DYNAMICS OF HERDING BEHAVIOUR IN INDIAN STOCK MARKET

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To

My Beloved Parents

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CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
CSMMD	Cross-sectional Absolute Mean and Median
LSV	Lakonishok, Shleifer and Vishny
BVMT	Bourse des Valeurs Mobileres de Tunis (Tunisiann Stock Market)
TUNINDEX	Tunisia Stock Exchange
NYSE	New York Stock Exchange
AMEX	American Stock Exchange
ETFs	Exchange-Traded Fund
TWSE	Taiwan Stock Exchange Weighted Index
US	United States
USA	United States of America
UN	United Nation
EUR	EURO
KRW	South Korean Won
GBP	Great Britain Pound
JPY	Japanese Yen
OTCE	Over the Counter Exchange
FII	Foreign Institutional Investment
QFIIs	Qualified Foreign Institutional Investment
ADR	American Depository Receipt
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
MIMIC	Multiple Indicator using Multiple Cause Model
DCC-GARCH	Dynamic Conditional Correlation GARCH
BRIC	Brazil, Russia, India, China
UK	United Kingdome
NASDAQ	National Association of Securities Dealers Automated Quotations
BSE	Bombay Stock Exchange
BOLT	BSE On-line Trading
MF	Mutual Funds

S&P-500	Standard & Poor's 500
CMIE	Center for Monitoring Indian Economy
RBI	Reserve Bank of India
NBER	National Bureau of Economic Research
M-DCC-GARCH	Multivariate Dynamic Conditional Correlation GARCH
ANOVA	Analysis of Variance
ADF	Augmented Dickey Fuller
PP	Phillips-Perron
AR	Autoregressive Model
OLS	Ordinary Least Square
CCC	Constant Conditional Correlation
DCC	Dynamic Conditional Correlation
VCC	Varying conditional correlation
CSSD	Cross-sectional Standard Deviation
CSAD	Cross-Sectional Absolute Deviation of Returns
SMB	Small Minus Big
HML	High Minus Low
T-Bill	Treasury Bill
ADF	Augmented Dickey Fuller Test
PP	Philip-Perron Test
ABSRMBSE	Absolute Value of the Market Return
SQRMBSE	Square of the Market Return
MRBSE	Cross-Sectional Standard Deviation of Beta (Market factor: BSE)
SMBBSE	Cross-Sectional Standard Deviation of Beta (Size factor: BSE)
HMLBSE	Cross-Sectional Standard Deviation of Beta (Value Facto:Beta)
CSADBSE	Cross-Sectional Absolute Deviation of Returns BSE
SMBBSEH	Extracted Herding Measure :Towards the Size Factor
HMLBSEH	Extracted Herding Measure: Towards the Value Factor
SEBI	Security Exchange Board of India
MFI	Mutual Fund Investment
IIs	Institutional Investment

VOLBSE	log volatility of the Index/Market
EQFIIBSE	Net Foreign Institutional Investment(normalized)
EQMFIBSE	Net Mutual Fund Investment(normalized)
NETBSE	Net Institutional Investments(normalized)
MRBSE	Log Cross Sectional Standard Deviation of Market Beta
MRBSEH	Herding Measure Extracted Through the State Space Model using MRBSE
VOLBSE	Log Market Volatility
VOLUMEBSE	Log Market Volume
RBSE	Market Return of the Index - BSE
VOVOLURBSEH	Herding Measure Extracted Through the State Space Model by using Market Volume, Market Return and Market Volatility as Controlling Variable
ALLEXCEPTNET	Herding Behaviour Extracted Through the State Space Model When the Net Institutional Investment is Excluded
ALLWITHNET	Herding Behaviour Extracted Through the State Space Model When Net FII Flow And Net Mutual Fund Flow Excluded
CSADFIIDOWN	Cross-Sectional Absolute Deviation of Stock Return when Net FII is Low
CSADFIIUP	Cross-sectional Absolute Deviation of Stock Return when Net FII is UP
CSADVOLUP	Cross-sectional Absolute Deviation of Stock Return when Market Volatility is Down
CSADVOLUME DOWN	Cross-sectional Absolute Deviation Of Stock Return when Market Volume is Low
CSADVOLUME UP	Cross-sectional absolute deviation of stock return when Market Volume is UP
RMTVOLUP	Absolute Return of the Market when Market Volatility is UP
RMTVOLUME DOWN	Absolute Return of the Market when Market Volume Is Down
RMTFIIDOWN	Absolute Return of the Market when Net FII is Down
RMTVOLDOWN	Absolute Return of the Market when market volatility is Down
RMTVOLUME UP	Absolute Return of the Market when FII is UP
RMTFIIUP	Absolute Return of the Market when Market Volume is Up
SRMTVOLDOWN	Square of the Market Return when Market Volatility is Down
SRMTFIIUP	Square of the Market Return when FII is up

SRMTVOLUME DOWN	Square of the Market Return when Market Volume Is Down
SRMTVOLUP	Square of the Market Return when Market volatility is Up
SRMTFIIDOWN	Square of the Market Return when FII is Down
SRMTVOLDOWN	Square of the Market Return when Volume is Down

CHAPTER- I

INTRODUCTION

1.1. Preamble

Human have lived a long time without investments but in modernity nearly everyone is interested in the prospect of investing[1]. The term “investment” is one of the widely discussed idioms in financial economics, which means “the act of investing effort or resources for profit or any other benefit”[2]. The need for investment may be different for different people and the aim of investment may be many folds. It may be as a source or an additional source of income, to earn a higher rate of return, appreciate his idle savings or to make a provision against to juggle the expenses or uncertainty in the future.

In the contemporary world, investment is a methodically optimal process, which seeks out the finest opportunity to gain profitable returns or to grab more out of the available resources with minimum bearable risk. The investment decision is not a guess work, but a process includes a series of activities, which require creative and deliberate efforts and conscious thinking. It is a cycle of actions, in which one uses his or her potentials, ability and skill to analyze the opportunities, imitate or to take timely decision and to assume risk akin with the investment. Sharpe and et al. (1998) explained this as, “the investor should find out answer for why, what, when and which related with the different aspects of investment decisions”[3].

In India, the investment arena is highly sophisticated and this process got its pace during the early 1990s with the ongoing economic liberalization and globalization process coupled with robust domestic demand. Further, the introduction of online trading system made stock market investment common and it become possible for anyone to easily follow the market and an ‘*e*-trade’[4] account would allow him to follow his investment and enable him to make timely decisions. Today Indian stock market considered as an investment dome by both domestic as well as foreign

1 Considered the whole human history
2 Based on Word Net 3.0, Farlex clipart collection. © 2003-2012 Princeton University, Farlex Inc.
3 Sharpe, W., Alexander G., J., and Bailey J., W. (1998). Investments. (6th Edition), Prentice Hall, New Jersy.
4 Through Electronic Trading Account

institutional investors and the growth and increased number of participants in the market (Foreign and Local) has attracted researchers and analysts to discuss the different issues related to stock markets.

