Chapter 2
Trends in Indian Stock Market: Scope for Designing Profitable Trading Rule?

Abstract This chapter explores the latent structure in the Indian stock market, along with its sectors, around the financial crisis. To understand the market structure, the study makes use of exploratory factor analysis. It also tracks the factor scores along with the cycles in the respective indexes to scrutinize the underlying market behavior. Apart from looking for the latent structure, the chapter seeks to explore the following issues: How the market has behaved over the period of study? What are the trends at sectoral level? Are they similar, or otherwise to the market trends? Are the trends independent of the selection of the stock market exchanges and whether, and how financial crisis could affect such trends? The rationale behind such analyses is to see whether there has been any discernible change in the market structure before and after the shock. A clear behavioral pattern would hint toward an inefficient market and possible scope for designing profitable portfolio mix.

Keywords Indian stock market · Bombay stock exchange · National stock exchange · Stock market cycle · Structural break · Exploratory factor analysis

In the business world, the rearview mirror is always clearer than the windshield.

Warren Buffett

2.1 Introduction

The presence of momentum trading and the resultant trial put on the efficient market hypothesis have attracted the attention of financial analysts and researchers. Momentum trading is a result of irrational investor behavior or "psychological biases" or "biased self-attribution", and may lead to, in extreme cases, herd behavior, formation of bubble, and subsequent panic and crashes in financial market. The speculative bubble generated by momentum trading inflate, becomes

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'self-fulfilling' until they eventually burst with their far-reaching, ruinous impact on real economy. The crash is usually followed by an irrational, negative bubble. Momentum trading thus leads to irrational movement in prices in both directions and its presence is a serious attack on the myth that a capitalist system is self-regulating heading toward a stable equilibrium. Rather, as noted by Shiller and others, it is an unstable system susceptible to "irrational exuberance" and "irrational pessimism".

Ours is a study that explores the possible presence of momentum trading in the Indian stock market in recent years, particularly in light of the recent global financial melt-down of 2007–2008. Given the close connection between financial melt-down and speculative trading, the relevance of the study is obvious. The study starts with an exploration of the trend and latent structure in the Indian stock market around the crisis and eventually tries to relate the instability to the speculative trading.

2.2 Trends and Latent Structure in Indian Stock Market

While analyzing the trends in the Indian stock market around the financial crisis of 2007–2008, the study uses some benchmark stock market indexes along with different sectoral indexes. The Bombay stock exchange (BSE) and the National stock exchange (NSE) are the two oldest and largest stock market exchanges in India and hence, could be taken as representatives of the Indian stock market. The study analyzes the trends, their similarities and dissimilarities, in the two exchanges to get a complete description of Indian stock market movements. While analyzing the market trends the study concentrates on the following:

How the market has behaved over the period of study. Has there been any latent structure in the market?
What are the trends at sectoral level? Are they similar, or otherwise, to the market trends?
Are the trends independent of the selection of the stock market exchanges?
Whether and how financial crisis could affect the market trends?

Before we go into the detailed analysis let us briefly report on the market index and the sectoral indexes that the study picks up from the two exchanges.The study uses daily price data for all the market and sectoral indexes for the period ranging from January 2005 to September 2012. The price data are then used to calculate daily return series using the formula $R_t = \ln(P_t/P_{t-1})$, where P_t is the price on the t'th day.

2.2.1 The Market and the Sectors: Bombay Stock Exchange

The study considers BSE SENSEX or BSE Sensitive Index or BSE 30 as the market index from BSE. BSE SENSEX, which started in January 1986 is a value-weighted index composed of 30 largest and most actively traded stocks in BSE. The SENSEX is regarded as the pulse of the domestic stock markets in India. These companies account for around 50 % of the market capitalization of the BSE. The base value of the SENSEX is 100 on April 1, 1979, and the base year of BSE-SENSEX is 1978–1979. Initially, the index was calculated on the 'full market capitalization' method. However, it has switched to the free float method since September 2003. The stocks represent different sectors such as, housing related, capital goods, telecom, diversified, finance, transport equipment, metal, metal products and mining, FMCG, information technology, power, oil and gas, and healthcare.

As far as the sectoral indexes are concerned, we select 11 market capitalization weighted sectoral indexes introduced by BSE in 1999. These are BSE AUTO, BSE BANKEX, BSE CD, BSE CG, BSE FMCG, BSE IT, BSE HC, BSE PSU, BSE METAL, BSE ONG, and BSE POWER. Of these indexes, only BANKEX has its base year in 2000. All the others have base year in 1999 with base value of 100 in February 1999. The indexes represent different sectors in the Indian economy namely, automobile, banking, consumer durables, capital goods, fast moving consumer goods, information technology, healthcare, public sector unit, metal, oil and gas, and power, respectively.

2.2.2 *The Market and the Sectors: National Stock Exchange*

The NSE is the stock exchange located at Mumbai, India. In terms of market capitalization, it is the 11th largest index in the world. By daily turnover and number of trades, for both equities and derivative trading it is the largest index in India. NSE has a market capitalization of around US$1 trillion and over 1,652 listings as of July 2012. NSE is mutually owned by a set of leading financial institutions, banks, insurance companies, and other financial intermediaries in India but its ownership and management operate as separate entities. In 2011, NSE was the third largest stock exchange in the world in terms of the number of contracts traded in equity derivatives. It is the second fastest growing stock exchange in the world with a recorded growth of 16.6 %. As far as the sectoral indexes are concerned, we select some market capitalization weighted sectoral indexes introduced by NSE. These are CNX BANK, CNX COMMO, CNX ENERGY, CNX FINANCE, CNX FMCG, CNX IT, CNX METALS, CNX MNC, CNX PHARMA, CNX PSU BANK, CNX PSE, CNX INFRA, and CNX SERVICES. The indexes represent different sectors in the Indian economy namely Bank, Consumptions sector, Energy, Finance, FMCG, IT, Metal, MNC, Pharmaceutical, Public Sector Unit, Infrastructure, and Services.

The study is conducted and market trends are analyzed over three phases in the Indian stock market:

1. The entire period: 2005 January to 2012 September. The trends obtained for this entire period could be taken as the 'average' market trend.
2. The prologue of crisis: 2005 January to 2008 January.
3. The aftermath of crisis: 2008 February to 2012 September.

The phases are constructed using the methods of detecting a structural break in a financial time series. Any financial crisis could well be thought of as a switch in regime that is often reflected in a structural break in the market volatility. In that way, a financial crisis could possibly be associated with a volatility break or regime switches that might lead to financial crises. While identifying volatility breaks, we use the same methodology, introduced originally by Inclan and Tiao (1994), and used in our earlier studies (2011, 2012). We recapitulate the methodology briefly in the following sections.

2.3 Detection of Structural Break in Volatility

The parameters of a typical time series do not remain constant over time. It makes paradigm shifts in regular intervals. The time of this shift is the structural break and the period between two breakpoints is known as a regime. There have been several studies aimed at measuring the breakpoints. As usual, a majority of them are in the stock market. As only the algorithm used to detect the breakpoints is important rather than the underlying time series, the following section discusses those studies with important breakthroughs in the algorithm.

The first group of studies was able to detect only one unknown structural breakpoint. Perron (1990, 1997a), Hansen (1990, 1992), Banerjee et al. (1992), Perron and Vogelsang (1992), Chu and White (1992), Andrews (1993), Andrews and Ploberger (1994), Gregory and Hansen (1996), did some major works in this area. Studies by Nelson and Plosser (1982), Perron (1989), Zivot and Andrews (1992) tested unit root in presence of structural break. Bai (1994, 1997) considered the distributional properties of the break dates.

The second group of studies was an improvement over the first as it was able to detect multiple structural breaks in a financial time series, most importantly endogenous breakpoints. Significant contributions were made by Zivot and Andrews (1992). Perron (1989, 1997b), Bai and Perron (2003), Lumsdaine and Papell (1997) tests for unit root allowing for two breaks in the trend function. Hansen (2001) considers multiple breaks, although he considers the breaks to be exogenously given.

The major breakthrough was the study by Inclan and Tiao (1994), who proposed a test to detect shifts in unconditional variance, that is, the volatility. This test is used extensively in financial time series to identify breaks in volatility (Wilson et al. 1996; Aggarwal et al. 1999; Huang and Yang 2001). This test was later modified by (Sansó et al. 2004) to account for conditional variance as well.

Hsu et al. (1974) proposed in their study a model with non-stationary variance which is subjected to changes. This is probably the first work involving structural breaks in variance. Hsu's later works in 1977, 1979, and 1982 were aimed at detecting a single break in variance in a time series. Abraham and Wei (1984) discussed methods of identifying a single structural shift in variance. An improvement came in the study of Baufays and Rasson (1985) who addressed the issue with multiple breakpoints in their paper. Tsay (1988) also discussed ARMA models allowing for outliers and variance changes and proposed a method for detecting the breakpoint in variance. More recently, Cheng (2009) provided an algorithm to detect multiple structural breakpoints for a change in mean as well as a change in variance.

This study does not explicitly incorporate any regime switching model but considers the period between two breaks as a regime. Schaller and Norden (1997) used Markov Switching model to find very strong evidence of regime switch in CRSP value-weighted monthly stock market returns from 1929 to 1989. Marcucci (2005) used a regime switching GARCH model to forecast volatility in S&P500 which is characterized by several regime switches. Structural breaks and regime switch is addressed by Ismail and Isa (2006) who used a SETAR-type model to test structural breaks in Malaysian Ringgit, Singapore Dollar, and Thai Baht.

Theoretically, volatility break dates are structural breaks in variance of a given time series. Structural breaks are often defined as persistent and pronounced macroeconomic shifts in the data generating process. Usually, the probability of observing any structural break increases as we expand the period of study. The methodology used in this chapter is the line of analysis followed by Inclan and Tiao (1994). In the following section, we briefly recapitulate the methodology.

We may start from a simple AR(1) process as that described in (2.1)

$$\begin{aligned} y_t &= \alpha + \rho y_{t-1} + \varepsilon_t \\ E\varepsilon_t^2 &= \sigma^2 \end{aligned} \tag{2.1}$$

Here ε_t is a time series of serially uncorrelated shocks. If the series is stationary, the parameters α, ρ and σ^2 are constant over time. By definition, a structural break occurs if at least one of the parameters changes permanently at some point in time (Hansen 2001). The time point where the parameter changes value is often termed as a "break date". According to Brooks (2002), structural breaks are irreversible in nature. The reasons behind occurrence of structural breaks, however, are not very specified. Economic and non-economic (or even unidentifiable) reasons are equally likely to bring about structural break in volatility. (Valentinyi-Endrész 2004).

2.3.1 Detection of Multiple Structural Breaks in Variance: The ICSS Test

The Iterative Cumulative Sum of Squares (or the ICSS) algorithm by Inclan and Tiao (1994) can very well detect sudden changes in unconditional variance for a stochastic process. Hence, the test is often used to detect multiple shifts in volatility. The algorithm starts from the premise that over an initial period, the time series under consideration displays a stationary variance. The variance changes following a shock to the system and continues to be stationary till it experiences another shock in the future. This process is repeated over time till we identify all the breaks. Structural breaks can effectively capture regime switches (Altissimo and Corradi 2003; Gonzalo and Pitarakis 2002; Valentinyi-Endrész 2004). The different tests for identifying volatility breaks isolate dates where conditional volatility moves from one stationary level to another. The idea is similar to those lying behind the Markov regime switching models, where a system jumps from one volatility regime to another.

2.3.1.1 The Original Model: Breaks in Unconditional Variance

The original model of Inclan and Tiao (1994) are reproduced as follows:

Let $C_k = \sum_{t=1}^{k} a_t^2,\ k = 1,\ldots,$ T is the cumulative sum of squares for a series of independent observations $\{a_t\}$, where $a_t \sim iidN(0,\sigma^2)$ and $t = 1, 2, \ldots, T$, σ^2 is the unconditional variance.

$$\sigma^2 = \begin{cases} \tau_0, & 1 < t < \kappa_1 \\ \tau_1, & \kappa_1 < t < \kappa_2 \\ & \cdots \\ \tau_{N_T}, & \kappa_{N_T} < t < T \end{cases} \tag{2.2}$$

where $1 < \kappa_1 < \kappa_2 < \cdots \kappa_{N_T} < T$ are the breakpoints, that is, where the breaks in variances occur. N_T is the total number of such changes for T observations. Within each interval, the variance is $\tau_j^2, j = 0, 1, \ldots, N_T$

The centralized or normalized cumulative sum of squares is denoted by D_k where

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \rightarrow D_0 = D_T = 0 \tag{2.3}$$

C_T is the sum of squared residuals for the whole sample period.

If there is no volatility shift D_k will oscillate around zero. With a change in variance, it will drift upward or downward and will exhibit a pattern going out of some specified boundaries (provided by a critical value based on the distribution of D_k) with high probability. If at some k, say $k*$, the maximum absolute value of D_k, given by $\max_k \left|\sqrt{T/2D_k}\right|$ exceeds the critical value, the null hypothesis of constant variance is rejected and $k*$ will be regarded as an estimate of the change point. Under variance homogeneity, $\sqrt{T/2D_k}$ behaves like a Brownian bridge asymptotically.

For multiple breakpoints, however, the usefulness of the D_k function is questionable due to "masking effect". To avoid this, Inclan and Tiao designed an iterative algorithm that uses successive application of the D_k function at different points in the time series to look for possible shift in volatility.

