
		500	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1000	95.3%	0.1932	0.0229	0.3124	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.0343	0.2243	98.9%	0.0978	0.2449	0.3649
(1,1)		250	95.5%	0.5438	0.1529	0.2746	98.5%	2.1892	0.2918	0.6957
		500	95.4%	0.3457	0.0074	0.4473	99.2%	04337	0.1636	0.2862
		1000	95.1%	0.0212	0.0790	0.2007	99%	0	0.2022	0.2223
		1500	94.8%	0.0832	0.0343	0.2243	98.9%	0.0978	0.2449	0.3649
(1,2)		250	94.8%	0.0832	0.0343	0.2243	98.8%	0.3798	0.2918	0.6957
		500	95.5%	0.5438	3.9676e-004	0.6364	99.1%	0.1045	0.1636	0.2862
		1000	95.4%	0.3457	0.0074	0.4473	99%	0	0.1636	0.2223
		1500	94.7%	0.1860	0.0138	0.3087	98.9%	0.0978	0.2449	0.3649
(2,1)		250	95%	0	0.8550	0.9576	98.8%	0.3798	0.4573	0.6957
		500	95.5%	0.5438	3.9676e-004	0.6364	99.1%	0.1045	0.1292	0.2862
		1000	95.4%	0.3457	0.0074	0.4473	99.1%	0.1045	0.2022	0.2862
		1500	94.8%	0.0832	0.0343	0.2243	98.9%	0.0978	0.2449	0.3649
(2,2)		250	95%	0	0.1193	0.2219	98.6%	1.4374	0.3980	1.8636
		500	95.2%	0.0853	0.2121	0.3958	99.1%	0.1045	0.1636	0.2862
		1000	95.4%	0.3457	0.0074	0.4473	99%	0	0.2022	0.2223
		1500	94.6%	0.3287	0.0025	0.4422	98.9%	0.0978	0.2449	0.3649

Nikkei again, similar to the EGARCH model with normal distribution throws surprisingly good results. It shows a hundred percent success at 95 per cent level of confidence and the range of nominal coverage is at a tight 94.6 per cent to 95.5 per cent and all the models pass the three tests of coverage. Moving on to the 99 per cent level, not only is the band of nominal coverage very tight between 98.5 to 99.2 percentages but all the models comfortably clears the conditional coverage tests and hence all the different varieties of the EGARCH (1, 1) for Nikkei with Student – t distribution qualifies to be compared with the successful models of the other two markets.

Table 5.24 EGARCH (1, 2) for Nikkei with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRcc	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	95.3%	0.1932	0.0229	0.3124	98.6%	1.4374	0.3980	1.8636
		500	95.3%	0.1932	0.9019	1.1914	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0138	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.7%	0.1860	0.0229	0.3087	98.3%	4.0910**	0.5886	4.7139
(2,0)		250	95.1%	0.0212	0.1529	0.2746	98.4%	3.0766	0.5209	3.6297
		500	95.3%	0.1932	0.9019	1.1914	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.6%	0.3287	0.4059	0.8456	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	95.1%	0.0212	0.1529	0.2746	98.6%	2.4374	0.3980	1.8636
		500	95.3%	0.1932	0.9019	1.1914	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.7%	0.1860	0.0138	0.3087	98.3%	4.0910**	0.5886	4.7139
(0,2)		250	95.1%	0.0212	0.1529	0.2746	98.4%	3.0766	0.5209	3.6297
		500	95.4%	0.3457	0.7931	1.2330	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.6%	0.3287	0.4059	0.8456	98.3%	4.0910**	0.5886	4.7139
(1,1)		250	95.1%	0.0212	0.0790	0.2007	98.5%	2.1892	0.4573	2.6768
		500	95.4%	0.3457	0.7931	1.2330	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.7%	0.1860	0.0138	0.3087	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	94.9%	0.0209	0.0642	0.1899	98.6%	1.4374	0.3980	1.8636
		500	95.2%	0.0853	1.0172	1.2009	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.6%	0.3287	0.4059	0.8456	98.3%	4.0910**	0.5886	4.7139
(2,1)		250	95%	0	0.1037	0.2063	98.6%	1.4374	0.3980	1.8636
		500	95.4%	0.3457	0.7931	1.2330	98.7%	0.8306	0.3428	1.1996
		1000	95.3%	0.1932	0.0229	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.6%	0.3287	0.4059	0.8456	98.3%	4.0910**	0.5886	4.7139
(2,2)		250	95.2%	0.0853	0.1193	0.3958	98.6%	1.4374	0.3980	1.8636
		500	95.3%	0.1932	0.2121	1.1914	98.8%	0.3798	0.2918	0.6957
		1000	95.3%	0.1932	0.0074	0.3124	98.3%	4.0910**	0.5886	4.7139
		1500	94.6%	0.3297	0.0025	0.8456	98.3%	4.0910**	0.5886	4.7139

EGARCH (1, 2) produces the same sort of result at the 95 per cent confidence level. True to the nature of the index as found in the earlier models, all the tested models pass three tests with ease. But there are some failures at the 99 per cent level. 16 out of the 32 models tested fail unconditional coverage even as all of them passed both the other tests conducted. The failures were found to be in the models that used the larger number of observations, viz. 1000 and 1500.

Table 5.25 EGARCH (2, 1) for Nikkei with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95.1%	0.0212	0.9956	1.1173	98.6%	1.4374	0.3980	1.8636
		500	95.2%	0.0853	0.2121	0.3958	99.1%	0.1045	0.1636	0.2862
		1000	95.5%	0.5438	0.6908	1.3267	98.7%	0.8306	0.3428	1.1996
		1500	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
(2,0)		250	95.2%	0.0853	2.6826	2.8663	98.7%	0.8306	2.0028	2.8595
		500	95%	0	0.8550	0.9576	98.9%	0.0978	0.2449	0.3649
		1000	95.4%	0.3457	0.7931	1.2330	98.6%	1.4374	0.3980	1.8636
		1500	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
(0,1)		250	95%	0	2.2008	2.3034	98.6%	1.4374	1.7458	3.2114
		500	95.4%	0.3457	1.4900	1.9300	99.1%	0.1045	0.1636	0.2862
		1000	95.4%	0.3457	0.7931	1.2330	98.7%	0.8306	0.3428	1.1996
		1500	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
(0,2)		250	95%	0	2.2008	2.3034	98.7%	0.8306	0.3428	1.1996
		500	95.1%	0.0212	0.9956	1.1173	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.6908	1.3267	98.6%	1.4374	0.3980	1.8636
		1500	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
(1,1)		250	91.9%	17.1758*	0.6111	27.0582*	94.8%	89.2681*	3.4280	1.1996
		500	95.4%	0.3457	1.4900	1.9300	99%	0	0.2022	0.2223
		1000	95.4%	0.3457	0.7931	1.2330	98.7%	0.8306	0.3428	1.1996
		1500	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
(1,2)		250	95.3%	0.1932	1.3128	1.6023	98.3%	4.0910**	1.1211	5.2464
		500	95.2%	0.0853	1.1481	1.3318	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.9019	1.1914	98.6%	1.4374	0.3980	1.8636
		1500	94.7%	0.1860	0.0138	0.3087	98.5%	2.1892	0.4573	2.6768
(2,1)		250	95.4%	0.3457	0.3613	0.8012	98.6%	1.4374	1.7458	3.2114
		500	95.4%	0.3457	1.4900	1.9300	99%	0	0.2022	0.2223
		1000	95.4%	0.3457	0.7931	1.2330	98.6%	1.4374	0.3980	1.8636
		1500	94.7%	0.1860	0.0138	0.3087	98.5%	2.1892	0.4573	2.6768
(2,2)		250	94.5%	0.5105	1.2272	1.8509	98.4%	4.0910**	0.5209	3.6297
		500	95.2%	.0853	1.1481	1.3318	98.7%	0.8306	0.3428	1.1996
		1000	95.5%	0.5438	0.6908	1.3267	98.7%	0.8306	0.3428	1.1996
		1500	94.7%	0.1860	0.0138	0.3087	98.5%	2.1892	0.4573	2.6768

Except for the ARMA (1, 1) model with 250 observations, all other models at 95 per cent level of confidence clear the three tests. The above mentioned model fails both in the unconditional and conditional coverage tests though it clears the independence test. But as seen in all models already the main impediment comes at the 99 per cent level. But here again Nikkei shows better performance as compared to the other two markets. Only ARMA (1, 1), (1, 2) and (2, 2), with 250 observations each fail in the back testing. In short, 29 out of 32 models for Nikkei qualify for the next round of tests.

Table 5.26 EGARCH (2, 2) for Nikkei with Student – t Distribution

			95				99			
ARMA	EGARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95%	0	2.2008	2.3034	98.3%	4.0910**	0.5886	4.7139
		500	95.2%	0.0853	0.0468	0.2305	98.9%	0.0978	0.2449	0.3649
		1000	95.2%	0.0853	0.0468	0.2305	98.4%	3.0766	0.5209	3.6297
		1500	94.5%	0.5105	0.3208	0.9444	98.3%	4.0910**	0.5886	4.7139
(2,0)		250	95.1%	0.0212	0.9956	1.1173	98.2%	5.2251**	0.6606	5.9221
		500	95.2%	0.0853	1.0172	1.2009	98.8%	0.3798	0.2918	0.6957
		1000	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		1500	94.5%	0.5105	0.3208	0.9444	98.3%	4.0910**	0.5886	4.7139
(0,1)		250	95.1%	0.0212	0.9956	1.1173	98.3%	4.0910**	0.5886	4.7130
		500	95.1%	0.0212	0.0790	0.2007	98.9%	0.0978	0.2449	0.3649
		1000	95.2%	0.0853	0.0468	0.2305	98.4%	3.0766	0.5209	3.6297
		1500	94.5%	0.5105	0.3208	0.9444	98.3%	4.0910%	0.5886	4.7139
(0,2)		250	94.8%	0.0832	1.7731	1.9631	98.2%	5.2251**	0.6606	5.9221
		500	95.3%	0.1932	0.9019	1.1914	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.4%	3.0766	0.5209	3.6297
		1500	94.4%	0.7308	0.2461	1.0922	98.3%	4.0910**	0.5886	4.7139
(1,1)		250	94.7%	0.1860	0.5016	0.7966	97.9%	9.2840*	0.9019	10.2284*
		500	95.1%	0.0212	0.0790	0.2007	98.7%	0.8306	0.3428	1.1996
		1000	95.2%	0.0853	0.0468	0.2305	98.3%	4.0910**	0.5886	4.7139
		1500	94.5%	0.5105	0.3208	0.9444	98.3%	4.0910**	0.5886	4.7139
(1,2)		250	94.7%	0.1860	1.5787	1.8738	97.9%	9.2840*	0.9019	10.2284*
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.3%	4.0910**	0.5886	4.7139
		1500	94.5%	0.5105	0.3208	0.9444	98.3%	4.0910**	0.5886	4.7139
(2,1)		250	94.6%	0.3287	0.4059	0.8456	97.9%	9.2840*	0.9019	10.2284*
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.3%	4.0910**	0.5886	4.7139
		1500	94.4%	0.7308	0.2461	1.0922	98.3%	4.0910**	0.5886	4.7139
(2,2)		250	94.6%	0.3287	2.8744	3.3141	98.1%	6.4725*	0.7368	7.2477**
		500	95%	0	0.1193	0.2219	98.6%	1.4374	0.3980	1.8636
		1000	95.2%	0.0853	0.0468	0.2305	98.3%	4.0910**	0.5886	4.7139
		1500	94.2%	1.2843	1.9320	3.3358	98.2%	5.2251**	0.6606	5.9221

Moving on to the more complicated EGARCH (2, 2) model, it can be observed that the 95 per cent level of confidence again does a very good job of predicting the Value-at-Risk figure. All the models simultaneously clear the three tests. But 95 per cent allows for too much failure that could often be tolerated neither by the industry nor by regulators. So it would be better to have a look at the more prudent 99 per cent level of confidence as well. Only 12 of the 32 models clear all the back testing procedure and hence only they qualify for the next round of testing. Test for independence is cleared by all the models, but majority of them fail either in unconditional or conditional coverage.

Table 5.27 GARCH (1, 1) for Nifty with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.8	0.0832	0.0343	0.2243	97.8	10.8382*	0.4435	11.3262*
		500	94.4	0.7308	0.2461	1.0922	98.1	6.4725*	0.8032	7.3141**
		1000	95.2	0.0853	0.1481	1.3318	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.7	0.1860	0.0138	0.3087	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	0.2461	1.0922	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,1)		250	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	0.2461	1.0922	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.7	0.1860	0.0138	0.3087	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	0.2461	1.0972	98.2	5.2251**	0.9535	6.2150**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,2)		250	94.5	0.5105	1.2272	1.8509	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	0.2461	1.0922	98.2	5.2251**	0.9535	6.2150**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8120	0.9259	2.8217	98.5	2.1892	1.5151	3.7346
(1,1)		250	94.6	0.3287	1.3968	1.8366	97.7	12.4853*	0.3507	12.8825*
		500	94.4	0.7308	0.2461	1.0922	98.2	5.2251**	0.9535	6.2150**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,1)		250	94.5	0.5105	1.2272	1.8509	97.9	9.2840*	0.5493	9.8758*
		500	94.4	0.7308	0.2461	1.0922	98.2	5.2251**	0.9535	6.2150**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8210	0.9259	2.8217	98.5	2.1892	1.5151	3.7346
(2,2)		250	94.3	0.9889	0.9238	2.0301	97.9	9.2840*	0.5493	9.8758*
		500	94.3	0.9889	0.9238	2.0301	98.1	6.4725*	0.8032	7.3141**
		1000	95.2	0.0853	1.1481	1.3318	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8210	0.9259	2.8217	98.5	2.1892	1.5151	3.7346

A combined analysis of the EGARCH model with Student – t distributional assumption shows that while Nikkei is seen to be more predictable among the markets studied, the predictability of Nifty and Nifty Junior is much poorer. Further, 95 per cent level of confidence give good results but quality of result deteriorates substantially as we move from 95 to 99 per cent level of confidence. Comparing the models that passed the back testing, we find that none of the models are able to give consistent result across all the markets. At the most, they do a good job in two markets. Hence, neither does the EGACH with Student – t distribution able to give at least a single model passing all the tests across the three markets.

This is the standard model for volatility and hence prediction of Value-at-Risk. As with the earlier models the standard GARCH model with normal distributional assumption also gives a cent percent record at the 95 per cent level of confidence. But the results lose its quality as a shift is made from 95 to the 99 per cent level. Models with all ARMA orders with observations except 1500 numbers fail either in unconditional or conditional coverage tests. Only ARMA models with 1500 observations clear all the coverage tests and hence only they qualify to be compared with other markets.

Table 5.28 GARCH (1, 2) for Nifty with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,2)	250	94.6	0.3287	4.7724**	5.2121	98.1	6.4725*	0.8032	7.3141**
		500	94.4	0.7308	1.0696	1.9157	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.4	0.7308	4.1007**	4.9468	98.2	5.2251**	0.9535	6.2150**
		500	94.2	1.2843	3.4887	4.8925	98.2	5.2251**	0.9535	6.2150**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,1)		250	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		500	94.6	0.3287	1.3968	1.8366	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		500	94.2	1.2843	3.4887	4.8925	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,1)		250	94.6	0.3287	1.3968	1.8366	97.8	10.8382*	0.4435	11.3262*
		500	94.4	0.7308	1.0696	1.9157	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,2)		250	94.4	0.7308	1.0696	1.9157	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.9238	2.0301	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8210	0.9259	2.8217	98.5	2.1892	1.5151	3.7346
(2,1)		250	94.3	0.9889	2.1478	3.2542	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.9238	2.0301	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8210	0.9259	2.8217	98.5	2.1892	1.5151	3.7346
(2,2)		250	94.3	0.9889	0.9238	2.0301	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	3.2041	4.9421	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8120	0.9259	2.8217	98.5	2.1892	1.5151	3.7346

Results for GARCH (1, 2) look very similar to the earlier one. All except one model, ARMA (2, 0), succeeds in the coverage tests at the 95 per cent level. The sole failure is due to interdependence among failures. All the models clear the test for independence at the 99 per cent level of significance. But just like the earlier model, only those ARMA orders that have 1500 observations as the length of input give good predictive capacity by clearing all the three tests. Thus there are 8 surviving models out of 32 that were tested and they automatically qualify for the comparison with other markets.

Table 5.29 GARCH (2, 1) for Nifty with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	94.7	0.1860	0.5016	0.7966	97.8	10.8382*	0.4435	11.3262*
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.2	0.0853	1.1481	1.3318	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.6	0.3287	0.4059	0.8456	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,1)		250	94.7	0.1860	0.5016	0.7966	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.8	0.0832	0.0343	0.2243	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,1)		250	95.4	0.3457	1.4900	1.9300	98.3	4.0910**	0.5886	4.7139
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,2)		250	94.5	0.5105	1.2272	1.8509	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,1)		250	94.5	0.5105	1.2272	1.8509	97.9	9.2840*	0.5493	9.8758*
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,2)		250	94.3	0.9889	0.7894	2.1932	98.6	1.4374	0.4435	11.3262*
		500	95	0	23.8284*	9.9192*	98.8	0.3798	15.6763*	45.8876*
		1000	94.9	0.0209	1.1481	1.3318	99.1	0.1045	0.8032	7.3141**
		1500	94.8	0.0832	0.9287	2.7408	98.9	0.0978	1.5167	3.7059

All the models with GARCH (2, 1) also produce a strikingly similar result. All, except ARMA (2, 2) with 500 observations, pass the three tests at the 95 per cent confidence level. But most of them fail at the more stringent 99 per cent level. Like the earlier two types of models tested for Nifty, this one also gives good predictability only for those models that have an input range of 1500 observations. Hence, 8 such models from each of the ARMA specification out of the 32 tested here pass all the three tests of coverage.

Table 5.30 GARCH (2, 2) for Nifty with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,2)	250	95	0	0.8550	0.9576	97.8	10.8382*	0.4435	11.3262*
		500	94.1	1.6162	1.7289	3.4668	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.8	0.0832	1.7731	1.9631	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	1.7289	3.4668	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346
(0,1)		250	95	0	0.8550	0.9576	97.8	10.8382*	0.4435	11.3262*
		500	94.2	1.2843	0.7894	2.1932	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.8	0.0832	1.7731	1.9631	97.7	12.4853*	2.5738	15.1056*
		500	94	1.9842	2.9335	5.0415	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	96	2.2534	0.1002	2.4353	98.6	1.4374	1.7458	3.2114
(1,1)		250	94.4	0.7308	1.0696	1.9157	97.8	10.8382*	0.4435	11.3262*
		500	94	1.9842	1.5382	3.6462	98	7.8272*	0.6688	8.5365**
		1000	95.4	0..3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.6	1.4374	1.7458	3.2114
(1,2)		250	94.4	0.7308	1.0696	1.9157	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	0.6662	2.4042	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.6	1.4374	1.7458	3.2114
(2,1)		250	94.5	0.5105	1.2272	1.8509	97.9	9.2840*	0.5493	9.8758*
		500	94	1.9842	1.5382	3.6462	98	7.8272*	0.6688	8.5365**
		1000	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150
		1500	95.9	1.8120	0.0616	1.9574	98.6	1.4374	1.7458	3.2114
(2,2)		250	94.3	0.9889	0.9238	2.0301	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	3.2041	4.9421	98	7.8272*	0.6688	8.5365**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346

GARCH (2, 2) model for Nifty with normal distribution also follows its family of models in the performance in coverage tests with all of the models passing the three tests at the 95 per cent level of confidence. The model repeats the performance of its class of models discussed just above by being selectively clearing the coverage tests at the 99 per cent level of significance. Like the three models already analyzed, GARCH (2, 2) also gives good predictability only for those models that takes 1500 observations as the data used for analysis purposes. Hence, in this case as well, only 8 out of the 32 models tested qualify to be rated as successful models in predicting Value-at-Risk.

Table 5.31 GARCH (1, 1) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LRi_{nd}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,1)	250	94.9%	0.0209	3.7266	2.8523	98.2%	5.2251	0.6606	5.9221
(1,0)		500	93.8%	2.8260	2.4326	5.3867	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.5%	0.5105	2.6187	3.2424	97.8%	10.8382*	2.8613	13.7440*
		1500	95.6%	0.7885	1.8835	2.7620	97.9%	9.2840*	3.1714	12.4979*
(2,0)		250	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	0.6688	8.5365**
		500	94%	1.9842	2.9335	5.0415	97.6%	14.2244*	5.5746**	19.8446*
		1000	94.4%	0.7308	2.3766	3.2227	97.9%	9.2840*	3.1714	12.4979*
		1500	95.6%	0.7885	1.8835	2.7620	98%	7.8272*	3.5057	11.3734*
(0,1)		250	94.6%	0.3287	4.7724**	5.2121	98.2%	5.2251	0.6606	5.9221
		500	94%	1.9842	2.9335	5.0415	97.5%	16.0430*	5.1413	21.2349*
		1000	94.5%	0.5105	1.2272	1.8509	97.9%	9.2840*	3.1714	12.4979*
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	3.5057	11.3734*
(0,2)		250	94.9%	0.0209	3.7266	3.8523	98%	7.8272*	0.6688	8.5365**
		500	94.1%	1.6162	3.2041	4.9421	97.4%	17.9466*	5.5746	19.8446*
		1000	94.7%	0.1860	1.5787	1.8737	97.9%	9.2840*	3.1714	12.4979*
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	3.5057	11.3734*
(1,2)		250	94.2%	1.2843	3.4887	4.8925	97.4%	17.9466*	1.8308	19.8301*
		500	93.8%	2.8260	2.4326	5.3867	97.5%	16.0430*	5.1414**	21.2349*
		1000	94.6%	0.3287	2.8744	3.3141	97.9%	9.2840*	3.1714	12.4979*
		1500	95.2%	0.0853	2.6826	2.8663	97.8%	10.8382*	6.5279**	17.4105*
(1,1)		250	94.1%	1.6162	5.0453**	6.7832**	97.4%	17.9466*	1.8308	19.8301*
		500	93.9%	2.3877	4.3561**	6.8697**	97.5%	16.0430*	5.1413**	21.2349*
		1000	94.7%	0.1860	1.5781	1.8738	97.9%	9.2840*	3.1714	12.4979*
		1500	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	3.5057	11.3734*
(2,1)		250	94.3%	0.9889	3.7874	4.8938	97.5%	16.0430*	2.0598	18.1535*
		500	93.9%	2.3877	2.6764	5.1900	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.6%	0.3287	1.3968	1.8366	97.9%	9.2840*	3.1714	12.4979*
		1500	95.4%	0.3457	1.4900	1.9300	97.8%	10.8382*	2.8613	13.7440*
(2,2)		250	93.9%	2.3877	2.6764	5.1900	97.3%	19.9292*	1.6190	21.6029*
		500	93.9%	2.3877	1.3597	3.8733	97.5%	16.0430*	5.1413**	21.2349*
		1000	94.7%	0.1860	1.5787	1.8737	97.9%	9.2840*	3.1714	12.4979*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	3.1714	12.4979*

An observation of the results for the basic Heteroscedasticity model for Nifty Junior shows that the model does a good job in predicting Value-at-Risk at the 95 per cent level of confidence. Only three models, ARMA (0, 1) with 250 observations and (1, 1) with 250 and 500 observations fail to produce good results. The former failed in the test for independence while the latter ones failed in independence as well as conditional coverage tests. But true to the trend followed up to this point, predictability declines to abysmally low levels at the 99 per cent level. Only one model, ARMA (1, 0) with 250 observations, passes all the tests at both 99 and 95 per cent levels of significance.