1.1.1 Bombay Stock Exchange (BSE)

Bombay Stock Exchange, "SENSEX", was established as "The Native Shares and Stock Brokers Association" in 1875. It is one of the major stock exchanges in India with a nationwide reach. The SENSEX, the benchmark equity index recognized worldwide with nearly 5211, listed companies (Excluding Permitted Companies) and nearly 10900 listed scrips. BSE has facilitated an efficient platform for raising capital for the corporate needs and provides facility for trading a number of instruments like equity and debt instruments, derivatives and mutual funds etc. The companies listed on BSE carries a total market capitalization of 166,700 Crore rupees as on March, 2013[5]and also it is the 5th largest[6] in the world's leading exchanges (on May 2012). BSE introduced its first stock index "SENSEX" in 1986 and launched the index in January 1989 with the base as 100 (Base year: 1983-84).

It gives attention to the varied needs of investors and market participants and developed thirty indices[7] with varied objectives. These include six broad indices, five strategic indices, three thematic, three volatility and thirteen segment specific indices. Bombay Stock Exchange switched to an electronic trading system in 1995, named as BSE On-line trading (BOLT), an automated screen-based trading platform and has currently the capacity to handle 8 million orders per day. 'BSEWEBX.CO', the first centralized exchange-based internet trading system is another attraction of BSE, which provides the investors to trade from anywhere in the world on their platform. The various market statistics about the Bombay Stock exchange are shown in Table III.I below.

5. Source : http://www.bseindia.com/
6. Source : http://www.bseindia.com/
7. As on 30th April -2013 , Source : http://www.bseindia.com/

Table I.I

Details of Market Statistics: BSE SENSEX for the Years 2002 - 2012

Year	Equity Turnover (₹ Cr.)	Market Capitalization (₹ Cr.)	FII			SENSEX	Type of Members (Nos.)						Client Statistics (Nos.)
			Buy (₹ Cr.)	Sell (₹ Cr.)	Net (₹ Cr.)	Index Closing	Individuals	Indian Companies	FIIs	Total Members	No. of Towns	No. of Cities	
2002-2003	314073	572197	134112	120012	14100	3049	212	481	20	713	-	-	-
2003-2004	502618	1539595	209892	158742	51150	5591	206	495	20	721	8449	409	-
2004-2005	518716	1698428	325851	292236	33615	6493	202	550	19	771	10338	416	-
2005-2006	816074	3022191	615413	579042	36371	11280	180	675	19	874	13443	425	-
2006-2007	956185	3545041	819863	843081	-23218	13072	180	723	22	925	14984	411	-
2007-2008	1578856	5138015	1272323	1277646	-5323	15644	178	755	23	956	15197	391	-
2008-2009	1100074	3086076	766301	904528	-138227	9709	175	809	23	1007	15402	349	-
2009-2010	1378809	6165620	598810	555955	42855	17528	173	821	23	1017	15531	324	-
2010-2011	1103466	6214912	530840	485879	44962	19445	215	1103	22	1340	15669	285	-
2011-2012	667022	6214912	341440	350734	-9294	17404	206	1150	28	1384	15742	259	20998337
2012-2013	548632	6532252	53259	47449	5810	18836	208	1147	30	1385	15716	229	23903917

Source: http://www.bseindia.com/, details as on 31st march of the corresponding year. “-” data not available,.

1.1.2 BSE-500 Index

The index launched in August 9, 1999 and it consist 500 Scrips. It represents 93%of the total market capitalization[8] of BSE, covers 20 major industries of the economy and follows free-float methodology for the calculation of index. This index considered 1998-99 as the base year and the base value fixed at 1000 points with a view to compare with other similar indices.

1.2 History of Modern Finance

Researchers, specifically on the stock market have been very active over the past 60 years. One can see different schools of thoughts, disciplines and sub disciplines, which explored the past, present and future subject events in the area of finance and investments in depth. There are large number of path breaking studies in modern finance which mainly discuss the behavior of stock returns in different aspects. If we search the history of the conceptual and empirical researches in modern finance, it can be found that Markowitz's theory(1952,1959)Capital Asset Pricing Model (1960's) the quantitative model for measuring systematic risk introduced by Treynor, Sharpe, Lintner, and Mossin, Efficient Market Hypothesis by Samuelson and Fama (1960s), the Modigliani-Miller approach, the Black- Scholes-Merton approach for option pricing (in 1970^{s}) and the introduction of the concept of behavioral finance in the late seventies are some of the major breakthroughs. All these tools and theories ultimately provided a better understanding about the market. These tools and theories enabled the investor to assess and manage the risk and return associated with the assets.

The discussion on investments especially the price behavior of the stock starts with the theory of Markowitz, a single-period model for portfolio selection explained with a number of assumptions that the risk of the investment can be measured by the variance (or standard deviation) of the portfolio's return. The Markowitz portfolio selection model helps one to plot the efficient frontier of risky assets and provides a useful framework for selecting an optimal combination of risky funds. However, this

8. Source: http://www.bseindia.com/, As on 31st March 2012.

model does not provide guidance with respect to the risk-return relationship for individual assets.

The Capital Asset Pricing Model (CAPM) is an extension of the portfolio theory of Markowitz and is widely used in security valuation, risk analysis, estimation of cost of capital and evaluation of the performance of portfolios. The basic attraction of the CAPM is the theoretical support and the simplicity and the model offers a powerful tool to measure risk and the relation between expected return of the assets in the market[9].The essence of this model is that the expected return on any asset is a positive linear function of its beta, the measure of risk that explains the cross-section of expected return of the asset. However, from late 70'[s] onwards many questioned this theory and the ability of beta to explain the return of an asset and raised the influence of many other factors and anomalies in predicting return of an asset and the way it used to explain the market efficiency.

1.2.1 Efficient Market Hypothesis (EMH)

Market efficiency is one of the most debated topics in finance like asset pricing theories and has been discussed enormously by the investment community and researchers over the past 40 years. The history of efficient market theory goes back to 1889 and the concepts were clearly mentioned in a book by George Gibson titled "*The Stock Markets of London, Paris and New York", which* explained that when "shares become publicly known in an open market, the value which they acquire may be regarded as the judgment of the best intelligence concerning them"(Gibson, 1889)[10]. The work of Bachelier (1900), who documented the statistical independence in stock returns, indicate that today's return signals do not explain tomorrow's return (either sign or magnitude). Bachelier explained these 65 years before Samuelson (1965) who elucidated the concept of efficient markets by using martingale approach. Bachelier presumed that "*The mathematical expectation of the speculator is zero*" and this work was way ahead of his time and was ignored until it was rediscovered by Savage in (1955)"[11].

9. The predictive power of the model is questioned by number of studies during the late seventies and eighties.
10. Cited Swell (2011) , history of efficient market hypothesis
11. *Ibid.* See the same for the history

Fama synthesized the existing literature, proposed the Efficient Market Hypothesis (EMH) in its current form in the year 1970 and was the first to consider the joint hypothesis problem. He defined efficient financial market as one, where the security prices always fully reflect the available information. The theory asserts that financial market is "informationally efficient" and the term “efficient” means that “the market is capable of quickly digesting new information on the economy, an industry, or the value of an enterprise and accurately impounding it into security prices. Hagin (1979) explained how markets perform in such a scenario. In an efficient market, the investors cannot expect more or less return than a fair return for the risks they assume because the price of the asset will be adjusted within an arbitrarily small but finite amount of time. LeRoy (1976) explained, “at its most general level, the theory of efficient capital markets is just the theory of competitive equilibrium applied to the financial asset market”.