2.3.1.2 Modified ICSS Test: Breaks in Conditional Variance

The modified ICSS test is reproduced and used in this study. Sansó et al. (1994) found significant size distortions for the ICSS test in presence of excessive kurtosis and conditional heteroscedasticity. This makes original ICSS test invalid in the context of financial time series that are often characterized by fat tails and conditional heteroscedasticity. As a remedial measure, they introduced two tests to explicitly consider the fourth moment properties of the disturbances and the conditional heteroscedasticity.

The first test, or the k_1 test, makes the asymptotic distribution free of nuisance parameters for *iid* zero mean random variables.

$$\begin{aligned} \kappa_1 &= \sup_k \left| T^{-1/2} B_k \right|, \quad k = 1,\ldots,\mathrm{T} \\ B_k &= \frac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{n}_4 - \hat{\sigma}^4}}, \quad \hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4 \text{ and } \hat{\sigma}^4 = T^{-1} C_T \end{aligned} \tag{2.4}$$

This statistic is free of any nuisance parameter. The second test, the κ_2 test solves the problems of fat tails and persistent volatility.

$$\kappa_2 = \sup_k \left| T^{-1/2} G_k \right| \tag{2.5}$$

where $G_k = \hat{\omega}_4^{-\frac{1}{2}} (C_k - \frac{k}{T} C_T)$

$\hat{\omega}_4$ is a consistent estimator of ω_4. A nonparametric estimator of ω_4 can be expressed as

$$\hat{\omega}_4 = \frac{1}{T} \sum_{i=1}^{T} (\varepsilon_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T} \sum_{l=1}^{m} \omega(l,m) \sum_{t=1}^{T} (\varepsilon_t^2 - \hat{\sigma}^2)(\varepsilon_{t-1}^2 - \hat{\sigma}^2) \tag{2.6}$$

$\omega(l,m)$ is a lag window, such as Bartlett and defined as $\omega(l,m) = [1 - l/(m+1)]$. The bandwidth m is chosen by Newey-West (1994) technique. The κ_2 test is more powerful than the original Inclan-Tiao test or even the $\kappa_1$test and is best fit for our purpose.

The use of the above-mentioned tests on our data set identifies the sub-phases mentioned earlier. One point, however, is to be noted while considering these sub-phases. The period of aftermath might be found to be characterized by further fluctuations in the Indian stock market, some of which might even be capable of generating further financial market crisis. However, analysts often consider it too early to call this period another era of financial crisis. This period of financial turmoil and vulnerability should be better treated as aftershocks of the crisis of 2007–2008 than altogether a new eon of crisis. Moreover, the fluctuations in recent years are yet to be comparable to the older ones in terms of their overall devastating impact on the real economy. Our study hence is built particularly around the financial crisis of 2007–2008. And hence, the crisis period and its aftermath are exclusively in terms of this financial crisis.

2.4 Identifying Trends in Indian Stock Market: The Methodology

The latent structure in the market could be best analyzed by using an exploratory factor analysis (EFA). EFA is a simple, nonparametric method for extracting relevant information from large correlated data sets (Hair et al. 2010). It could reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified structures that often underlie it. In EFA, each variable (X_i) is expressed as a linear combination of underlying factors (F_i). The amount of variance each variable shares with others is called communality. The covariance among variables is described by common factors and a unique factor (U_i) for each variable. Hence,

$$X_i = A_{i1}F_1 + \cdots + A_{im}F_m + V_iU_i \tag{2.7}$$

$$\text{and } F_i = W_{i1}X_1 + \cdots + W_{ik}X_k \tag{2.8}$$

where, $A_{i1}$is the standardized multiple regression coefficient of variable i on factor j; V_i is the standardized regression coefficient of variable i on unique factor i; m is the number of common factors; W_i's are the factor scores, and k is the number of variables. The unique factors are uncorrelated with each other and with common factors.

The appropriateness of using EFA on a data set could be judged by Bartlett's test of sphericity and the Kaiser-Meyar-Olkin (KMO) measure. The Bartlett's test of sphericity tests the null of population correlation matrix to be an identity matrix. A statistically significant Bartlett statistic indicates the extent of correlation among variables to be sufficient to use EFA. Moreover, KMO measure of sampling adequacy should exceed 0.50 for appropriateness of EFA.

In factor analysis, the variables are grouped according to their correlation so that variables under a particular factor are strongly correlated with each other. When variables are correlated they will share variances among them. A variable's communality is the estimate of its shared variance among the variables represented by a specific factor.

Through appropriate methods, factor scores could be selected so that the first factor explains the largest portion of the total variance. Then a second set, uncorrelated to the first, could be found so that the second factor accounts for most of the residual variance and so on. This chapter uses the Principal Component method where the total variance in data is considered. The method helps when we isolate minimum number of factors accounting for maximum variance in data.

Factors with eigenvalues greater than 1.0 are retained. An eigenvalue represents the amount of variance associated with the factor. Factors with eigenvalues less than one are not better than a single variable, because after standardization, each variable has a variance of 1.0.

Interpretation of factors will require an examination of the factor loadings. A factor loading is the correlation of the variable and the factor. Hence, the squared loading is the variable's total variance accounted by the factor. Thus, a 0.50 loading implies that 25 % of the variance of the variable is explained by the factor. Usually, factor loadings in the range of ±0.30 to ±0.40 are minimally required for interpretation of a structure. Loadings greater than or equal to ±0.50 are practically significant while loadings greater than or equal to ±0.70 imply presence of well-defined structures.

The initial or unrotated factor matrix, however, shows the relationship between the factors and the variables where factor solutions extract factors in the order of their variance extracted. The first factor accounting for the largest amount of variance in the data is a general factor where almost every variable has significant loading. The subsequent factors are based on the residual amount of variance. Such factors are difficult to interpret as a single factor could be related to many variables. Factor rotation provides simpler factor structures that are easier to interpret. With rotation, the reference axes of the factors are rotated about the origin, until some other positions are reached. With factor rotation, variance is re-distributed from the earlier factor to the latter. Effectively, one factor will be significantly correlated with only a few variables and a single variable will have high and significant loading with only one factor. In an orthogonal factor rotation, as the axes are maintained at angles of 90°, the resultant factors will be uncorrelated to each other. Within the orthogonal factor rotation methods, VARIMAX is the most popular method where the sum of variances of the required loading of the factor matrix is maximized. There are, however, oblique factor rotations where the reference axes are not maintained at 90° angles. The resulting factors will not be totally uncorrelated to each other. This chapter will use that method of factor rotation which will fit the data best.

The study then employs Cronbach's alpha as a measure of internal consistency. In theory a high value of alpha is often used as evidence that the items measure an underlying (or latent) construct. Cronbach's alpha, however, is not a statistical test. It is a coefficient of reliability or consistency.

The standardized Cronbach's alpha could be written as: $a = \frac{N.\bar{c}}{\bar{v}+(N-1).\bar{c}}$

Here N is the number of items (here markets); $\bar{c}$ is the average inter-item covariance among the items and $\bar{v}$ is the average variance. From the formula, it is clear that an increase in the number of items increases Cronbach's alpha. Additionally, if the average inter-item correlation increases, Cronbach's alpha increases as well (holding the number of items constant). This study uses Cronbach's alpha to check how closely related a set of markets are as a group and whether they indeed form a 'group' among themselves.

2.5 Trends and Latent Structure in Indian Stock Market: Bombay Stock Exchange

1. *Trends over the entire period: 2005 January to 2012 September*

The study starts from an analysis of correlation among the different indexes. Table 2.1 suggests presence of statistically significant correlation among market as well as sectoral returns over the entire study period.

To justify the use of EFA over the chosen data set we consider the KMO and Bartlett's tests for data adequacy. The KMO measure of sampling adequacy takes a value of 0.873 and Bartlett's test statistic of sphericity is significant at one percent level of significance implying validity of using EFA on our data set.

Based on eigenvalue a single factor (eigenvalue 8.784) is extracted that explains 73.2 % of total variability. The single factor contains all the indexes that are highly loaded in that factor. The Cronbach's alpha stands at 0.9631 and declines with exclusion of each index. This makes the extracted structure a valid one (Table 2.2).

The presence of a single structure implies the presence of a single dominant trend in the market. All the sectors and the market move in similar fashion and direction (as reflected in their positive loadings on the factor). The indexes are highly correlated and together they reflect a distinct and broad market trend. The detailed analysis of such broad, dominant trend could be of further interest.

Analysis of market trend: use of factor score

In EFA, factors represent latent constructs. From a practical standpoint, researchers often estimate scores on a latent construct (i.e., factor scores) and use them instead of the set of items that load on that factor. While constructing a factor score, researchers could use the sum or average of the scores on items loading on that factor. However, the procedure could be refined and made statistically acceptable by using the information contained in the factor solution. The problem with such elementary construction of factor score is that simple average uses only the information that the set of items load on a given factor. The process fails if items have different loadings on the factor. In such cases, some items, with relatively high loadings, are better measures of the underlying factor (i.e., more highly correlated with the factor) than others. Therefore, construction of 'good' factor scores requires attaching higher weights to items with high loadings and vice versa. The weights that are used to combine scores on observed items to form factor scores could be obtained through some form of least squares regression. Thus, the factor scores obtained serve as estimates of their corresponding unobserved counterparts.

The use of EFA on our data set extracts a single factor that could be thought of as representing the broad trend in the stock market. However, the stock market trend could not be properly or effectively analyzed until and unless we could get some proxy for this trend. Individual items in the factors (the market index and all the sectoral indexes) could be analyzed separately but the process will provide us

Table 2.1 Correlation matrix among BSE index returns (2005–2012)

	AUTO	BANK	SENSEX	CD	CG	FMCG	HC	IT	PSU	METAL	ONG
BSE AUTO											
BSE BANK	0.727										
BSE SENSEX	0.822	0.892									
BSE CD	0.660	0.611	0.0681								
BSE CG	0.747	0.780	0.866	0.664							
BSE FMCG	0.607	0.557	0.690	0.527	0.564						
BSE HC	0.687	0.639	0.744	0.631	0.668	0.613					
BSE IT	0.575	0.585	0.758	0.501	0.577	0.488	0.557				
BSE PSU	0.770	0.824	0.881	0.701	0.821	0.622	0.734	0.569			
BSE METAL	0.749	0.731	0.847	0.672	0.757	0.585	0.680	0.589	0.818		
BSE ONG	0.701	0.726	0.883	0.610	0.736	0.572	0.667	0.590	0.833	0.766	
BSE POWER	0.763	0.792	0.885	0.691	0.887	0.610	0.713	0.587	0.899	0.803	0.796

All correlations are statistically significant at 1 % level of significance

Table 2.2 Factor loadings in the single factor extracted: entire period

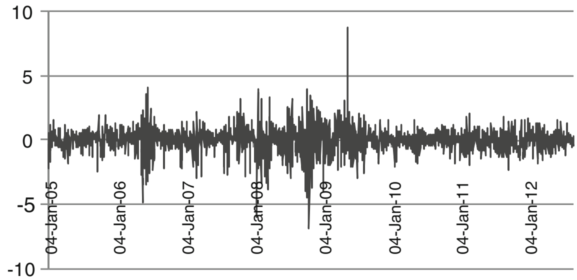
BSE AUTO	0.862	BSE HC	0.812
BSE BANK	0.871	BSE IT	0.714
BSE SENSEX	0.974	BSE PSU	0.930
BSE CD	0.773	BSE METAL	0.882
BSE CG	0.891	BSE ONG	0.871
BSE FMCG	0.719	BSE POWER	0.926

with hardly any insight regarding the broad trend. We could instead construct the factor score for our single extracted factor. These factor scores then could serve as a proxy for the latent structure of the market. That is where the study moves next.

The movement or behavior of market trends (given by the factor scores), henceforth described as the *stock market* is depicted in Fig. 2.1. As is evident from the diagram, the stock market movement is highly volatile, characterized by the presence of volatility clustering where periods of high (low) volatility are followed by periods of high (low) volatility. However, from the simple plot it is difficult to form any idea regarding the trends and nature of movements properly.

The trend could be better analyzed if it is possible to bring out the nature of the cycle inherent in the series. For this purpose, the study uses the method of band pass (frequency) filter. The band pass (frequency) filters are used to isolate the cyclical component of a time series by specifying a range for its duration. The band pass filter is a linear filter that takes a two-sided weighted moving average of the data where cycles in a "band", given by a specified lower and upper bound, are "passed" through, or extracted, and the remaining cycles are "filtered" out. To use a band pass filter, we have to first specify the 'periods' to 'pass through. The periods are defined in terms of two numbers (P_L and P_U) based on the units of the frequency of the series used. There are different band pass filters that differ in their treatment of the moving average. The study uses the full sample asymmetric filter, where the weights on the leads and lags are allowed to differ. The asymmetric filter is time-varying with the weights both depending on the data and changing for each observation. The study uses the Christiano–Fitzgerald (CF) form of this filter. As a rule of thumb, P_L and P_U are set as 1.5 and 8 years for yearly data. The ranges for daily data should be adjusted accordingly. The series is found to be level stationary using Augmented Dickey Fuller test statistic (null hypothesis of unit root is

Fig. 2.1 Movements in factor scores, BSE (2005–2012)



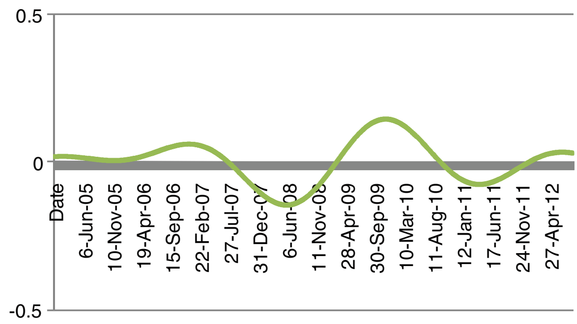


Fig. 2.2 Cycle in the BSE return (2005–2012)

rejected at one percent level of significance). We chose to de-trend the data before filtering. The cycle is depicted in Fig. 2.2.