Table 5.32 GARCH (1, 2) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	94.4%	0.7308	2.3766	3.2227	97.6%	14.2244*	2.3071	16.5771*
		500	93.5%	4.3455**	4.8476**	9.3276**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.4%	0.7308	2.3766	3.2227	97.8%	10.8382*	2.8613	13.7440*
		1500	95.6%	0.7885	1.8835	2.7620	97.8%	10.8382*	6.5279**	17.4105*
(2,0)		250	94.4%	0.7308	2.3766	3.2227	97.6%	14.2244*	0.2700	14.5401*
		500	93.7%	3.2988	5.5771**	9.0041**	97.6%	14.2244*	5.5746**	19.8446*
		1000	94.5%	0.5105	2.6187	3.2424	97.9%	9.2840*	3.1714	12.4979*
		1500	95.6%	0.7885	1.8835	2.7620	97.9%	9.2840*	7.0527*	16.3792*
(0,1)		250	94.5%	0.5105	2.6187	3.2424	97.7%	12.4853*	2.5738	15.1056*
		500	93.7%	3.2988	5.5771**	9.0041**	97.5%	16.0430*	5.1413**	21.2349*
		1000	94.6%	0.3287	1.3968	1.8366	97.9%	9.2840*	3.1714	12.4979*
		1500	95.4%	0.3457	1.4900	1.9300	97.9%	9.2840*	7.0527*	16.3792*
(0,2)		250	94.4%	0.7308	2.3766	3.2227	97.4%	17.9466*	1.8308	19.8301*
		500	93.8%	2.8260	5.9618**	8.9159**	97.6%	14.2244*	5.5746**	19.8446*
		1000	94.7%	0.1860	1.5787	1.8737	97.9%	9.2840*	3.1714	12.4979*
		1500	95.4%	0.3457	1.4900	1.9300	97.9%	9.2840*	7.0527*	16.3792*
(1,1)		250	93.8%	2.8260	8.1903*	11.1444*	97.4%	17.9466*	1.8308	19.8301*
		500	93.6%	3.8054	7.2738*	11.2115*	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.7%	0.1860	1.5787	1.8737	97.9%	9.2840*	3.1714	12.4979*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	7.0527*	16.3792*
(1,2)		250	94%	1.9842	4.6932**	6.8012**	97.4%	17.9466*	1.8308	19.8301
		500	93.7%	3.2988	5.5771**	9.0041**	97.5%	16.0430*	5.1413**	21.2349*
		1000	94.6%	0.3287	2.8744	3.3141	97.9%	9.2840*	3.1714	12.4979*
		1500	95.2%	0.0853	2.6826	2.8663	97.8%	10.8382*	6.5279**	17.4105*
(2,1)		250	94%	1.9842	4.6932**	6.8012**	97.3%	19.9292*	1.6190	21.6029*
		500	93.7%	3.2988	5.5771**	9.0041**	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.6%	0.3287	1.3968	1.8366	97.9%	9.2840*	3.1714	12.4979*
		1500	95.4%	0.3457	1.4900	1.9300	97.7%	12.4853*	6.0360**	18.5679*
(2,2)		250	93.7%	3.2988	5.5771**	9.0041**	97.4%	17.9466*	1.8308	19.8301*
		500	93.8%	2.8260	1.1932	4.1473	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.7%	0.1860	1.5787	1.8737	97.9%	9.2840*	3.1714	12.4979*
		1500	95.3%	0.1932	1.3128	1.6023	97.8%	10.8382*	6.5279**	17.4105*

Predictability worsens for Nifty Junior when we move from GARCH (1, 1) to GARCH (1, 2) not only at the 99 per cent level but also at the 95 per cent level. 11 of the 32 models fail at the former level of confidence mainly due to interdependence among the failures. Hence, they fail in conditional coverage test as well. Failure at 95 per cent level was just a pre-runner in this case. There are found to be no successful models at this level of significance. Half of the models fail in the independence test even and none of the models successfully complete either unconditional or conditional coverage tests. Nominal coverage at 95 per cent level go as low as 93.7 per cent on the down side while that at the 99 per cent goes down to 97.3, implying 27 failures out of 1000 predicted values.

Table 5.33 GARCH (2, 1) for Nifty Junior with Normal Distribution

		95					99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95.4%	0.3457	0.3613	0.8012	98%	7.8272*	0.6688	8.5365**
		500	95.6%	0.7885	0.022	0.8807	98.2%	5.2251	0.6606	5.9221
		1000	96.4%	4.5530**	0.0792	4.7056	98.5%	2.1892	0.4573	2.6768
		1500	97%	9.7686**	0.0112	9.8407*	98.7%	0.8306	0.3428	1.1996
(2,0)		250	95.4%	0.3457	0.3613	0.8012	98%	7.8272*	0.6688	8.5365**
		500	95.6%	.7885	0.0022	0.8807	98.2%	5.2251	0.6606	5.9221
		1000	96.3%	3.8953**	0.1184	4.0892	98.6%	1.4374	0.3980	1.8636
		1500	97%	9.7686**	0.0112	9.8407*	98.7%	0.8306	0.3428	1.1996
(0,1)		250	95.2%	0.0853	0.2121	0.3958	98.1%	6.4725	0.8032	7.3141**
		500	95.6%	0.7885	0.0022	0.8807	98.2%	5.2251	0.6606	5.9221
		1000	96.3%	3.8953**	0.1184	4.0892	98.5%	2.1892	0.4573	2.6768
		1500	97%	9.7686**	0.0112	9.8407*	98.7%	0.8306	0.3428	1.1996
(0,2)		250	95.3%	0.1932	0.2815	0.5710	97.9%	9.2840*	0.5493	9.8758*
		500	95.6%	0.7885	0.0022	0.8807	98.1%	6.4725	0.7368	7.2477**
		1000	96.3%	3.8953**	0.1184	4.0892	98.5%	2.1892	0.4573	2.6768
		1500	96.9%	8.7393**	0.0016	8.8039**	98.7%	0.8306	0.3428	1.1996
(1,1)		250	94.6%	0.3287	1.3968	1.8366	97.7%	12.4853*	0.3507	12.8825*
		500	95.5%	0.5438	0.4517	1.0877	98.1%	6.4721	0.7368	7.2477**
		1000	96.3%	3.8953**	0.1184	4.0892	98.5%	2.1892	0.4573	2.6768
		1500	96.9%	8.7393**	0.0016	8.8039**	98.7%	0.8306	0.3428	1.1996
(1,2)		250	95.6%	0.7885	0.5531	1.4316	98.3%	4.0910	0.5886	4.7139
		500	95.5%	0.5438	3.9676e-004	0.6364	98.1%	6.4721	0.7368	7.2477**
		1000	96.5%	5.2684**	0.0476	5.3873	98.5%	2.1892	0.4573	2.6768
		1500	97%	9.7686**	0.0112	9.8407*	98.6%	1.4374	1.7458	3.2114
(2,1)		250	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910	0.5886	4.7139
		500	95.5%	0.5438	3.9676e-004	0.6364	98.1%	6.4721	0.7368	7.2477**
		1000	96.3%	3.8953**	0.1184	4.0892	98.5%	2.1892	0.4573	2.6768
		1500	96.9%	8.7393**	0.0016	8.8039**	98.6%	1.4374	0.3980	1.8636
(2,2)		250	95.4%	0.3457	3.2216	3.6615	98.3%	4.0910	0.5886	4.7139
		500	95.4%	0.3457	0.0074	0.4473	98%	7.8272*	0.8172	8.6849**

Results for the GARCH (2, 1) model are more wide spread. Half of the models tested at the 95 per cent level successfully clear all the tests. None of the models failed in the test for independence. But a model to be a complete success it has to simultaneously pass the three tests at the 99 per cent level as well. Though half of the models emerged successful at the 95 per cent level, most of them are seen to fail at the narrower confidence band either due to insufficiency of conditional or unconditional coverage.

Only six models, ARMA (1, 0), (2, 0), (0, 1) at 500 observation and (1, 2), (2, 1) and (2, 2) at 250 observations make the cut at this level.

Table 5.34 GARCH (2, 2) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	94.4%	0.7308	1.0696	1.9157	97.3%	19.9292*	1.6190	21.6029*
		500	94.1%	1.6162	1.7289	3.4668	97.8%	10.8382*	0.9909	11.8736*
		1000	94.8%	0.0832	3.4280	3.6180	98.2%	5.2251	0.6606	5.9221
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	3.5057	11.3734*
(2,0)		250	94.5%	0.5105	0.3208	0.9444	97.6%	14.2244*	2.3071	16.5771*
		500	94.1%	1.6162	3.2041	4.9421	97.9%	9.2840*	0.9019	10.2284*
		1000	94.7%	0.1860	3.1440	3.4390	98.1%	6.4721	0.7368	7.2477**
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	0.6688	8.5365**
(0,1)		250	94.4%	0.7308	1.0696	1.9157	97.4%	17.9466*	1.8308	19.8301*
		500	94.1%	1.6162	3.2041	4.9421	97.8%	10.8382*	0.9909	11.8736*
		1000	94.8%	0.0832	3.4280	3.6180	98.1%	6.4721	0.7368	7.2477**
		1500	95.4%	0.3457	1.4900	1.9300	97.9%	9.2840*	3.1714	12.4979*
(0,2)		250	94.5%	0.5105	0.3208	0.9444	97.5%	16.0430*	2.0598	18.1535*
		500	93.9%	2.3877	4.3561**	6.8697**	97.8%	10.8382*	0.9909	11.8736*
		1000	94.7%	0.1860	3.1440	3.4390	98%	7.8272*	0.8172	8.6849**
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	0.6688	8.5365**
(1,1)		250	94.6%	0.3287	2.8744	3.3141	97.7%	12.4853*	1.0841	13.6160*
		500	94.1%	1.6162	3.2041	4.9421	97.7%	12.4853*	1.0841	13.6160*
		1000	94.7%	0.1860	3.1440	3.4390	98%	7.8272*	0.8172	8.6849**
		1500	95.2%	0.0853	1.1481	1.3318	98%	7.8272*	0.6688	8.5365**
(1,2)		250	94.6%	0.3287	1.3968	1.8366	97.8%	10.8382*	0.9909	11.8736*
		500	94.1%	1.6162	3.0241	4.9421	97.7%	12.4853*	0.3507	12.8825*
		1000	94.8%	0.0832	3.4280	3.6180	98.1%	6.4721	0.7368	7.2477**
		1500	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	0.6688	8.5365**
(2,1)		250	94.4%	0.7308	0.2461	1.0922	97.8%	10.8382*	0.9909	11.8736*
		500	94%	1.9842	1.5382	3.6462	97.8%	10.8382*	0.9909	11.8736*
		1000	95%	0	2.2008	2.3034	98.1%	6.4721	0.7368	7.2477**
		1500	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	0.6688	8.5365**
(2,2)		250	94.4%	0.7308	1.0696	1.9157	97.8%	10.8382*	0.9909	11.8736*
		500	94%	1.9842	1.5382	3.6462	97.8%	10.8382*	0.9909	11.8736*
		1000	95%	0	2.2008	2.3034	98.1%	6.4721	0.7368	7.2477**
		1500	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	0.6688	8.5365**

Result for GARCH (2, 2) model is more typical of the earlier models reviewed. There are no across the board failures at the 95 per cent level. Only ARMA (0, 2) with 500 observations fail to pass the tests with a nominal coverage of 93.9 per cent. However, when it comes to the next level of significance, failures is the norm than exception. Though all the models pass test of independence, only one model, ARMA (1, 0) with

1000 observations, pass all the tests together with those at the 95 per cent significance level.

Table 5.35 GARCH (1, 1) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.8%	0.0832	0.0343	0.2243	98.7%	1.4374	0.3428	0.1996
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	99%	0	0.2022	0.2223
(2,0)		250	94.9%	0.0209	0.1676	0.2933	98.6%	1.4374	0.3980	1.8636
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(0,1)		250	94.8%	0.0832	0.0343	0.2243	98.8%	0.3798	0.2928	0.6957
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	99%	0	0.2022	0.2223
(0,2)		250	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(1,1)		250	94.5%	0.5105	0.0002	0.6240	98.9%	0.0978	0.2918	0.3649
		500	95.3%	0.1932	0.0229	0.3124	99%	0	0.2918	0.2223
		1000	95.4%	0.3457	0.0074	0.4473	99.2%	0.4337	0.1292	0.5790
		1500	94.8%	0.0832	0.2238	0.4138	99%	0	0.2449	0.2223
(1,2)		250	94.6%	0.3287	0.0025	0.4422	98.8%	0.3798	0.2449	0.6957
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2022	0.6957
		1000	95.3%	0.1932	0.0229	0.3124	99.2%	0.4337	0.1292	0.5790
		1500	94.8%	0.0832	0.2238	0.4138	98.9%	0.0978	0.2022	0.3649
(2,1)		250	94.6%	0.3287	0.0025	0.4422	98.7%	1.4374	0.3428	1.1996
		500	95.1%	0.0212	0.0790	0.2007	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(2,2)		250	94.2%	1.2843	0.0467	1.4505	98.7%	1.4374	0.3428	1.1996
		500	95.1%	0.0212	0.0790	0.2007	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0790	0.2007	99.2%	0.4337	0.1292	0.5790
		1500	94.8%	0.0832	0.2238	0.4138	98.9%	0.0978	0.2449	0.3649

The basic GARCH model for Nikkei does exceedingly well as compared to the other two indices. All the models pass not only the tests at the 95 per cent confidence level but also at the stricter 99 per cent level of confidence as well. Nominal coverage varies in a very narrow band of 94.5 per cent to 95.3 per cent for the 95 per cent level of confidence and between 98.7 to 99.2 at the 99 per cent level of confidence. Hence, all the different varieties of models of GARCH (1, 1) for Nikkei with normal distribution qualify to be compared with the successful models of other markets.

Table 5.36 GARCH (1, 2) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	95.4%	0.3457	0.0074	0.4473	98.6%	1.4374	0.3980	1.8636
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	1.4374	0.3980	1.8636
(2,0)		250	94.9%	0.0209	0.0642	0.1899	98.4%	3.0766	0.5209	3.6297
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1500	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636
(0,1)		250	95.3%	0.1932	0.0229	0.3124	98.6%	1.4374	0.3980	1.8636
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.8%	03798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	1.4374	0.3980	1.8636
(0,2)		250	95%	0	0.1037	0.2063	98.5%	2.1892	0.4573	2.6768
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636
(1,1)		250	94.4%	0.7308	0.0070	0.8531	98.6%	1.4374	0.3980	1.8636
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.6%	0.3287	0.3594	0.7991	98.6%	1.4374	0.3980	1.8636
(1,2)		250	94.6%	0.3287	0.0025	0.4422	98.7%	1.4374	0.3428	1.8636
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636
(2,1)		250	94.6%	0.3287	0.0027	0.3313	98.6%	1.4374	0.3976	1.8350
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	16.7665*	16.9502*	97.8%	10.8382*	11.0867*	21.9694*
		1500	94.9%	0.0209	14.5673*	14.6929*	97.7%	12.4853*	10.3801*	22.1919*
(2,2)		250	94.4%	0.7308	0.0070	0.8531	98.6%	1.4374	0.3980	1.8636
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1500	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636

This model also does a good job of predicting Value-at-Risk of Nikkei. However, the percentage success is not as convincing as the GARCH (1, 1) model. Two of the models, ARMA (2, 1) with 1000 and 1500 observations fail in the test for independence as well as that for conditional coverage at the 95 per cent level and the same models fails at the 99 per cent level also in all of the three tests. Hence, except for these two models, the rest 30 out of the 32 models comfortably clear the rigors of back testing to be eligible for promotion to the next round.

Table 5.37 GARCH (2, 1) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observation	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95.3%	0.1932	1.3128	1.6023	989.9%	0.0978	0.2449	0.3649
		500	95.1%	0.0212	0.0790	0.2007	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0790	0.2007	99.1%	0.1045	0.1636	0.2823
		1500	94.9%	0.0209	0.1676	0.2933	99%	0	0.2022	0.2223
(2,0)		250	94.6%	0.3287	1.3968	1.8366	98.9%	0.0978	0.2449	0.3649
		500	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2862
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(0,1)		250	94.8%	0.0832	0.6082	0.7983	98.7%	0.8306	0.3428	1.1996
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	99.1%	0.1045	0.1636	0.2862
		1500	94.9%	0.0212	0.1676	0.2933	99%	0	0.2022	0.2223
(0,2)		250	94.6%	0.3287	0.4059	0.8456	98.8%	0.3798	0.2918	0.6957
		500	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2863
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(1,1)		250	94.6%	0.3287	0.0025	0.4422	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	06957
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.2238	0.4138	99%	0	0.2022	0.2223
(1,2)		250	94.7%	0.1860	0.0138	0.3087	98.7%	0.8306	0.3428	1.1996
		500	94.9%	0.0209	0.1676	0.2933	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.2238	0.4138	98.9%	0.0978	0.2449	0.3649
(2,1)		250	94.7%	0.1860	0.0138	0.3087	98.7%	0.8306	0.3428	1.1996
		500	94.9%	0.0209	0.1676	0.2933	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2862
		1500	94.5%	0.5105	0.4386	1.0623	98.8%	0.3798	0.2918	0.6957
(2,2)		250	94.3%	0.9889	0.0225	1.1289	98.6%	1.4374	0.3980	1.8636
		500	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1000	94.9%	0.0209	0.1676	0.2933	99.1%	0.1045	0.1636	0.2862
		1500	94.8%	0.0832	0.2238	0.4138	98.9%	0.0978	0.2449	0.3649

Nikkei again differs from the other markets in terms of predictability by being extremely compliant. While the other markets produce more or less fair amount of accuracy in prediction at the 95 per cent level of confidence and fails more often at the 99 per cent level, Nikkei produces good predictability at both levels of confidence. In this particular case too, all the models tested for Nikkei passes the three tests of coverage at both the 95 and 99 per cent levels of significance thereby enabling them to be eligible for comparison with such models from the other two markets tested.

Table 5.38 GARCH (2, 2) for Nikkei with Normal Distribution.

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{cc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.1%	0.0212	0.1529	0.2746	98.4%	3.0766	0.5209	3.6297
		500	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0832	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	0.1.4374	0.3980	1.8636
(2,0)		250	94.7%	0.1860	0.0138	0.3087	98.3%	4.0910**	0.5886	4.7139
		500	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	1.4374	0.3980	1.8636
(0,1)		250	95.3%	0.1932	0.0229	0.3124	98.4%	3.0766	0.5209	3.6297
		500	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.2918	0.6957
		1000	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	1.4374	0.3980	1.8636
(0,2)		250	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		500	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636
(1,1)		250	94.6%	0.3287	0.3594	0.7991	98.5%	2.1892	0.4573	2.6768
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	1.4374	0.3980	1.8636
(1,2)		250	94.9%	0.0209	0.1676	0.2944	98.6%	1.4374	0.3980	1.8636
		500	95.1%	0.0212	0.1529	0.2746	98.8%	0.3798	0.2918	0.6957
		1000	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1500	94.9%	0.0209	0.1676	0.2933	98.6%	1.4374	0.3980	1.8636
(2,1)		250	94.9%	0.0209	0.1676	0.2933	98.6%	1.4374	0.3980	1.8636
		500	95.2%	0.0853	0.0468	0.2305	98.8%	0.3798	0.2918	0.6957
		1000	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1500	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636
(2,2)		250	94.4%	0.7308	0.5253	1.3714	98.6%	1.4374	0.3980	1.8636
		500	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1000	95%	0	0.1193	0.2219	98.8%	0.3798	0.2918	0.6957
		1500	94.7%	0.1860	0.2878	0.5827	98.6%	1.4374	0.3980	1.8636

Moving on to the more complicated GARCH (2, 2) model, it is found that higher levels of model building does not really affect the outcome as clearly suggested by the table above. All the models pass unconditional and conditional coverage as well as test for independence at the 95 per cent level of confidence. But two models, ARMA (2, 0) and (0, 2), fail to pass all the tests at the 99 per cent level of confidence. The failure of the models is due to lack of unconditional coverage. Despite this, 30 out of 32 varieties of

GARCH (2, 2) models tested passed all the hurdles and hence, it is safe to think that GARCH (2, 2) gives god predictability in calculating Value-at-Risk for Nikkei with normal distribution.

A comparison of the successful models from the three markets again produces disappointing results. Though each market independently gave a number of successful models, none of such models could prove efficient in all the three markets studied. Nikkei again gave predictability much above that of the Indian markets and the study could not find any significant relation between length of data used and predictive accuracy neither could there be found any substantial change in the predictability between lower and higher level models. Hence, it is found that the conventional GARCH model with its four variations and 128 sub variations could not throw up any winner in terms of across the board predictability.

Table 5.39 GARCH (1, 1) for Nifty with Student– t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.5	0.5105	1.2272	1.8509	97.8	10.8382*	0.4435	11.3262*
		500	94.7	0.1860	0.5016	0.7966	98	7.8272*	3.5057	11.3734*
		1000	95.2	0.0832	1.1481	1.3318	98.2	5.2251**	4.2565**	9.5179*
		1500	96	2.2534	0.1002	2.4353	98.4	3.0766	5.1359**	8.2448**
(2,0)		250	94.6	0.3287	1.3968	1.8366	97.9	9.2840*	0.5493	9.8758*
		500	94.6	0.3287	0.4059	0.8456	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	3.8666**	10.3775*
		1500	96	2.2534	0.1002	2.4353	98.5	2.1892	5.6335**	7.8530**
(0,1)		250	94.5	0.5105	1.2272	1.8509	97.8	10.8382*	0.4435	11.3262*
		500	94.6	0.3287	0.4059	0.8456	98	7.8272*	3.5057	11.3734*
		1000	95.1	0.0212	1.1481	1.3318	98.1	6.4725*	3.8666**	10.3775*
		1500	96	2.2534	0.1002	2.4353	98.4	3.0766	5.1359**	8.2448**
(0,2)		250	94.7	0.1860	1.5787	1.8737	97.9	9.2840*	0.5493	9.8758*
		500	94.5	0.5105	0.3208	0.9444	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	3.8666**	10.3775*
		1500	96	2.2534	0.1002	2.4353	98.5	2.1892	5.6335**	7.8530**
(1,1)		250	94.6	0.3287	1.3968	1.8366	97.9	9.2840*	0.4435	11.3262*
		500	94.5	0.5105	0.4059	0.8456	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	3.8666**	10.3775*
		1500	96	2.2534	0.1002	2.4353	98.5	2.1892	5.6335**	7.8350**
(1,2)		250	94.6	0.3287	1.4015	1.7302	97.9	9.2840*	0.5504	9.8345*
		500	94.5	0.5105	0.3208	0.9444	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	0.9535	6.2150**
		1500	96	2.2534	0.1002	2.4353	98.5	2.1892	5.6335**	7.8350**
(2,1)		250	94.5	0.5105	1.2272	1.8509	97.8	10.8382*	0.4435	11.3262*
		500	94.5	0.5105	0.3208	0.9444	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	0.9535	6.2150**
		1500	96	2.2534	0.1002	2.4353	98.5	2.1892	5.6335**	7.8350**
(2,2)		250	94.4	0.7308	1.0696	1.9157	97.8	10.8382*	0.4435	11.3262*
		500	94.7	0.1860	0.5016	0.7966	98.1	6.4725*	0.8032	7.3141**
		1000	95.1	0.0212	0.9956	1.1173	98.2	5.2251**	0.9535	6.2150**
		1500	96.1	2.7469	0.1486	2.9751	98.5	2.1892	5.6335**	7.8350**

The earlier models tested with GARCH had assumed a normal distribution of the returns, but in reality, returns have a fatter tail than normal approximating it to Student – t distribution. Hence, the same type of models may be tested with such an assumption. Here, the results for Nifty is shown and will be followed by those for Nifty Junior and Nikkei. As with most other models studied so far, GARCH (1, 1) with Student – t distributional assumption gives cent percent predictability at 95 per cent level. However, none of the models pass all the three tests together at the 99 per cent level of confidence. All of them fail conditional coverage test and more than half fail both, test for independence and unconditional coverage. And the study could not produce any successful model at all.