The basic theoretical foundation of the efficient market hypothesis lay on the following arguments. First, the rational expectations of the investors, second some investors, who act irrationally and third to the extent that investors are irrational in similar ways, they are met by the rational arbitrageurs who eliminate their influence on prices[12]. As per the theory, an investor cannot earn abnormally high return (risk adjusted) based on the information available to him at the time, out of his investment, i.e. it is impossible for an investor consistently to outperform the market. The core idea behind this theory is that the market will assimilate all the available information by adjusting the price of the security, Fama (1970). Further, noted that the frictions like information costs; transaction costs etc. will affect the level of efficiency of the market. A higher level of market efficiency is possible through free flow of information to all market participants, which is the outcome of lower market frictions; this ultimately leads to increase in the number of participants, the trading volume and thereby enhances the liquidity and efficiency of the market.

[12]. Shliefer, A. (2000). Inefficient Markets: An Introduction to Behavioural Finance, Oxford University Press, I[st] Edirtion USA.

1.2.2 Criticism of Efficient Market Hypothesis

The concept of efficient market hypothesis has been the subject of rigorous academic research since its inception. The dominance of the concept was widely accepted by academic and financial community. However, over the last two decades, the theoretical and empirical basis of the efficient market hypothesis have been questioned by many researchers especially by the behavioral economists and proponents of behavioral finance, who argue that price adjustment process is not quick enough as EMH suggests and significant and systematic deviations of prices from the fundamental value are expected to continue for long time intervals.

There are a large number of striking events in favor of behaviorists to explain the inconsistencies of the real market with the Efficient Market Hypothesis, including the various anomalies and market microstructure, different crashes in the capital market, bubbles and numerous emotional bias led incidents that have affected financial markets. The crises of 1987, the dot com bubble (2003), the crash of (2007-2008) are some of the examples for such crash and bubbles, which continued for long period. Mitchell (1989) argued that the large market decline before the (1987) crash was caused by rational response to an unanticipated tax proposal, which in turn triggered a temporary liquidity crunch due to unexpected sales volume that was more than expected by the market to be able to handle.

The proponents of behavioral finance argue that the cognitive or emotional biases, either individual or collective, produce anomalies in market prices and thereby deviate from the concept of efficient market hypothesis. There are many factors (rational as well as irrational), which drive the behavior of the investor and the investors frequently make irrational decisions. For this reason the market price does not always represent a fair estimate of fundamental value of the underlying security. "However the proponents of efficient market hypothesis have the opinion that any observed anomalies will eventually be priced out of the market or explained by appeal to market microstructure. These issues further indicate the necessity to distinguish between individual biases and social biases; the former can be averaged out by the market, while the other creates feedback loops that drive the market further away from the equilibrium of the fair price", Akintoye (2008).

In another context, Shefrin (2002) explains that investor psychology can drive market prices and fundamental values very far apart"[13]. Malkiel (2003) noted that, "As long as stock markets exist; the collective judgment of investors will sometimes make mistakes. Undoubtedly, some market participants are demonstrably less than rational, may lead to irregularities in pricing. This may lead even predictable patterns in stock returns and can appear over time or even persist for short periods. Moreover, the market cannot be perfectly efficient, or there would be no incentive for professionals to uncover the information that gets so quickly reflected in market prices". These arguments stress the importance of behavioral traits in financial activities and the need to consider the arguments of behavioral finance.

1.3. Behavioural Finance

"All people (even smart ones) are affected by psychological biases" _ John R.Nofsinger, In his book, Investment Madness: How Psychology Affects your Investing.

The study of human behavior is one of the most fascinating endeavors throughout human history and there have been many attempts by psychologists and behaviorists to formalize the understanding of human behavior. The American Heritage Dictionary[14] defines psychology as "the science that deals with mental processes and behavior". In contemporary times, psychological principles are widely applied in a variety of perspectives and in a wide range of settings in human learning and social interaction. Understanding psychological factors is inevitable because realizing behavior enhances the ability of one for better understanding the people, the situation and the decision making process and hence enhances the quality of the resultant actions.

The history of modern behavioral finance dates back to the works of Daniel Kahneman and Amos Tversky and other behavioural finance researchers, like Wermer, De Bondt, Robert J. Shiller, Andrei Shleifer and Richard Thaler who were the main proponents of behavioral finance since 1980's, whereas Slovic (1969) explained the investment process from a behavioral point of view. Today the application of Psychological principles is not only limited to clinical purposes but

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[13] .Shefrin, H. (2000). Beyond Greed and Fear: Understanding Behavioural Finance and the Psychology of Investing. Oxford University Press. I[st] Edition, USA

14 The American Heritage Medical Dictionary, (2007), (2004). Houghton Mifflin Company.

also used in many other disciplines, such as Sociology, Education, Linguistics, History, Marketing, Finance and Economics. As Shefrin (2009) [15] noted, "behavioral finance is the application of Psychology to financial decision making and financial markets. 'Behaviouralising' finance is the process of replacing neoclassical assumptions with its behavioral counterparts". Further, Sewell (2007)[16] defined behavioral finance as "the study of the influence of psychology on the behavior of financial practitioners and the subsequent effect on markets. Behavioral finance is of interest because it helps to explain why and how markets might be inefficient". At the same time, it is also noted that the concept of behavioral finance is broader and it not only applies the psychological principle, but it also incorporates the ideas of all other social sciences to explain the various issues that arise in real practice, Shiller (2003).

Further, Shiller (2003) in one of his lectures explained, "behavioral finance is more broadly a kind of revolution that has occurred in economics and finance over the last few decades"[17]. It is an extension of behavioral economics and is comparatively a new discipline, which incorporates psychology and other disciplines into finance and explains what we do and how people behave in the market. Keynes (1936) highlighted the role of psychology in economics and argued that sentiments reflect unrealistic optimism or pessimism, which leads to booms and busts. Further, he also noted that security prices often diverge from its fundamental values and explained its effect on employment, income and money and they have valid resemblance to the explanations of modern behavioral finance.

Behavioral finance analyzes the psychological underpinnings of human behavior in the financial market and explains the circumstances and conditions under which the actions of investors influence the pricing of assets, the changes in financial markets and the ultimate effect and implications on corporate finance and the real economy. It has been proved that psychology plays an important role in human behavior and decision making and the psychologically led behavior is the reasons for many of the booms and busts in the financial markets, Shiller (2000). Behavioural finance focuses on the economic decisions and examines the effects of cognitive, social and

15 Shefrin,H. (2009). Foundations and Trends in Finance. Vol. 4, papers.ssrn.com/sol3/
16. Cited as 2010 in reference
17. http://www.youtube.com/watch?v=chSHqogx2CI

emotional factors of individuals and institutions and their impact on the market prices, returns and the resources. It also uses the theories for assessing and explaining the risks and savings in the financial markets. Here behavioral finance offers insights and explains why investors behave so in certain situations and how it affects the risk and return and thereby the pricing of assets in the market. The behavioral finance argues that people often experience cognitive and emotional biases and behave ostensibly in an irrational manner. It tries to analyze how the information is processed and explain how the emotions of human beings are working and how these emotions and biases influence the decision making process. The fundamental principle of behavioral finance is that people are irrational or they are not completely rational, but most of the theories in finance and economics are developed on the basis of the rationality of the investors.