The return-cycle for the stock market enables us to identify the ups and downs in BSE. The *stock market* as a whole experiences a boom during the phases namely, 2006–2007, 2009–2010, and since early 2012. The market as a whole slides down from its peak over the periods namely, 2007–2008 and 2010–2011. Our analysis is concentrated around the first cycle.

The trend is further analyzed through an examination of the risk-return relationship in the market as a whole. The variance of a series could serve as a good proxy for the risk of the series. As is suggested by the simple plot of the *stock market* return, the series is characterized by volatility clustering or volatility pooling. Moreover the series is negatively skew (skewness −0.23), highly peaked (kurtosis 6.65), and non-normal. Such a series is best analyzed by an appropriate GARCH family model and risk for such a series is proxied best by its conditional variance.

The *stock market* is modeled best by Exponential GARCH (EGARCH) model, an asymmetric GARCH model of order (1, 1). The study uses the version of the model first proposed by Nelson in 1991. The EGARCH (1, 1) model can be specified as:

$$\log\left(\sigma_t^2\right) = \omega + \alpha(|z_{t-1}| - E(|z_{t-1}|)) + \gamma z_{t-1} + \beta\log(\sigma_{t-1}^2); \text{ where } \varepsilon_{t-1} = \sigma_{t-1}z_{t-1} \tag{2.9}$$

The dependent variable is not the conditional variance, but rather the log of conditional variance. Hence the leverage effect is exponential rather than quadratic in the EGARCH model. The EGARCH model overcomes the most important limitation of the GARCH model by incorporating the leverage effect. If $\alpha > 0$ and $\gamma = 0$, the innovation in $\log\left(\sigma_t^2\right)$ is positive (negative) when z_{t-1} is larger (smaller) than its expected value. And if $\alpha = 0$ and $\gamma < 0$, the innovation in $\log\left(\sigma_t^2\right)$ is positive (negative) when z_{t-1} is negative (positive). Another significant improvement of the EGARCH process is that it contains no inequality constraint, and by parameterizing the $\log\left(\sigma_t^2\right)$ can take negative value so there are fewer restrictions on the model. Lastly, the EGARCH process can capture volatility persistence quite effectively. $\log\left(\sigma_t^2\right)$ can easily be checked for volatility

Table 2.3 Application of EGARCH model on factor score for BSE (2005–2012)

Dependent variable: factor score for BSE (2005–2012)				
Method: ML—ARCH (Marquardt)—student's t distribution				
Included observations: 1909				
Convergence achieved after 23 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(1) + C(2)*ABS(RESID(−1)/@SQRT(GARCH(−1))) + C(3) *RESID(−1)/@SQRT(GARCH(−1)) + C(4)*LOG(GARCH(−1))				
	Variance equation			
	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	−0.18787	0.023173	−8.10761	5.16E-16
C(2)	0.226826	0.028853	7.861378	3.80E-15
C(3)	−0.11943	0.017101	−6.98381	2.87E-12
C(4)	0.961732	0.007329	131.2155	0
T-DIST. DOF	7.678726	0.986114	7.786851	6.87E-15
R-squared	1.11E-15	Mean dependent var		−4.71E-08
Adjusted R-squared	−0.0021	S.D. dependent var		1
S.E. of regression	1.00105	Akaike info criterion		2.433343
Sum squared resid	1908	Schwarz criterion		2.447891
Log likelihood	−2,317.63	Hannan-Quinn criter.		2.438697
Durbin–Watson stat	1.804131			

persistence by looking at the stationarity and ergodicity conditions. However, the EGARCH model is also not free from its drawbacks. This model is difficult to use for there is no analytic form for the volatility term structure.

As is suggested by Table 2.3, the *stock market* is characterized by asymmetric response of volatility toward positive and negative announcements in the market. The market reacts more toward the negative news than toward the good news.

The conditional volatility for the series is saved and depicted in Fig. 2.3.

The conditional variance, after de-trending, exhibits significant cyclical pattern (Fig. 2.4).

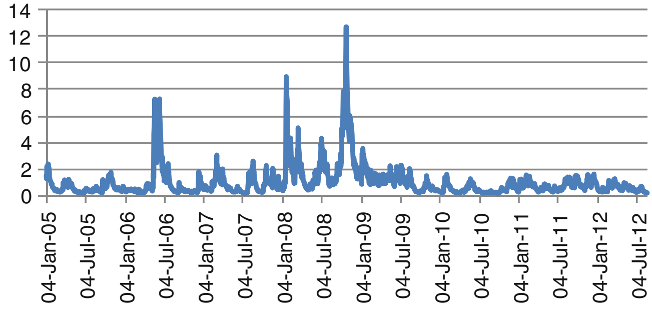


Fig. 2.3 BSE conditional variance (2005–2012)

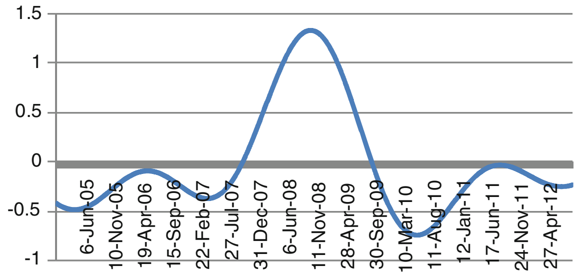


Fig. 2.4 Cycle in the factor score BSE conditional variance (2005–2012)

The conditional volatility has been significantly higher during the period of financial crisis of 2007–2008. The two other peaks are not at all significant compared to this peak. Thus, although the return cyclebrings out two significant peaks in BSE return, conditional variance cycle rules out one and suggests presence of a single high-volatile period in the market. The peak of 2010–2011 is not associated with a very high volatility. This justifies our choice of financial crisis of 2007–2008 as the most significant financial crisis of recent years. The cycle of 2010–2012 is yet to be designated as a true financial crisis. Interestingly, the nature of cycle of conditional variance is completely opposite to the cyclical nature of the return series. Return peaks are always associated with low conditional variance or conditional variance slumps. This is further analyzed and depicted in Fig. 2.4. The nature of time-varying conditional correlation between stock market return and conditional variance brings out the negative relationship between risk and return in the market.

The conditional correlation has been computed using a multivariate GARCH technique that models the variance–covariance matrix of a financial time series. This section makes use of Diagonal Vector GARCH (VECH) model of Bollerslev et al. (1988). In a Diagonal VECH model the variance–covariance matrix of stock market returns is allowed to vary over time. This model is particularly useful, unlike the BEKK model of Baba et al. (1990), with more than two variables in the conditional correlation matrix (Scherrer and Ribarits 2007). However, it is often difficult to guarantee a positive semi-definite conditional variance–covariance matrix in a VECH model (Engel and Kroner 1993; Brooks and Henry 2000). Following the methodology of Karunanayake et al. (2008) this study avoids this problem by using the unconditional residual variance as the pre-sample conditional variance. This is likely to ensure positive semi-definite variance–covariance matrix in a diagonal VECH model. Since, we are more interested in volatility co-movement and spill over, the mean equation of the estimated diagonal VECH model contains only the constant term. In the n dimension variance–covariance matrix, H, the diagonal terms will represent the variance and the non-diagonal terms will represent the covariances. In other words, in

$$H_t = \begin{matrix} h_{11t} & \cdots & h_{1nt} \\ \cdots & \cdots & \cdots \\ h_{n1t} & \cdots & h_{nnt} \end{matrix}$$

h_{iit} is the conditional variance of 'ith market in time t; h_{ijt} is the conditional covariance between the ith and jth market in period t ($i \neq j$). The conditional variance depends on the squared lagged residuals and conditional covariance depends on the cross lagged residuals and lagged covariances of the other series (Karunanayake et al. 2008). The model could be represented as:

$$\mathrm{VECH}(H_t) = C + \mathrm{A.VECH}(\varepsilon_{t-1}\varepsilon'_{t-1}) + \mathrm{B.VECH}(H_{t-1}) \tag{2.10}$$

A and B are $\frac{N(N+1)}{2} \times \frac{N(N+1)}{2}$ parameter matrices. C is $\frac{N(N+1)}{2}$ vector of constant. a_{ii} in matrix A, that is the diagonal elements show the own spillover effect. This is the impact of own past innovations on present volatility. The cross diagonal terms (a_{ij}, $i \neq j$) show the impact of pat innovation in one market on the present volatility of other markets. Similarly, b_{ii} in matrix B shows the impact of own past volatility on present volatility. Likewise, b_{ij} represents cross volatility spill over or the impact of past volatility of the ith market on the present volatility of jth market. For our purpose, a_{ij}'s and b_{ij}'s are more important.

As pointed out by Karunanayake et al. (2008) an important issue in estimating a diagonal VECH model is the number of parameters to be estimated. To solve the problem, Bollerslev et al. (1988) suggested use of a diagonal form of A and B. A related issue is to ensure the positive semi-definiteness of the variance–covariance matrix. The condition is easily satisfied if all of the parameters in A, B, and C are positive with a positive initial conditional variance–covariance matrix. Bollerslev et al. (1988) suggested some restrictions to impose that have been followed by Karunanayake et al. (2008). They used maximum likelihood function to generate these parameter estimates by imposing some restriction on the initial value. If θ be the parameter for a sample of T observations, the log likelihood function will be:

$$T(\theta) = \sum_{t=1}^{T} l_r(\theta), \quad \text{where} \quad l_t(\theta) = \frac{N}{2}\ln(2\pi) - \frac{1}{2}ln|H_t| - \frac{1}{2}\epsilon'_t H_t^{-1}\epsilon_t \tag{2.11}$$

The presample values of θ can be set to be equal to their expected value of zero (Bollerslev et al. 1988). The Ljung Box test statistic could further be used to test for remaining ARCH effects. For a stationary time series of T observations and a multivariate process of order (p, q) the Ljung Box test statistic is given as:

$$Q = T^2 \sum_{j=1}^{s} (T-j)^{-1} tj\left\{ C_{Y_t}^{-1}(0) C_{Y_t}(j) C_{Y_t}^{-1}(0) C'_{Y_t}(j) \right. \tag{2.12}$$

Y_t is VECH (y_t, y'_t), $C_{Y_t}(j)$ is the sample autocovariance matrix of order j, s is the number of lags used, T is the number of observations. For large sample, the test statistic is distributed as a χ^2 under the null hypothesis of no remaining ARCH effect.

A multivariate GARCH of appropriate order has been estimated for the data on factor scores for BSE return and BSE conditional variance and the conditional correlation values have been saved. The movement in this conditional correlation

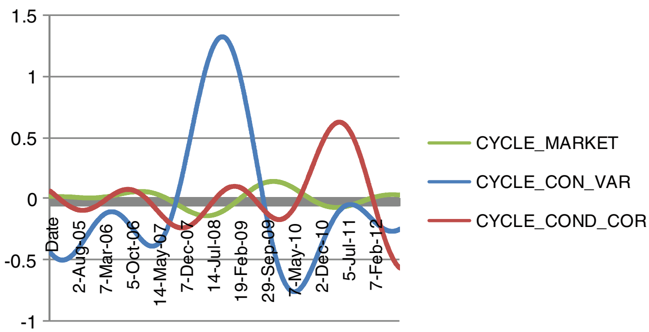


Fig. 2.5 Return-risk relationship BSE (2005–2012)

reflects the risk-return relationship in the context of BSE. During most of the time period, particularly during the financial crisis of 2007–2008, risk and return had been perfectly negatively correlated (correlation coefficient = −1). For only a short period of time, risk and return was perfectly positively correlated (correlation coefficient = +1). This suggests the presence of dominantly negative (perfect) risk-return relationship in BSE. More interestingly, correlation coefficient was either +1 or −1. Only for a short period of time (during August 2010 to January 2012) correlation coefficient remained positive and fluctuated. The characteristics in conditional correlation could further be traced in the cycle in conditional correlation (Fig. 2.5).

The analysis of overall market trend would now be supplemented by analyses of market trend before and after the crisis.

2. *The trends in the pre-crisis period: 2005 January to 2008 January*

The analysis of trends in the market in the pre-crisis period starts from identification of latent structure in the market.

Table 2.4 suggests presence of statistically significant correlation among market as well as sectoral returns during the pre-crisis.The correlation coefficients are more or less the same in magnitude compared to those for the entire period.

The use of EFA over the pre-crisis data set is further justified by the favorable values of the KMO measure of sampling adequacy and Bartlett's tests for data adequacy. The KMO measure of sampling adequacy takes a value of 0.885 and Bartlett's test statistic of sphericity is significant at one percent level of significance implying validity of using EFA on the pre-crisis data set.

On the basis of eigenvalue a single factor (eigenvalue 8.908) is extracted that explains 74.2 % of total variability. Both the eigenvalue and the total variability explained by the single factor extracted are higher than those obtained for the *entire period*. Once again, the single factor contains all the indexes that are highly loaded in that factor. The Cronbach's alpha stands at 0.9650 (which is higher than the *entire period*) and declines with exclusion of each index. This makes the extracted structure, once again a valid one (Table 2.5).