Table 5.40 GARCH (1, 2) for Nifty with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,2)	250	94.6	0.3287	4.7724**	5.2121	98.1	6.4725*	0.8032	7.3141**
		500	94.4	0.7308	1.0696	1.9157	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.4	0.7308	4.1007**	4.9468	98.2	5.2251**	0.9535	6.2150**
		500	94.2	1.2843	3.4887	4.8925	98.2	5.2251**	0.9535	6.2150**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,1)		250	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		500	94.6	0.3287	1.3968	1.8366	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.7	0.1860	3.1440	3.4390	98.1	6.4725*	0.8032	7.3141**
		500	94.2	1.2843	3.4887	4.8925	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,1)		250	94.6	0.3287	1.3968	1.8366	97.8	10.8382*	0.4435	11.3262*
		500	94.4	0.7308	1.0696	1.9157	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,2)		250	94.4	0.7308	1.0696	1.9157	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.9238	2.0301	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8210	0.9259	2.8217	98.5	2.1892	1.5151	3.7346
(2,1)		250	94.3	0.9889	2.1478	3.2542	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.9238	2.0301	98.3	4.0910**	1.1211	5.2464
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8210	0.9259	2.8217	98.5	2.1892	1.5151	3.7346
(2,2)		250	94.3	0.9889	0.9238	2.0301	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	3.2041	4.9421	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	0.9535	6.2150**
		1500	95.9	1.8120	0.9259	2.8217	98.5	2.1892	1.5151	3.7346

Observing the results for the GARCH (1, 2) model, it is seen that except for two models, ARMA (1, 0) and (2, 0) at 250 observations, all the models pass the unconditional coverage tests with nominal coverage ranging from 94.1 to 95.9. Model failures are due to interdependence among exceptions. An interesting pattern is found when a move is made to the 99 per cent level. All ARMA models that use 1500 as the data length clears all the tests of coverage and all other models fail without exception. This was found for Nifty with normal distribution as well. Hence, there are 8 surviving models for GARCH (1, 2) with Student – t distribution.

Table 5.41 GARCH (2, 1) for Nifty with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	94.7	0.1860	0.5016	0.7966	97.8	10.8382*	0.4435	11.3262*
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.2	0.0853	1.1481	1.3318	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.6	0.3287	0.4059	0.8456	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,1)		250	94.7	0.1860	0.5016	0.7966	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.8	0.0832	0.0343	0.2243	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,1)		250	95.4	0.3457	1.4900	1.9300	98.3	4.0910**	0.5886	4.7139
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	1.3128	1.6023	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(1,2)		250	94.5	0.5105	1.2272	1.8509	98	7.8272*	0.6688	8.5365**
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,1)		250	94.5	0.5105	1.2272	1.8509	97.9	9.2840*	0.5493	9.8758*
		500	94.3	0.9889	0.1816	1.2880	98.1	6.4725*	0.8032	7.3141**
		1000	95.4	0.3457	1.4900	1.9300	98.2	5.2251**	0.9535	6.2150**
		1500	95.8	1.4215	0.7899	2.2972	98.5	2.1892	1.5151	3.7346
(2,2)		250	94.3	0.9889	0.7894	2.1932	98.6	1.4374	0.4435	11.3262*
		500	95	0	23.8284*	9.9192*	98.8	0.3798	15.6763	45.8876*
		1000	94.9	0.0209	1.1481	1.3318	99.1	0.1045	0.8032	7.3141**
		1500	94.8	0.0832	0.9287	2.7408	98.9	0.0978	1.5167	3.7059

In the GARCH (2, 1) model, only one model, ARMA (2, 2) with 500 observations, fails to make it to the successful model list at the 95 per cent level of confidence. That is found to be due to the clustering of failures as seen by the huge chi square value for the test of independence. However, things take a turn for the worse moving on to the 99 per cent level of confidence. Similar to the previous model checked, all the models fail to produce good accuracy in prediction except those with 1500 observations as the number of data points used to predict Value-at-Risk.

Table 5.42 GARCH (2, 2) for Nifty with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,2)	250	95	0	0.8550	0.9576	97.8	10.8382*	0.4435	11.3262*
		500	94.1	1.6162	1.7289	3.4668	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346
(2,0)		250	94.8	0.0832	1.7731	1.9631	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	1.7289	3.4668	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346
(0,1)		250	95	0	0.8550	0.9576	97.8	10.8382*	0.4435	11.3262*
		500	94.2	1.2843	0.7894	2.1932	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346
(0,2)		250	94.8	0.0832	1.7731	1.9631	97.7	12.4853*	2.5738	15.1056*
		500	94	1.9842	2.9335	5.0415	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	96	2.2534	0.1002	2.4353	98.6	1.4374	1.7458	3.2114
(1,1)		250	94.4	0.7308	1.0696	1.9157	97.8	10.8382*	0.4435	11.3262*
		500	94	1.9842	1.5382	3.6462	98	7.8272*	0.6688	8.5365**
		1000	95.4	0..3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.6	1.4374	1.7458	3.2114
(1,2)		250	94.4	0.7308	1.0696	1.9157	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	0.6662	2.4042	98	7.8272*	0.6688	8.5365**
		1000	95.4	0.3457	1.4900	1.9300	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.6	1.4374	1.7458	3.2114
(2,1)		250	94.5	0.5105	1.2272	1.8509	97.9	9.2840*	0.5493	9.8758*
		500	94	1.9842	1.5382	3.6462	98	7.8272*	0.6688	8.5365**
		1000	95.5	0.5438	1.6801	2.3161	98.2	5.2251**	0.9535	6.2150
		1500	95.9	1.8120	0.0616	1.9574	98.6	1.4374	1.7458	3.2114
(2,2)		250	94.3	0.9889	0.9238	2.0301	97.9	9.2840*	0.5493	9.8758*
		500	94.1	1.6162	3.2041	4.9421	98	7.8272*	0.6688	8.5365**
		1000	95.3	0.1932	1.3128	1.6023	98.1	6.4725*	0.8032	7.3141**
		1500	95.9	1.8120	0.0616	1.9574	98.5	2.1892	1.5151	3.7346

GARCH (2, 2) model with Student – t distribution also follows the path taken by the same but simpler types of models. It clears all the tests of coverage at the 95 per cent level of confidence quite comfortably with nominal coverage ranging from 94 to 96. Same performance is repeated for the test of independence at 99 per cent level. But 3/4th of the models fail to make the cut when unconditional and conditional coverage test results are checked. Only the models whose volatility or variance was predicted using 1500 data points in to the past could make progress from those tests. Next tables in line are those for Nifty Junior with same models.

Table 5.43 GARCH (1, 1) for Nifty Junior with Student t - Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.5%	0.5105	6.6114*	7.2351**	97.6%	14.2244*	0.2700	14.5401*
		500	93.8%	2.8260	4.0337**	6.9878**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.7%	0.1860	3.1440	3.4390	97.8%	10.8382*	2.8613	13.7440*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	3.1714	12.4979*
(2,0)		250	94.4%	0.7308	8.6263*	9.4724*	97.6%	14.2244*	0.2700	14.5401*
		500	93.9%	2.3877	2.6764	5.1900	97.2%	21.9880*	3.9913**	26.0361*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	3.5057	11.3734*
(0,1)		250	94.6%	0.3287	7.0444	7.4842**	97.5%	16.0430*	0.2010	16.2946*
		500	93.7%	3.2988	3.7257	7.1547**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.7%	0.1860	3.1440	3.4390	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	97.9%	9.2840*	3.1714	12.4979*
(0,2)		250	94.4%	0.7308	6.1954*	7.0415**	97.6%	14.2244*	0.2700	14.5401*
		500	93.8%	2.8260	4.0337**	6.9878**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	3.5057	11.3734*
(1,1)		250	94.2%	1.2843	6.3642*	8.8778**	97.6%	14.2244*	0.2010	16.2946*
		500	93.8%	2.8260	3.7257	7.1547**	97.4%	17.9466*	4.3513**	24.3352*
		1000	94.8%	0.0832	3.7266	3.8523	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.4900	1.9300	97.9%	9.2840*	3.1714	12.4979*
(1,2)		250	94.2%	1.2843	7.6697*	9.0735**	97.6%	14.2244*	0.2700	14.5401*
		500	93.8%	2.8260	2.4326	5.3867	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	3.1714	12.4979*
(2,1)		250	94.2%	1.2843	7.6697*	9.0735**	97.6%	14.2244*	0.2700	14.5401*
		500	93.7%	2.8260	3.4280	7.1547**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.8%	0.0832	3.7257	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	3.1714	12.4979*
(2,2)		250	94.1%	1.6162	5.0453**	6.7832**	97.6%	14.2244*	1.1817	15.4517*
		500	93.8%	2.8260	2.4326	5.3867	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.9%	0.0209	3.7266	3.8523	98%	7.8272*	3.5057	11.3734*
		1500	95.1%	0.0212	0.9956	1.1173	98%	7.8272*	3.5057	11.3734*

GARCH (1, 1) for Nifty Junior with Student – t distribution does not do as good a job as was done by the previous models even at the 95 per cent level. 13 models fail either in the test for independence or conditional coverage. Only 19 out of 32 models clear all the tests and the nominal coverage band is between 93.7 and 95.4. Results go in to the worst as the 99 per cent level is reviewed. None of the models pass either unconditional or conditional coverage tests. Hence, no models could be found from GARCH (1, 1) for Nifty Junior with Student – t distribution that is eligible for comparison with other markets.

Table 5.44 ARCH (1, 2) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	94.3%	0.9889	8.1390*	9.2454*	97.7%	12.4853*	0.3507	12.8825*
		500	93.8%	2.8260	4.0337**	6.9878**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.7%	0.1860	3.1440	3.4390	97.8%	10.8382*	2.8613	13.7440*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840	3.1714	12.4979*
(2,0)		250	94.4%	0.7308	8.6263*	9.4724*	97.6%	14.2244*	0.2700	14.5401*
		500	93.9%	2.3877	1.3597	3.8733	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.3128	1.6023	98%	7.8272*	3.5057	11.3734*
(0,1)		250	94.5%	0.5105	4.4289**	5.0526	97.5%	16.0430*	0.2010	16.2946*
		500	93.7%	3.2988	3.7257	7.1547**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.7%	0.1860	3.1440	3.4390	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	97.9%	9.2840*	3.1747	12.4979*
(0,2)		250	94.1%	1.6162	7.2177*	8.9557**	97.6%	14.2244*	0.2700	14.5401*
		500	93.8%	2.8260	2.4326	5.3867	97.4%	17.9466*	4.7341**	22.7334*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	98%	7.8272*	3.5057	11.3734*
(1,1)		250	94%	1.9842	6.7287*	8.8907**	97.5%	16.0430*	0.2010	16.2946*
		500	93.6%	3.8054	3.4317	7.3694**	97.3%	19.9292*	4.3513**	24.3352
		1000	94.9%	0.0209	3.7266	3.8523	98%	7.8272*	3.5057	11.3734*
		1500	95.4%	0.3457	1.4900	1.9300	97.9%	9.2840*	3.1714	12.4979*
(1,2)		250	94.2%	1.2843	7.6697*	9.0735**	97.6%	14.2244*	0.2700	14.5401*
		500	93.7%	3.2988	3.7257	7.1547**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	3.1714	12.4979*
(2,1)		250	94%	1.9842	4.6932**	6.8012**	97.3%	19.9292*	1.6190	21.6029*
		500	93.7%	3.2988	3.7257	7.1547**	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.8%	0.0832	3.4280	3.6180	98%	7.8272*	3.5057	11.3734*
		1500	95.3%	0.1932	1.3128	1.6023	97.9%	9.2840*	3.1714	12.4979*
(2,2)		250	94.1%	1.6162	5.0453**	6.7832**	97.5%	16.0430*	0.2010	16.2946*
		500	93.8%	2.8260	2.4326	5.3867	97.3%	19.9292*	4.3513**	24.3352*
		1000	94.9%	0.0209	3.7266	3.8523	97.9%	9.2840*	3.5057	11.3734*
		1500	95.1%	0.0212	0.9956	1.1173	98%	7.8272*	3.5057	11.3734*

A very similar result to the just preceding set of models is obtained for GARCH (1, 2) as well. Exactly 13 models fail in either of the tests at 95 per cent level of significance and none of the models qualify unconditional and conditional coverage and test for independence simultaneously. The only difference with the earlier model is that ARMA (1, 0) with 1500 observations clear the unconditional coverage test but fails in the more rigorous conditional coverage test. Thus, there are no surviving models for Nifty Junior from GARCH (1, 2) with Student – t distribution either.

Table 5.45 GARCH (2, 1) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	94.7%	0.9889	3.1440	3.4390	97.7%0	10.8382*	1.0841	13.6160*
		500	94.2%	1.2843	1.9320	3.3358	97.7%	10.8382*	0.3507	12.8825*
		1000	95.2%	0.0853	2.6826	2.8663	98.1%	6.4725*	0.8032	7.3141**
		1500	95.1%	0.0212	2.4327	2.5564	98.3%	4.0910**	1.1211	5.2464
(2,0)		250	94.9%	0.0209	3.7266	3.8523	97.8%	10.8382*	0.9909	11.8736*
		500	94.4%	0.7308	2.3766	3.2227	97.9%	9.2840%	0.5493	9.8758*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95.1%	0.0212	2.4347	2.5564	98.1%	6.4725*	0.8032	7.3141**
(0,1)		250	94.7%	0.1860	3.1440	3.4390	97.7%	10.8382*	1.0841	13.6160*
		500	94.2%	1.2843	1.9320	3.3358	97.9%	9.2840*	0.5493	9.8758*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95.1%	0.0212	0.9956	1.1173	98%	7.8272*	0.6688	8.5365**
(0,2)		250	94.8%	0.0832	3.4353	3.5185	97.7%	12.4853*	1.0830	13.5683*
		500	94.4%	0.7308	2.3766	3.2227	97.8%	10.8382*	0.4435	11.3262*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95.1%	0.0212	0.9956	1.1173	98%	7.8272*	0.6688	8.5365**
(1,1)		250	94.5%	0.5105	4.42**	5.0526	97.6%	14.2244*	1.1817	15.4517*
		500	94.4%	0.7308	2.3766	3.2227	97.7%	12.4853*	0.3507	12.8825*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95.1%	0.0212	0.9956	1.1173	98.1%	6.4725*	0.7368	7.2477**
(1,2)		250	94.7%	0.1860	3.1440	3.4390	97.7%	12.4853*	1.0841	13.6160*
		500	94.4%	0.7308	1.0696	1.9157	97.9%	9.2840*	0.9019	10.2284*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95%	0	2.2008	2.3034	98.1%	6.4725*	0.7368	7.2477**
(2,1)		250	94.6%	0.3287	2.8744	3.3141	97.7%	12.4853*	1.0841	13.6160*
		500	94.5%	0.5105	1.2272	1.8509	97.8%	10.8382*	0.4435	14.5401*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95.1%	0.0212	0.9956	1.1173	98.2%	5.2251**	0.6606	8.5365**
(2,2)		250	94.4%	0.7308	2.3766	3.2227	97.7%	10.8382*	1.0841	13.6160*
		500	94.4%	0.7308	1.0696	1.9157	97.7%	10.8382*	0.3507	12.8825*
		1000	95.3%	0.1932	2.9447	3.2342	98%	7.8272*	0.6688	8.5365**
		1500	95%	0	2.2008	2.3034	98.2%	5.2251**	0.6606	5.9221

GARCH (2, 1) with Student – t distribution does comparatively better than the earlier models for Nifty Junior at the 95 per cent level of confidence. Only one model, ARMA (1, 1) with 250 observations fail in the test for independence. All other models clear all the three tests. But, like all other models so far tested, GARCH (2, 1) also gives poor result at the 99 per cent level of significance. Though all the models pass the test for independence, none of them could make any headway in either of the other tests. Hence, this one also does not give any successful models capable of being passed on in to the next round.

Table 5.46 GARCH (2, 2) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	94.6%	0.3287	2.8744	3.3141	97.7%	12.4853*	1.0841	13.6160*
		500	94.1%	1.6162	3.2041	4.9421	97.6%	14.2244*	0.2700	14.5401*
		1000	95.2%	0.0853	2.6826	2.8663	98.1%	6.4725*	0.8032	7.3141**
		1500	95.1%	0.0212	2.4347	2.5564	98.2%	5.2252**	0.9535	6.2150**
(2,0)		250	94.9%	0.0209	3.7266	3.8523	97.8%	10.8382*	0.9909	11.8736*
		500	94.4%	0.7308	2.3766	3.2227	97.8%	10.8382*	0.4435	11.3262*
		1000	95.1%	0.0212	2.4347	2.5564	98%	7.8272*	0.6688	8.5365**
		1500	95%	0	2.2008	2.3034	98%	7.8272*	0.6688	8.5365**
(0,1)		250	94.4%	0.7308	4.7724	5.2121	97.7%	12.4853*	1.0841	13.6160*
		500	94.3%	0.9889	2.1478	3.2542	97.8%	10.8382*	0.4435	11.3262*
		1000	95.2%	0.0853	2.6826	2.8663	98%	7.8272*	0.6688	8.5365**
		1500	95.2%	0.0853	1.1481	1.3318	98.1%	6.4725*	0.8032	7.3141**
(0,2)		250	94.7%	0.1860	3.1440	3.4390	97.7%	12.4853*	1.0841	13.6160*
		500	94.4%	0.7308	2.3766	3.2227	97.7%	12.4853*	0.3507	12.8825*
		1000	95.1%	0.0212	2.4347	2.5564	98%	7.8272*	0.6688	8.5365**
		1500	95%	0	2.2008	2.3034	98%	7.8272*	0.6688	8.5365**
(1,1)		250	94.5%	0.5105	4.42**	5.0526	97.6%	14.2244*	1.1817	15.4517*
		500	94.4%	0.7308	2.3766	3.2227	97.6%	14.2244*	0.2700	14.5401*
		1000	95.1%	0.0212	2.4347	2.5564	98%	7.8272*	0.6688	8.5365**
		1500	95.1%	0.0212	0.9956	1.1173	97.9%	9.2840*	3.1714	12.4979*
(1,2)		250	94.7%	0.1860	3.1440	3.4390	97.6%	14.2244*	1.1817	15.4518*
		500	94.3%	0.9889	2.1478	3.2542	97.6%	14.2244*	0.2700	14.5401*
		1000	95.1%	0.0212	2.4347	2.5564	98%	7.8272*	0.6688	8.5365**
		1500	95%	0	2.2008	2.3034	97.9%	9.2840*	3.1714	12.4979*
(2,1)		250	94.6%	0.3287	2.8744	3.3141	97.7%	12.4853*	1.0841	13.6160*
		500	94.3%	0.9889	2.1478	3.2542	97.6%	14.2244*	0.2700	14.5401*
		1000	95.1%	0.0212	2.4347	2.5564	98%	7.8272*	0.6688	8.5365**
		1500	95.2%	0.0853	1.1481	1.3318	98%	7.8272*	0.6688	8.5365**
(2,2)		250	94.6%	0.3287	2.8744	3.3141	97.6%	14.2244*	1.1817	15.4517*
		500	94.1%	1.6162	1.7289	3.4668	97.6%	14.2244*	0.2700	14.5401*
		1000	95.3%	0.1932	2.9447	3.2342	98%	7.8272*	0.6688	8.5365**
		1500	95%	0	2.2008	2.3034	98.1%	6.4725*	0.7368	7.2477**

This is the model with the highest level of complication among its family of models tested in this study. 95 per cent level of significance, as usual, gives quite strong result. Except for ARMA (1, 1) with 250 observations, all the other models pass the three tests. However, things again change for the worse when it comes to the 99 per cent level. Though all the models passed the test for independence, none of them could pass either the unconditional or conditional coverage test, again contributing no models for the next round of investigation.

Table 5.47 GARCH (1, 1) for Nikkei with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.9%	0.0209	0.0642	0.1899	98.8%	0.3798	0.2918	0.6957
		500	95.1%	0.0212	0.0790	0.2007	99.1%	0.1045	0.1636	0.2862
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	99%	0	0.2022	0.2223
(2,0)		250	94.7%	0.1860	0.0138	0.3087	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	99.1%	0.1045	0.1636	0.2862
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(0,1)		250	94.9%	0.0209	0.0642	0.1899	98.7%	0.8306	0.3428	1.1996
		500	95.1%	0.0212	0.0790	0.2007	99.1%	0.1045	0.1636	0.2223
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.95	0.0209	0.1676	0.2933	99%	0	0.2022	0.2862
(0,2)		250	94.8%	0.0832	0.0343	0.2243	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	99.1%	0.1045	0.1636	0.2862
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(1,1)		250	94.6%	0.3287	0.0343	0.2243	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.0790	0.2007	99%	0	0.1292	0.5790
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(1,2)		250	94.6%	0.3287	0.0025	0.4422	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(2,1)		250	94.9%	0.0209	0.0343	0.1899	98.7%	0.8306	0.3428	1.1996
		500	95.1%	0.0212	0.0790	0.2007	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(2,2)		250	94.5%	0.5105	0.0003	0.6240	98.7%	0.8306	0.3428	1.1996
		500	95.2%	0.0853	0.0468	0.2305	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0003	0.6364	99.2%	0.4345	0.1292	0.5790
		1500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649

Similar to the other models tested on Nikkei, GARCH (1, 1) with Student – t distribution also produce handsome result. Nominal coverage is between a tight 94.6 to 95.5 per cent and all the models tested clears the coverage tests including the test for independence. Unlike the other two markets, which produce contrary result at the 99 per cent level of confidence, Nikkei is seen to be equally successful at this level also with all of the tested models again clearing the three back testing procedures thereby enabling the models to be promoted to the next round of testing involving other markets as well.