It has been observed much time that human behavior points to anomalies that contradict the basic theories, which predict all that, will happen in future and the allusion of behavioral economics lies in this point of fact. Traditional economics explains that people are rational and try to earn more with less risk. Behavioral finance challenges these theories based on the psychological experiments, which have been carried out through the decades and it incorporates the insights from psychology into the theories of financial economics. The proponents of behavioral finance explain that human beings are biased in taking their decisions and posit that asset price often does not reflect rational or fundamental values in the financial market. Further the study of Kahneman and Tversky (1972), and (1973), Tversky and Kahneman (1974), (1991) have provided numerous experimental evidences that the rational agent assumptions are systematically violated. Their study proved that individuals in their decision making tend to overemphasize the recent information and underemphasize the past or prior information". Further, De-Bondt and Thaler (1985)[18]; argued that even professional analysts tend to overreact to new information, and challenged the Efficient Market Hypothesis and put forth these concepts into mainstream discussions.

18.De Bondt,W,.F,.M. and Thaler,R.,H. (1985).Does the Stock Market Overreact?. Journal of Finance, 40, 793 805.

1.4. Traditional Finance Vs Behavioral Finance

There are many differences in the thoughts and perceptions of traditional finance and behavioral finance and there are a number of arguments in considering behavioral economics as a different school of thought. The neo classical theory argues that the individual behavior is rational but the practice of behavioral finance and the supporting scientific methods are different. Barber and Odean (1999) explained that "financial economics assumes individuals behave with extreme rationality and these deviations from rationality are often systematic, but behavioral finance relaxes the traditional assumptions of financial economics by incorporating these observable, systematic and very human departures from rationality into standard models of financial markets".

The distinction between behavioral and main stream economists is that they hold different normative conceptions of economics as science[19]. Tomer (2007) analyzed the characteristics of behavioral economics and compared different strands of behavioral economics with the main stream economics in six dimensions and concluded that behavioral economics is a school of thought distinguished by the fact that it is much less narrow, rigid, intolerant, mechanical, separate, and individualistic than modern economics.

The main difference between traditional finance and behavioural finance lies in the fact that the former discusses how investors manage their portfolio, whereas the latter explains how the investor actually behaves in the market and the corresponding effect on the asset pricing and argues that the pricing of asset is not only based on the risk and return of the asset but is also affected by sentiments and many other psychological 'biases' and 'heuristics'. Behavioral finance closely combines individual behavior and market phenomena and uses knowledge taken from both psychological field and financial theory, Fromlet (2001) but traditional finance considers that investors have perfect information about the economic conditions and the market events and they exploit this information to make rational judgments. The theories of traditional finance are based on the rationality of the investors, argue that people use, process data appropriately and correctly and make decisions subject to

[19].Tomer,J.F. (2007),what is behavioural economics. *The Journal of Socio-Economics*. 36, 463–479.

their analyses but behavioral finance recognizes that people often use estimations made according to a rough and ready practical rule for decision making. Further, people are guided by logic, reasoning and independent judgment but behavioral finance suggests that often investors are addicted to feeling or emotion-based sentiments.

Traditional finance explains that the price of an asset in the market is an unbiased estimate of its intrinsic value but behavioral research found that there is disagreement between market price and fundamental values of assets. Further, Rabin (1998) explained, “Economics has conventionally assumed that each individual has stable and coherent preferences and that rationally maximizes those preferences but Psychological research suggests various modifications to this conception of human choice”. Traditional finance is mostly supported by tested methods, logical analysis and empirical field testing but behavioral finance often fails since human behavior is complex and attending to all facets of human behavior is neither feasible nor possible.

1.5. Importance of Behavioral Finance in the Capital Market

There is large number of examples for the sentiment driven stock market movement throughout the world markets. Even though the concept of behavioral finance has been introduced and discussed over the last three to four decades, researches in behavioral finance got its pace and momentum only at the beginning of this century. For the last two decades, the field of behavioral finance has proposed many examples for the significant failure of equilibrium rational choice models in explaining the real economic behavior[20]. It discusses many issues from the stock market and it has argued that high volatility and market crashes often happen not only because of the fundamental issues, but the investor’s emotions and sentiments also play an important role in such events. Financial economists appear to agree that security-price volatility and trading volume should vary directly with the divergence of investor opinion, Schwartz (1988)[21]. Further Miller (1977) also noted that unless arbitrage opportunities are complete, larger divergence of opinion will lead not only to greater price volatility but also lead to higher equilibrium market prices. Another

20 See the studies,Schleifer(2000),, Hirschleifer (2001), Barberis and Thaler(2003), etc.
21 Cited by Oslone, R.(1998).Financial Analysts Journal - March/April

important argument is from Robert Shiller[22], who partially supported the efficient market hypothesis and explained that investor's psychological and sociological beliefs exert a greater influence on the market than good economic sense.

While discussing the importance of behavioral finance in the capital market it is worth mentioning the report that "the importance of behavioral finance has dramatically increased in the aftermath of the financial crisis and both wealth management institutions and other investors leveraging key tenets of behavioral finance to rebuild investor trust and confidence and drive further innovation into their offerings and service models"[23]. Even if the practices and principles of behavioral finance have not been widely incorporated into wealth management, today investment companies and analysts seek the principles and researches of behavioral finance to solve many issues and challenges of the highly tough current investment arena. Further limited information and investor's biased responses to information challenge many of the predictions of the Efficient Market Hypothesis, which is considered as one of important theories in finance where it many a time contradicted reality and experience. Further behavior finance answers to a number of questions about the irrational behavior of investors. In addition to this understanding, investor psychology will add value to devising unique trading strategies and to take the advantage of profit opportunities due to the mispricing in the market.

Further Shiller[24] (2006) by correcting Ross (2005,) argued in his article that "The fact that behavioral finance is beginning to play an important role in public policy, such as in social security reform, belies this. In fact, behavioral finance draws on a wide expanse of knowledge from all the social sciences that offer real and tangible alternatives". Individual investors, who are often less informed than the institutional investors suffer more in the market while the institutions use their information to take advantage of the market. The efficient market theory which was built on the assumption that the investors are fully rational; who hastily update their beliefs follow 'Bayes-rule' when they receive new information and that they maximize expected utility while making their choices with uncertain outcomes. This suggests that one can take only little advantage from the market since the information is

22 Shiller,R.J. (1990). Market Volatility. 6th edition (1999), MIT press.
23 Source: World wealth report- 2010.
24 Shiller, R. J. (2006). Tools for financial innovation: neoclassical versus behavioral finance. The Financial Review, 41(1), 1–8

assimilated quickly to prices leaving little room to take advantage through trade, but it is not true in practice.

Behavioural finance offers salvation to neo-classical finance through explaining many issues that challenged the theories of finance and suggests a combination of both neoclassical finance and behavioural finance to solve the real issues in the market. Mullainathan and Thaler (2000) argued that financial markets have greater arbitrage opportunities than other markets and behavioural factors might be thought to be less important here, but they showed that even the limits of arbitrage create anomalies that the psychology of decision making helps explain. Since saving for retirement requires both complex calculations and willpower, behavioural factors are essential elements of any complete descriptive theory". All this explain the relevance and importance of behavioural finance and shows the inevitable role of behavioural finance in the field of investment. Further voluminous studies in decision science, cognitive and evolutionary psychology indicate that modern finance is behaviourally flawed.