Table 2.4 Correlation matrix among BSE index returns (2005–2008)

	AUTO	BANK	SENSEX	CD	CG	FMCG	HC	IT	PSU	METAL	ONG
BSE AUTO											
BSE BANK	0.693										
BSE SENSEX	0.857	0.842									
BSE CD	0.691	0.541	0.656								
BSE CG	0.769	0.693	0.850	0.633							
BSE FMCG	0.686	0.562	0.753	0.569	0.638						
BSE HC	0.760	0.659	0.802	0.670	0.724	0.670					
BSE IT	0.650	0.572	0.785	0.507	0.606	0.495	0.606				
BSE PSU	0.812	0.794	0.897	0.692	0.812	0.685	0.787	0.610			
BSE METAL	0.765	0.673	0.837	0.648	0.752	0.663	0.728	0.592	0.834		
BSE ONG	0.747	0.678	0.876	0.612	0.728	0.657	0.718	0.603	0.869	0.760	
BSE POWER	0.780	0.716	0.855	0.660	0.867	0.652	0.750	0.588	0.894	0.794	0.783

All correlations are statistically significant at 1 % level of significance

Table 2.5 Factor loadings in the single factor extracted: pre-crisis period

BSE AUTO	0.894	BSE HC	0.861
BSE BANK	0.818	BSE IT	0.733
BSE SENSEX	0.971	BSE PSU	0.943
BSE CD	0.760	BSE METAL	0.879
BSE CG	0.882	BSE ONG	0.879
BSE FMCG	0.776	BSE POWER	0.909

The presence of a single structure implies the presence of a single dominant trend in the market even in the *pre-crisis* period. All the sectors and the market move in similar fashion and direction (as reflected in their positive loadings on the factor). The indexes are highly correlated and together they reflect a distinct and broad market trend. The detailed analysis of such broad, dominant trend in the *pre-crisis* period would be our further area of analysis.

Analysis of market trend in pre-crisis period: use of factor score

The use of EFA on our *pre-crisis* data set extracts a single factor that could be thought of as representing the broad trend in the stock market in the *pre-crisis* period. However, this stock market trend cannot be properly or effectively analyzed until and unless we could get some proxy for this trend. Just like the previous case, we have constructed the factor score for our single extracted factor for the *pre-crisis* period. These factor scores then serve as a proxy for the latent structure of the *pre-crisis* market.

The movement or behavior of market trends (given by the factor scores), henceforth described as the *stock market in pre-crisis period*, is depicted in Fig. 2.6. As is evident from the diagram, the stock market movement is highly volatile, characterized by the presence of volatility clustering where periods of high (low) volatility are followed by periods of high (low) volatility. However, from the simple plot it is difficult to form any idea regarding the trends and nature of movements properly. The trend in the *pre-crisis period* resembles that for the *entire Period.*

The trend could be better analyzed if it is possible to bring out the nature of the cycle inherent in the series. The cycle is generated once again using the method of band pass (frequency) filter in its CF form. The *pre-crisis* series is found to be level stationary using Augmented Dickey Fuller test statistic (null hypothesis of unit root is rejected at one percent level of significance). We chose to de-trend the data before filtering. The cycle is depicted in Fig. 2.7.

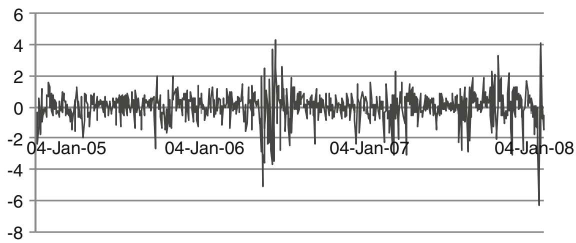


Fig. 2.6 Movements in factor scores, BSE (2005–2008)

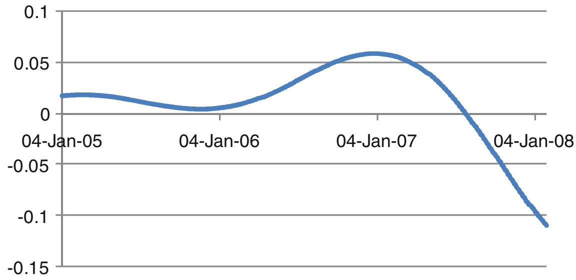


Fig. 2.7 Cycle in the BSE return (2005–2008)

The cycle for the stock market enables us to identify the ups and downs in returns in the BSE in the *pre-crisis* period. As suggested by our earlier analysis, the *stockmarket* as a whole experienced a boom during the phases namely, 2006–2007, 2009–2010, and since early 2012. The market as a whole slides down from its peak over the periods namely, 2007–2008 and 2010–2011. An analysis of the *pre-crisis* period return shows distinct cycle that is different from the cycle that we obtained from our earlier analysis of the entire period. If we could take the *pre-crisis* period separately, and not as a part of the entire period, a small peak could be traced during the period of 2005–2006. This peak was not very prominent in the cycle for the entire period. There has been another significant peak in the *pre-crisis* period that could be traced during the period of 2007–2008. The market in the *pre-crisis* period started declining just toward the end of the period namely in January 2008.

The trend is further analyzed through examination of the risk-return relationship in the market as a whole. The variance of a series could serve as a good proxy for the risk of the series. As is suggested by the simple plot of the *stock market* return, the series is characterized by volatility clustering or volatility pooling. Moreover, the series is negatively skew (skewness −0.25), highly peaked (kurtosis 8.65), and non-normal. Such a series is best analyzed by an appropriate GARCH family model and risk for such a series is proxied best by its conditional variance.

The *stock market* is modeled best by EGARCH, an asymmetric GARCH model of order (1, 1, 1). As is suggested by Table 2.6, the *stock market* in the *pre-crisis* period is characterized by asymmetric response of volatility toward positive and negative announcements in the market. The market reacts more toward the negative news than toward the good news.

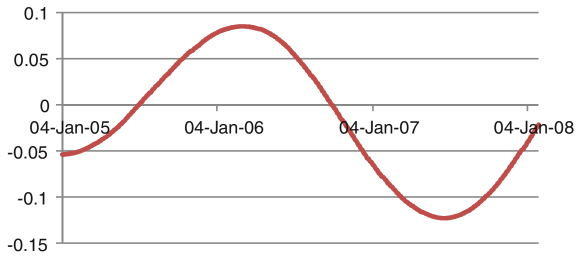
The conditional volatility for the *pre-crisis* series is saved and depicted in Fig. 2.8.

The conditional variance, after de-trending, exhibits significant cyclical pattern. The conditional volatility has been significantly higher during the period of 2005–2006. The conditional volatility was significantly lower during mid-2007. However, just before the crisis was to set in, conditional volatility started mounting. Thus risk in a market (given by the conditional variance) starts escalating as the market approaches a crisis. The risk-return relationship in the market is further analyzed and depicted in Fig. 2.9. The nature of time-varying conditional

Table 2.6 Application of EGARCH model on factor score for BSE (2005–2008)

Dependent Variable: Return in the *pre-crisis* period				
Method: ML—ARCH (Marquardt)—Student's t distribution				
Included observations: 771 after adjustments				
Convergence achieved after 20 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(1) + C(2)*ABS(RESID(−1)/@SQRT(GARCH(−1))) + C(3) *RESID(−1)/@SQRT(GARCH(−1)) + C(4)*LOG(GARCH(−1))				
	Variance equation			
	Coefficient	Std. error	z-statistic	Prob.
C(1)	−0.230081	0.051685	−4.451629	0
C(2)	0.252992	0.062029	4.078632	0
C(3)	−0.235055	0.039617	−5.933215	0
C(4)	0.882705	0.024141	36.56491	0
T-DIST. DOF	6.19328	1.366128	4.533454	0
R-squared	0	Mean dependent var		0.000391
Adjusted R-squared	−0.005222	S.D. dependent var		1.00059
S.E. of regression	1.003199	Akaike info criterion		2.424167
Sum squared resid	770.9089	Schwarz criterion		2.454307
Log likelihood	−929.5162	Hannan-Quinn criter.		2.435765
Durbin–Watson stat	1.780743			

Fig. 2.8 Cycle in the factor score BSE conditional variance (2005–2008)



correlation brings out the presence of a positive relationship between risk and return in the market. While the correlation fluctuates, it started declining since mid-2007 and approached zero toward the beginning of the crisis.

Hence, the analysis of *pre-crisis* period reveals few notable characteristics of Indian stock market:

- Indian stock market is dominated by a "single" trend where all the sectors and the market move together. The trend in the pre-crisis period is stronger than the 'average' (the trend for the entire period) market trend.
- The entire stock market is characterized by significant volatility with volatility clustering.

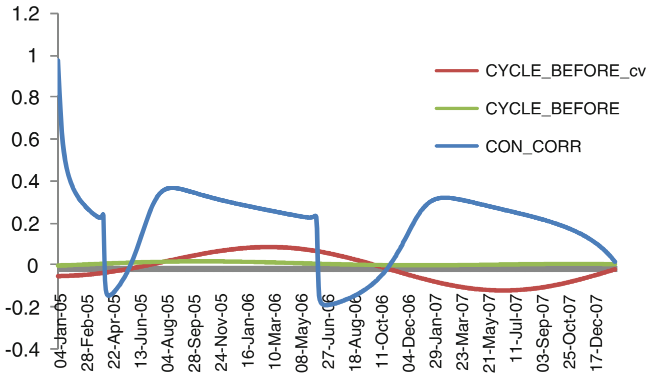


Fig. 2.9 Return-risk relationship BSE (2005–2008)

- Asymmetric response of volatility toward good and bad news where volatility responds more toward bad news. The leverage effect is more pronounced in the *pre-crisis* period (coefficient = −0.23) compared to the entire period (−0.11)
- Returns start falling and risks start mounting as the market approaches a crisis.
- Market is mostly characterized by a positive risk-return relationship. However, the correlation coefficient between risk and return starts declining as the market approaches crisis. Just before the crisis sets in, the correlation coefficient becomes zero.

3. *The trends in the post-crisis period: 2008 February to 2012 September*

The analysis of market trend in the post-crisis period starts from identification of latent structure in the market. Table 2.7 suggests presence of statistically significant correlation among market as well sectoral returns during the post-crisis period. The correlation coefficients are more or less the same in magnitude compared to those for the *entire* and *pre-crisis* period.

The use of EFA over the post-crisis period data set is once again justified by the favorable values of the KMO measure of sampling adequacy and Bartlett's tests for data adequacy. The KMO measure of sampling adequacy takes a value of 0.866 and Bartlett's test statistic of sphericity is significant at one percent level of significance implying validity of using EFA on the post-crisis data set.

On the basis of eigenvalue a single factor (eigenvalue 8.740) is extracted that could explains 72.83 % of total variability. Both the eigenvalue and the total variability explained by the single factor extracted are lower than those obtained for the *entire period* as well as for the *pre-crisis* period. Once again, the single factor contains all the indexes that are highly loaded in that factor. The Cronbach's alpha stands at 0.9625 (which is lower than those obtained for the *entire period* as well as for the *pre-crisis period*) and declines with exclusion of each index. This makes the extracted structure, once again a valid one (Table 2.8).

Table 2.7 Correlation matrix among BSE index returns (2008–2012)

	AUTO	BANK	SENSEX	CD	CG	FMCG	HC	IT	PSU	METAL	ONG
BSE AUTO											
BSE BANK	0.747										
BSE SENSEX	0.807	0.914									
BSE CD	0.642	0.652	0.698								
BSE CG	0.739	0.817	0.873	0.683							
BSE FMCG	0.559	0.571	0.667	0.499	0.532						
BSE HC	0.643	0.646	0.725	0.607	0.652	0.563					
BSE IT	0.537	0.592	0.747	0.501	0.566	0.493	0.536				
BSE PSU	0.745	0.847	0.878	0.707	0.832	0.578	0.698	0.549			
BSE METAL	0.742	0.760	0.853	0.687	0.759	0.539	0.657	0.588	0.810		
BSE ONG	0.678	0.750	0.887	0.609	0.739	0.524	0.644	0.585	0.815	0.768	
BSE POWER	0.756	0.831	0.902	0.710	0.899	0.589	0.698	0.589	0.904	0.809	0.802

All correlations are statistically significant at 1 % level of significance

Table 2.8 Factor loadings in the single factor extracted: post-crisis period

BSE AUTO	0.844	BSE HC	0.787
BSE BANK	0.900	BSE IT	0.705
BSE SENSEX	0.977	BSE PSU	0.924
BSE CD	0.781	BSE METAL	0.883
BSE CG	0.897	BSE ONG	0.867
BSE FMCG	0.686	BSE POWER	0.936

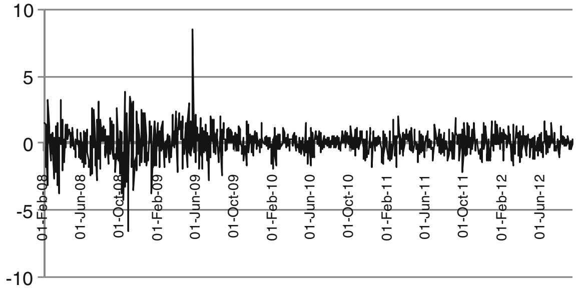


Fig. 2.10 Movements in factor scores, BSE (2008–2012)

The presence of a single structure implies the presence of a single dominant trend in the market even in the *post-crisis* period. All the sectors and the market move in similar fashion and direction (as reflected in their positive loadings on the factor). The indexes are highly correlated and together they reflect a distinct and broad market trend. The detailed analysis of such broad, dominant trend in the *post-crisis* period would be our further area of analysis.