Table 5.48 GARCH (1, 2) for Nikkei with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{cc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	95.2%	0.4337	0.2121	0.3958	98.6%	1.4374	0.3980	1.8636
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.2918	0.6957
		1500	94.6%	0.3287	0.3594	0.7991	98.6%	1.4374	0.3980	1.8636
(2,0)		250	94.9%	0.0209	0.0642	0.1899	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.6%	0.3287	0.3594	0.7991	98.6%	1.4374	0.3980	1.8636
(0,1)		250	95.2%	0.0853	0.2121	0.3958	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2918	0.3649
		1000	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.2449	0.6957
		1500	94.6%	0.3287	0.3594	0.7991	98.6%	1.4374	0.3980	1.8636
(0,2)		250	94.8%	0.0832	0.0343	0.2243	98.5%	2.1892	0.4573	2.6768
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.6%	0.3287	0.3594	0.7991	98.6%	1.4374	0.3980	1.8636
(1,1)		250	94.9%	0.0209	0.0642	0.1899	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.6%	0.3287	0.3594	0.7991	98.6%	1.4374	0.3980	1.8636
(1,2)		250	94.8%	0.0832	0.2238	0.4138	98.6%	1.4374	0.3980	1.8636
		500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0790	0.2007	98.8%	0.3798	0.2918	0.6957
		1500	94.7%		0.2878	0.5827	98.6%	1.4374	0.3980	1.8636
(2,1)		250	94.6	0.3287	0.0790	0.4138	98.4	3.0766	0.3980	0.3649
		500	95.1%	0.0212	1.3128	0.2007	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	).0002	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(2,2)		250	94.6%	0.3287	0.0025	0.4422	98.4%	3.0766	0.5209	3.6297
		500	95.2%	0.0853	0.0468	0.2305	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0002	0.6364	99.2%	0.4337	0.1292	0.5790
		1500	95%	0	0.1193	0.2219	98.9%	0.0978	0.2449	0.3649

Models look very healthy and rosy again when they are tested in the particular case of Nikkei. Nominal coverage again takes a narrow route between 94.6 and 95.5 per cent and all the models clear the three coverage tests at the 95 per cent level of significance. Even when taking 99 per cent as the level of confidence, none of the models fail in the coverage tests with nominal coverage varying between 98.4 per cent – in a single instance only – and 99.2 per cent. Thus all the models under GARCH (2, 2) with Student – t distribution progress in to the next round of testing.

Table 5.49 GARCH (2, 1) for Nikkei with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95%	0	0.1037	0.2063	98.9%	0.0978	0.2449	0.3649
		500	95.3%	0.1932	0.0229	0.3124	99%	0	0.2022	0.2223
		1000	95.3%	0.1932	0.0229	0.3124	99.2%	0.4337	0.1292	0.5790
		1500	95%	0	0.1193	0.2219	99%	0	0.2022	0.2223
(2,0)		250	95%	0	0.1037	0.2063	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	99%	0	0.2022	0.2223
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2862
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(0,1)		250	95%	0	0.1048	0.1048	99%	0	0.2020	0.2022
		500	95.3%	0.1932	0.0229	0.3124	99%	0	0.2022	0.2223
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2862
		1500	94.9%	0.0209	0.1676	0.2933	99%	0	0.2022	0.2223
(0,2)		250	95.1%	0.0212	0.1529	0.2746	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.1193	0.2219	99%	0	0.2022	0.2223
		1000	95.2%	0.0853	0.0468	0.2305	99.1%	0.1045	0.1636	0.2862
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(1,1)		250	94.7%	0.1860	0.0138	0.3087	98.7%	0.8306	0.3428	1.1996
		500	95.1%	0.0212	0.0790	0.2007	98.9%	0.0978	0.2449	0.3649
		1000	95.4%	0.3457	0.0074	0.4473	99.1%	0.1045	0.1636	0.2862
		1500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
(1,2)		250	94.8%	0.0832	0.0343	0.2243	98.8%	0.3798	0.2918	0.6957
		500	94.9%	0.0209	0.1676	0.2933	98.9%	0.0978	0.2449	0.3649
		1000	95.4	0.3457	0.0074	0.4473	99.1	01045	0.1636	0.2862
		1500	94.9	0.0209	0.1676	0.2933	98.9	0.0978	0.2449	0.3649
(2,1)		250	94.8	0.0832	0.0343	0.2243	98.8	0.3798	0.2918	1.1996
		500	95	0	0.1193	0.2219	99	0	0.2022	0.3649
		1000	95.2	0.0853	0.0468	0.2305	99.1	0.1045	0.1636	1.1996
		1500	94.7	0.1860	0.2878	0.5827	98.6	1.4374	0.3980	1.8636
(2,2)		250	94.5%	0.5105	0.0002	0.6240	98.8	0.3798	0.2918	0.6957
		500	95	0	0.1193	0.2219	98.9	0.0978	0.2449	0.3649
		1000	95.2	0.0853	0.0468	0.2305	99.1	0.1045	0.1636	0.2862
		1500	94.9%	0.0209	0.1676	0.2933	98.9	0.0978	0.2449	0.3649

For all practical reasons, GARCH (2, 1) with Student – t does a very similar job to its predecessors in terms of predictability of Value-at-Risk. Nominal coverage is even tighter than the previous models for 95 per cent level between 94.5 and 95.3 per cent and all the models clear the coverage tests at that level of confidence. Results are not the least different for the 99 per cent confidence level. With nominal coverage varying at such tight ranges, 32 out of 32 models qualify themselves for the next round.

Table 5.50 GARCH (2, 2) for Nikkei with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.3%	0.1932	0.0229	0.3124	98.8	0.3798	0.2918	0.6957
		500	95.2	0.0853	0.0468	0.2305	98.9	0.0978	0.2449	0.3649
		1000	95.3	0.1932	0.0229	0.3124	99.2	0.4337	0.1292	0.5790
		1500	94.9	0.0209	0.1676	0.2933	99	0	0.2022	0.2223
(2,0)		250	95.3	0.1932	0.0229	0.3124	98.6	1.4374	0.3980	0.3649
		500	95	0	0.1193	0.2219	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		1500	94.6	0.3287	0.3594	0.7991	98.6	1.4374	0.3980	1.8636
(0,1)		250	95.3	0.1932	0.0229	0.3124	98.9	0.0978	0.2449	1.8636
		500	95.2	0.0853	0.0468	0.2305	98.9	0.0978	0.2449	0.3649
		1000	95.3	0.1932	0.0229	0.3124	98.8	0.3798	0.2918	0.6957
		1500	94.6	0.3287	0.3594	0.7991	98.6	1.4374	0.3980	1.8636
(0,2)		250	95.3	0.1932	0.0229	0.3124	98.6	1.4374	0.3980	1.8636
		500	95	0	0.1193	0.2219	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		1500	94.6	0.3287	0.3594	0.7991	98.6	1.4374	0.3980	1.8636
(1,1)		250	94.9	0.0209	0.1676	0.2933	98.7	0.8306	0.3428	1.1996
		500	95	0	0.1193	0.2219	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		1500	94.6	0.3287	0.3594	0.7991	98.6	1.4374	0.3980	1.8636
(1,2)		250	95	0	0.1193	0.2219	98.7	0.8306	0.3428	1.1996
		500	95	0	0.1193	0.2219	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		1500	94.7	0.1860	0.2878	0.5827	98.6	1.4374	0.3980	1.8636
(2,1)		250	95	0	0.1193	0.2219	98.7	0.8306	0.3428	1.1996
		500	95.1	0.0209	0.0790	0.2007	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	98.7	0.8306	0.3428	1.1996
		1500	94.7	0.1860	0.2878	0.5827	98.7	0.8306	0.3980	1.8636
(2,2)		250	94.7	0.1860	0.2878	0.5827	98.6	1.4374	0.3980	1.8636
		500	95	0	0.1193	0.2219	98.8	0.3798	0.2918	0.6957
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		1500	94.7	0.1860	0.2878	0.5827	98.6	1.4374	0.3980	1.8636

Even at the highest level of complication of the simplest model, Nikkei is seen to produce top accuracy in terms of risk prediction as compared to the other two markets. The model is able to maintain its hundred per cent record in keeping with the tradition of its predecessors in case of Nikkei. All models pass the three coverage tests not only at the 95 per cent level of confidence but at the 99 per cent level as well. Hence, all the models qualify to be compared themselves with similar successful models from the other markets.

Analyzing successful models from the three markets is the next step in back testing. The study has already found that there is no successful model in the case of Nifty Junior and hence, any chances of a model clearing the tests in all the markets is shattered at the outset itself though the study found hundred per cent success for all the models in case of Nikkei and 24 out 128 models clearing the tests from Nifty. Hence, GARCH models with Student – t distribution also fail in producing even a single model capable of passing all the tests across the three markets.

Table 5.51 GJR (1, 1) for Nifty with Normal Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.4	0.7308	0.2461	0.5710	97.8	10.8382*	0.3980	11.3262*
		500	94.9	0.0209	0.1676	0.2933	97.8	10.8382*	0.4435	11.3262*
		1000	95.5	0.5438	0.4517	1.0877	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(2,0)		250	94.4	0.7308	0.2461	1.0922	97.8	10.8382*	0.4435	11.3262*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.2	5.2251**	0.9535	6.2150**
(0,1)		250	94.5	0.5105	0.0002	0.6240	97.8	10.8382*	0.4435	11.3262*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(0,2)		250	94.3	0.9889	0.2461	1.0922	97.9	9.2840*	0.4435	11.3262*
		500	94.8	0.0832	0.1676	0.2933	97.9	9.2840*	0.6688	8.5365**
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.7899	2.2972	98.2	5.2251**	0.9535	6.2150**
(1,1)		250	94.5	0.5105	0.0002	0.6240	97.9	9.2840*	0.5493	9.8758*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.2	5.2251**	0.9535	6.2150**
(1,2)		250	94.3	0.9889	0.1816	1.2880	97.9	9.2840*	0.5493	9.8758*
		500	94.8	0.0832	0.2238	0.4138	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.2	5.2251**	0.9535	6.2150**
(2,1)		250	94.3	0.9889	0.1816	1.2880	97.8	10.8382*	0.4435	11.3262*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.9535	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.1972	98.2	5.2251**	0.5493	6.2150**
(2,2)		250	94.4	0.7308	0.0070	0.8531	97.8	10.8382*	0.4435	11.3262*
		500	94.6	0.3287	0.4059	0.8456	97.9	9.2840*	0.5493	9.8758*
		1000	95.5	0.5438	0.4517	1.0877	97.9	9.2840*	0.5493	9.8758*
		1500	95.9	1.8120	0.9259	2.8217	98.2	5.2251**	0.9535	6.2150**

In addition to the Exponential GARCH that the study has already employed to assess the impact of involving asymmetric behavior of stock market on the performance of risk prediction, there is one more model called the GJR model that is also capable of doing the same thing though in a different way. Next set of tables will deal with back testing conducted on the results found using such model.

Table 5.52 GJR (1, 2) for Nifty with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LRuc	LRind	LR_{cc}
(1,0)	(1,2)	250	94.9%	0.0209	0.2461	0.5710	98%	7.8272*	0.3980	11.3262*
		500	95.2%	0.0853	0.1676	0.2933	98.1%	6.4725*	0.4435	11.3262*
		1000	95.5%	0.5438	0.4517	1.0877	98.3%	4.0910**	0.5493	9.8758*
		1500	95.7%	1.0807	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(2,0)		250	94.4%	0.7308	0.2461	1.0922	97.9%	9.2840*	0.4435	11.3262*
		500	94.7%	0.1860	0.1676	0.2933	98%	7.8272*	0.5493	9.8758*
		1000	95.1%	0.0212	0.2815	0.5710	98.2%	5.2251**	0.5493	9.8758*
		1500	95.6%	0.7885	0.7899	2.2972	98.4%	3.0766	0.9535	6.2150**
(0,1)		250	94.8%	0.0832	0.0002	0.6240	98%	7.8272*	0.4435	11.3262*
		500	95.1%	0.0212	0.1676	0.2933	98.1%	6.4725*	0.5493	9.8758*
		1000	95.3%	0.1932	0.2815	0.5710	98.3%	4.0910**	0.5493	9.8758*
		1500	95.6%	0.7885	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(0,2)		250	94.5%	0.5105	0.2461	1.0922	97.9%	9.2840*	0.4435	11.3262*
		500	95.1%	0.0212	0.1676	0.2933	98.1%	6.4725*	0.6688	8.5365**
		1000	95.4%	0.3457	0.2815	0.5710	98.2%	5.2251**	0.5493	9.8758*
		1500	95.6%	0.7885	0.7899	2.2972	98.4%	3.0766	0.9535	6.2150**
(1,1)		250	94.3%	0.0989	0.0002	0.6240	98%	7.8272*	0.5493	9.8758*
		500	95.1%	0.0212	0.1676	0.2933	98.1%	6.4725*	0.5493	9.8758*
		1000	95.4%	0.3457	0.2815	0.5710	98.3%	4.0910*	0.5493	9.8758*
		1500	95.7%	1.0809	0.6657	1.8344	98.5%	2.1892	0.9535	6.2150**
(1,2)		250	94.4%	0.7308	0.1816	1.2880	97.9%	9.2840*	0.5493	9.8758*
		500	94.7%	0.1860	0.2238	0.4138	98%	7.8272*	0.5493	9.8758*
		1000	95.2%	0.0853	0.2815	0.5710	98.1%	6.4725*	0.5493	9.8758*
		1500	95.7%	1.0809	0.6657	1.8344	98.5%	2.1892	0.9535	6.2150**
(2,1)		250	94.3%	0.0989	0.1816	1.2880	98%	7.8272*	0.4435	11.3262*
		500	95.1%	0.0212	0.1676	0.2933	98.1%	6.4725*	0.9535	9.8758*
		1000	95.4%	0.3457	0.2815	0.5710	98.3%	4.0910*	0.5493	9.8758*
		1500	95.7%	1.0809	0.7899	2.1972	98.4%	3.0766	0.5493	6.2150**
(2,2)		250	94.4%	0.7308	0.0070	0.8531	97.9%	9.2840*	0.4435	11.3262*
		500	94.7%	0.1860	0.4059	0.8456	98%	7.8272*	0.5493	9.8758*
		1000	95.2%	0.0853	0.4517	1.0877	98.1%	6.4725*	0.5493	9.8758*
		1500	95.7%	1.0809	0.9259	2.8217	98.5%	2.1892	0.9535	6.2150**

GJR (1, 1) for Nifty with normal distribution does not spring any surprises and follows more or less the path shown by the earlier conditional volatility models. All the varieties of the model clear the coverage tests at the 95 per cent level of confidence. But is already clear, the real test comes at the 99 per cent level and that is exactly where this type of model also buckles. Though all the models clear the test for independence, none of them could clear either of the other coverage tests. Nominal coverage goes as low as 97.8 on the down side, implying 22 failures out of 1000 predictions, whereas the optimum would have been 10. Hence, none of the models can be carried forward to the next round of tests.

Table 5.53 GJR (2, 1) for Nifty with Normal Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	94.6	0.3287	0.0025	0.4422	97.8	10.8382*	0.4435	11.3262*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.5493	9.8758*
		1000	95.4	0.3457	0.3613	0.8012	97.9	9.2840*	0.5493	9.8758*
		1500	95.6	0.7885	0.5531	1.4316	98.1	6.4725*	0.8032	7.3141**
(2,0)		250	94.5	0.5105	0.3208	0.9444	97.8	10.8382*	0.4435	11.3262*
		500	94.8	0.0832	0.2238	0.4138	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(0,1)		250	94.6	0.3287	0.0025	0.4422	97.8	10.8382*	0.4435	11.3262*
		500	94.8	0.0832	0.2238	0.4138	98	7.8272*	0.6688	8.5365**
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(0,2)		250	94.5	0.5105	0.3208	0.9444	97.8	10.8382*	0.4435	11.3262*
		500	94.8	0.0832	0.2238	0.4138	98	7.8272*	0.6688	8.5365**
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(1,1)		250	94.6	0.3287	2.5020	1.8344	98.3	4.0910**	0.6622	11.3262*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.6688	8.5365**
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(1,2)		250	94.5	0.5105	0.3208	0.9444	97.9	9.2840*	0.5493	9.8758*
		500	94.9	0.0209	0.1676	0.2933	98.1	6.4725*	0.8032	7.3141**
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(2,1)		250	94.5	0.5105	0.3208	0.9444	97.8	10.8382*	0.4435	11.3262*
		500	94.9	0.0209	0.1676	0.2933	98	7.8272*	0.6688	8.5365**
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(2,2)		250	94.6	0.3287	0.0025	0.4422	97.8	10.8382*	0.4435	11.3262*
		500	94.7	0.1860	0.0138	0.3087	97.8	10.8382*	0.4435	11.3262*
		1000	95.4	0.3457	0.3613	0.8012	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0.8032	7.3141**

No improvement happens as a shift is made from GJR (1, 1) to (1, 2). Predictability is cent per cent accurate at the 95 per cent level of confidence and the nominal coverage varies in a tight range of 94.6 per cent to 95.7 per cent. However, things do not remain the same at the 99 per cent level of confidence. All models pass the test for independence but, only those ARMA models that uses 1500 observations for prediction of variance shows success in the unconditional coverage test but even they lose their exalted position as conditional coverage test is conducted. In short, GJR (1, 2) also do not produce any models capable of satisfying all the coverage tests

Table 5.54 GJR (2, 2) for Nifty with Normal Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	94.6%	0.3287	0.0025	0.4422	98.2%	5.2251**	0.4435	11.3262*
		500	94.8%	0.0832	0.1676	0.2933	98.1%	6.4725*	0.5493	9.8758*
		1000	95.3%	0.1932	0.3613	0.8012	98.3%	4.0910**	0.5493	9.8758*
		1500	95.6%	0.7885	0.5531	1.4316	98.4%	3.0766	0.8032	7.3141**
(2,0)		250	94.5%	0.5105	0.3208	0.9444	98%	7.8272*	0.4435	11.3262*
		500	94.6%	0.3287	0.2238	0.4138	98.1%	6.4725*	0.5493	9.8758*
		1000	94.9%	0.0209	0.2815	0.5710	98.3%	4.0910**	0.5493	9.8758*
		1500	95.6%	0.7885	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(0,1)		250	94.3%	0.9889	0.0025	0.4422	97.9%	9.2840*	0.4435	11.3262*
		500	94.9%	0.0209	0.2238	0.4138	98.1%	6.4725*	0.6688	8.5365**
		1000	95.4%	0.3457	0.2815	0.5710	98.4%	3.0766	0.5493	9.8758*
		1500	95.7%	1.0807	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(0,2)		250	94.6%	0.3287	0.3208	0.9444	98%	7.8272*	0.4435	11.3262*
		500	95%	0	0.2238	0.4138	98.2%	5.2251**	0.6688	8.5365**
		1000	95.4%	0.3457	0.2815	0.5710	98.4%	3.0766	0.5493	9.8758*
		1500	95.6%	0.7885	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(1,1)		250	94.5%	0.5105	2.5020	1.8344	98%	7.8272*	0.6622	11.3262*
		500	94.6%	0.3287	0.1676	0.2933	98.1%	6.4725*	0.6688	8.5365**
		1000	94.9%	0.0209	0.2815	0.5710	98.3%	4.0910*	0.5493	9.8758*
		1500	95.6%	0.7885	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(1,2)		250	94.3%	0.9889	0.3208	0.9444	97.9%	9.2840*	0.5493	9.8758*
		500	94.9%	0.0209	0.1676	0.2933	98.1%	6.4725*	0.8032	7.3141**
		1000	95.4%	0.3457	0.2815	0.5710	98.4%	3.0766	0.5493	9.8758*
		1500	95.7%	1.0807	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(2,1)		250	94.6%	0.3287	0.3208	0.9444	98%	7.8272*	0.4435	11.3262*
		500	95%	0	0.1676	0.2933	98.1%	6.4725*	0.6688	8.5365**
		1000	95.4%	0.3457	0.2815	0.5710	98.4%	3.0766	0.5493	9.8758*
		1500	95.6%	0.0788	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(2,2)		250	94.7%	0.1860	0.0025	0.4422	98.2%	5.2251**	0.4435	11.3262*
		500	94.9%	0.0209	0.0138	0.3087	98.3%	4.0910**	0.4435	11.3262*
		1000	95.4%	0.3457	0.3613	0.8012	98.5%	2.1892	0.5493	9.8758*
		1500	95.7%	1.0807	0.7899	2.2972	98.4%	3.0766	0.8032	7.3141**

The only difference that this model makes with respect to the earlier model is in the backward direction. While the GJR (1, 2) model produced 8 successful model out of 32 after the unconditional coverage test, GJR (2, 1) fails in this respect also and predictably does not have any success at all in the conditional coverage test too at the 99 per cent level of confidence, though all the models clear the test for independence. Things are the same at the 95 per cent level of confidence. 32 out of 32 models comfortable clears the three tests at that level of significance and the nominal coverage ranges between a handsome 94.3 per cent to 95.8 per cent.

Table 5.55 GJR (1, 1) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	95.2%	0.0853	1.5118	1.2371	98%	7.8272*	0.8164	8.4636*
		500	95%	0	0.8550	0.9576	98.3%	4.0910**	0.5886	4.7139
		1000	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
		1500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(2,0)		250	95%	0	4.0404	4.1430	97.9%	9.2840*	0.9019	10.2284*
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.2291
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(0,1)		250	94.8%	0.0832	1.7731	1.9631	98%	7.8272*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.8%	0.0832	3.4280	3.6180	97.9%	9.2840*	0.9019	10.2284*
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(1,1)		250	94.7%	0.1860	1.5787	1.8737	98%	7.8272*	0.8172	8.66849*
		500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.7%	0.1860	1.5787	1.8737	98%	7.8272*	0.8172	8.6849**
		500	94.6%	0.3287	0.4059	0.8456	98.1%	6.4725*	0.7368	7.2477**
		1000	95.4%	0.3457	1.4900	1.9300	98.2%	5.2251**	0.6606	5.9221
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(2,1)		250	94.6%	0.3287	2.8744	3.3141	97.8%	10.8382*	0.9909	11.8736*
		500	94.6%	0.3287	0.4059	0.8456	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.4%	0.7308	2.3766	3.2277	97.9%	9.2840*	0.9019	10.2284*
		500	95%	0	0.8550	0.9576	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297

All the models perform well at the lower confidence level tested in the study. In fact 32 out of the 32 models pass unconditional and conditional coverage test as well as the test for independence and thereby make no deviations from the earlier models tested in the study. So does the 99 band of confidence level, but in a completely different way. Again, the test for independence is cleared by all the models, however, only 13 models makes it in to the conditional coverage criteria after clearing unconditional coverage test. All these models stumble at the conditional coverage criteria thereby nullifying the chance of GJR model with normal distribution contributing a model to be the best forecaster of risk

Table 5.56 GJR (1, 2) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	94.9%	0.0209	1.5118	1.2371	98%	7.8272*	0.8164	8.4636*
		500	95.2%	0.0853	0.8550	0.9576	98.1%	6.4725*	0.5886	4.7139
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5209	3.6297
		1500	95.7%	1.0807	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(2,0)		250	94.4%	0.7308	4.0404	4.1430	97.9%	9.2840*	0.9019	10.2284*
		500	94.7%	0.1860	0.6082	0.7983	98%	7.8272*	0.6606	5.2291
		1000	95.1%	0.0212	1.6801	2.3161	98.2%	5.2251**	0.5886	4.7139
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(0,1)		250	94.8%	0.0832	1.7731	1.9631	98%	7.8272*	0.8172	8.6849**
		500	95.1%	0.0212	0.6082	0.7983	98.1%	6.4725*	0.6606	5.9221
		1000	95.3%	0.1932	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.6%	0.7885	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.5%	0.5105	3.4280	3.6180	97.9%	9.2840*	0.9019	10.2284*
		500	95.1%	0.0212	0.6082	0.7983	98.1%	6.4725*	0.6606	5.9221
		1000	95.4%	0.3457	1.6801	2.3161	98.2%	5.2251**	0.5886	4.7139
		1500	95.6%	0.7885	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(1,1)		250	94.3%	0.0989	1.5787	1.8737	98%	7.8272*	0.8172	8.66849*
		500	95.1%	0.0212	2.1004	3.2691	98.1%	6.4725*	0.5209	3.6297
		1000	95.4%	0.3457	1.6801	2.3161	98.3%	4.0910*	0.5886	4.7139
		1500	95.7%	1.0809	2.1004	3.2691	98.5%	2.1892	0.5209	3.6297
(1,2)		250	94.4%	0.7308	1.5787	1.8737	97.9%	9.2840*	0.8172	8.6849**
		500	94.7%	0.1860	0.4059	0.8456	98%	7.8272*	0.7368	7.2477**
		1000	95.2%	0.0853	1.4900	1.9300	98.1%	6.4725*	0.6606	5.9221
		1500	95.7%	1.0809	1.8835	2.7620	98.5%	2.1892	0.5209	3.6297
(2,1)		250	94.3%	0.0989	2.8744	3.3141	98%	7.8272*	0.9909	11.8736*
		500	95.1%	0.0212	0.4059	0.8456	98.1%	6.4725*	0.6606	5.9221
		1000	95.4%	0.3457	1.6801	2.3161	98.3%	4.0910*	0.5886	4.7139
		1500	95.7%	1.0809	2.1004	3.2691	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.4%	0.7308	2.3766	3.2277	97.9%	9.2840*	0.9019	10.2284*
		500	94.7%	0.1860	0.8550	0.9576	98%	7.8272*	0.7368	7.2477**
		1000	95.2%	0.0853	1.6801	2.3161	98.1%	6.4725*	0.5886	4.7139
		1500	95.7%	1.0809	1.8835	2.7620	98.5%	2.1892	0.5209	3.6297

Though GJR model with normal distribution gives poor result for Nifty, it has done surprisingly well for Nifty Junior. All the models are seen to pass the three tests at the 95 per cent level of confidence with nominal coverage ranging from 94.4 per cent to 95.6 per cent at the worst. Though results at the 99 per cent level are worse, they are much above what was found for the earlier cases. All models pass test for independence. ARMA (1, 0) with 1000 and 1500 observations, ARMA (2, 0), (0, 1) and (0, 2), (1, 2), (2, 1) and (2, 2) with 1500 observations, and ARMA (1, 1) with 500 and 1500 observations clear all the tests of coverage.