1.6. Advantage of Behavioural Finance

There is no doubt that behavioural finance has found its place in the arena of financial research. This explains why market participants make systematic errors and the effect of such sentiments and emotions on prices and return, which ultimately leads to market inefficiencies and explains how other participants arbitrage such market inefficiencies for making profit. In addition to this, it strives to recognize the role of human behaviour and applies insights from all of the social sciences to finance and sheds light on irrational deviations from traditional decision-making models to explain economic and financial phenomena.

Understanding the investor's behaviour helps the firms and advisors to tackle various issues in more volatile and less certain environment. understanding of the emotions, biases, penchant and affinity of investors in making choices and decisions and one can effectively use this for analyzing the market conditions, counseling the investors, wealth management, better decision making, planning and also to set goals. Behavioural finance explains many anomalies in the market and this can be used for more effective asset allocation framework where traditional theories often fail to explain the anomalies of the market.

In addition, behavioural finance explains the asymmetric effect of risk and return by using the psychological overlay and understanding different behavioural issues in the market will help investors, analysts and wealth managers to avoid emotion-driven speculation and helps them to follow suitable investment strategy. The behavioural explanation can be used effectively for the modeling of securities prices and it explains many anomalies that cannot be explained by traditional finance theories. Analysts also use behavioural finance as the theoretical basis for technical analysis.

Voluminous studies on behavioural finance have contributed theoretically and empirically and proved that investor psychology plays an important role in investor's trading behaviour and thereby it can influence the market movements. Behavioural finance focuses on the investor's irrationality in their reactions to information and the decision making process to analyze and understand anomalous pricing behaviour of assets and the market. The irrationality of the investor arises from psychological biases and heuristics and leads to mispricing of assets. Hence the asset price may deviate from predictions of traditional market models which ultimately lead to market inefficiency[25]. The researchers pointed out a number of behavioural traits, biases and other anomalies, which contradicts the existing traditional financial theories and these include over reaction, under reaction, mean reversion, herd instinct etc.

1.7. Herding Behaviour

Human beings are highly interactive with other members of the society and there exists a normal interdependence and symbiosis among the members and their behaviour is often natural and individually rational. Herding is one of the common behavioural traits shown by almost all type of creatures in the world and human beings are also not exempted from this. The herd instinct is innate in the human mind and there is a rather widespread tendency among people to behave mechanically or unconsciously imitate what most others do. "Herding theory has its roots in Keynes (1930), who focused on the motivations to imitate and follow the crowd in a world of

25. See: Thaler (2005), Shleifer (2000), Shefrin (2000, 2009).

uncertainty"[26]. Herd behaviour denotes the tendency to imitate or follow other individual or groups and this behaviour has been observed not only in financial markets but also in other areas of human life. Herding indicates an inefficient market and this behaviour is explained as a correlated behaviour, which arises when investors suppress their own private information, and imitates or follows others' actions or decisions. This is an accidental spontaneous reaction (unplanned) from the part of an investor to follow others to the negative or positive movement of the market or to the negative or positive price movement of an asset or an industry.

In the stock market herding behaviour is one of the strongest and most dangerous emotional illnesses expected from the investor, which may lead to fairly disastrous results in the market. The herd mentality may be motivated by many factors such as conformity or peer pressure, cascades, fear, fads, reputation and it may arise due to mimicking or imitating a whole group or crowd. The herding may spawn out from a formal or informal group's decisions or may arise due to pseudo consensus, common convention or rituals, bandwagon effect, i.e. trend of following or joining the majority or due to crowd hysteria (e.g. crashes)etc. Usually it is not easy for an investor to keep away from herding or following the crowd and the herding behaviour can create a massive selling or buying in the market. This behavior spreads and causes the price either to drop or hike, which eventually leads to the mispricing of assets.

Herding has different stages, in the first stage the investor may look into his surroundings and try to learn what other participants do in the market and he changes according to market and follows others and finally turns in to the bunching up of buying or selling or turns in to mass uniform behaviour. Christie and Hwang, (1995) explained herding as the behaviour of an "Individual who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its prediction" and as a result, the difference of opinion of investors is relatively small.

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26. Cited Baddeley and et al.(2010).

1.7.1. Meaning and Definition of Herding Behaviour

Many experts have defined herding and some of them are as follows …

1. "The average tendency of a group of managers to buy or sell a particular stock at the same time, relative to what could be expected if money managers traded independently", Lakonishok, Shlifer and Vishny (1992).
2. "Behaviour patterns that are correlated across individuals" Devenow and Welch (1996).
3. ''A group of investors trading in the same direction over a period of time", Nofsinger and Sias (1999).
4. "The behaviour, although individually rational, produces group behaviour that is, in a well-defined sense, irrational. This herd like behaviour is said to arise from an information cascade", Shiller (2000).
5. "An obvious intend by investors to copy the behaviour of other investors", Bikhchandani and Sharma (2000).
6. "The tendency to accumulate on the same side of the market", Hirshleifer and Teoh (2003).
7. "Herding is often used to describe as the correlation in trades resulting from interactions between investors", Chiang and et.al (2010).
8. The decisions of a player are positively influenced by the decisions of the other players, this is referred to as herding behaviour", Hot (2009).

In the financial market, herding defined as the psychologically or emotionally driven tendency of the investors to follow the actions or to imitate the crowd. It is the behavior shown by the investor to join mechanically the market consensus as other participants do. By analyzing the definitions given by different authors, it can be concluded that herding arises in the market when the investors decide to imitate the actions or decisions of other investors; they heavily buy or sell same stocks in the same direction over a period and track each other's investment strategies.

1.7.2. Why Herding Behaviour

Herding behavior may occur because of many reasons and literature on this subject suggests a number of arguments why investors show herding behavior. The basic reason is that it is an innate trait in every individual to follow the crowd, through which they may feel more secure as they are part of a group. Further, human history explains this evolutionary instinct, which is deeply rooted in the human mind. Herding may take place due to the belief that others have superior information. Another approach focuses on reputational herding based on principal-agent relationship. Banerjee (1992) explained that herding exists when “everybody is doing what everyone else is doing even when their private information suggests doing something else.” Chang and et al. (2000) pointed out that this behavior may happen because of high degree of government intervention and due to low quality of information disclosure. This may also happen with the existence of speculators with relatively short investment horizons.

Hirshleifer and et al. (1994) noted that under some conditions, investors will focus only on a subset of securities ("herding"), while neglecting other securities with identical exogenous characteristics. Herding arises due to irrational investment choices made by noise traders (De Long et.al., 1990; Bouchaud and Cont, 1998). Calvo and Mendoza (2000) argue that the combination of costly information and diversified portfolios generates incentives for rational herding by international portfolio investors.

Celen and et.al (2004) noted, “An informational cascade implies a herd” and explain that an informational cascade occurs when a large number of individuals ignore their private information while making a decision. Further, the fear of loss, lack of competitive edge for decision making and suspicion of own information also leads to herding. DHulst and Rodgers (1999) pointed that herding effect arises when groups of agents share information.