Analysis of market trend in post-crisis period: use of factor score

The use of EFA on our *post-crisis* data set extracts a single factor that could be thought of as representing the broad trend in the stock market in the *post-crisis* period. However, to analyze this stock market trend properly and effectively, we need to get some proxy for this trend. Just like the previous two cases, we have constructed the factor score for our single extracted factor for the *post-crisis* period. These factor scores then serve as a proxy for the latent structure of the *post-crisis* market.

The movement or behavior of market trends (given by the factor scores), henceforth described as the *stock market in post-crisis period*, is depicted in Fig. 2.10. As it is evident from the diagram, the stock market movement is highly volatile, characterized by the presence of volatility clustering where periods of high (low) volatility are followed by periods of high (low) volatility. However, from the simple plot it is difficult to form any idea regarding the trends and nature of movements properly. The trend in the *post-crisis period* resembles those for the *entire* as well as the *pre-crisis periods.* The volatility is significantly higher during the period of February 2008 to March 2009: the period when stock market was sliding.

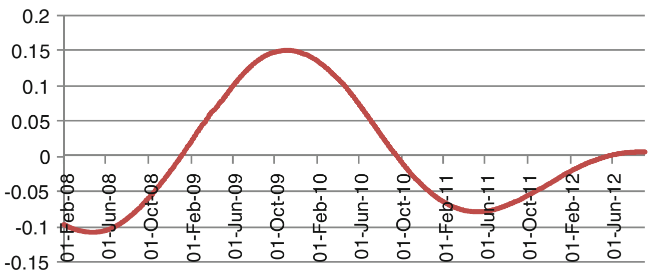


Fig. 2.11 Cycle in the BSE (2008–2012)

The trend could be better analyzed if it is possible to bring out the nature of the cycle inherent in the series. The cycle in the *post-crisis* market return movement is depicted in Fig. 2.11. The cycle is generated once again using the same method of band pass (frequency) filter in its CF form. The *post-crisis* series is found to be level stationary using Augmented Dickey Fuller test statistic (null hypothesis of unit root is rejected at one percent level of significance). We chose to de-trend the data before filtering. The cycle is depicted in Fig. 2.11.

The cycle for the stock market enables us to identify the ups and downs in returns in the BSE in the *post-crisis* period. The return was lower during the period of 2008–2009, the period of crisis. Return increased gradually over the year of 2009 and reached a peak in November 2009. Return dipped since then and made a gradual, but not very significant improvement since mid-2011. The trend is further analyzed through examination of the risk-return relationship in the market as a whole in the *post-crisis* period. The variance of a series could serve as a good proxy for the risk of the series. As is suggested by the simple plot of the *stock market* return, the series is characterized by volatility clustering or volatility pooling. Moreover, the series is negatively skew (skewness −0.26), highly peaked (kurtosis 7.65), and non-normal. Such a series is best analyzed by an appropriate GARCH family model and risk for such a series is proxied best by its conditional variance.

The *stock market* is modeled best by EGARCH, an asymmetric GARCH model of order (1, 1). As is suggested by Table 2.9 the *stock market* in the *post-crisis* period is characterized by asymmetric response of volatility toward positive and negative announcements in the market. The market reacts more toward the negative news than toward the good news.

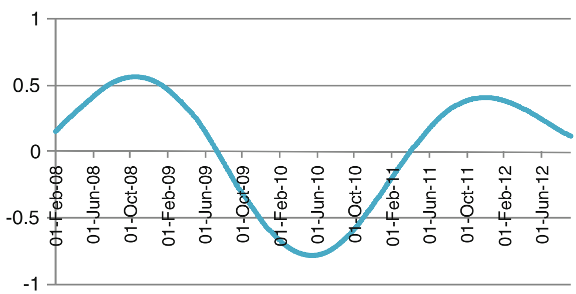
The conditional volatility for the *post-crisis* series is saved and depicted in Fig. 2.12.

The conditional variance, after de-trending, exhibits significant cyclical pattern. The conditional volatility has been significantly higher during the period of 2008–2009. The conditional volatility was significantly lower during late 2009–2011. Thus, volatility and hence risk, remained significantly higher during the period of crisis. The risk-return relationship in the market is further analyzed and depicted in Fig. 2.13. The nature of time-varying conditional correlation

Table 2.9 Application of EGARCH model on factor score for BSE (2008–2012)

Dependent variable: return in the *post-crisis* period				
Method: ML—ARCH (Marquardt)—Student's t distribution				
Included observations: 1137				
Convergence achieved after 28 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(1) + C(2)*ABS(RESID(−1)/@SQRT(GARCH(-1))) + C(3) *RESID(−1)/@SQRT(GARCH(−1)) + C(4)*LOG(GARCH(−1))				
	Variance equation			
	Coefficient	Std. error	z-statistic	Prob.
C(1)	−0.14429	0.025556	−5.64629	0
C(2)	0.17386	0.03189	5.451858	0
C(3)	−0.08342	0.017128	−4.87047	0
C(4)	0.983369	0.005623	174.8838	0
T-DIST. DOF	11.02265	1.913501	5.760461	0
R-squared	0	Mean dependent var		−1.76E-08
Adjusted R-squared	−0.00353	S.D. dependent var		1
S.E. of regression	1.001765	Akaike info criterion		2.422552
Sum squared resid	1136	Schwarz criterion		2.444699
Log likelihood	−1372.22	Hannan–Quinn criter.		2.430917
Durbin–Watson stat	1.814822			

Fig. 2.12 Cycle in the factor score BSE conditional variance (2008–2012)



brings out the presence of a positive relationship between risk and return in the market. During the period of 2008, the correlation coefficient was negative, implying a negative risk-return relationship in the market. Since then the risk-return relationship has been mostly positive, with some exceptions during 2010–2011 and during late 2012. The conditional correlation cycle in the *post-crisis* period is, however, smoother compared to that in the *pre-crisis* period.

Hence, the analysis of *post-crisis* period reveals few notable characteristics of Indian stock market:

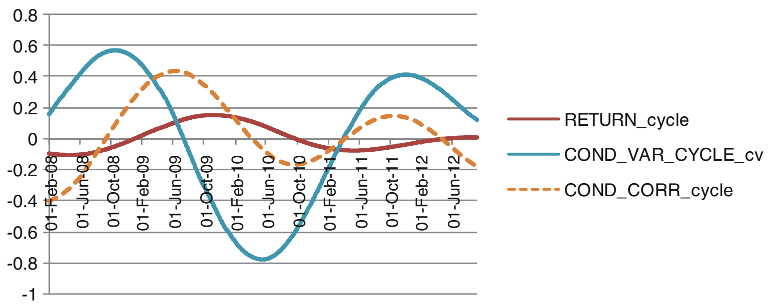


Fig. 2.13 Return-risk relationship BSE (2008–2012)

- Indian stock market is dominated by a "single" trend where all the sectors and the market move together. The trend in the post-crisis period is weaker than the 'average' (the trend for the entire period) market trend as well as the trend in the pre-crisis period.
- The market is characterized by significant volatility with volatility clustering.
- Asymmetric response of volatility toward good and bad news where volatility responds more toward bad news. The leverage effect is less pronounced in the *post-crisis* period (coefficient = −0.08) compared to that in the entire period (−0.11) and in the pre-crisis period (−0.23).
- Returns start falling and risks start mounting as the market plunges into a crisis.
- Market is mostly characterized by a positive risk-return relationship. However, the correlation coefficient between risk and return starts declining and becomes negative as the market dips into crisis.

The trends in BSE: Any 'Signal' to frame profitable trading strategy?

Over the past 8 years, the Indian stock market, as represented by the BSE, is dominated by a "single" trend where all the sectors and the market move together. The latent structure of the market is constructed of all the sectors and the market Index. The structure has remained unchanged over the past 8 years and has been independent of the cycles in the economy. Moreover, the trend in the post-crisis period is weaker than the 'average' (the trend for the entire period) market trend, whereas the trend in the pre-crisis period is stronger than the 'average'. This is revealed by the EFA where the single factor extracted could account for more variability (as given by the values of the Eigenvectors) in the pre-crisis period than for the post-crisis period. Further analysis of eigenvalue and eigenvector composition might provide us with significant signals that might be useful as an indicator of future events. For example, if a unique eigenvector composition is consistently observed before a market crash or period of market growth, then this unique eigenvector provides a signal that can be responded to in the future. As the economy passes through different stages, and market forces change, the eigenvectors might be expected to change to describe the new situation. Thus, an analysis of trends in Eigenvector might help us identify pattern and trend in market

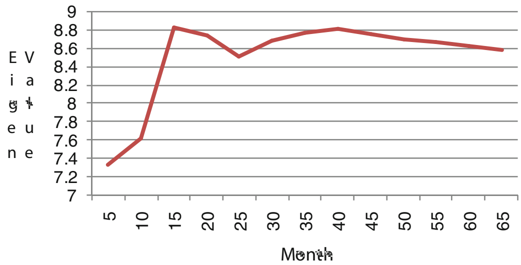


Fig. 2.14 Nature of eigenvalue for BSE (2005–2012)

movements. This in turn might help investors design strategies that would reduce risk and increase gains.

As suggested by our earlier analysis, the market is dominated by a single trend. The single eigenvalue, however, is changing from month to month (Fig. 2.14). The fraction of market variation captured by the first eigenvector thus changes over time. The movements are sometime marked by sharp changes.

Starting from January 2005, eigenvalue increases sharply over the first 15 months. It then falls gradually and reaches a slump during the 25th month. The following months (25th to 40th) witnessed a moderate rise in eigenvalue. The 45th to 65th months witnessed a fall in eigenvalue. The movement in the eigenvalue might indicate the fact that the periods between 0th and 10th month and between 25th and 40th month might be associated with some significant market event so that a larger portion of market variability is being captured by the first (in this context, the single) eigenvector. Thus, when the market experiences or passes through some 'extra-ordinary' events, some 'unique' or 'special' trend persists in the market. As the economy reverts back to its 'normal' state this 'special' trend weakens in the sense that the variability captured by the first factor declines steadily. For investors this information might be extremely useful in designing profitable trading strategy. To be more specific, if it is possible to identify when this special trend would set in or how long it would last, investors might be able to design strategies to make profit out of market movements. The movements in the first factor eigenvalue reveal few more observations. The eigenvalue increases during the periods of recovery and reaches maximum just before the peak. During a stable period, however, the eigenvalue falls or reaches a plateau. Therefore, the 'special' trend persists during the phases of recovery and weakens during the periods of recession or stability. The market crash could be predicted from a high eigenvalue of the first factor and high eigenvalue could be associated with market crash. In Indian context, hence, there is immense scope for the investors to use this piece of information to design profitable trading strategyin BSE.

Apart from the presence of a special trend in the market, BSE is characterized by the presence of significant volatility in stock return. The volatility responds asymmetrically toward good and bad news with sharper reaction toward bad news. The asymmetric responses (the 'leverage' effect) tend to be sharper during the pre-crisis period rather than in the post-crisis period. The 'normal' positive relationship between risk and return seems to exist in the market. However, the correlation coefficient between risk and return starts declining and becomes negative (or even zero) as the market dips into crisis. Distinct and persistent trends thus are perceptible in the Indian stock market leaving the efficient market hypothesis on trial. Such trends could skillfully be used by investors to design profit making strategies to beat the market.

Let us now consider the other stock exchange, namely the NSE and explore whether the movements and other characteristics in the NSE resemble the trends in BSE. While exploring the issues, we shall be following the same methodologies that were followed in the previous sections. Hence, we are not repeating the methodology, but reporting the results only focusing on the analytical discussion.

2.6 Trends and Latent Structure in Indian Stock Market: National Stock Exchange

1. *Trends over the entire period: 2005 January to 2012 September*

The analysis of market movement in NSE starts from the analysis of correlation among the different indexes. Table 2.10 reveals significant correlation pattern in the NSE.

While statistically significant correlation exists among the sectoral returns, correlation between the market and the sectoral returns has been almost negligible. This is in sharp contrast with the trends in BSE. While in BSE all the sectors and the market were intertwined, NSE market is likely to be segregated from the sectors as a whole. Such a simple correlation analysis, however, hardly suffices to establish such segregation. EFA might help us better analyze the trends.

The KMO measure of sampling adequacy takes a value of 0.89 and Bartlett's test statistic of sphericity is significant at one percent level of significance implying validity of using EFA on our data set.

On the basis of eigenvalue, two factors are extracted. The first factor with an eigenvalue of 9.129, explains 70 % of total variability. The second factor has an eigenvalue of 1.006 and explains 8 % of total variability. The first factor contains all the sectoral indexes that are highly loaded in that factor. The Cronbach's alpha stands at 0.95 and declines with exclusion of each index. This makes the extracted structure a valid one. The second factor contains the market index only (Table 2.11).

Identification of two factors reveals presence of two structures, and hence two dominant trends in the NSE. All the sectors move in similar fashion and direction (as reflected in their positive loadings on the factor) and together they constitute the broad, dominant trend in NSE. The sectoral returns however are completely dissociated from the market trend. The sectoral trend happens to be more dominant than the market itself. The detailed analysis of such broad, dominant trend could be of further interest.