Table 5.57 GJR (2, 1) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95%	0	0.1037	0.2063	98.5%	2.1892	0.4573	2.6768
		500	94.5%	0.5105	0.0002	0.6240	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.6%	1.4374	0.3980	1.8636
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(2,0)		250	95%	0	0.8550	0.9576	98.4%	3.0766	0.5209	3.6297
		500	94.5%	0.5105	0.0002	0.6240	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(0,1)		250	95%	0	0.1037	0.2063	98.5%	2,1892	0.4573	2.6768
		500	94.5%	0.5105	0.0002	0.6240	98.3%	4.0910**	0.5886	4.7139
		1000	95.3%	0.1932	1.3128	1.6023	98.5%	2.1892	0.4573	2.6768
		1500	95.6%	0.0785	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.8%	0.0832	1.7731	1.9631	98.4%	3.0766	0.5209	3.6297
		500	94.5%	0.5105	0.0002	0.6240	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.5%	2.1892	0.4573	2.6768
		1500	95.6%	0.0785	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(1,1)		250	94.6%	0.3287	1.3968	1.8366	98.4%	3.0766	0.5209	3.6297
		500	94.5%	0.5105	0.0002	0.6240	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.5%	2.1892	0.4573	2.6768
		1500	95.6%	0.0785	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.6%	0.3287	1.3968	1.8366	98.3%	4.0910**	0.5886	4.7139
		500	94.5%	0.5105	0.4386	1.0623	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,1)		250	94.6%	0.3287	1.3968	1.8366	98.3%	4.0910**	0.5886	4.7139
		500	94.5%	0.5105	0.4386	1.0623	98.4%	3.0766	0.5209	3.6297
		1000	95.4%	0.3457	1.4900	1.9300	98.5%	2.1892	0.4573	2.6768
		1500	95.6%	0.0785	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.7%	0.1860	0.5016	0.7966	98.2%	5.2251**	0.6606	5.9221
		500	94.8%	0.0832	0.2238	0.4138	98.3%	4.0910**	0.5886	4.7139
		1000	95.5%	0.5438	1.6801	2.3161	98.6%	1.4374	0.3980	1.8636
		1500	95.6%	0.0785	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297

This model produces good results at the 95 per cent level of significance by managing to get all varieties of models passed in all the three tests and is able to keep the nominal coverage at manageable levels. Results take a hit when a move is made from the 95 to the 99 per cent level of confidence. Test for independence is cleared quite comfortably by all the models in this case also. But only those ARMA models pass the unconditional coverage tests which use 1500 observations for prediction of standard deviation. More models pass conditional coverage test but due to failure in the unconditional coverage, they do not satisfy the condition of clearance in all the three tests simultaneously.

Table 5.58 GJR (2, 2) for Nifty Junior with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	94.6%	0.3287	0.1037	0.2063	98.2%	5.2251**	0.4573	2.6768
		500	94.8%	0.0832	0.0002	0.6240	98.1%	6.4725*	0.5886	4.7139
		1000	95.3%	0.1932	1.4900	1.9300	98.3%	4.0910**	0.3980	1.8636
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(2,0)		250	94.5%	0.5105	0.8550	0.9576	98%	7.8272*	0.5209	3.6297
		500	94.6%	0.3287	0.0002	0.6240	98.1%	6.4725*	0.5886	4.7139
		1000	94.9%	0.0209	1.4900	1.9300	98.3%	4.0910**	0.4573	2.6768
		1500	95.6%	0.7885	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(0,1)		250	94.3%	0.9889	0.1037	0.2063	97.9%	9.2840*	0.4573	2.6768
		500	94.9%	0.0209	0.0002	0.6240	98.1%	6.4725*	0.5886	4.7139
		1000	95.4%	0.3457	1.3128	1.6023	98.4%	3.0766	0.4573	2.6768
		1500	95.7%	1.0807	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.6%	0.3287	1.7731	1.9631	98%	7.8272*	0.5209	3.6297
		500	95%	0	0.0002	0.6240	98.2%	5.2251**	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.4573	2.6768
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(1,1)		250	94.5%	0.5105	1.3968	1.8366	98%	7.8272*	0.5209	3.6297
		500	94.6%	0.3287	0.0002	0.6240	98.1%	6.4725*	0.5886	4.7139
		1000	94.9%	0.0209	1.4900	1.9300	98.3%	4.0910*	0.4573	2.6768
		1500	95.6%	0.7885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.3%	0.9889	1.3968	1.8366	97.9%	9.2840*	0.5886	4.7139
		500	94.9%	0.0209	0.4386	1.0623	98.1%	6.4725*	0.5886	4.7139
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.4573	2.6768
		1500	95.7%	1.0807	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,1)		250	94.6%	0.3287	1.3968	1.8366	98%	7.8272*	0.5886	4.7139
		500	95%	0	0.4386	1.0623	98.1%	6.4725*	0.5209	3.6297
		1000	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.4573	2.6768
		1500	95.6%	0.07885	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.7%	0.1860	0.5016	0.7966	98.2%	5.2251**	0.6606	5.9221
		500	94.9%	0.0209	0.2238	0.4138	98.3%	4.0910**	0.5886	4.7139
		1000	95.4%	0.3457	1.6801	2.3161	98.5%	2.1892	0.3980	1.8636
		1500	95.7%	1.0807	1.8835	2.7620	98.4%	3.0766	0.5209	3.6297

This model produces good predictive accuracy in the case of Nifty Junior and is much better than GJR (1, 1) or GJR (1, 2) that have already been applied in the same as well as different market. All the models pass test for independence as well as conditional and unconditional coverage. Predictive accuracy deteriorates at the 99 per cent level but except for all ARMA models except (2, 1) with 500 observations and (1, 2), (2, 1) and (2, 2) at 250 observations pass the three tests at 99 per cent level of confidence as well. Hence, Nifty Junior does much better in terms of predictability than its senior counterpart under GJR with normal distribution and this model is observed to be the best for it.

Table 5.59 GJR (1, 1) for Nikkei with Normal Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		500	95.3	0.91932	0.2815	0.5710	99	0	0.2022	0.2223
		1000	95	0	0.1193	0.2219	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(2,0)		250	94.9	0.0978	0.1676	0.2933	98.8	0.3798	0.2918	0.6957
		500	95.3	0.1932	0.2815	0.5710	99	0	0.2022	0.2223
		1000	95	0	0.1193	0.2219	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(0,1)		250	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		500	95.3	0.1932	0.2815	0.5710	99	0	0.2022	0.2223
		1000	95	0	0.1193	0.2219	99.2	0.4337	0.1292	0.5790
		1500	95.2	0.0853	0.2121	0.3958	98.9	0.0978	0.2449	0.3649
(0,2)		250	95	0	0.1193	0.2219	98.7	0.8306	0.3428	1.1996
		500	95.3	0.1932	0.2815	0.5710	99	0	0.2022	0.2223
		1000	95	0	0.1193	0.2219	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(1,1)		250	94.9	0.0209	0.1676	0.2933	98.9	0.0978	0.2449	0.3649
		500	95.3	0.1932	0.2815	0.5710	98.9	0.0978	0.2449	0.3649
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	95.2	0.0853	0.2121	0.3958	98.9	0.0978	0.2449	0.3649
(1,2)		250	94.7	0.1860	0.0138	0.3087	98.9	0.0978	0.2449	0.3649
		500	95.2	0.0853	0.2121	0.3958	98.9	0.0978	0.2449	0.3649
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(2,1)		250	94.7	0.1860	0.0138	0.3087	98.9	0.0978	0.2449	0.3649
		500	95.2	0.0853	0.2121	0.3958	99	0	0.2022	0.2223
		1000	95.1	0.0978	0.0790	0.2007	99.2	0.4337	0.1292	0.5790
		1500	95	0	0.1037	0.2063	98.8	0.3798	0.2918	0.6957
(2,2)		250	94.8%	0.0832	0.2238	0.4138	98.8	0.3798	0.2918	0.6957
		500	95.2	0.0832	0.2121	0.3958	98.8	0.3798	0.2918	0.6957
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	94.9	0.0209	0.0642	0.1899	98.8	0.3798	0.2918	0.6957

After analyzing this final model from the GJR family with normal distribution, it is obvious that this type of model fits the Nifty Junior data best. As with most other models there are no exceptions at the 95 per cent level of significance and the nominal coverage is in a tight range. 13 out of the 32 models clear conditional coverage test too and there are no failures in the test for independence. Except for ARMA (1, 0), (2, 0) and (1, 1) all other models give accurate predictions at 1000 and 1500 observations and all other models give good result at 1500 observations.

In the case of this model also Nikkei keeps its reputation for being a very predictable market in terms of risk. All the models clear the coverage tests not only at the 95 per cent level of significance as is the case with other two markets but also at the 99 per cent level of significance. Nominal coverage at both the levels of confidence is also in a very small range. Thus, all the models of GJR (1, 1) with normal distribution for Nikkei qualify for the next round of back testing.

Table 5.60 GJR (1, 2) for Nikkei with Normal Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
((1,0)	(1,2)	250	95.2%	0.4337	0.0790	0.2007	98.6%	1.4374	0.2918	0.6957
		500	95%	0	0.2815	0.5710	98.9%	0.0978	0.2022	0.2223
		1000	95.3%	0.1932	0.1193	0.2219	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2449	0.3649
(2,0)		250	94.9%	0.0209	0.1676	0.2933	98.7%	0.8306	0.2918	0.6957
		500	95%	0	0.2815	0.5710	98.9%	0.0978	0.2022	0.2223
		1000	95.1%	0.0212	0.1193	0.2219	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2918	0.6957
(0,1)		250	95.2%	0.0853	0.0790	0.2007	98.7%	0.8306	0.2918	0.6957
		500	95%	0	0.2815	0.5710	98.9%	0.0978	0.2022	0.2223
		1000	95.3%	0.1932	0.1193	0.2219	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.2121	0.3958	98.6%	1.4374	0.2449	0.3649
(0,2)		250	94.8%	0.0832	0.1193	0.2219	98.5%	2.1892	0.3428	1.1996
		500	95%	0	0.2815	0.5710	98.9%	0.0978	0.2022	0.2223
		1000	95.1%	0.0212	0.1193	0.2219	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2918	0.6957
(1,1)		250	94.9%	0.0209	0.1676	0.2933	98.7%	0.8306	0.2449	0.3649
		500	95%	0	0.2815	0.5710	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0468	0.2305	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.2121	0.3958	98.6%	1.4374	0.2449	0.3649
(1,2)		250	94.8%	0.0832	0.0138	0.3087	98.6%	1.4374	0.2449	0.3649
		500	95%	0	0.2121	0.3958	98.9%	0.0978	0.2449	0.3649
		1000	95.1%	0.0212	0.0468	0.2305	98.8%	0.3798	0.1292	0.5790
		1500	94.7%	0.1860	0.1529	0.2746	98.6%	1.4374	0.2918	0.6957
(2,1)		250	94.6	0.3287	0.0138	0.3087	98.4%	3.0766	0.2449	0.3649
		500	95.1%	0.0212	0.2121	0.3958	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0790	0.2007	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1037	0.2063	98.9%	0.0978	0.2918	0.6957
(2,2)		250	94.6%	0.3287	0.2238	0.4138	98.4%	3.0766	0.2918	0.6957
		500	95.2%	0.0853	0.2121	0.3958	99%	0	0.2918	0.6957
		1000	95.5%	0.5438	0.0468	0.2305	99.2%	0.4337	0.1292	0.5790
		1500	95%	0	0.0642	0.1899	98.9%	0.0978	0.2918	0.6957

This model also enables Nikkei to keep its clean sheet as far as predictive accuracy is concerned. All the models, whether at the 95 per cent level or the 99 per cent level, comfortably clears the coverage tests and their nominal coverage also fairly betters that of the other markets. Thus, by being extremely compliant to predictive techniques employed Nikkei has enabled GJR (1, 2) with normal distribution to have all of its model progress in to the next round where they will be compared with similar successful models from the other two markets.

Table 5.61 GJR (2, 1) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
		500	95.4	0.3457	0.3613	0.8012	98.9	0.0978	0.2449	0.3649
		1000	94.8	0.0823	0.2238	0.4138	99.1	0.1045	0.1636	0.2862
		1500	95.2	0.0853	0.2121	0.3958	98.9	0.0978	0.2449	0.3649
(2,0)		250	95	0	0.1037	0.2063	98.7	0.8306	0.3428	1.1996
		500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2918	0.3649
		1000	94.8	0.0832	0.2238	0.4138	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2449	0.6957
(0,1)		250	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
		500	95.4	0.3457	0.3613	0.8012	98.9	0.0978	0.2449	0.3649
		1000	94.8	0.0832	0.2238	0.4138	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(0,2)		250	95	0	0.1037	0.2063	98.6	1.4374	0.3980	1.8636
		500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
		1000	94.9	0.0209	0.1676	0.2933	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0209	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(1,1)		250	94.9	0.0209	0.1037	0.2063	98.6	1.4374	0.2449	1.8636
		500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.1045	0.1636	0.2862
		1500	95.2	0.0853	0.0468	0.2305	98.9	0.0978	0.1636	0.3649
(1,2)		250	95	0	0.1037	0.2063	98.7	0.8306	0.3428	1.1996
		500	94.8	0.0832	0.0343	0.2243	98.8	0.3798	0.2918	0.6957
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.1045	0.1636	0.2862
		1500	95	0	0.1037	0.2063	98.8	0.3798	0.2918	0.6957
(2,1)		250	94.9	0.0209	0.1529	0.2746	98.6	1.4374	0.2918	1.1996
		500	95	0	0.1037	0.2063	98.8	0.3798	0.2918	0.6957
		1000	95	0	0.1193	0.2219	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.1636	0.6957
(2,2)		250	95	0	0.1037	0.2063	98.8	0.3798	0.2918	0.6957
		500	94.9	0.0209	0.0642	0.1899	98.8	0.3798	0.2918	0.6957
		1000	94.9	0.0209	0.1676	0.2933	99.1	0.1045	0.1636	0.2862
		1500	94.8	0.0832	0.0343	0.2243	98.8	0.3798	0.2918	0.6957

GJR (2, 1) with normal distribution produces even better results in the prediction of Value-at-Risk figure. Nominal coverage at the 95 per cent level varies between 94.8 per cent and 95.2 per cent which is the best result available so far and all of the models pass the coverage tests also including the test for independence. Nominal coverage at 99 per cent is also quite good i.e. between 98.6 and 99.1 per cent. Without exception, all the models tested for Nikkei with GJR (2, 1) and normal distribution also progress in to the next round.

Table 5.62 GJR (2, 2) for Nikkei with Normal Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.3	0.1932	0.1529	0.2746	98.8	0.3798	0.2449	0.3649
		500	95.2	0.0853	0.3613	0.8012	98.9	0.0978	0.2449	0.3649
		1000	95.3	0.1932	0.2238	0.4138	99.2	0.4337	0.1636	0.2862
		1500	94.9	0.0209	0.2121	0.3958	99	0	0.2449	0.3649
(2,0)		250	95.3	0.1932	0.1037	0.2063	98.6	1.4374	0.3428	1.1996
		500	95	0	0.1529	0.2746	98.9	0.0978	0.2918	0.3649
		1000	95.1	0.0212	0.2238	0.4138	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.1529	0.2746	98.6	1.4374	0.2449	0.6957
(0,1)		250	95.3	0.1932	0.1529	0.2746	98.9	0.0978	0.2918	0.6957
		500	95.2	0.0853	0.3613	0.8012	98.9	0.0978	0.2449	0.3649
		1000	95.3	0.1932	0.2238	0.4138	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.1529	0.2746	98.6	1.4374	0.2449	0.3649
(0,2)		250	95.3	0.1932	0.1037	0.2063	98.6	1.4374	0.3980	1.8636
		500	95	0	0.1529	0.2746	98.9	0.0978	0.2918	0.6957
		1000	95.1	0.0212	0.1676	0.2933	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.1529	0.2746	98.6	1.4374	0.2918	0.6957
(1,1)		250	94.9	0.0209	0.1037	0.2063	98.7	0.8306	0.2449	1.8636
		500	95	0	0.1529	0.2746	98.9	0.0978	0.2918	0.6957
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.0468	0.2305	98.6	1.4374	0.1636	0.3649
(1,2)		250	95	0	0.1037	0.2063	98.7	0.8306	0.3428	1.1996
		500	95	0	0.0343	0.2243	98.9	0.0978	0.2918	0.6957
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.1636	0.2862
		1500	94.7	0.1860	0.1037	0.2063	98.6	1.4374	0.2918	0.6957
(2,1)		250	95	0	0.1529	0.2746	98.7	0.8306	0.2918	1.1996
		500	95.1	0.0209	0.1037	0.2063	98.9	0.0978	0.2918	0.6957
		1000	95.1	0.0212	0.1193	0.2219	98.7	0.8306	0.1636	0.2862
		1500	94.7	0.1860	0.1529	0.2746	98.7	0.8306	0.1636	0.6957
(2,2)		250	94.7	0.1860	0.1037	0.2063	98.6	1.4374	0.2918	0.6957
		500	95	0	0.0642	0.1899	98.8	0.3798	0.2918	0.6957
		1000	95.1	0.0212	0.1676	0.2933	98.8	0.3798	0.1636	0.2862
		1500	94.7	0.1860	0.0343	0.2243	98.6	1.4374	0.2918	0.6957

GJR (2, 2) for Nikkei with normal distribution follows the trend set by the earlier models. Nominal coverage at both levels of significance is hovering around 95 per cent. All the models pass conditional and unconditional test as well as the test for independence in a convincing manner. Things are the same when a move is made to the 99 per cent level. Nominal coverage is at 98.7 on the down side and 99.2 on the upside. Hence, there are no surprises in the coverage tests also. All the 32 models tested pass the whole range of tests. Thus, all the models of GJR (2, 2) for Nikkei with normal distributional assumption are fit to be passed on to the next round of tests.

The result for this family of model is a foregone conclusion. At the initial level itself, it is seen that none of the models could pass the tests for Nifty thereby nullifying the effect of whatever that happened after the conclusion for Nifty was available. Hence, it is safe to conclude that GJR with normal distribution also could not contribute any model that is able to stand the back testing in all the three markets studied.

Table 5.63 GJR (1, 1) for Nifty with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	94.5	0.5105	0.0002	0.6240	97.6	14.2244*	0.2700	14.5401*
		500	94.8	0.0832	0.2238	0.4138	97.6	14.2244*	0.2700	14.5401*
		1000	95.5	0.5438	0.4517	1.0877	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.2	5.2251**	0.9535	6.2150**
(2,0)		250	94.4	0.7308	0.0070	0.8531	97.6	14.2244*	0.2700	14.5401*
		500	94.7	0.1860	0.0138	0.3087	97.6	14.2244*	0.2700	14.5401*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.9	1.8120	0.9259	2.8217	98.2	5.2251**	0.9535	6.2150**
(0,1)		250	94.4	0.7308	0.0070	0.8531	97.6	14.2244*	0.2700	14.5401*
		500	94.8	0.0832	0.2238	0.4138	97.6	0.7308	0.2700	14.5401*
		1000	95.5	0.5438	0.4517	1.0877	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.2	5.2251**	0.9535	6.2150**
(0,2)		250	94.5	0.5105	0.0002	0.6240	97.7	12.4853*	0.3507	12.8825*
		500	94.7	0.1860	0.0138	0.3087	97.6	14.2244*	0.2700	14.5401*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.9	1.8120	0.9259	2.8217	98.2	5.2251*	0.9535	6.2150**
(1,1)		250	94.5	0.5105	0.0070	0.6240	97.6	14.2244*	0.3507	14.5401*
		500	94.8	0.0832	0.2238	0.4138	97.7	12.4853*	0.3507	12.8825*
		1000	95.4	0.3457	0.3613	0.8012	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.2	5.2251**	0.9535	6.2150**
(1,2)		250	94.4	0.7308	0.0002	0.8531	97.6	14.2244*	0.3507	14.5401*
		500	94.7	0.1860	0.0138	0.3087	97.7	12.4853*	0.3507	12.8825*
		1000	95.4	0.3457	0.3613	0.8012	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.2	10.8382*	0.9535	6.2150**
(2,1)		250	94.4	0.7308	0.0070	0.6240	97.6	14.2244*	0.2700	12.8825*
		500	94.7	0.1860	0.0138	0.3087	97.7	12.4853*	0.3507	12.8825*
		1000	95.4	0.3457	0.3613	0.8012	97.9	9.2840*	0.5493	9.8758*
		1500	95.9	10.8120	0.9259	2.8217	98.2	5.2251**	0.9535	6.2150**
(2,2)		250	94.5	0.5105	0.0002	0.4138	97.7	12.4853*	0.3507	12.8825*
		500	94.6	0.3287	0.0025	0.4422	97.7	12.4853*	0.3507	12.8825*
		1000	95.4	0.3457	0.3613	0.8012	98	7.8272*	0.6688	8.5365**
		1500	95.8	1.4215	0.9259	2.2972	98.2	5.2251**	0.9535	6.2150**

The final set of models from the conditional heteroskedasticity family tested in the study is the GJR model with Student – t distributional assumption the result of which are reviewed below. This model seeks to represent asymmetry as well as fat tailed nature found in financial data series.