It is also noted that by following leader one can eliminate the search cost or information cost and lack of information also leads to herding. Generally, acquiring information has cost and this motivates small investors to herd around the giants in the field; it may be a financial analyst or any other institutional investor or anyone else in the market. Another reason for herding is reputation and this may happen when the compensation structure of managers' contract has a benchmark; some average performers herd other managers, Bikhchandani and Sharma (2001).

1.7.3. Consequences of Herding Behaviour

Man being a social animal, herding behavior will bring group conformity and social cohesion, but in portfolio management and corporate finance, herding often has a number of atrocious effects on the market. Like other behavioural biases herding also leads to market inefficiency and moves the price away from fundamentals inflates the situation and magnifies the effect of certain factors. Herding results in market instability and often this behaviour arises when an investor simply mimics other investors; this may lead to inefficient decision making and the suboptimal use of information because the investor suppresses his privileged information and follows the crowd without knowing the real scenario.

Bikhchandani et al. (1992) noted that in financial market, herding may "lead to observed behavior patterns that are correlated across individuals and that bring about systematic, erroneous decision making by entire populations". In portfolio management herding on the same stocks will increase serial correlation over time and will lead to more continuous up days, which ultimately attract more buyers and end up with more up days. Herding behavior is also cause for bubbles and bursts, leads to panics, crashes, and substantial losses of welfare and fragility in the financial system. Further, Scharfstein and Stein (1990), Hirshleifer and Teoh (2003) noted that intentional herding is often cause for higher price volatility and destabilizing of stock prices, and hence badly affects the stability of the market. Choi and Sias (2009) explained that the noise in prices or the destabilized stock prices further drive to mispricing, this would result in subsequent return reversals. Park and et al. (2011) pointed out that herding could induce lower liquidity. Specific investments favored by the crowd are often mispriced and the values are usually based on optimism but not on the basis of fundamentals. Chiang et al. (2010) opined that "a long-run consequence of this behavior, it may lead to instability and inefficiency if the market correction fails to make the market price and the fundamental value converge". In addition to this, frequent shifting from one security to another can decay the profit earned by the investors.

1.7.4. Types of Herding Behaviour

Herding behavior explains the situations where large number of participants does similar actions. The basic instinct of herd behavior starts from the price movements of assets or the trend of the market or by observing the actions of other investors. While herding, usually the investor judges the risk in relative terms regardless of the fundamentals. Herding behaviour arises when there is an obvious intent by market participants to copy the behaviour of other investors and it denotes the situations where large number of agents makes similar decisions.

Herding arises when the investors decide to mimic the observed actions of others or movements in the market and it may come in different flavors. Literature regarding the subject explains several kinds of herding behaviour. Imperfect information, reputational reasons, and compensation structures can be the reasons for herding, Bikhchandani and Sharma (2001). In general, researchers divide herding into intentional herding (sentiment driven/rational) and unintentional (spurious/irrational) herding. Further, Bikhchandani and Sharma (2001) noted that, "Intentional herding may be inefficient and is usually characterized by fragility and idiosyncrasy".

Types of Rational Herding

Figure I.I

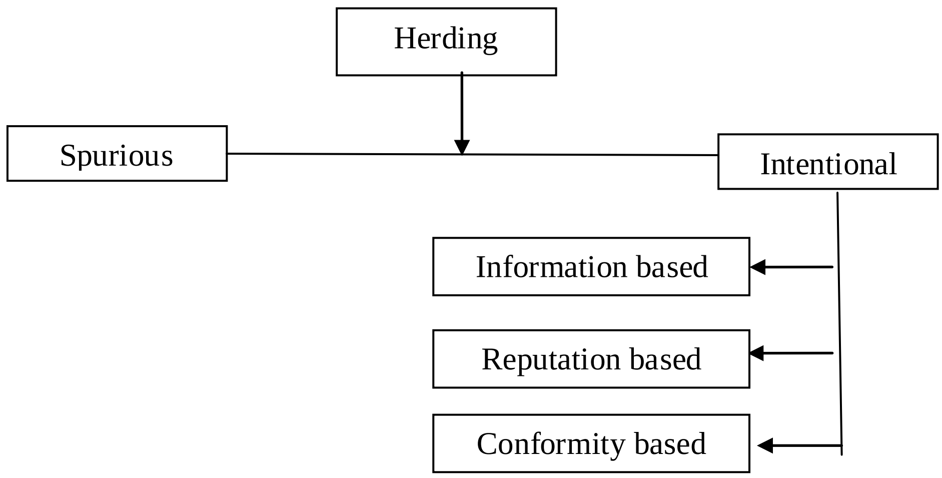

Fig I.I. Source: Risk Management, Rational Herding and Institutional Investors, a Macro View, P-789

Several studies pointed out that in a market with noise traders, the herd behaviour need not always necessarily be irrational. The rational view focuses on “investor psychology and holds that agents centers on externalities, optimal decision-making being distorted by information difficulties or incentive issues, while the irrational view of herd behaviour stresses on investor psychology and holds that agents behave like lemmings, following one another blindly and foregoing rational analysis”, Devenow and Welch(1996).

It has been noted in these literature that spurious herding (also known as “unintentional herding” in Lakonishok et al. (1992), Bikhchandani and Sharma (2001), may occur when investors face similar decision problems. This type of herding arises when similar information is available for decision makers and they take similar decisions without necessarily observing each other because of the simultaneous reaction to certain signals. Hirshleifer and et al. (1994) explained the same as this may happen, when the “investors may receive similar type of private information and analyzes the same signals”. Further, spurious herding may also arise if the opportunity sets of investors differs, Bikhchandani and Sharma (2001). In spurious herding, the trading actions of agents do not always correlate and is an efficient outcome of portfolio selection of different market participants.

The basic difference between spurious herding and intentional herding is that the former is based on independent analysis or on the same information or is based on a common reaction towards certain news or a particular event, but the latter is by observing the behavior of other market participants, often by neglecting private information. Further investors’ professions, educational backgrounds may also influence trading on stocks with certain characteristics, such as liquidity and size, Falkenstein (1996). Spurious herding may arise when a group of investors face similar issues and accordingly take similar decisions. This may also arise, when the opportunity sets of different investors differ, Bikhchandani and Sharma (2001), whereas intentional herding leads to inefficiency of the market or system.

Zhou and Lai (2006) noted that spurious herding arises when the agents react similarly to the publicly available information or different opportunity sets faced by investors. Generally, this type of behaviour is based on fundamentals and it denotes the efficiency of the market while intentional herding destabilizes the market and increases volatility. Empirical distinguishing between these two types of herding is difficult because a number of factors jointly have the potential to influence an investment decision. At the same time there are attempts from different researchers to differentiate between these two types of behavior.

In intentional herding, investors obviously mimic others irrationally. This type of herding may arise because of informational cascade, reputational or conformity reasons. In information cascades, every individual acts rationally and unintentionally and follows the public choice, independent of their private signals based on their rational choice. Bedke and et al. (2009) noted, “The theory of informational cascades shows that rational herding behaviour can arise even if all the analysts are making a sincere and serious effort to make the best possible forecast”. Anderson and Holt (1997) explained that an information cascade “is a pattern of matching decisions and it occurs when people observe and follow ‘the crowd’, which can be rational if the information revealed in earlier decisions outweighs one’s own private information”.