Analysis of market trend in NSE: use of factor score

The use of EFA on our data set for NSE extracts two factors that could be thought of as representing the broad trends in the stock market. Now we construct

Table 2.10 Correlation matrix among NSE index returns (2005–2012)

	Como	Energy	Finance	FMCG	Infra	IT	Metal	MNC	Pharma	PSE	PSU Bank	Service
ENERGY	0.93											
FINANCE	0.82	0.79										
FMCG	0.69	0.65	0.63									
INFRA	0.90	0.87	0.84	0.67								
IT	0.67	0.65	0.65	0.55	0.66							
METAL	0.89	0.76	0.73	0.61	0.79	0.61						
MNC	0.86	0.80	0.78	0.79	0.85	0.67	0.77					
PHARMA	0.71	0.66	0.63	0.63	0.69	0.59	0.61	0.72				
PSE	0.93	0.92	0.79	0.66	0.88	0.62	0.78	0.81	0.68			
PSUBANK	0.67	0.63	0.79	0.51	0.68	0.47	0.59	0.63	0.50	0.66		
SERVICE	0.89	0.87	0.93	0.68	0.93	0.82	0.78	0.83	0.70	0.86	0.72	
MARKET	0.10	0.10	0.13	0.05	0.09	0.10	0.10	0.08	0.03	0.09	0.11	0.13

Table 2.11 Factor loadings in the factors extracted: entire period

Sectors	1	2
Commodity	0.958	–
Energy	0.916	–
Finance	0.893	–
FMCG	0.772	–
Infrastructure	0.939	–
IT	0.756	–
Market	–	0.986
Metal	0.855	–
MNC	0.913	–
Pharmaceutical	0.779	–
PSE	0.922	–
PSUBank	0.741	–
Service	0.954	–

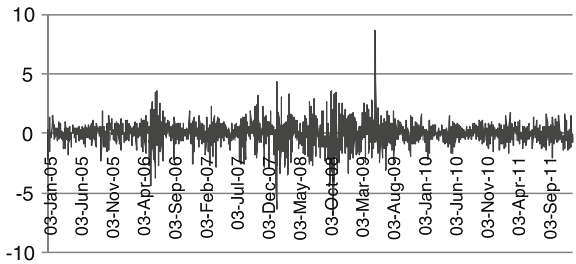


Fig. 2.15 Movements in factor scores for factor 1(NSE sector) (2005–2012)

factor scores for the two uncorrelated factors. These factor scores, just like our earlier analysis, would serve as a proxy for the latent structure of the market and help us analyze the stock market trend in proper or effective way.

The factor scores for the first factor would depict the movement or behavior at the sectoral level. Such trends will henceforth be described as the *sectoral trend.* The sectoral trend is depicted in Fig. 2.15. As is evident from the diagram, the sectoral return movement is highly volatile, characterized by the presence of volatility clustering where periods of high (low) volatility are followed by periods of high (low) volatility. The period of financial crisis that is the period of 2007–2009 is characterized by high volatility.

The factor scores for the second factor reflects the movement in NSE market index and would be henceforth described as reflecting the *market trend*. The market trend is depicted in Fig. 2.16. Just like the trends at the sectoral level, the market movements volatile are characterized by the presence of volatility clustering where periods of high (low) volatility are followed by periods of high (low) volatility. The period of financial crisis that is the period of 2007–2009 is characterized by high volatility.

However, from the simple plot it is difficult to form any proper or conclusive idea regarding the trends and nature of movements.

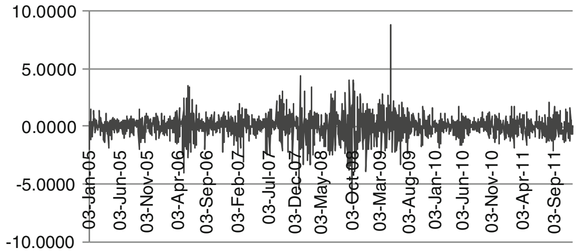


Fig. 2.16 Movements in factor scores for factor 2 (NSE market) (2005–2012)

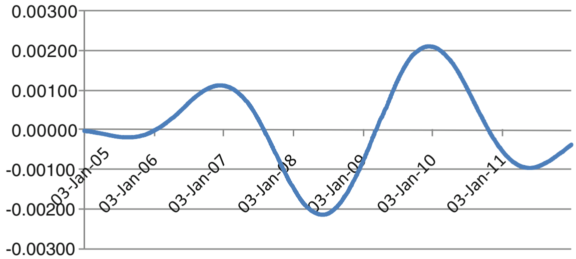


Fig. 2.17 Cycle in the sectoral return (NSE) (2005–2012)

Just like our earlier analysis, trends at market and sectoral levels would now be analyzed by bringing out the nature of the cycle inherent in the series. Toward the purpose, the study uses once again the method of band pass (frequency) filter. Both the series are found to be level stationary using Augmented Dickey Fuller test statistic (null hypothesis of unit root is rejected at one percent level of significance). We chose to de-trend the data before filtering. The cycle for the sectoral return is depicted in Fig. 2.17.

The cycle for the sectoral return enables us to identify the ups and downs in NSE sectoral indexes. The *sectors* as a whole experience a boom during the phases namely, 2006–2007, 2009–2010, and since early 2012. The trends are similar to those experienced in the context of BSE. The *sectors* as a whole slide down from its peak over the periods namely, 2007–2008 and 2010–2011. Our analysis is concentrated around the first cycle. This cycle, however, is in terms of return in the sectors.

The market return cycle is depicted in Fig. 2.18. The nature of the cycle is exactly similar to those experienced at the sectoral level.

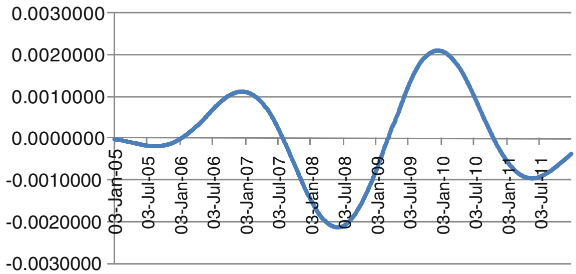


Fig. 2.18 Cycle in the market return (NSE) (2005–2012)

Although the two latent structures in the market are uncorrelated, the cycles are similar at the sectoral as well as at the market level. States of economy (recovery or recession) are having similar impacts on sectoral and market level.

The trend is further analyzed through an examination of the risk-return relationship in the market as a whole. The variance of a series could serve as a good proxy for the risk of the series. As is suggested by the simple plot of the *market* and *sectoral* return, the two series are characterized by volatility clustering or volatility pooling. Moreover, the two series are negatively skew, highly peaked, and non-normal. Such series are best analyzed by an appropriate GARCH family model and risk for such a series is proxied best by its conditional variance.

The two series are modeled best by simple GARCH model of order (1, 1). The two series are hence not characterized by asymmetric response of volatility toward positive and negative announcements in the market. There is no evidence that the market or the sectors reacts more toward the negative news than toward the good news. The sectoral return as a whole is characterized by significant presence of ARCH (or, the news) effect and GARCH (the own past volatility) impacts. The ARCH effect (0.12), however, is weaker than the GARCH effect (0.87). Hence, past volatility, rather than past news at the sectoral level has relatively stronger impact on present volatility of the sectoral return. The market return is also characterized by significant presence of ARCH (0.11) and GARCH (0.88) effects with GARCH effects stronger than the ARCH effects. The results are similar to those obtained for the sectoral level. The ARCH effect at the sectoral level is marginally higher and GARCH effect is marginally lower compared to the market level.

The conditional volatility for the sectoral return is saved and depicted in Fig. 2.19.

The conditional variance, after de-trending, exhibits significant cyclical pattern (Fig. 2.20).

The conditional volatility has been significantly higher during the period of financial crisis of 2007–2008. The two other peaks are not at all significant compared to this peak. The trend reminds us about the trend in BSE over the same period. Once again, the nature of cycle of conditional variance is completely opposite to the cyclical nature of the return series. Return peaks are always associated with low conditional variance or conditional variance slumps. This is further analyzed and

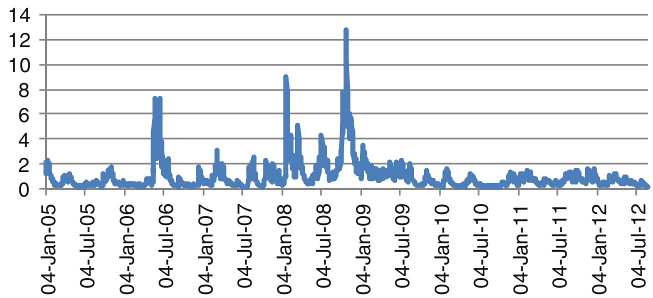
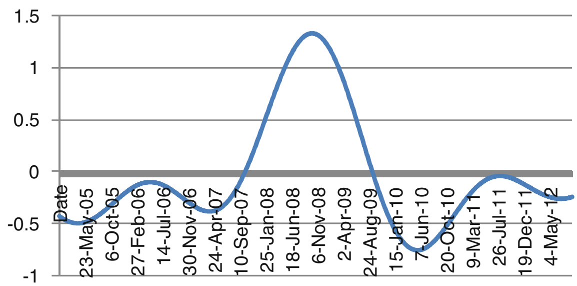


Fig. 2.19 NSE sectoral conditional variance (2005–2012)

Fig. 2.20 Cycle in the NSE sectoral conditional variance (2005–2012)



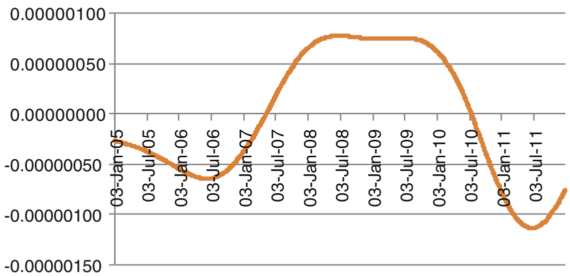
depicted in Fig. 2.21. The nature of time-varying conditional correlation between sectoral return in NSE and conditional variance is used to bring out the relationship between risk and return at the sectoral level in NSE. Like the previous section, the conditional correlation has been computed using a multivariate GARCH technique that models the variance–covariance matrix of a financial time series. A multivariate GARCH of appropriate order has been estimated for the data on two factor scores for NSE return and NSE conditional variance and the conditional correlation values have been saved. The movement in this conditional correlation reflects the risk-return relationship in the context of NSE.

The risk-return relationship has been negative and falling until mid-2006. During the period that immediately preceded the crisis, risk-return relationship started rising. However, it remained negative until mid 2007. As crisis set in, the risk-return relationship became positive and continued to rise. As crisis continued, risk-return relationship at the NSE sectoral level remained constant and positive. However, as the economy was recovering, the conditional correlation between risk and return started dwindling. Eventually, the risk-return relationship became negative.

Let us now consider the conditional variance at the market level. The market is highly volatile and the volatility has been significantly higher during the period of financial crisis. The trend could be better analyzed if we could consider the cycle in volatility at the market level (Fig. 2.22).

The cycle in market return volatility in NSE is depicted in Fig. 2.23. The nature of the cycle is similar, however not identical, to that in the sectoral return. Volatility remained constant at a very high level during the period of financial crisis. Volatility has been much lower during the pre-crisis and the post-crisis periods.

Fig. 2.21 Cycle of risk-return relationship at NSE sectoral level (2005–2012)



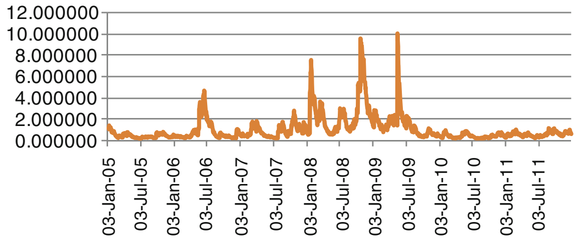


Fig. 2.22 NSE market conditional variance (2005–2012)

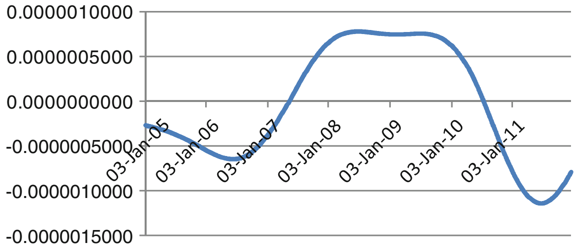


Fig. 2.23 Cycle in the NSE market conditional variance (2005–2012)

However, volatility started mounting as the market was approaching the crisis. As the market was recovering volatility dwindled to reach the floor.

The risk-return relationship at the market level, however, has been different at the market level rather than at the sectoral level in NSE. Risk-return relationship has been negative during the period of January 2005 to January 2007. However, as the economy was approaching the crisis since mid-2006, the correlation between risk and return started rising. As the economy was plunging into crisis, the correlation fluctuated but remained negative. The correlation became positive only in the post-crisis period and eventually started dwindling since mid-2010 (Fig. 2.24).

The analysis of overall market trend would now be supplemented by analyses of market trend before and after the crisis.

2. *The trends in NSE in the pre-crisis period: 2005 January to 2008 January*

The analysis of trends in the market in the pre-crisis period starts from identification of latent structure in the market.