Table 5.64 GJR (1, 2) for Nifty with Student – t Distribution

			95				99			
ARMA	GJR	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	95.4%	0.3457	0.0002	0.6240	98%	7.8272*	0.2700	14.5401*
		500	94.8%	0.0832	0.2238	0.4138	98.2%	5.2251**	0.2700	14.5401*
		1000	95.5%	0.5438	0.4517	1.0877	98.3%	4.0910**	0.5493	9.8758*
		1500	95.4%	0.3457	0.7899	2.2972	98.4%	3.0766	0.9535	6.2150**
(2,0)		250	95.5%	0.5438	0.0070	0.8531	98.1%	6.4725*	0.2700	14.5401*
		500	94.8%	0.0832	0.0138	0.3087	98.2%	5.2251**	0.2700	14.5401*
		1000	95.5%	0.5438	0.2815	0.5710	98.3%	4.0910**	0.5493	9.8758*
		1500	95.4%	0.3457	0.9259	2.8217	98.4%	3.0766	0.9535	6.2150**
(0,1)		250	95.3%	0.1932	0.0070	0.8531	98%	7.8272*	0.2700	14.5401*
		500	94.8%	0.0832	0.2238	0.4138	98.2%	5.2251**	0.2700	14.5401*
		1000	95.5%	0.5438	0.4517	1.0877	98.3%	4.0910**	0.5493	9.8758*
		1500	95.4%	0.3457	0.6657	1.8344	98.4%	3.0766	0.9535	6.2150**
(0,2)		250	94.8%	0.0832	0.0002	0.6240	98.1%	6.4725*	0.3507	12.8825*
		500	94.9%	0.0209	0.0138	0.3087	98.2%	5.2251**	0.2700	14.5401*
		1000	95.5%	0.5438	0.2815	0.5710	98.3%	4.0910**	0.5493	9.8758*
		1500	95.4%	0.3457	0.9259	2.8217	98.4%	3.0766	0.9535	6.2150**
(1,1)		250	95.1%	0.0212	0.0070	0.6240	98.1%	6.4725*	0.3507	14.5401*
		500	94.7%	0.1860	0.2238	0.4138	98.2%	5.2251**	0.3507	12.8825*
		1000	95.5%	0.5438	0.3613	0.8012	98.3%	4.0910**	0.5493	9.8758*
		1500	95.4%	0.3457	0.7899	2.2972	98.4%	3.0766	0.9535	6.2150**
(1,2)		250	94.9%	0.0209	0.0002	0.8531	98%	7.8272*	0.3507	14.5401*
		500	94.8%	0.0832	0.0138	0.3087	98.1%	6.4725*	0.3507	12.8825*
		1000	95.5%	0.5438	0.3613	0.8012	98.2%	5.2251**	0.5493	9.8758*
		1500	95.4%	0.3457	0.7899	2.2972	98.4%	3.0766	0.9535	6.2150**
(2,1)		250	95.1%	0.0212	0.0070	0.6240	98.1%	6.4725*	0.2700	12.8825*
		500	94.8%	0.0832	0.0138	0.3087	98.1%	6.4725*	0.3507	12.8825*
		1000	95.5%	0.5438	0.3613	0.8012	98.3%	4.0910**	0.5493	9.8758*
		1500	95.4%	0.3457	0.9259	2.8217	98.4%	3.0766	0.9535	6.2150**
(2,2)		250	94.9%	0.0209	0.0002	0.4138	98%	7.8272*	0.3507	12.8825*
		500	94.8%	0.0832	0.0025	0.4422	98.1%	6.4725*	0.3507	12.8825*
		1000	95.5%	0.5438	0.3613	0.8012	98.4%	3.0766	0.6688	8.5365**
		1500	95.4%	0.3457	0.9259	2.2972	98.4%	3.0766	0.9535	6.2150**

The model accounting for asymmetry and presence of fat tails in the data do not really make much of a change to the essentials of the findings. All models clear coverage tests and the nominal coverage at the 95 per cent level of confidence are also at an astonishingly low level. The next step is a movement to the 99 per cent level of confidence. As with most other models, this one also clears the test for independence across the model varieties. But only ARMA (0, 1) with 500 observations manages the unconditional coverage and even that fails at the crucial conditional coverage test. Hence, there are no survivors from this model also.

Table 5.65 GJR (2, 1) for Nifty with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	94.5	0.5105	0.0002	0.6240	97.6	14.2244*	0.2700	14.5401*
		500	94.9	0.0209	0.1676	0.2933	97.7	12.4853	0.3507	12.8825*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.7	1.0807	0.6657	1.8344	98.1	6.4725*	0.8032	7.3141**
(2,0)		250	94.4	0.7308	0.0070	0.8531	97.6	14.2244*	0.2700	14.5401*
		500	94.9	0.0209	0.0642	0.1899	97.7	12.4853	0.3507	12.8825*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0.8032	7.3141**
(0,1)		250	94.4	0.7308	0.0070	0.8531	97.6	14.2244*	0.2700	15.5401*
		500	95	0	0.1193	0.2219	07.7	12.4853*	0.3507	12.8825*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0.8032	7.3141**
(0,2)		250	94.5	0.5105	0.0002	0.6240	97.7	12.4853*	0.3507	12.8825*
		500	94.8	0.0832	0.0343	0.2243	97.7	12.4853*	0.3507	12.8825*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0.8032	7.3141**
(1,1)		250	94.5	0.5105	0.0700	0.6240	07.6	14.2244*	0.2700	12.8825*
		500	94.9	0.0209	0.1676	0.2933	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0..8032	7.3141**
(1,2)		250	94.4	0.7308	0.8531	0.8531	97.6	14.2244*	0.2700	11.3262*
		500	94.9	0.0209	0.0642	0.1899	97.8	12.4853*	0.4435	11.3262*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0.8032	7.3141**
(2,1)		250	94.4	0.7308	0.0700	0.6240	97.6	14.2244*	0.2700	7.3141**
		500	94.8	0.0832	0.0343	0.2243	97.9	9.2840*	0.5493	9.8758*
		1000	95.3	0.1932	0.2815	0.5710	97.9	9.2840*	0.5493	9.8758*
		1500	95.8	1.4215	0.7899	2.2972	98.1	6.4725*	0.8032	7.3141**
(2,2)		250	94.5	0.5105	0.0700	0.6240	97.7	12.4853*	0.3507	12.8825*
		500	94.7	0.1860	0.2878	0.5827	97.8	10.8382*	0.4435	11.3262*
		1000	95.5	0.5438	0.4517	1.0877	97.9	9.2840*	0.5493	9.8758*
		1500	95.9	1.8120	0.9259	2.8217	98.1	6.4725*	0.8032	7.3141**

GJR (1, 2) for Nifty with Student – t distribution also fares equally well at the 95 per cent level of confidence by strictly lying within a low band in terms of nominal coverage and clearing all the coverage test with aplomb. Test for independence is cleared once again at the 99 per cent level. However, the progress ends there. Except for the ARMA models with 1500 and ARMA (2, 2) with 1000 observations, all models fail in the unconditional coverage test. And these 9 models that pass the unconditional coverage test stumbles at the conditional coverage test thereby once again returning no models to the successful model basket

Table 5.66 GJR (2, 2) for Nifty with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.4%	0.3457	0.0002	0.6240	98%	7.8272*	0.2700	14.5401*
		500	94.7%	0.1860	0.1676	0.2933	98.2%	5.2251**	0.3507	12.8825*
		1000	95.2%	0.0853	0.2815	0.5710	98.5%	2.1892	0.5493	9.8758*
		1500	95.5%	0.5438	0.6657	1.8344	98.4%	3.0766	0.8032	7.3141**
(2,0)		250	95.3%	0.1932	0.0070	0.8531	98.1%	6.4725*	0.2700	14.5401*
		500	94.8%	0.0832	0.0642	0.1899	98.2%	5.2251**	0.3507	12.8825*
		1000	95.2%	0.0853	0.2815	0.5710	98.6%	1.4374	0.5493	9.8758*
		1500	95.5%	0.5438	0.7899	2.2972	98.4%	3.0766	0.8032	7.3141**
(0,1)		250	95.3%	0.1932	0.0070	0.8531	98%	7.8272*	0.2700	15.5401*
		500	94.8%	0.0832	0.1193	0.2219	98.2%	5.2251**	0.3507	12.8825*
		1000	95.2%	0.0853	0.2815	0.5710	98.5%	2.1892	0.5493	9.8758*
		1500	95.4%	0.3457	0.7899	2.2972	98.4%	3.0766	0.8032	7.3141**
(0,2)		250	95.1%	0.0212	0.0002	0.6240	98.3%	4.0910**	0.3507	12.8825*
		500	94.7%	0.1860	0.0343	0.2243	98.2%	5.2251**	0.3507	12.8825*
		1000	95.2%	0.0853	0.2815	0.5710	98.5%	2.1892	0.5493	9.8758*
		1500	95.5%	0.5438	0.7899	2.2972	98.4%	3.0766	0.8032	7.3141**
(1,1)		250	95%	0	0.0700	0.6240	98%	7.8272*	0.2700	12.8825*
		500	94.7%	0.1860	0.1676	0.2933	98.2%	5.2251**	0.5493	9.8758*
		1000	95.3%	0.1932	0.2815	0.5710	98.5%	2.1892	0.5493	9.8758*
		1500	95.5%	0.5438	0.7899	2.2972	98.4%	3.0766	0..8032	7.3141**
(1,2)		250	94.9%	0.0209	0.8531	0.8531	98%	7.8272*	0.2700	11.3262*
		500	94.5%	0.5105	0.0642	0.1899	98.2%	5.2251**	0.4435	11.3262*
		1000	95.3%	0.1932	0.2815	0.5710	98.4%	3.0766	0.5493	9.8758*
		1500	95.4%	0.3457	0.7899	2.2972	98.4%	3.0766	0.8032	7.3141**
(2,1)		250	95.1%	0.0212	0.0700	0.6240	98.1%	6.4725*	0.2700	7.3141**
		500	94.6%	0.3287	0.0343	0.2243	98.2%	5.2251**	0.5493	9.8758*
		1000	95.2%	0.0853	0.2815	0.5710	98.5%	2.1892	0.5493	9.8758*
		1500	95.5%	0.5438	0.7899	2.2972	98.4%	3.0766	0.8032	7.3141**
(2,2)		250	94.9%	0.0209	0.0700	0.6240	98%	7.8272*	0.3507	12.8825*
		500	94.6%	0.3287	0.2878	0.5827	98.2%	5.2251**	0.4435	11.3262*
		1000	95.4%	0.3457	0.4517	1.0877	98.5%	2.1892	0.5493	9.8758*
		1500	95.6%	0.7885	0.9259	2.8217	98.4%	3.0766	0.8032	7.3141**

GJR (2, 1) for Nifty with Student – t distributions also does a very similar job to its predecessors by giving out good result at the 95 per cent level of confidence. All the models pass the tests at that level and nominal coverage remains at subdued levels. All the 32 models pass the test for independence at the 99 per cent level of significance. However, predictability declines drastically as a move is made towards unconditional coverage test where, only ARMA (1, 0) and (2, 0) with 500 observations survive and predictability decline to zero at the conditional coverage test implying zero survivorship for GARCH (2, 1) with Student – t distribution.

Table 5.67 GJR (1, 1) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	95.4%	0.3457	0.3613	0.8012	98%	7.8272*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,0)		250	95.5%	0.5438	0.0322	2.3161	98.1%	6.4725*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,1)		250	95.3%	0.1932	0.2815	0.5710	98%	7.8272*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.8%	0.0832	0.2815	0.1899	98.1%	6.4725*	0.5209	8.6849**
		500	94.9%	0.0209	0.0642	0.2305	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910*	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5886	3.6297
(1,1)		250	95.1%	0.0212	0.3613	0.1899	98.1%	6.4725*	0.5209	8.6849**
		500	94.7%	0.1860	0.5016	0.7966	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.9%	0.0209	0.0322	2.3161	98%	7.8272*	0.5209	8.6849**
		500	94.8%	0.0832	0.0343	0.2243	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.2%	5.2251**	0.6606	5.9221
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,1)		250	95.1%	0.0212	0.2815	0.5710	98.1%	6.4725*	0.8172	7.2477**
		500	94.8%	0.0832	0.0343	0.2243	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.9%	0.0209	0.2815	0.1899	98%	7.8272*	0.5209	3.6297
		500	94.8%	0.0832	0.0343	0.2243	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297

Nominal coverage of GJR (2, 2) with Student – t distribution for Nifty varies between 94.6 and 95.5 at the 95 per cent level of confidence and the results for unconditional and conditional coverage tests as well as the test for independence are cleared by all the models. Test for independence is once again cleared at the 99 per cent level of significance. However, only half of the models, all ARMA models with 250 and 500 numbers of observations, could make it to the conditional coverage test and all of them are seen to be failing at this level. Thus, there are no surviving models for Nifty from any of the GJR models tested leaving further analysis of result to be of academic interest only.

Nifty Junior is seen to produce better result than its senior counterpart Nifty for GJR (1, 1) with Student – t distribution. All the models pass the three tests of coverage at the 95 per cent level. Though the results take a small beating as a move is made towards the 99 per cent level, they are much better than what was available for Nifty. All models pass independence test and all the models with 1500 number of observations as well as ARMA (2, 2) with 1000 observations pass unconditional as well as conditional coverage tests. Result for conditional coverage test independently is better than that for the unconditional one.

Table 5.68 GJR (1, 2) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(1,2)	250	95.4%	0.3457	0.3613	0.8012	98%	7.8272*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,0)		250	95.5%	0.5438	0.0322	2.3161	98.1%	6.4725*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,1)		250	95.3%	0.1932	0.2815	0.5710	98%	7.8272*	0.8172	8.6849**
		500	94.8%	0.0832	0.6082	0.7983	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,2)		250	94.8%	0.0832	0.2815	0.1899	98.1%	6.4725*	0.5209	8.6849**
		500	94.9%	0.0209	0.0642	0.2305	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5886	3.6297
(1,1)		250	95.1%	0.0212	0.3613	0.1899	98.1%	6.4725*	0.5209	8.6849**
		500	94.7%	0.1860	0.5016	0.7966	98.2%	5.2251**	0.6606	5.9221
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.9%	0.0209	0.0322	2.3161	98%	7.8272*	0.5209	8.6849**
		500	94.8%	0.0832	0.0343	0.2243	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.2%	5.2251**	0.6606	5.9221
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,1)		250	95.1%	0.0212	0.2815	0.5710	98.1%	6.4725*	0.8172	7.2477**
		500	94.8%	0.0832	0.0343	0.2243	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.3%	4.0910**	0.5886	4.7139
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.9%	0.0209	0.2815	0.1899	98%	7.8272*	0.5209	3.6297
		500	94.8%	0.0832	0.0343	0.2243	98.1%	6.4725*	0.7368	7.2477**
		1000	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297

Results for GJR (1, 2) for Nifty Junior with Student – t distribution are the same as the one for GJR (1, 1) except for the details in value. All the models pass the coverage tests as well as test for independence at the 95 per cent level of significance. And the same specification of models that passed the all the test at the 99 per cent level of significance for the GJR (1, 1) pass the range of tests in this case also. Thus, GJR (1, 2) for Nifty Junior with Student – t distribution returns 9 out of 32 models to be compared with the successful models from the other markets.

Table 5.69 GJR (2, 1) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,1)	250	95.4%	0.3457	0.3613	0.8012	98%	7.8272*	0.8172	8.6849**
		500	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,0)		250	95.3%	0.1932	0.0343	0.2243	98.1%	6.4725*	0.8172	7.2477**
		500	94.8%	0.0832	0.0343	0.2243	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.6%	1.4374	0.3980	1.8636
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(0,1)		250	95.3%	0.1932	0.3613	0.8012	98%	7.8272*	0.5209	8.6849**
		500	94.8%	0.0832	0.0343	0.2243	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,2)		250	95.1%	0.0212	0.0343	0.2243	98.3%	4.0910**	0.8172	7.2477**
		500	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(1,1)		250	95%	0	0.3613	0.8012	98%	7.8272*	0.8172	8.6849**
		500	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		1000	95.3%	0.1932	1.3128	1.6023	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.9%	0.0209	0.0343	0.2243	98%	7.8272*	0.8172	7.2477**
		500	94.5%	0.5105	0.0002	0.6240	98.2%	5.2251**	0.6606	5.9221
		1000	95.3%	0.1932	1.4128	1.6023	98.4%	3.0766	0.5209	3.6297
		1500	95.4%	0.3457	3.2216	3.6615	98.4%	3.0766	0.5209	3.6297
(2,1)		250	95.1%	0.0212	0.0002	0.3087	98.1%	6.4725*	0.5209	7.2477**
		500	94.6%	0.3287	0.0025	0.4422	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.9%	0.0209	0.3613	0.2243	98%	7.8272*	0.8172	3.6297
		500	94.6%	0.3287	1.8835	2.7620	98.2%	5.2251**	0.5209	5.9221
		1000	95.4%	0.3457	0.1037	0.2063	98.5%	2.1892	0.2918	0.6957
		1500	95.6%	0.7885	1.4900	1.9300	98.4%	3.0766	0.4573	2.6768

Results improve to a greater extent when GJR (2, 1) and its different variations are used for Value-at-Risk prediction. All models pass the coverage tests at the 95 per cent level as has always been the case. But the number of successful model increase from the last model tested at the 99 per cent level of significance. All ARMA models except those, which use 250 and 500 number of observations for the prediction of standard deviation successfully clear all the coverage tests. Hence, half of the models i.e. 16 out of 32 become eligible for the next round of testing.

Table 5.70 GJR (2, 2) for Nifty Junior with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.4%	0.3457	0.3613	0.8012	98%	7.8272*	0.8172	8.6849**
		500	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,0)		250	95.3%	0.1932	0.0343	0.2243	98.1%	6.4725*	0.8172	7.2477**
		500	94.8%	0.0832	0.0343	0.2243	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.6%	1.4374	0.3980	1.8636
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(0,1)		250	95.3%	0.1932	0.3613	0.8012	98%	7.8272*	0.5209	8.6849**
		500	94.8%	0.0832	0.0343	0.2243	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.4%	0.3457	1.4900	1.9300	98.4%	3.0766	0.5209	3.6297
(0,2)		250	95.1%	0.0212	0.0343	0.2243	98.3%	4.0910**	0.8172	7.2477**
		500	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(1,1)		250	95%	0	0.3613	0.8012	98%	7.8272*	0.8172	8.6849**
		500	94.7%	0.1860	0.0138	0.3087	98.2%	5.2251**	0.6606	5.9221
		1000	95.3%	0.1932	1.3128	1.6023	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(1,2)		250	94.9%	0.0209	0.0343	0.2243	98%	7.8272*	0.8172	7.2477**
		500	94.5%	0.5105	0.0002	0.6240	98.2%	5.2251**	0.6606	5.9221
		1000	95.3%	0.1932	1.4128	1.6023	98.4%	3.0766	0.5209	3.6297
		1500	95.4%	0.3457	3.2216	3.6615	98.4%	3.0766	0.5209	3.6297
(2,1)		250	95.1%	0.0212	0.0002	0.3087	98.1%	6.4725*	0.5209	7.2477**
		500	94.6%	0.3287	0.0025	0.4422	98.2%	5.2251**	0.6606	5.9221
		1000	95.2%	0.0853	1.1481	1.3318	98.5%	2.1892	0.4573	2.6768
		1500	95.5%	0.5438	1.6801	2.3161	98.4%	3.0766	0.5209	3.6297
(2,2)		250	94.9%	0.0209	0.3613	0.2243	98%	7.8272*	0.8172	3.6297
		500	94.6%	0.3287	1.8835	2.7620	98.2%	5.2251**	0.5209	5.9221
		1000	95.4%	0.3457	0.1037	0.2063	98.5%	2.1892	0.2918	0.6957
		1500	95.6%	0.7885	1.4900	1.9300	98.4%	3.0766	0.4573	2.6768

GJR (2, 2) for Nifty Junior with Student – t distribution produces exactly the same sort of result as the one by GJR (2, 1). While, all the models clear the coverage tests and the test for independence at the 95 per cent level of confidence, just as the previous model, only half of them are seen to be able to pass those tests at 99 per cent level. Independence tests are passed by all of them and more than ¾th clear the conditional coverage test but only half of them could make the unconditional test good. The next four tables will review the results obtained for Nikkei using the same models as above.

Table 5.71 GJR (1, 1) for Nikkei with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(1,1)	250	95	0	0.1193	0.2219	98.8	0.3798	0.2918	0.6957
		500	95.1	0.0212	0.1529	0.2746	99.2	0.4337	0.1292	0.5790
		1000	95.3	0.1932	0.0229	0.3124	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(2,0)		250	95	0	0.1193	0.2219	98.8	0.3798	0.1292	0.6957
		500	95.2	0.0853	0.2121	0.3958	99.2	0.4337	0.2918	0.5790
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.4337	0.2918	0.6957
(0,1)		250	95	0	0.1193	0.2219	98.9	0.978	0.2449	0.3649
		500	95.1	0.0212	0.1529	0.2746	99.2	0.4337	0.1292	0.5790
		1000	95.3	0.1932	0.0229	0.3124	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(0,2)		250	95.1	0.0212	0.0790	0.2219	98.7	0.8306	0.3428	1.1996
		500	95.2	0.0853	0.2121	0.3958	99.2	0.4337	0.1292	0.5790
		1000	95.2	0.0853	0.0468	0.2746	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2007	98.8	0.3798	0.2918	0.6957
(1,1)		250	95.1	0.0212	0.1193	0.2219	98.7	0.8306	0.3428	1.1996
		500	95.2	0.0853	0.2121	0.3958	99.1	0.1045	0.1636	0.2862
		1000	95.3	0.1932	0.0229	0.3124	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(1,2)		250	95	0	0.1193	0.2219	98.8	0.3798	0.3428	0.3649
		500	95.2	0.0853	0.2121	0.3958	99.1	0.1045	0.1636	0.2862
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(2,1)		250	95.1	0.0212	0.1193	0.2219	98.7	0.8306	0.1292	1.1996
		500	95.2	0.0853	0.2121	0.3958	99.2	0.4337	0.1292	0.5790
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(2,2)		250	95.1	0.0212	0.0790	0.2219	98.7	0.8306	0.3428	1.1996
		500	95.3	0.1932	0.0229	0.3124	99	0	0.2022	0.2223
		1000	95.2	0.0853	0.0468	0.2305	99.2	0.4337	0.1292	0.5790
		1500	95	0	0.1037	0.2063	98.8	0.3798	0.2918	0.6957

Nominal coverage for Nikkei is seen to be varying among just 4 decimal points i.e. between 95 and 95.3 which is the best available so far. As a corollary, all the models of GJR (1, 1) for Nikkei with Student – t distribution clear the coverage tests. Though, nominal coverage at 99 per cent level does not look so healthy, still it is at comfortable level and all the models pass the three tests of coverage with ease paving way for all the models to take themselves to the next round of back testing.