Reputational herding assumes that financial analysts make strategic use of an information asymmetry. Scharfstein and stein (1990) noted that for reputational herding, agents have more correlated signals conditionally on the state of the world and professional managers may disregard their private information and trade with others because they are subject to the reputation risk of acting differently from others. Graham (1999) explained that an analyst with high reputation and low ability is likely to herd with public information if it is inconsistent with his private information and it is found that herding is common when private signals are positively correlated among analysts. Hong and et al.(2000) noted that various models on reputational herding observe the source of herding as learning over time about some exogenous characteristic of agents such as ability and their reputation or ‘‘career concerns’’ which will lead agents to ignore their private information and make them tend to herd around others. Further the fear of false forecast, compensation or incentives, decision situations (whether long or short), external signals about the behaviour of group members, risk of the analyst losing job also lead to this type of herding .

Wermers (1999) quoted four reasons for institutional investors herding and explained that this may happen because of the reputational risk of acting differently from other managers, or their action is decided based on the correlated private information they receive. This may also arise when they infer private information from the prior trades of better informed managers or trade in the same direction. Another important reason is that institutional investors share an aversion to stocks with certain characteristics, such as liquidity or less risky or any other particular sector.

In sentiment-driven intentional herding, the investors imitate other market participants in their decisions regardless of the fundamental and the privileged information, results of similar type of action (buying or selling) of the same stocks. Intentional herding may be either rational or irrational, De-Long and et al. (1990), Froot and et al. (1993). Further, De-Long et al. (1990) pointed out that pure intentional herding behaviour is closely related to the theory of noise trading and Bikhchandani, Welch (1992), Banerjee (1992) noted that rational traders take their decision by observing the trading behaviour of other market participants while assuming that others have better information. The output of intentional herding may not necessarily be efficient because the investors take their decisions based on that of the other participants rather than analyzing the available information, which ultimately brings instability and excess volatility in the market.

1.8. Contagion Effect

The business landscape of the world has been changing very fast and the concept of fence- free, boundary-less free economy has offered a global business scenario and led to a new international business order and is stupendous in many aspects. Over the last two centuries, capital market has grown many folds, especially during the period of economic and financial liberalization. Further, the increased interest of foreign institutional investors in emerging markets has brought a more globally integrated financial system throughout the world. The new business order has redrawn the economic and industrial boundaries and brought about competition, prospect for growth, challenges, opportunities and firm inter linkage and mutual dependency among countries.

The newly emerged business paradigm is enormously dynamic and the frequent shifts and contagion effect have influenced many countries politically, socially, culturally, economically and in many other aspects positively and negatively. The dynamism of the newly developed 'global financial structure' and the link between the countries have triggered shifts in economies and made an immediate chain reaction in other countries and created much financial havoc many a time. It is also noted that in many crises, shocks were transmitted from one economy to other even where the fundamental linkages are not present or even strong. If we consider the history of the last two decades, one can see many examples of bubbles and crashes in the financial market, which happened in one country and spread to the neighboring economies or even worldwide very fast.

The literature in this field explain many reasons for the inter linkage between countries and these include the macroeconomic fundamentals, the efficacy and costs of capital controls, competitiveness effect, the existing financial system in the country, the exchange-rate regime and herding and contagion etc. Contagion can happen through different channels and the transmission of shocks may often be beyond the fundamental linkage. It can be seen that most of the crises are regional but it has not only affected a particular region and many a time it has spread worldwide and the effect has been experienced globally.

During a crisis one can expect huge shifts in the financial market and it can be found that the crises have affected developing countries more than developed countries. The contagion arises when there are shocks, the consequences are over and above the expectations of investors and hence the reactions of investors are in accordance. During crises or shocks, different kinds of investors may change their positions in the market at the same point of time rationally or as per the market sentiments. Generally investors panic and they accept the behaviour of the crowd, act against their private information and rationally or irrationally follow the behaviour of others.

In financial markets, contagion is explained as the excess correlation, i.e. correlation over and above what one would expect from economic fundamentals, Bekaert and et al. (2005). In literature, contagion and its different forms have been discussed widely and have been defined by many authors. The general definition given to the contagion effect is “the increase in the probability of crisis after the occurrence of a crisis elsewhere”. Forbes and Rigobon (2002) have analysed contagion as “a significant increase in the correlation between international stocks”, which is explained as the increase in the probability of crisis beyond the effect of linkages between fundamentals and distinguishes interdependence from contagion. Further it is explained that there exists a high level of cross market correlation throughout the world markets and there by the transmission of a crisis from one country to another cannot be considered as contagion if the operation of the channel does not change across regimes but it is by mere interdependence and is explained on the basis of structural breaks in the correlation and the break in the series is interpreted as evidence of contagion.

In addition, Kuusk and et al. (2011) explained this as “a structural break in the linear transmission mechanism of financial shocks, leading to panic, herding or switches in investor’s expectations and contagion requires a change in the structure of stock market linkages and an increase in these linkages during crises has to be statistically significant”. In models explaining herding behaviour, contagion is also defined as spillovers that cannot be explained in terms of fundamentals.

Contagion is considered as a feature of financial crises and it mostly affects the most vulnerable countries due to weak fundamentals or due to the panic behaviour where market sentiment acts as the main driving force, which usually arises out of informational asymmetry. Regarding potential herding and contagion, it has been found in history that, any small panic or similar trading signal can become a booster, leading to sentiments and loss of confidence. In addition, the source of information and information transmission matter because different sources influence differently during crises and investors exhibit herding behaviour, which magnifies the effects of shock and create evil effects. As Kodres and Pritsker (2002) noted, “The theoretical models of equity market behaviour suggest that information asymmetry can cause herding behaviour or contagion, there by pushing these countries into poor equilibrium and financial distress”.

Contagion may arise due to rational or irrational herding behaviour which happens when investors simultaneously pullout from markets or because of the market’s overreaction to a shock. As a result, the expectation becomes self-fulfilling when the herding behaviour causes a collapse of the market despite sound fundamentals. It is also noted that international investors also play an important role in spreading crises by pulling out from the market based on their privileged information or to save their investments from what they experienced in another market. This will also trigger the sentiments of other investors to pull out from the market and ultimately leads to the collapse of the system.

If we analyze contagion, there will be a large plunge in the value of assets in one market and this is associated with a similar effect in another market or country. Similarly, one can expect spillover effects and parallel movements of different markets and transmission of shocks from one crisis-affected country to other economies beyond the fundamental and financial links. At the same time the interdependence can be distinguished in the sense that contagion requires a sensible change in the structure of stock market linkage and a significant increase in cross market linkage but the non-significant change in cross market linkage is inter dependence.

It has been noted by many researchers that herding behaviour plays an important role in financial contagion especially during the period of crisis and bubbles. Chiang et al. (2007) explained that contagion effects spread financial risk across markets and herding activity intensifies market crises. Herding behaviour takes place when investors mimic others in their investment decisions without considering the changes in fundamentals. As per World Bank[27], "Contagion occurs when events in one emerging market change investors behaviour in other emerging markets, regardless of whether the economic fundamentals of the latter have been affected or not. In these types of situations the investors infer and expect that the shocks will spread across the countries and get panic and run away from countries that do not necessarily share fundamental linkages. Kyle and Xiong (2001) noted financial contagion as "the rapid spread from one market to another of declining prices, declining liquidity, increased volatility, and increased correlation associated with the financial intermediaries' own effect on the markets in which they trade".