Table 2.12 suggests presence of statistically significant correlation among different sectoral returns. The market returns however are not strongly correlated

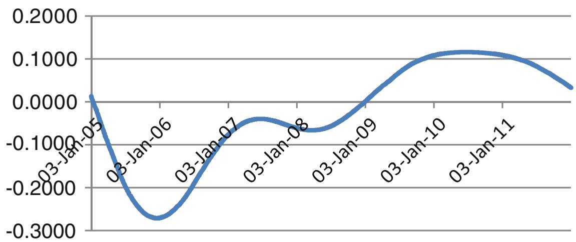


Fig. 2.24 Cycle of risk-return relationship at NSE market level (2005–2012)

Table 2.12 Correlation matrix among NSE index returns (2005–2008)

	Como	Energy	Finance	FMCG	Infra	IT	Metal	MNC	Pharma	PSE	PSU bank	Service
ENERGY	0.94											
FINANCE	0.79	0.76										
FMCG	0.75	0.71	0.65									
INFRA	0.91	0.87	0.81	0.72								
IT	0.67	0.64	0.64	0.57	0.67							
METAL	0.85	0.71	0.67	0.65	0.76	0.60						
MNC	0.87	0.80	0.76	0.84	0.86	0.67	0.75					
PHARMA	0.76	0.71	0.67	0.68	0.74	0.61	0.65	0.76				
PSE	0.95	0.96	0.77	0.71	0.88	0.65	0.77	0.82	0.73			
PSUBANK	0.75	0.70	0.91	0.59	0.75	0.55	0.63	0.70	0.63	0.71		
SERVICE	0.88	0.86	0.90	0.70	0.92	0.84	0.74	0.83	0.74	0.86	0.82	
MARKET	0.18	0.17	0.24	0.11	0.18	0.18	0.14	0.15	0.09	0.17	0.22	0.24

with the sectoral returns. The results are same as those obtained for the entire period.

The use of EFA over the pre-crisis data set is further justified by the favorable values of the KMO measure of sampling adequacy and Bartlett's tests for data adequacy. The KMO measure of sampling adequacy takes a value of 0.897 and Bartlett's test statistic of sphericity is significant at one percent level of significance implying validity of using EFA on the pre-crisis data set.

On the basis of eigenvalue two factors are retained that are uncorrelated with one another. This signifies the presence of two dominant but distinct trends in the NSE during the pre-crisis period. The first factor with an eigenvalue of 9.373 could explain 72 % of total variability. All the sectoral indexes have strong and positive loading in the first factor. The Cronbach's alpha stands at 0.9750 (which is higher than the *entire period*) and declines with exclusion of each index. This makes the extracted structure a valid one. Thus the sectors are strongly connected, move in similar fashion and direction and together they constitute the dominant trend in the market in the pre-crisis period.The second factor has the market index with strong loading in it. The market thus is completely decoupled from the sectors that are closely connected among themselves. The second factor with an eigenvalue of 1.01 could explain only 7.76 % of total variability in the NSE (Table 2.13).

The detailed analysis of such broad, dominant trend in the *pre-crisis* period would be our further area of analysis.

Analysis of market trend in NSE in pre-crisis period: use of factor score

Factor scores are constructed for the two factors extracted for the NSE. The factor scores for the first factor represent the sectoral behavior in the market. The market movement will be proxied by the second factor score. The movement or behavior of sectoral returns as a whole (given by the factor scores), henceforth described as the *sectors in pre-crisis period*, is depicted in Fig. 2.25. As is evident from the diagrams, the market as well as sectoral movements are highly volatile, characterized by the presence of volatility clustering where periods of high (low)

Table 2.13 Factor loadings in the factors extracted: pre-crisis period (NSE)

	Factor 1	Factor 2
Commodity	0.958	–
Energy	0.915	–
Finance	0.853	–
FMCG	0.819	–
Infrastructure	0.933	–
IT	0.747	–
Market	–	0.966
Metal	0.833	–
MNC	0.919	–
Pharmaceutical	0.83	–
PSE	0.929	–
PSUBANK	0.797	–
Service	0.933	–

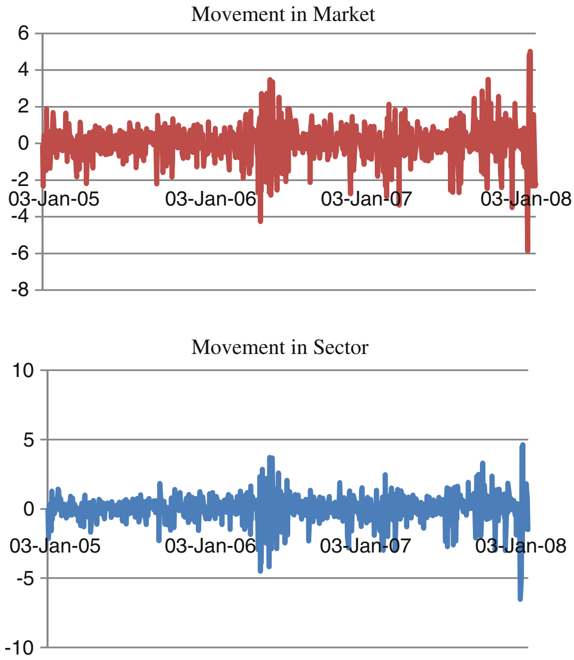


Fig. 2.25 Movements in factor scores, NSE (2005–2008)

volatility are followed by periods of high (low) volatility. However, from the simple plots it is difficult to form any idea regarding the trends and nature of movements properly. The trend in the *pre-crisis period* resembles that for the *entire Period.*

The trend could be better analyzed if it is possible to bring out the nature of the cycle inherent in the series. The cycle in the *pre-crisis* sectoral and market movements are depicted in Fig. 2.26. The cycles are generated once again using the method of band pass (frequency) filter in its CF form. Both the *pre-crisis* series

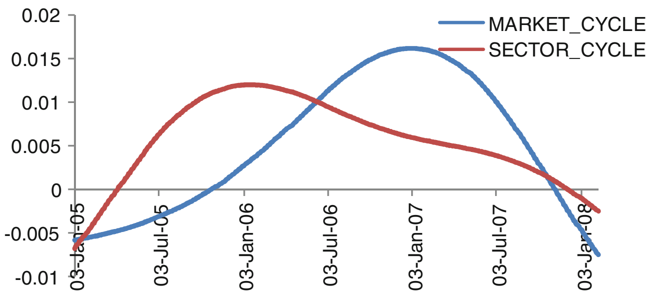


Fig. 2.26 Cycles in the NSE return (2005–2008)

are found to be level stationary using Augmented Dickey Fuller test statistic (null hypothesis of unit root is rejected at one percent level of significance). We chose to de-trend the data before filtering. The sectoral return reached top during January 2006 and falls then after. The market, however, reached peak in January 2007 and then plummeted. As the market was riding high, the sectors were offering higher returns than the market ("beating the market", perhaps). During the recession, sectoral returns remained considerably lower than the market return. The sectoral peak, however, has been lower than the market peak.

The trend is further analyzed through examination of the risk-return relationship in the market as a whole. The variance of a series could serve as a good proxy for the risk of the series. As is suggested by the simple plots of the market and sectoral returns, the series are characterized by volatility clustering or volatility pooling. Moreover, the series are negatively skew, highly peaked, and non-normal. Such series are best analyzed by an appropriate GARCH family model and risk for such a series are proxied best by their conditional variance.

The NSE return is modeled best by simple GARCH model of order (1, 1). The market, as well as sectors as a whole is characterized by significant ARCH and GARCH effects. The ARCH coefficients are 0.21 and 0.26 respectively for the market and the sector. The GARCH coefficients for the market and sectors as a whole are 0.71 and 0.67 respectively. Thus past volatility impacts on present volatility are stronger than the news impact for the market as well as sectors. Past volatility impacts however are relatively stronger and news impacts are relatively weaker for the market rather than the sectors. This is in line with the results obtained for the entire period. The conditional volatilities for the *pre-crisis* series are saved and depicted in Fig. 2.27.

The conditional variance, after de-trending, exhibits significant cyclical pattern. Both the cycles in the conditional variance have been of inverted u shape. Volatility increased, reached a top and then fell for both the sector and the market. When market volatility was rising, sectoral volatility was higher than the market volatility up to a certain point. The sectoral volatility reached its peak much before the crisis had set in and much before the market volatility did so. The conditional volatility in market increased significantly and remained high as the economy was approaching the crisis. The diagram shows a comparative study of risks (given by

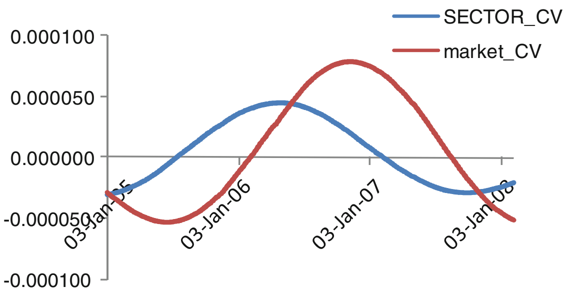


Fig. 2.27 Cycle in the factor score conditional variance (NSE: 2005–2008)

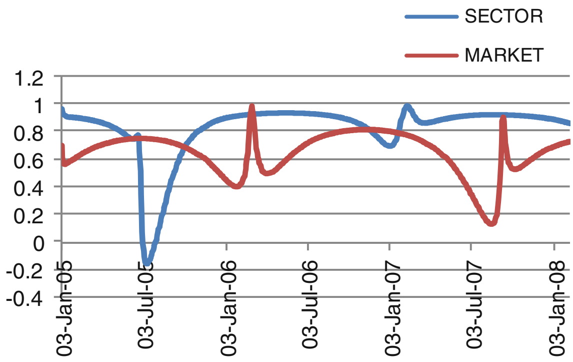


Fig. 2.28 Return-risk relationship NSE (2005–2008)

the conditional variance) at the sectoral and the market level. The risk-return relationship in the NSE is further analyzed and depicted in Fig. 2.28.

The nature of time-varying conditional correlation brings out the presence of a positive relationship between risk and return in the NSE as a whole. While the correlation fluctuates, it started declining sharply since early-2007 for the market and plummeted to a very low level in mid-2007. The risk-return correlation in the market was increasing sharply during the recession. The sectoral correlation has mostly been higher than the correlation at the market level. The sectoral correlation dropped to a low level only during mid-2005. The financial crisis of 2007–2008 did not have much impact on the risk-return correlation at the sectoral level. For most of the times, the value of correlation coefficient remained higher than 0.8.

3. *The trends in the post-crisis period: 2008 February to 2012 September*

The analysis of market trend in the post-crisis period starts from identification of latent structure in the market.

Table 2.14 suggests presence of statistically significant correlation among sectoral returns during the post-crisis period. The correlation between the market and the sector, however, has been quite low and in significant. The results are similar to those obtained for the previous phases. The correlation coefficients are more or less the same in magnitude compared to those for the *entire* and *pre-crisis* period.

The use of EFA over the post-crisis period data set is once again justified by the favorable values of the KMO measure of sampling adequacy and Bartlett's tests for data adequacy. The KMO measure of sampling adequacy takes a value of 0.875 and Bartlett's test statistic of sphericity is significant at one percent level of significance implying validity of using EFA on the post-crisis data set.

On the basis of eigenvalue, once again, two factors are extracted that are uncorrelated to each other. The first factor with an eigenvalue 9.007 explains 69.29 % of total variability. The second factor with eigenvalue of 1.009 explains 7.76 % of total variability. Both the eigenvalue and the total variability explained by the single factor extracted are lower than those obtained for the *entire period* as

Table 2.14 Correlation matrix among NSE index returns (2008–2012)

	Energy	Finance	FMCG	Infra	IT	Metal	MNC	Pharma	PSE	Psubank	Service	Market
Como	0.930	0.843	0.632	0.902	0.673	0.924	0.851	0.672	0.922	0.608	0.890	0.039
Energy	1.000	0.802	0.601	0.864	0.661	0.790	0.792	0.638	0.901	0.575	0.867	0.047
Finance	0.802	1.000	.637	0.863	0.673	0.777	0.800	0.617	0.817	0.719	0.939	0.069
FMCG	0.601	0.637	1.000	0.635	0.562	0.569	0.748	0.582	0.602	0.437	0.667	0.010
Infra	0.864	0.863	0.635	1.000	0.662	0.814	0.846	0.666	0.883	0.626	0.930	0.031
IT	0.661	0.673	0.562	0.662	1.000	0.622	0.675	0.578	0.611	0.434	0.819	0.057
Metal	0.790	0.777	0.569	0.814	0.622	1.000	0.788	0.583	0.782	0.551	0.808	0.065
MNC	0.792	0.800	0.748	0.846	0.675	0.788	1.000	0.687	0.796	0.582	0.838	0.035
Pharma	0.638	0.617	0.582	0.666	0.578	0.583	0.687	1.000	0.638	0.417	0.680	−0.013
PSE	0.901	0.817	0.602	0.883	0.611	0.782	0.796	0.638	1.000	0.611	0.858	0.023
Psubank	0.575	0.719	0.437	0.626	0.434	0.551	0.582	0.417	0.611	1.000	0.652	0.039
Service	0.867	0.939	0.667	0.930	0.819	0.808	0.838	0.680	0.858	0.652	1.000	0.061
Market	0.047	0.069	0.010	0.031	0.057	0.065	0.035	−0.013	0.023	0.039	0.061	1.000

Table 2.15 Factor loadings in the factors extracted (NSE): post-crisis period

	Factor 1	Factor 2
Commodity	0.957	–
Energy	0.916	–
Finance	0.919	–
FMCG	0.734	–
Infrastructure	0.942	–
IT	0.767	–
Market	–	0.992
Metal	0.876	–
MNC	0.909	–
Pharmaceutical	0.744	–
PSE	0.916	–
PSUBANK	0.690	–
Service	0.964	–

well as for the *pre-crisis* period. Once again, the first factor contains all the sectoral indexes that are highly and positively loaded in that factor. The Cronbach's alpha stands at 0.9525 (which is lower than those obtained for the *entire period* as well as for the *pre-crisis period*) and declines with exclusion of each index. This makes the extracted structure, once again a valid one. The second factor has the market index with strong loading in it (Table 2.15).