Table 5.72 GJR (1, 2) for Nikkei with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
((1,0)	(1,2)	250	95.2%	0.4337	0.1193	0.2219	98.6%	1.4374	0.2918	0.6957
		500	95%	0	0.1529	0.2746	98.9%	0.0978	0.1292	0.5790
		1000	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2449	0.3649
(2,0)		250	94.9%	0.0209	0.1193	0.2219	98.7%	0.8306	0.1292	0.6957
		500	95%	0	0.2121	0.3958	98.9%	0.0978	0.2918	0.5790
		1000	95.1%	0.0212	0.0468	0.2305	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2918	0.6957
(0,1)		250	95.2%	0.0853	0.1193	0.2219	98.7%	0.8306	0.2449	0.3649
		500	95%	0	0.1529	0.2746	98.9%	0.0978	0.1292	0.5790
		1000	95.3%	0.1932	0.0229	0.3124	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2449	0.3649
(0,2)		250	94.8%	0.0832	0.0790	0.2219	98.5%	2.1892	0.3428	1.1996
		500	95%	0	0.2121	0.3958	98.9%	0.0978	0.1292	0.5790
		1000	95.1%	0.0212	0.0468	0.2746	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2007	98.6%	1.4374	0.2918	0.6957
(1,1)		250	94.9%	0.0209	0.1193	0.2219	98.7%	0.8306	0.3428	1.1996
		500	95%	0	0.2121	0.3958	98.9%	0.0978	0.1636	0.2862
		1000	95.1%	0.0212	0.0229	0.3124	98.8%	0.3798	0.1292	0.5790
		1500	94.6%	0.3287	0.1529	0.2746	98.6%	1.4374	0.2918	0.6957
(1,2)		250	94.8%	0.0832	0.1193	0.2219	98.6%	1.4374	0.3428	0.3649
		500	95%	0	0.2121	0.3958	98.9%	0.0978	0.1636	0.2862
		1000	95.1%	0.0212	0.0468	0.2305	98.8%	0.3798	0.1292	0.5790
		1500	94.7%	0.1860	0.1529	0.2746	98.6%	1.4374	0.2918	0.6957
(2,1)		250	94.6	0.3287	0.1193	0.2219	98.4%	3.0766	0.1292	1.1996
		500	95.1%	0.0212	0.2121	0.3958	99%	0	0.1292	0.5790
		1000	95.5%	0.5438	0.0468	0.2305	99.2%	0.4337	0.1292	0.5790
		1500	94.9%	0.0209	0.1529	0.2746	98.9%	0.0978	0.2918	0.6957
(2,2)		250	94.6%	0.3287	0.0790	0.2219	98.4%	3.0766	0.3428	1.1996
		500	95.2%	0.0853	0.0229	0.3124	99%	0	0.2022	0.2223
		1000	95.5%	0.5438	0.0468	0.2305	99.2%	0.4337	0.1292	0.5790
		1500	95%	0	0.1037	0.2063	98.9%	0.0978	0.2918	0.6957

GJR (1, 2) with Student – t distribution also does quite well in terms of predictive ability despite not having a closely bunched nominal coverage as in the case of GJR (1, 1). All the models pass the three tests at 95 per cent level of significance as well as at the 99 per cent level of significance. This model also enables Nikkei to have clean sheet in terms of models success in risk prediction and all the models tested can automatically be included for comparison with successful models from the other two markets.

Table 5.73 GJR (2, 1) for Nikkei with Student – t Distribution

			95				99			
ARMA	GARCH	Observations	Coverage	LRuc	LRind	LRcc	Coverage	LRuc	LRind	LRcc
(1,0)	(2,1)	250	95.1	0.0212	0.0790	0.2007	98.9	0.0978	0.2449	0.3649
		500	95	0	0.1037	0.2063	99	0	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(2,0)		250	95	0	0.1193	0.2007	98.8	0.3798	0.2918	0.6957
		500	94.9	0.0978	0.0642	0.1899	99.1	0.1045	0.1636	0.2862
		1000	94.8	0.0832	0.0343	0.2746	98.8	0.3798	0.2918	0.6957
		1500	95.1	0.0212	0.1529	0.2219	98.8	0.3798	0.2918	0.6957
(0,1)		250	95.1	0.0212	0.0790	0.1899	98.9	0.0978	0.2449	0.6957
		500	95.1	0.0212	0.1529	0.2746	99	0	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(0,2)		250	95	0	0.1193	0.2007	98.8	0.3798	0.1292	0.6957
		500	94.9	0.0209	0.0642	0.1899	99	0	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(1,1)		250	95.1	0.0212	0.0790	0.1899	98.9	0.0978	0.2449	0.3649
		500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.0978	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
(1,2)		250	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.2918	0.6957
		500	94.8	0.0832	0.0343	0.2223	99	0	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	99.2	0.4337	0.1292	0.5790
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.4337	0.2918	0.6957
(2,1)		250	95	0	0.1193	0.1899	98.9	0.0978	0.2449	0.3649
		500	94.6	0.3287	0.0025	0.4422	99	0	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	99.1	0.1045	0.1636	0.2862
		1500	95.1	0.0212	0.1529	0.2746	98.8	0.3798	0.2918	0.6957
(2,2)		250	95.1	0.0212	0.0790	0.2007	98.9	0.0978	0.1292	0.6957
		500	95	0	0.1193	0.2219	98.9	0.0978	0.2449	0.2223
		1000	94.9	0.0978	0.0025	0.4422	99.1	0.1045	0.6606	0.2862
		1500	95	0	0.1676	0.2933	98.8	0.3798	0.1636	0.6957

GJR (2, 1) with Student – t distribution is also able to maintain the performance of other models in delivering consistent result for Nikkei. All the models pass the three tests of coverage at the 95 per cent level of confidence. Results do not worsen at the 99 per cent level also as the entire models pass that one quite convincingly. Nominal coverage ranges from 94.6 to 95.1 in case of 95 per cent level and between 98.8 and 99.2 in case of the 99 per cent level. Hence, once again, all the models qualify for the next round.

Table 5.74 GJR (2, 2) for Nikkei with Student – t Distribution

			95				99			
ARMA	GJR GARCH	Observations	Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Coverage	LR_{uc}	LR_{ind}	LR_{cc}
(1,0)	(2,2)	250	95.3%	0.1932	0.0790	0.2007	98.8	0.3798	0.2449	0.3649
		500	95.2	0.0853	0.1037	0.2063	98.9	0.0978	0.2022	0.2223
		1000	95.3	0.1932	0.0790	0.2007	99.2	0.4337	0.1636	0.2862
		1500	94.9	0.0209	0.1529	0.2746	99	0	0.2449	0.3649
(2,0)		250	95.3	0.1932	0.1193	0.2007	98.6	1.4374	0.2918	0.6957
		500	95	0	0.0642	0.1899	98.9	0.0978	0.1636	0.2862
		1000	95.1	0.0212	0.0343	0.2746	98.8	0.3798	0.2918	0.6957
		1500	94.6	0.3287	0.1529	0.2219	98.6	1.4374	0.2918	0.6957
(0,1)		250	95.3	0.1932	0.0790	0.1899	98.9	0.0978	0.2449	0.6957
		500	95.2	0.0853	0.1529	0.2746	98.9	0.0978	0.2022	0.2223
		1000	95.3	0.1932	0.0790	0.2007	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.1529	0.2746	98.6	1.4374	0.2449	0.3649
(0,2)		250	95.3	0.1932	0.1193	0.2007	98.6	1.4374	0.1292	0.6957
		500	95	0	0.0642	0.1899	98.9	0.0978	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.1529	0.2746	98.6	1.4374	0.2918	0.6957
(1,1)		250	94.9	0.0209	0.0790	0.1899	98.7	0.8306	0.2449	0.3649
		500	95	0	0.1529	0.2746	98.9	0.0978	0.2449	0.3649
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.1636	0.2862
		1500	94.6	0.3287	0.1529	0.2746	98.6	1.4374	0.2449	0.3649
(1,2)		250	95	0	0.0790	0.2007	98.7	0.8306	0.2918	0.6957
		500	95	0	0.0343	0.2223	98.9	0.0978	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	98.8	0.3798	0.1292	0.5790
		1500	94.7	0.1860	0.1529	0.2746	98.6	1.4374	0.2918	0.6957
(2,1)		250	95	0	0.1193	0.1899	98.7	0.8306	0.2449	0.3649
		500	95.1	0.0209	0.0025	0.4422	98.9	0.0978	0.2022	0.2223
		1000	95.1	0.0212	0.0790	0.2007	98.7	0.8306	0.1636	0.2862
		1500	94.7	0.1860	0.1529	0.2746	98.7	0.8306	0.2918	0.6957
(2,2)		250	94.7	0.1860	0.0790	0.2007	98.6	1.4374	0.1292	0.6957
		500	95	0	0.1193	0.2219	98.8	0.3798	0.2449	0.2223
		1000	95.1	0.0212	0.0025	0.4422	98.8	0.3798	0.6606	0.2862
		1500	94.7	0.1860	0.1676	0.2933	98.6	1.4374	0.1636	0.6957

Result does not a look a bit different from what it was for the previous model. Though the nominal coverage levels take a bit of beating as compared to the earlier models, all the models pass unconditional and conditional coverage tests as well as the test for independence at both the 95 and 99 per cent levels of confidence making themselves available for comparison with similar successful model from the other two markets. Thus, GJR model with Student – t distribution also helps Nikkei maintain its perfect record in Value-at-Risk forecasting.

Next step in the back testing of the forecasted Value-at-Risk figures is to bring together all the successful models from the three markets tested and see whether there are any models that pass the coverage tests as well as the test for independence in all the three markets. However, it is clear at the outset itself that such an occurrence is impossible as there is no model from Nifty that clear all the coverage tests. Hence, it can be concluded that GJR model of forecasting standard deviation and hence Value-at-Risk does not have universal application and is not foolproof in giving perfect result in all situations.

5.5.6 Historical Simulation

Table 5.75 Historical Simulation for Nifty

H	95				99			
i Number of Observations	Nominal Coverage	LR_{uc}		LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
s 250	94%	1.9842	17.9864*	20.0944*	98.8%	0.3798	14.0119*	14.4158*
t 500	92.9%	8.2609*	13.3069*	21.7151*	98.4%	3.3066	16.4512*	58.5064*
o 1000	93.9%	2.3877	11.2652*	13.7787*	98.8%	0.3798	14.0119*	13.6137*
r 1500	95%	0	21.9262*	19.0005*	99%	0	16.5035*	15.5155*

Historical simulation is seen to have produced an extremely bad forecasting result for Nifty. It can be seen that none of the models under either of the confidence levels is able to get at least one model passed of all the three tests. All the models except the 500 observations one at 95 per cent level of confidence pass the unconditional coverage test, however, 8 out of 8 fail in the test for independence as well as the test for conditional coverage. It is observed that the failure is mainly due to lack of independence, which means that, the exceptions in historical simulation is coming in clusters. This is because of the incapability of the model to adjust itself quickly to a highly volatile situation. Another problem common with such models is the poor predictability at shorter horizons, for which, no real evidence is found from the study. As against the Heteroscedasticity models reviewed above, historical simulation produce almost identical results for 95 and 99 per cent levels of confidence.

Table 5.76 Historical Simulation for Nifty Junior

	95				99			
Number of Observations	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
250	94.7%	0.186	20.1341*	20.4290*	98.7%	0.8306	16.9442*	2.8591
500	94%	1.9842	28.9811*	31.0890*	98.4%	3.3066	23.4441*	19.3983*
1000	95.7%	1.0807	30.1540*	31.3226*	98.8%	0.3798	21.7241*	17.3967*
1500	96.8%	7.7765*	12.9720*	20.8136*	99.2%	0.4337	10.9279*	10.2370*

The result for Nifty Junior with historical simulation is very similar to the one obtained in the case of Nifty. Though all models except the one with 1500 observations at the 95 per cent level fail unconditional coverage, none of them, except the one with 250 observations, is able to clear any one of the remaining two tests at either 95 or 99 per cent levels of confidence. The mass failure is quite easily attributed to the lack of independence which is again due to the inherent rigidity of the model. Thus, neither is Nifty Junior able to produce a historical simulation model capable of passing the back tests.

Table 5.77 Historical Simulation for Nikkei

	95				99			
Number of Observations	Nominal Coverage	LRuc	LRind	LRcc	Nominal Coverage	LRuc	LRind	LRcc
250	95.4%	0.1045	3.2216	3.6615	99.1	0.4337	0.1627	0.2853
500	94.8%	0.4337	0.6081	0.7981	99.2	0.3798	0.1285	0.5783
1000	94.9%	0.4337	0.7259	0.8515	99.2	0.8306	0.1285	0.5783
1500	94.5%	0.3798	0.3208	0.9444	98.8	0.3798	0.2915	0.6954

Result for Nikkei is similar to the ones obtained for the earlier models. Like most of the Heteroscedasticity models, all the models tested for Nikkei clear the two coverage tests and the test for independence easily. Neither does the length of observations or the confidence level have any influence on the predictability as observed from the result. Bringing the three markets together, it is seen that no models are selected form historical simulation either as both Nifty and Nifty Junior fail miserably in back testing procedure. It is also observed that the length of data used in predicting Value-at-Risk has no bearing on the result. Neither does the confidence level affect it. The one big drawback observed is that, historical simulation has limited scope when the question of independence of failures arises. Inspite of the fact that the number of failures being the same as those for the Heteroscedasticity models, historical simulation fares worse than those models due to the lack of independence.

5.5.7 Exponentially Weighted Moving Average

Table 5.78 EWMA Method by NSE for Nifty

Number of Observations	Nominal Coverage	LRuc	LRind	LRcc
250	99.2%	0.4337	3.8542**	4.3040
500	99%	0	2.8500	2.9920
1000	99.2%	0.4337	3.8542**	4.3040
1500	99.5%	3.0937	3.2189	8.9403**

The exponentially weighted moving average (EWMA) used by NSE is seen to give attractive result for Value-at-Risk prediction. All the sampling windows clear the unconditional coverage test. However, 250 and 1000 fail in the test for independence and 1500 fail in the conditional coverage test. Hence, only the model that uses 500 as window size is seen to pass all the three tests and therefore is promoted to be compared to successful models from other markets.

Table 5.79 EWMA Method by NSE for Nifty Junior

Number of Observations	Nominal Coverage	LRuc	LRind	LRcc
250	98.8%	0.3798	9.2103*	7.6269**
500	98.9%	0.0978	9.2272*	7.6468**
1000	98.9%	0.0978	9.2272*	7.6914**
1500	98.9%	0.0978	9.2272*	7.6914**

Moving on to the result for Nifty Junior with the same model, it is seen that though all the models clear unconditional coverage test, none of them could clear either of the other two tests, thereby this variation of EWMA is not able to get any model through to the next round of back testing. Nominal coverage is seen at a very healthy 98.8 or 98.9. This point to the fact that as in the case of historical simulation, EWMA used by Nifty also fails in the case of clustering of failures or dependence among failures at least in the case of Nifty Junior.

Table 5.80 EWMA Used by NSE for Nikkei.

Number of Observations	Nominal Coverage	LRuc	LRind	LRcc
250	99.5%	3.0937	0.0501	3.1539
500	99.4%	1.8862	0.0722	1.9705
1000	99.3%	1.0156	0.0983	1.1280
1500	99.2%	0.4337	0.1285	0.5783

Nikkei is again seen to be different from the other two markets in terms of predictability. All the models clear the tests of coverage as well as the test for independence. Nominal coverage is seen to be ranging between 99.2 to 99.5. A comparison of the models across the three markets again reveals that there is no clear winner from this model either. Though Nikkei got all models passed, there was only one model progressing from Nifty and none at all from Nifty Junior. Hence, the EWMA model used by NSE too fails to throw up a model that has validity across the three markets, under different confidence levels and tests of coverage and independence.

5.5.8 Monte Carlo Simulation

Table 5.81 Monte Carlo Simulation for Nifty

	95				99			
Number of Observations	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
250	93.3	5.5238**	15.9610*	21.6235*	97.3	19.9292*	12.1942*	32.1781*
500	93.6	3.8054	21.4787*	25.4165*	96.7	33.3374*	16.5910*	49.9869*
1000	94.5	0.5105	15.0880*	15.7117*	97.6	14.2214*	14.1164*	23.9844*
1500	95.4	0.3457	18.3634*	18.7975*	98.0	7.8272*	12.6384*	20.5060*

A glance at the available result show that Monte Carlo fares poorly in case of Nifty. Except the window sizes with 500, 1000 and 1500 at 95 per cent level of confidence, no models pass any of the three tests under either level of confidence. Nominal coverage is spread around a rather awkward 93.3 and 95.4 at 95 per cent level and 96.7 to 98 at the 99 per cent level. Hence, there are no survivors from Nifty under Monte Carlo simulation.

Table 5.82 Monte Carlo Simulation for Nifty Junior

	95				99			
Number of Observations	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
250	94.3	0.9889	16.9397*	18.0460*	97.5	16.0430*	13.7292*	29.8228*
500	94.5	0.5105	30.2160*	30.8396*	97.6	14.2214*	14.5612*	28.8313*
1000	95.8	1.4215	27.9857*	23.4198*	97.7	12.4853*	21.1313*	33.6632*
1500	96.9	8.7393*	13.7107*	19.3547*	98.1	6.4725**	19.5462*	26.0571*

The case of Nifty Junior is exactly the same as that of Nifty. All window sizes except 250, 500 and 1000 at 95 per cent level of confidence fail in all tests. The above mentioned three models pass the unconditional coverage test at 95 per cent level but could go no further. Nominal coverage is narrower than Nifty with it ranging between 94.3 and 96.9 at 95 per cent level and between 97.5 and 98.1 at 99 per cent level of confidence.

Table 5.83 Monte Carlo Simulation for Nikkei

	95				99			
Number of Observations	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
250	95.5	0.5438	3.4316	4.1495	98.7	0.8306	0.3423	1.1990
500	95.6	0.0853	1.1480	3.4495	98.6	1.4374	1.6735	3.2107
1000	95.5	0.5438	0.4518	1.0722	98.7	0.8306	0.3423	1.1990
1500	95.0	0	0.8549	2.4005	98.4	3.0766	0.5205	3.6293

Nominal coverage itself varies in a tight range for Nikkei at both 95 and 99 per cent level of confidence. It is between 95 and 95.6 at 95 per cent level and between 98.4 and 98.7 at 99 per cent level. The only possibility for the models to fail from here would be lack of independence but as seen from the test for independence all the models comfortably clear that hurdle too. Hence, all the models tested for Nikkei qualifies for the next round of back testing. However, since, the other two markets could get none of their models to pass the tests, the study could find no successful model from this category also.

5.5.9 Hybrid Approach

Table 5.84 Hybrid Approach for Nifty at 95 Per Cent level

	0.94				0.96				0.98			
Observations	NC	LR_{uc}	LR_{ind}	LR_{cc}	NC	LR_{uc}	LRind	LR_{cc}	NC	LR_{uc}	LR_{ind}	LR_{cc}
250	94%	1.9842	17.9864*	20.0944*	94.7%	0.186	20.1341*	20.4290*	94%	1.9842	17.9864*	20.0944*
500	92.9%	8.2609*	13.3069*	21.7151*	94%	1.9842	28.9811*	31.0890*	94%	1.9842	28.9811*	31.0890*
1000	93.9%	2.3877	11.2652*	13.7787*	95.7%	1.0807	30.1540*	31.3226*	93.9%	2.3877	11.2652*	13.7787*
1500	95%	0	21.9262*	19.0005*	96.8%	7.7765*	12.9720*	20.8136*	96.8%	7.7765*	12.9720*	20.8136*

NC: Nominal Coverage

Hybrid approach also does not seem to be doing any better than either historical simulation or EWMA method even though it's a combination of the two methods. It has limited success in the unconditional coverage at different values of λ. None of the other two pass either of the two tests at λ value of 0.94, 0.96 or 0.98. Hence, no model could be found that passed all the back tests.

Table 5.85 Hybrid Approach for Nifty Junior at 95 Per Cent level

	0.94				0.96				0.98			
Observations	NC	LR_{uc}	LR_{ind}	LR_{cc}	NC	LR_{uc}	LRind	LR_{cc}	NC	LR_{uc}	LR_{ind}	LR_{cc}
250	94.7%	0.186	20.1341*	20.4290*	94%	1.9842	17.9864*	20.0944*	94%	1.9842	17.9864*	20.0944*
500	94%	1.9842	28.9811*	31.0890*	92.9%	8.2609*	13.3069*	21.7151*	94%	1.9842	28.9811*	31.0890*
1000	95.7%	1.0807	30.1540*	31.3226*	93.9%	2.3877	11.2652*	13.7787*	95.7%	1.0807	30.1540*	31.3226*
1500	96.8%	7.7765*	12.9720*	20.8136*	95%	0	21.9262*	19.0005*	95%	0	21.9262*	19.0005*

NC: Nominal Coverage

The case is not all different in the case of Nifty Junior. Though three models at λ value of 0.94 and 0.96 and all the four models at λ value of 0.98 pass the unconditional coverage test, all of them fail in the test for independence and test for correct conditional coverage. It can be observed that the failure is due to lack of independence than anything else as most of the models pass unconditional coverage but stumbles at the test for independence. Therefore, Nifty Junior again fails to throw up any successful model to the basket for comparison with other successful models from Nifty and Nikkei.

Table 5.86 Hybrid Approach for Nikkei at 95 Per Cent level

	0.94				**0.96**				**0.98**			
Observations	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Nominal Coverage	LR_{uc}	LRind	LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
250	95.4%	0.1045	3.2216	3.6615	95.5	0.5438	3.4316	4.1495	95.4%	0.1045	3.2216	3.6615
500	94.8%	0.4337	0.6081	0.7981	95.6	0.0853	1.1480	3.4495	94.8%	0.4337	0.6081	0.7981
1000	94.9%	0.4337	0.7259	0.8515	95.5	0.5438	0.4518	1.0722	95.5	0.5438	0.4518	1.0722
1500	94.5%	0.3798	0.3208	0.9444	95.0	0	0.8549	2.4005	94.5%	0.3798	0.3208	0.9444

Nikkei again looks an exception to the trend taken by the other two markets. It passes all the three tests comfortably at all the window sizes taking all the three values of λ. Hence, Nikkei gets all the models passed of the coverage and independence tests and all of them become eligible for comparison with promoted models from other markets. However, it was observed from the results before this that there was not a single model that cleared all the tests from the other two markets. So the search for a universal model from hybrid approach comes to a halt at the 95 per cent level of confidence itself.

Table 5.87 Hybrid Approach for Nifty at 99 Per Cent level

	0.94				0.96				0.98			
Observations	NC	LR_{uc}	LR_{ind}	LR_{cc}	NC	LR_{uc}	LRind	LR_{cc}	NC	LR_{uc}	LR_{ind}	LR_{cc}
250	99.2%	0.4337	3.8542**	4.3040	98.8%	0.3798	14.0119*	14.4158*	98.4%	3.3066	16.4512*	13.0336*
500	99%	0	2.8500	2.9920	98.4%	3.3066	16.4512*	58.5064*	98.8%	0.3798	14.0119*	13.6137*
1000	99.2%	0.4337	3.8542**	4.3040	98.8%	0.3798	14.0119*	13.6137*	98.8%	0.3798	14.0119*	14.4158*
1500	99.5%	3.0937	3.2189	8.9403**	99.0%	0	16.5035*	15.5155*	99.0%	0	16.5035*	15.5155*

NC: Nominal Coverage

Things get a little better while we move on to the 99 per cent level of confidence. All the models clear unconditional coverage test for λ value of 0.94, 0.96 and 0.98. But only, the model with 500 observations with λ = 0.94 clear all the tests and progress in to the next round. None of the other λ specifications could get any of the models passed of all the three tests though all of them managed to get through unconditional coverage test and the failures are again due to lack of independence.