The NSE is characterized by two distinct trends in the post-crisis period. The sectors constitute the broad, dominant trend and they, among themselves are strongly correlated and move in similar fashion and similar direction even in the *post-crisis* period. All the sectors and the market move in similar fashion and direction (as reflected in their positive loadings on the factor). The detailed analysis of the dominant trends in the *post-crisis* period would be our further area of analysis.

Analysis of market trend in post-crisis period: use of factor score

Just like the previous cases, we have constructed the factor scores for the two extracted factors for the *post-crisis* period. These factor scores would serve as a proxy for the latent structure of the *post-crisis* market.

The movement or behavior of market and sectoral trends (given by the factor scores), are depicted in Fig. 2.29. As is evident from the diagram, the market and sectoral movements are highly volatile, characterized by the presence of volatility clustering where periods of high (low) volatility are followed by periods of high (low) volatility. However, from the simple plot it is difficult to form any idea regarding the trends and nature of movements properly. The trend in the *post-crisis period* resembles those for the *entire* as well as the *pre-crisis periods.* The volatility is significantly higher during the period of February 2008 to March 2009: the period when stock market was sliding.

The trend could be better analyzed if it is possible to bring out the nature of the cycle inherent in the series. The cycles are generated once again using the same method of band pass (frequency) filter in its CF form. The *post-crisis* series are

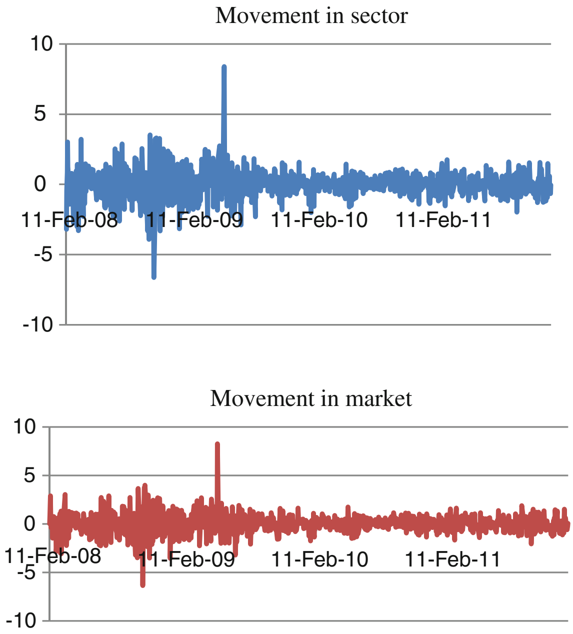


Fig. 2.29 Movements in factor scores, NSE (2008–2012)

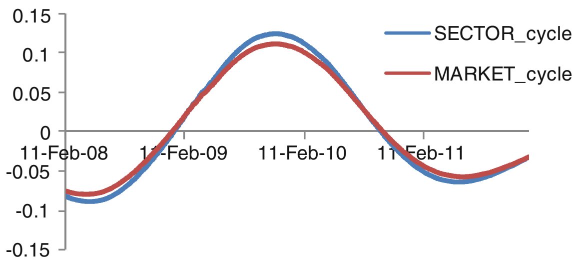


Fig. 2.30 Cycles in the sectoral and market return (NSE) (2008–2012)

found to be level stationary using Augmented Dickey Fuller test statistic (null hypothesis of unit root is rejected at one percent level of significance). We chose to de-trend the data before filtering. The cycles are depicted in Fig. 2.30.

The cycle for the stock market enables us to identify the ups and downs in returns in the NSE in the *post-crisis* period. The sectoral and market cycles are almost similar in nature. Both the cycles are inverted u-shaped. When the economy was recovering after the crisis, sectoral returns were marginally lower than the market return. Similar behavior was observed when economy is sliding down in recent years. The sectoral peak, however, is higher than the market peak. This relationship is completely different from that obtained for the pre-crisis period.

The trend in NSE is further analyzed through examination of the risk-return relationship at the market as well as sectoral level in the *post-crisis* period. As is suggested by the simple plot of the *stock market* returns, both the series are characterized by volatility clustering or volatility pooling. Moreover the series are

Table 2.16 Application of EGARCH model on first factor score for NSE (2008-2012)

Dependent Variable: SECTOR

Method: ML—ARCH (Marquardt)—Normal distribution

Included observations: 959 after adjustments

Convergence achieved after 33 iterations

Presample variance: backcast (parameter = 0.7)

LOG(GARCH) = C(2) + C(3)*ABS(RESID(−1)/@SQRT(GARCH(−1))) + C(4) *RESID(−1)/@SQRT(GARCH(−1)) + C(5)*LOG(GARCH(−1))

	Variance equation			
	Coefficient	Std. error	z-statistic	Prob.
C(1)	0.006771	0.021494	0.315034	0.7527
C(2)	−0.154017	0.021982	−7.006553	0.0000
C(3)	0.189606	0.026871	7.056247	0.0000
C(4)	−0.072713	0.015861	−4.584505	0.0000
C(5)	0.986357	0.004444	221.9540	0.0000
R-squared	−0.000046	Mean dependent var		−3.13E-08
Adjusted R-squared	−0.004239	S.D. dependent var		1.000000
S.E. of regression	1.002117	Akaike info criterion		2.432335
Sum squared resid	958.0441	Schwarz criterion		2.457704
Log likelihood	−1161.304	Hannan-Quinn criter.		2.441996
Durbin–Watson stat	1.922791			

negatively skew, highly peaked, and non-normal. Such series could be best analyzed by an appropriate GARCH family model and risks for such series are proxied best by the conditional variance.

The market is modeled best by EGARCH, an asymmetric GARCH model of order (1, 1). As is suggested by Table 2.16, the sectoral return in the *post-crisis* period is characterized by asymmetric response of volatility toward positive and negative announcements in the market. The sectoral return reacts more toward the negative news than toward the good news.

The market in the *post-crisis* period is also characterized by asymmetric response of volatility toward positive and negative announcements in the market. The market reacts more toward the negative news than toward the good news (Table 2.17).

This result is in sharp contrast to what we obtained for the pre-crisis period.The conditional volatility cycles for the *post-crisis* series are depicted in Fig. 2.31.

The conditional variance, after de-trending, exhibits significant cyclical pattern. The conditional volatility has been significantly higher during the period of 2008–2009. The conditional volatility was significantly lower during late 2009–2011. Thus, volatility and hence risk, remained significantly higher during the period of crisis. The risk cycles have been almost similar in nature for the market and the sectors as a whole. As risks were falling sectoral risks were

Table 2.17 Application of EGARCH model on second factor score for NSE (2008–2012)

Dependent Variable: MARKET				
Method: ML—ARCH (Marquardt)—Normal distribution				
Included observations: 959 after adjustments				
Convergence achieved after 43 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(2) + C(3)*ABS(RESID(−1)/@SQRT(GARCH(-1))) + C(4) *RESID(−1)/@SQRT(GARCH(−1)) + C(5)*LOG(GARCH(−1))				
	Variance equation			
	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.004767	0.022068	0.216029	0.8290
C(2)	−0.144538	0.023330	−6.195442	0.0000
C(3)	0.179236	0.028700	6.245237	0.0000
C(4)	−0.059043	0.013842	−4.265462	0.0000
C(5)	0.990431	0.004079	242.7968	0.0000
R-squared	−0.000023	Mean dependent var		−6.26E-08
Adjusted R-squared	−0.004216	S.D. dependent var		1.000000
S.E. of regression	1.002106	Akaike info criterion		2.461329
Sum squared resid	958.0219	Schwarz criterion		2.486699
Log likelihood	−1175.207	Hannan-Quinn criter.		2.470991
Durbin–Watson stat	1.922218			

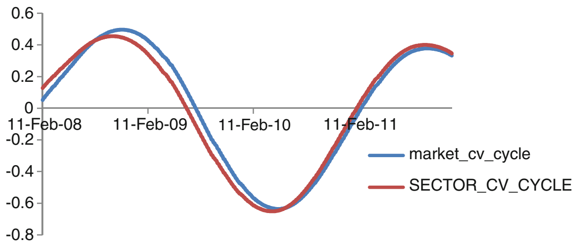


Fig. 2.31 Cycle in the NSE conditional variance (2008–2012)

marginally higher than the market risk. However, during any downfall in the market when risks were mounting sectoral risks almost coincide with the market risk.

The risk-return relationship in the NSE in the *post-crisis* period is further analyzed and depicted in Fig. 2.32. The nature of time-varying conditional correlation brings out the nature of risk-return relationship in the market. The correlation between risk and return in the market level fell just after the crisis and remained marginally positive over the entire *post-crisis* period. Risk-return relationship has been fluctuating and mostly negative at the sectoral level. The correlation became close to zero during the period of 2008–2009 when the economy was plummeted in crisis.

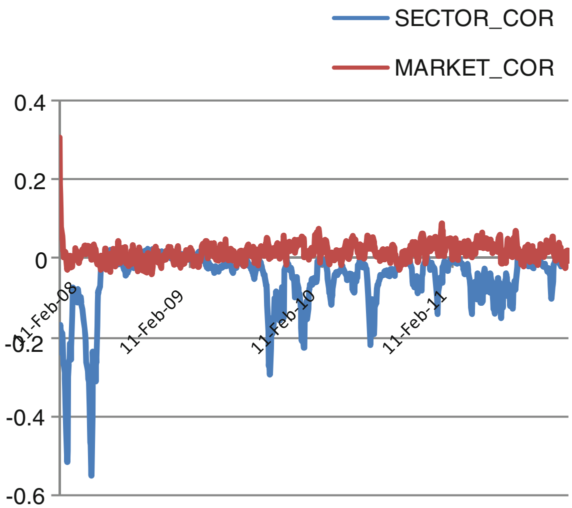


Fig. 2.32 Return-risk relationship BSE (2008–2012)

The trends in National Stock Exchange: Any 'Signal' to frame profitable trading strategy?

NSE has been dominated by two dominant trends in the market. The most dominant or 'market' trend is formed by all the sectors in the NSE. The sectors as a whole are completely decoupled from the market. The trend has lasted for the past 8 years. The sectors among themselves however are closely connected among themselves and move in similar fashion and in similar direction. Such dissociation between sectoral indexes and market index, that is independent of the states of the economy, might offer investors profitable business opportunities. Moreover, the trend in the post-crisis period is weaker than the 'average' (the trend for the entire period) market trend where as the trend in the pre-crisis period is stronger than the 'average'. This is revealed by the EFA where the single factor extracted could account for more variability (as given by the values of the eigenvectors) in the pre-

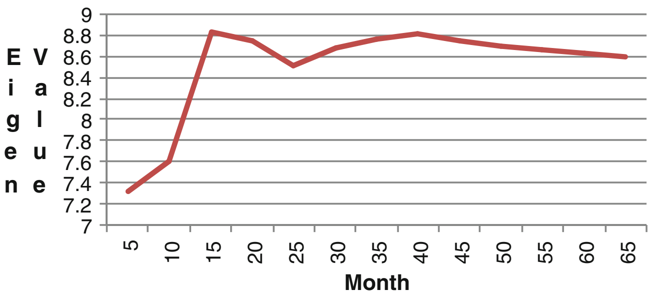


Fig. 2.33 Nature of eigenvalue for first factor in NSE (2005–2012)

crisis period than for the post-crisis period. In our earlier analysis of eigenvalue and eigenvector composition for BSE has revealed how that might provide us with significant signals that might be useful as an indicator of future events. The changing nature of eigenvalue for the first factor in NSE has been shown in Fig. 2.33. The eigenvalue has changed from month to month. The fraction of market variation captured by the first eigenvector thus changes over time. The movements are sometime marked by sharp changes.

Thus, just like BSE, when the market experiences or passes through some 'extra-ordinary' events, some 'unique' or 'special' trend persists in the market. As the economy reverts back to its 'normal' state this 'special' trend weakens in the sense that the variability captured by the first factor declines steadily. For investors this information might be extremely useful in designing profitable trading strategy. To be more specific, if it is possible to identify when this special trend would set in or how long it would last, investors might be able to design strategies to make profit out of market movements. The movements in the first factor eigenvalue reveal few more observations. The eigenvalue increases during the periods of recovery and reaches maximum just before the peak. During a stable period, however, the eigenvalue falls or reaches a plateau. Therefore, the 'special' trend persists during the phases of recovery and weakens during the periods of recession or stability. The market crash could be predicted from a high eigenvalue of the first factor and high eigenvalue could be associated with market crash. In the Indian context, hence, there is immense scope for investors to use this piece of information to design a profitable trading strategy in the National Stock Exchange.

While it is evident that some trading or fruitful investment strategies could be derived for the Indian stock market, it would be of interest to explore how such strategies could be framed. That is where we move to next.

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