Table 5.88 Hybrid Approach for Nifty Junior at 99 Per Cent level

	0.94				0.96				0.98			
Observations	NC	LR_{uc}	LR_{ind}	LR_{cc}	NC	LR_{uc}	LRind	LR_{cc}	NC	LR_{uc}	LR_{ind}	LR_{cc}
250	98.8%	0.3798	9.2103*	7.6269**	98.7%	0.8306	16.9442*	2.8591	98.8%	0.3798	21.7241*	17.3967*
500	98.9%	0.0978	9.2272*	7.6468**	98.4%	3.3066	23.4441*	19.3983*	98.4%	3.3066	23.4441*	19.3983*
1000	98.9%	0.0978	9.2272*	7.6914**	98.8%	0.3798	21.7241*	17.3967*	98.8%	0.3798	9.2103*	7.6269**
1500	98.9%	0.0978	9.2272*	7.6914**	99.2%	0.4337	10.9279*	10.2370*	98.7%	0.8306	16.9442*	2.8591

NC: Nominal Coverage

The first model to be noticed here is the 0.94 with 500 observations. Unfortunately, that model does not clear the test for independence and the test for correct conditional coverage. Hence, the sole survivor from Nifty does not get any support from its junior counterpart. Looking at the other models also throws a familiar picture. Though all of them clear test for correct unconditional coverage none of them could make the test for independence or test for correct conditional coverage.

Table 5.89 Hybrid Approach for Nikkei at 99 Per Cent level

	0.94				0.96				0.98			
Observations	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}	Nominal Coverage	LR_{uc}	LRind	LR_{cc}	Nominal Coverage	LR_{uc}	LR_{ind}	LR_{cc}
250	99.1%	3.0937	0.0501	3.1539	99.5%	0.4337	0.1627	0.2853	99.1%	3.0937	0.0501	3.1539
500	99.2%	1.8862	0.0722	1.9705	99.4%	0.3798	0.1285	0.5783	99.4%	0.3798	0.1285	0.5783
1000	99.2%	1.0156	0.0983	1.1280	99.3%	0.8306	0.1285	0.5783	99.2%	1.0156	0.0983	1.1280
1500	98.8%	0.4337	0.1285	0.5783	99.2%	0.3798	0.2915	0.6954	99.2%	0.3798	0.2915	0.6954

Nikkei maintains a spotless record at the 99 per cent level of confidence too. None of the models fail any of the tests at λ value of 0.94, 0.96 or 0.98. Hence, all the models make it to the next round. But again, since there is only one surviving model from Nifty and the same model is seen to fail for Nifty Junior, hybrid approach at 99 per cent level also fails to contribute a model performing equally well at different levels of confidences and window sizes in different markets.

5.6 Concluding Remarks

The study is aimed at finding the best performing Value-at-Risk model in terms of predictability across international markets under different confidence levels and window sizes. Empirical analysis is done for Nifty and Nifty Junior from India and Nikkei from Japan for a period of ten years from 1997 to 2007 for daily returns from these markets. The models tested are: naïve GARCH, EGARCH, GJR GARCH, Historical Simulation, Monte Carlo simulation, EWMA used by NSE and Hybrid method. Using window sizes of 250, 500, 1000 and 1500 days and confidence levels of 95 and 99 per cent, 1000 one day ahead out of sample forecasts are made and these are compared to the realized return on the next day using the back testing method developed by Christoffersen to see if the predicted figures represent the realized return. The study arrived at some interesting conclusions which are detailed below.

Taking the conditional volatility models, it is found that GJR GARCH model which accounts for asymmetry in the return series provides better forecasting ability as compared to the two other models tested. However, it produced no model which was equally successful in all the markets at both levels of confidence tested. But obviously as a ratio, it produced more successful models. Ordering of the GARCH terms are found not to be very important for predictive purposes though the simpler ones put a slightly better performance. Moving on to the window sizes, it is found rather surprisingly that the larger window size of 1500 gave better results compared to other three shorter window sizes followed by the shortest one ,i.e. 250 days. This point at the fact that long term data is needed to predict Value-at-Risk figures accurately. A surprising finding of the study is that, Nikkei is seen to be giving close to hundred per cent accuracy in prediction. This tendency gets violated only for the EGARCH model. This phenomenon was pointed out by Angelidis et al. (2004) in a similar study. The cause of this remains unanswered. There is nothing to choose between Nifty and Nifty Junior though the former is found to beat the latter in GARCH and EGARCH models and the latter emerges a comfortable winner in the GJR model. Between normal and Student – t distribution, the latter is found to be outperforming the former though not convincingly. This is obviously due to the distribution accounting for the fat tailed nature of the data that was found from the analysis of the basic statistics. With regard to the two confidence levels involved, it is found that 95 per cent does a whole lot better than the stricter 99 per cent level. This can be attributed to the exceptionally large magnitude of failures present in the data and indirectly hints at the fat tails. This success at the 95 per cent level does not make news for much comfort as most of the regulators and institutions prefer the stricter 99 per cent level.

Coming to the historical simulation, it is observed that though Nikkei does a very good job of predicting the day ahead Value-at-Risk, Nifty and Nifty Junior is found not to get even a single success either at the 95 or the 99 per cent level of confidence though all models except two are found to clear the unconditional coverage. This point to the inability of historical simulation to produce failures those are independent from each other. This is in fact not a surprising result as it is modeled in such a way as to unable to respond to recent changes in the return behavior .i.e. it responds with a lag. EWMA used by NSE is seen to produce better results than historical simulation. The model with 500 data pass all the three tests for Nifty and all the models pass the whole lot of tests for Nikkei. However, Nifty Junior spoils the show by returning not even a single model. The result for Monte

Carlo simulation is quite similar to that of historical simulation. All three markets are able to get the models pass the unconditional coverage test at 95 per cent level and Nikkei manages to scrape through the other two tests as well. However, Nifty and Nifty Junior could not get even a single model pass the other two tests. This again is found to be due to the clustering of failures. But these two markets are not able to get even a single model pass even the unconditional coverage test at the stricter 99 per cent level though Nikkei does it comfortably. Situation is the same for hybrid method also. Nikkei produces good predictability at both 95 and 99 per cent levels of confidence but neither Nifty nor Nifty Junior is able to get one successful model at either of the confidence levels checked. Hence, this model also fails to throw any successful model forward.

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Chapter 6

Summary and Conclusions

6.1 Introduction

The study is aimed at analyzing the inter-relationship between risk and return, and also attempting an exhaustive survey of the models currently used in measuring and managing risk by different interested parties. The background of the study has been set in the wake of the collapse of large investment banks in the last two decades due to faulty risk management practices. The objectives of the study are connected to the different steps involved in risk management such as: identification, measurement and control. The study has restricted itself to the first two parts, and is related to the period, October 1995 to January 2009. Control has been left out as it is more relevant at the applied rather than at the academic level. Identification part sees risk as emerging from foreign markets as it is a more quantifiable source of risk than most others. Risk has been identified as the volatility or variance of return. The study has used the spillover model to analyze the movement of volatility from one market to the other. For this, Vector Auto Regression (VAR) as well as conditional volatility models are used for three markets viz. Japan, India and the USA. The study also attempted an analysis of the existence of risk premium in the Indian equity market taking Nifty and Nifty Junior returns. This is aimed at finding the relevance of variance as a measure of risk which is being contested strongly in academic circles.

Identification naturally proceeds to measurement of risk. The study has used seven models to test their effectiveness in measuring risk and has subjected them to stringent back testing. The exercise was expected to throw up a model capable of fitting in to different markets and market assumptions with ease. The results that the empirical analysis has brought up are discussed in the next section.

6.2 Major Findings

1. The VAR model estimates for checking spillover of mean and volatility found S&P 500 to be potent enough to influence Nikkei and Nifty while the other two were not able to have any impact on the former. Neither could they produce any impact on each other. In fact, both Nikkei and Nifty acted as followers in international market while S&P 500 took the lead.

2. Analysis of the impulse response function again pointed at the supremacy of S&P 500 as none of the shocks to Nikkei and Nifty are found to have a major impact on S&P 500 while the shocks to the latter's return produced substantial effect on the other two markets. Nikkei is seen to be adjusting slower than Nifty to shocks on S&P 500. This is rather surprising as Nikkei is expected to be more efficient in information processing because of the huge volume of trade and maturity of the market participants.

3. An examination of variance decomposition analysis again underlines the same fact. S&P 500 explained a substantial portion of the error variance of Nikkei and Nifty. Nifty here is seen to have negligible explanatory power as compared to the other two.

4. Conditional volatility models show healthy spillover of mean across the three markets. In most cases it was so strong as to shadow the impact of the AR term itself. This points

at the extent of integration existing among international markets. Results did not change after the introduction of asymmetric term in the volatility model.

5. Volatility in all markets was found to be influenced by foreign market when residual of near foreign market was included in the spillover equation of domestic market. But the US is found to be behaving independently when asymmetric term is introduced in to volatility equation.

6. Spillover is found to be insignificant when the far foreign market is introduced in the spillover equation. This attests to the importance of chronological ordering of markets

7. Results are seen to change when all the markets are brought together in a single equation. The US market becomes completely independent in terms of mean and volatility spillover while dependency of Nikkei and Nifty on S&P 500 is seen to rise. Nifty is found to be a complete follower of Nikkei and S&P 500.

8. It is seen that there is no big difference between daily and weekly return on Indian indices in terms of statistical properties. However, weekly return showed poor auto-correlation suggesting weak explanatory power of past week in defining next week.

9. Analysis of risk premium using GARCH standard deviation and moving standard deviation produced negative but insignificant relation between return and standard deviation or risk. But inclusion of asymmetric term in volatility equation produced significant negative relation. This lays bare the previous findings of positive risk premium and adds strength to the batch of studies supporting negative or inconclusive relation between risk and return.

10. Addition of an auto-regressive term in the equation in order to reduce noise present in the data did not produce different results. The relation remained negative and

insignificant for GARCH and moving standard deviation induced results while it became negatively significant moving on to asymmetric volatility model.

11. Inclusion of 91 day Treasury bill as a means of checking robustness did not make any difference to the results. Thus the study empirically proves that there is no risk premium in Indian equity market taking standard deviation as a proxy for risk.

12. Among all the seven models and its different varieties tested, GJR GARCH is found to be doing better than other models in the back testing. This may be attributed to the asymmetry accounted for by the model. EWMA used by NSE also does a fair job though it falters in the case of Nifty Junior. Historical simulation does a bad job because of clustering of failures and its inability to adjust quickly to changing market conditions. Monte Carlo does slightly better than Historical simulation but no model passed all the criteria. Similar is the case with Hybrid approach.

13. Moving on to the window size, it is found that the larger, 1500 days, eclipse other window sizes. This may be due to the ability of this window size to capture the nature of the data over a sufficiently long period. This is an unexpected result considering the fact that a shorter duration data is expected to be defining future returns and volatility. This questions the wisdom of exponentially weighted moving averages.

14. The 95 per cent level of confidence gives much better back testing results than the 99 per cent level. This may be attributed to the large negative spikes appearing in the return series. The 99 per cent level of confidence may have missed all of those spikes.

15. Among the three markets tested, Nikkei gave an astonishingly good predictability of volatility except in case of a handful of models. This is against the extremely poor predictability returned by Nifty and Nifty Junior. This remains a mystery.

16. The Student – t distribution has given better results than normal distribution. This is obviously due to the presence of fat tails present in the return series. These fat tails are attested by the analysis of basic statistics as well.

17. Ordering of ARCH or GARCH coefficients are found not to produce any substantial changes in the back tests though the simpler models tend to give a slightly better prediction. This underlines the importance of parsimony of models.

6.3 Implications

The study has great practical importance both for the professionals and regulators. Importance of foreign market in the performance of domestic market has been asserted by the study in no uncertain terms. It has also justified the habit of looking towards the US market for cues on domestic market performance by emphasizing the role of the USA as the largest producer of information pertaining to financial markets. Regulators can adjust their safeguards by observing foreign market performance. General tendency of investors to assume greater risk in the hope of garnering higher profit is not approved by the findings of the study. It flatly rejects the idea of getting higher returns on a high risk investment. The study thus cautions speculators. Though it fails in producing a uniformly successful model across all markets in different conditions, it provides valuable guidelines in selecting models of Value-at-Risk prediction. The GJR GARCH with Student – t distribution is found to be giving better predictability among all the models tested. It also underlines the importance of going for a fat tailed distribution and asymmetric term in the volatility model. The study also cautions the adoption of the 99 per cent level of confidence without some additional safe guards.

6.4 Scope for Further Study

The study is one of the most comprehensive till date attempted with India at the centre stage of discussions. However, as with anything else this has also got enormous potential of improvement. The study has concentrated on identification and measurement of market risk thereby bypassing the control part. An empirical analysis on applying risk management technique for controlling risk has good potential. This is more important because some of the institutions that went bankrupt were using some or other of these techniques and yet failed due to chinks in control department. Another potential improvement is a study on the interaction of different risks. The recent credit crisis spread throughout the world not only in its own form but through market contagion as well. The mechanism of contagion of specific risks into other forms and steps to control it could be a very fertile field of research. Improvement could be brought in for back testing used in the last chapter as well. Model requirements vary between regulators and users. Regulators want more downside protection than others. Hence a back testing method that punishes too much allowance for risk and at the same time keeping itself well inside the confidence level can be an ideal one.

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Appendices

Appendix A1: Akaike – Schwarz Information Criteria

Lags	Akaike			Schwarz		
	NKR	NR	SPR	NKR	NR	SPR
1	3.5018	3.8640	3.1443	3.5185	3.8808	3.1612
2	3.5006	3.8622	3.1458	3.5245	3.8861	3.1697
3	3.4957	3.8640	3.1479	3.5268	3.8951	3.1790
4	3.4953	3.8626	3.1429	3.5336	3.9009	3.1811
5	3.4981	3.8635	3.1441	3.5436	3.9090	3.1811
6	3.5001	3.8655	3.1466	3.5528	3.9181	3.1993
7	3.5000	3.8676	3.1475	3.5599	3.9275	3.2074
8	3.4987	3.8657	3.1500	3.5657	3.9328	3.2171
9	3.4986	3.8665	3.1524	3.5729	3.9408	3.2267
10	3.4993	3.8667	3.1533	3.5808	3.9482	3.2348

NKR, NR and SPR stands for Nikkei, Nifty and S&P500 returns

Appendix A2: Basic EGARCH Model*

Parameters	Nikkei	Nifty	S&P500
τ	0.0265 (1.0580)	0.1060 (4.0226)	0.0315 (1.7575)
μ	-0.0144 (-0.6598)	0.0798 (4.0043)	-0.0217 (-0.9851)
α	-0.1020 (-6.2321)	-0.1112 (-5.2515)	-0.0756 (-5.8585)
β	0.1504 (6.8390)	0.2246 (7.6024)	0.0971 (5.8434)
γ	-0.0629 (-4.8342)	-0.1163 (-5.8639)	-0.1165 (-10.4870)
ρ	0.9754 (151.0892)	0.9261 (67.2974)	0.9847 (302.8820)
Skewness	0.0163	-0.2825	-0.0134
Kurtosis	4.6876	10.4605	5.8607
Ljung-Box Q (6 Lags)	9.3787	14.312	20.968
Ljung-Box Q (12 Lags)	16.675	32.743	26.337

t values are given in the parentheses, *This model is based on equations given in pages 41 and 43.

Appendix A3: Spillover Model of Near Market with EGARCH*

Parameters	**Nikkei**	**Nifty**	**S&P500**
τ	0.0118 (0.5010)	0.1078 (4.2287)	0.0212 (1.2111)
μ	-0.0628 (-3.0460)	0.0731 (3.7349)	-0.0407 (-1.8344)
η	0.4235 (18.2739)	0.2273 (11.9179)	0.0597 (5.4182)
α	-0.1086 (-6.2940)	-0.1406 (-6.0447)	-0.0784 (-6.1353)
β	0.1420 (6.2684)	0.2398 (7.6313)	0.0987 (6.0935)
γ	-0.0459 (-3.4843)	-0.1102 (-5.2302)	-0.1139 (-10.1233)
ρ	0.9674 (130.8373)	0.9174 (65.0500)	0.9856 (308.6498)
λ	0.0100 (3.2794)	0.0098 (2.8551)	0.0006 (0.7894)
Skewness	0.0177	-0.1903	0.0108
Kurtosis	4.7713	9.7700	5.9080
Ljung-Box(6 Lags)	9.9790	13.928	23.563
Ljung-Box(12 Lags)	17.871	30.424	29.348

t values are given in the parentheses, *This model is based on equations given in pages 41,43 and 44.

Appendix A4: Spillover Model of Far Market with EGARCH*

Parameters	Nikkei	Nifty	S&P500
τ	0.0220 (0.8764)	0.1033 (3.9222)	0.0280 (1.5749)
μ	-0.0227 (-1.0244)	0.0640 (3.2707)	-0.0748 (-3.3531)
η	0.0333 (2.1239)	0.1977 (8.6674)	0.1153 (8.7044)
α	-0.1033 (-6.1573)	-0.1069 (-4.9970)	-0.0782 (6.0689)
β	0.1472 (6.6480)	0.2262 (7.5191)	0.0970 (6.0029)
γ	-0.0628 (-4.7847)	-0.1211 (-5.7143)	-0.1114 (-10.0529)
ρ	0.9720 (143.7103)	0.9191 (62.1294)	0.9845 (251.0610)
λ	0.0019 (1.7557)	0.0013 (0.3053)	0.0011 (0.7132)
Skewness	0.0200	-0.2731	-0.0005
Kurtosis	4.6766	10.8009	6.0163
Ljung-Box(6 Lags)	9.6885	14.408	20.963
Ljung-Box(12 Lags)	16.667	33.149	25.842

t values are given in the parentheses, *This model is base on equations given in pages 41,43 and 44.

Appendix A5: Spillover Model with EGARCH*

Parameters	**Nikkei**	**Nifty**	**S&P500**
τ	0.0067 (0.2844)	0.1033 (4.0742)	0.0217 (1.2300)
μ	-0.0678 (-3.2117)	0.0622 (3.2125)	-0.0846 (-3.7789)
η_1	0.0255 (1.5905)(I)	0.1963 (10.0746)(J)	0.1073 (8.0818)(J)
η_2	0.4248 (18.2526)(U)	0.1293 (5.6776)(U)	0.0451 (4.0560)(I)
α	-0.1095 (-6.3595)	-0.1401 (-5.8688)	-0.0799 (-6.1969)
β	0.1371 (6.1756)	0.2446 (7.5843)	0.0978 (6.1236)
γ	-0.0442 (-3.3787)	-0.1189 (-5.4307)	-0.1117 (-9.7713)
ρ	0.9653 (129.6974)	0.9153 (63.9465)	0.9853 (256.9151)
λ_1	0.0019 (1.7231)(I)	0.0128 (3.3783)(J)	0.0003 (0.4690)(I)
λ_2	0.0100 (3.2463)(U)	0.0079 (1.6348)(U)	0.0010 (0.6432)(J)
Skewness	0.0199	-0.2021	0.0130
Kurtosis	4.7565	10.0571	6.0720
Ljung-Box(6 Lags)	10.463	13.691	22.637
Ljung-Box(12 Lags)	18.349	30.738	28.047

(i) Letters in the parentheses signify markets :I for Nifty, J for Nikkei and U for S&P500 (ii) Figures in the parentheses shows t values, *This model is based on equations given in pages 41,43 and 44.

Appendix A6: Risk-Return Trade Off with Moving Standard Deviation and T-Bill

Parameters	**NR**	**NJR**
Constant	3.0513 (2.3738)	2.7804 (2.9947)
Standard Deviation	-0.5192 (-1.2157)	-0.3856 (1.0385)
TB	-0.1628 (-1.5096)	-0.1847 (-1.6184)
R^2	0.0117	0.0093
Adjusted R^2	0.0077	0.0047
Durbin-Watson Statistic	1.9022	1.7943

Appendix A7: Risk-Return Trade Off with GARCH Standard Deviation and T-Bill

Parameters	**Normal**		**Student's t**	
	NR	NJR	NR	NJR
Constant	1.9139 (2.5139)	2.3022 (2.5082)	1.9449 (2.5198)	2.3494 (2.5387)
Standard Deviation	-0.1380 (-0.9302)	-0.1536 (-1.0836)	-0.1436 (-0.9544)	-0.1810 (-1.1406)
TB	-0.1822 (-1.7261)	-0.2107 (-1.4710)	-0.1832 (-1.7443)	-0.2017 (-1.3878)
R^2	0.0104	0.0112	0.0105	0.0115
Adjusted R^2	0.0063	0.0072	0.0064	0.0074
Durbin-Watson Statistic	1.9134	1.8162	1.9166	1.8168

Appendix A8: Risk-Return Trade Off with EGARCH Standard Deviation and T-Bill

Parameters	Normal		Student's t	
	NR	NJR	NR	NJR
Constant	2.1806 (2.9201)	2.2076 (2.4130)	2.3677 (3.1053)	2.5288 (2.7435)
Standard Deviation	-0.2808 (-1.9620)	-0.1011 (-0.6967)	-0.3461 (-2.2891)	-0.3080 (-1.9164)
TB	-0.1500 (-1.4228)	-0.2310 (-1.5959)	-0.1442 (-1.3758)	-0.1489 (-1.0217)
R^2	0.0164	0.0098	0.0191	0.0162
Adjusted R^2	0.0123	0.0058	0.0151	0.0122
Durbin-Watson Statistic	1.9845	1.8221	1.9897	1.8661

Appendix A9: Risk-Return Trade Off with Moving Standard Deviation and AR Term

Parameters	NR	NJR
Constant	2.9460 (2.1432)	3.2949 (2.1287)
AR(-1)	0.0452 (1.0001)	0.0973 (2.1613)
Standard Deviation	-0.5023 (-1.1733)	-0.3724 (-1.1548)
TB	-0.1577 (-1.4537)	-0.2288 (-1.7457)
R^2	0.0141	0.0215
Adjusted R^2	0.0080	0.0155
Durbin-Watson Statistic	1.9978	2.0210

Appendix A10: Risk-Return Trade Off with GARCH Standard Deviation and AR Term

Parameters	Normal		Student's t	
	NR	NJR	NR	NJR
Constant	1.7964 (2.3166)	2.0060 (2.1565)	1.8171 (2.3079)	2.0416 (2.1751)
AR(-1)	0.0435 (0.9465)	0.0952 (2.0516)	0.0426 (0.9239)	0.0946 (2.0424)
Standard Deviation	-0.1147 (-0.7621)	-0.0800 (-0.5507)	-0.1172 (-0.7647)	-0.1006 (-0.6192)
TB	-0.1782 (-1.6798)	-0.2184 (-1.5242)	-0.1797 (-1.7021)	-0.2113 (-1.4534)
R^2	0.0123	0.0200	0.0123	0.0202
Adjusted R^2	0.0062	0.0140	0.0062	0.0141
Durbin-Watson Statistic	2.0029	2.0257	2.0034	2.0257

Appendix A11: Risk-Return Trade Off with EGARCH Standard Deviation and AR Term

Parameters	Normal		Student's t	
	NR	NJR	NR	NJR
Constant	2.1272 (2.7197)	1.7928 (1.9145)	2.3298 (2.9181)	2.1985 (2.3195)
AR(-1)	0.0140 (0.2800)	0.1071 (2.1569)	0.0099 (0.2032)	0.0800 (1.6248)
Standard Deviation	-0.2621 (-1.6545)	0.0471 (0.2961)	-0.3329 (2.0191)	-0.1869 (-1.0662)
TB	-0.1524 (-1.4388)	-0.2682 (-1.8465)	-0.1459 (-1.3865)	-0.1801 (-1.2274)
R^2	0.0166	0.0196	0.0193	0.0217
Adjusted R^2	0.0106	0.0135	0.0133	0.0157
Durbin-Watson Statistic	2.0079	2.0254	2.0067	2.0239

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