27. Private capital flows to developing countries: the road to financial integration. (1997), world bank policy research report, Oxford University Press. p-124,

World Bank explained more distinctive aspects of contagion and defined Contagion as " the cross country transmission of shocks or the general cross-country spillover effects", which may happen at any time, i.e. not only at the time of financial crises and does not need to be related to crises but generally gets emphasized during crises. A restrictive definition explained contagion as the cross-country correlation, beyond any fundamental link and beyond common shocks among the countries", generally explained as sentiment driven, i.e., through herding behaviour. In a very restrictive definition contagion has been noted as the change in transmission mechanisms that have occurred through a significant increase in cross market correlations during crisis time, i.e. during turbulent time there is a relatively increased cross-country correlation when compared to the tranquil times. Lux (1995) explained that contagion refers to the results of the attempts of investors to infer information from others' actions and in bubbles herding then takes place as contagion of sentiment.

1.9. Herding and Contagion

Linking herding and contagion helps one to analyze the two phases of crisis transmission. It has been noted that there is rapid international transmission of shocks even if the economic linkages between the countries are weak. One of the reasons for this is explained as pure contagion and is attributed to herding, which arises out of informational asymmetry or informational inefficiency due to the failure in collecting data regarding the macroeconomic fundamentals about different markets. In literature, we can see many studies which explain the role of herding in contagion effect.

Khan and Park (2009), who tested the presence of contagion effect by analyzing the cross-country time-varying correlations among the stochastic components of the stock prices after controlling for macroeconomic fundamentals and global shocks among five Asian countries during crisis and tranquil periods, explained that herding contagion is principally caused by factors that are independent of economic fundamentals. Based on the view of Keynes (1936), Baddeley (2010), by analyzing Akerlof and Shiller's animal spirit, explained that the crisis or bubble will spread via storytelling, word of mouth and false intuitions feeding herding and contagion, i.e.

contagion resulting from herding behaviour need not depend on macro-economic factors.

Different methods used in the literature to examine the contagion effect and the effect of herding driven contagion is determined through comparing the time varying correlation between the markets during different periods. If there is a change in correlations, i.e. the correlation during crisis period is significantly higher than the historical correlations, it is expected that market sentiments have shifted and herding has affected the behaviour of investors.

It is noted that the main reasons for herding driven contagion is the information asymmetry, information frictions or non availability of information and the panic among the international investors during crisis. Further the “fear of being different” (See Calvo and Mendoza (2000), the reputational costs, variable costs, irrational excitement, rumors, loss of confidence in the country's economic prospects and the risk involved in investments lead the investors to observe the movements and price changes in the market and to mimic others’ actions.

Cipriani and et.al (2008[a]) showed that informational cascades could spread from one market to another, generating financial contagion. Informational spillovers are to be expected between correlated asset markets and he attributed the effects of long-lasting information spillover and informational asymmetries to the contagion effect and explained that the cascade in one market generates cascade in another market, which ultimately pushes the prices, even in the long run from the fundamentals.

Generally the cross correlation between economies are likely to originate from shock to the fundamentals of one country and is transmitted to the fundamentals of another country through one or more channels. A large number of researchers have pointed out that even if the fundamentals are strong, market imperfection or imperfect information will bring crises.

Irrational and speculative investors will boost such imperfections and finally it will lead to the collapse of the system. Eichengreen and et al. (1995) observed that during ERM[28]-crisis, the speculators and investors played an important role in boosting the

28. Exchange Rate Mechanism crisis-1992-93 , created a havoc between countries in the European union

crisis and only in few cases; the attack could be justified by the heterogeneous macroeconomic fundamentals, which point to the role of sentiments in boosting the crisis. Chiang and et.al (2007) explained the link between contagion and herding behaviour as “the spread of shocks from one market to another with a significant increase in correlation between markets, while herding describes the simultaneous behaviour of investors across different markets with high correlation coefficients in all markets”.

1.10. Summary

During the last two decades, the interest in capital markets has increased enormously throughout the world especially in developing countries. The stock market is being one of the major sources of long-term finance for industrial projects and provides ample opportunities to the investors. Different types of instruments, the large number of securities helps an investor to diversify his risk, and at the same time, it creates complexity in identifying the best investment opportunity. The progress and potential of the market have attracted many investors and researchers to discuss a number of issues and complexities in the market.

Transition in the financial market over the last two decades has been very fast and is still keeping its pace in terms of growth, expansion and absorbing technology and innovations. During this decade, it has been observed that market has been gradually transforming the investor’s landscape and the institutional investors decide mostly the movements of the market. Both foreign institutional investors and domestic institutional investors play an important role in emerging and developing markets all over the world. The brunt of the institutional investment on capital markets constitutes highly volatile and unpredictable market conditions and often the investors are unable to predict the movements of the market and these ultimately lead to sentiments and to the show of different behaviours in the market.

In the beginning of the 1980s, behavioural finance challenged the predictions of efficient market theorem and a large number of explanations have been offered by the theoretical and empirical studies for the different empirical discrepancies. Behavioural finance developed theories based on the social, psychological or cognitive and emotional biases to explain a number of stock market anomalies. These concepts argue that the information structure and the characteristics of investors systematically influence their investment decisions and thereby the market movements and asset prices, often destabilize the market and lead to market inefficiency. Behavioural finance attempts to fill these gaps by exploring the relationship among cognitive or psychological factors which lead to market inefficiency and asset mispricing.

Daniel Kahneman, Amos Tversky and other behaviourists have criticized the rationality- based finance theories with the cognitive-based decision making experiments and have showed how individuals' cognitive or psychological issues systematically affect the market and misprice the value of an asset. They raised the issues of biases under uncertainty, the prospects theory and the framing effect etc and questioned traditional financial theories and the fitness of the theories at least during certain particular conditions of the market. Further a large number of researchers like Shiller, Thaller , Lakonishok, Banerjee, Bikhchandani and Barbera etc and their studies explored different kinds of human behaviour and showed how they destabilize the market and contribute to mispricing of assets.

Further, a number of studies have revealed that, institutional investment in capital markets in many cases contributed positively in intensifying the magnitude and significance of herding especially in emerging markets. A large number of studies have found that during periods of extreme market conditions, the price volatility increases and the investors generally show the tendency to imitate others and they may herd towards the market consensus. Similarly in many cases the crisis is contagious because of the herding behaviour shown by the investors in the market. Today the market is highly complex, highly volatile and unpredictable. Cost of information is more and there is informational asymmetry in the market. Hence, a simple mistake and lack of knowledge may lead to loss of money. This will also persuade investors to follow the crowd even though they have their own private information.

CHAPTER- II

REVIEW OF LITERATURE

2.1 Introduction

Investors show varied number of behaviour in the financial market and it also varies with different states[29] of the market. The set of behaviour emanating from the investors in different market situation and its consequences in the market are explained by the behavioural finance. This branch of finance analyses the cognitive and psychological issues related with the investment decisions and explains the various issues with the help of human psychology and financial theories. It stresses the view that investor's emotion has a major role to play in the market movements and this can lead to mispricing of assets. Until 1990's modern financial theories mostly ignored the role of psychological and cognitive aspects of the investor's in decision making and their ultimate effect in the pricing of assets.

The theory of efficient market hypothesis (EMH) suggests that; information quickly gets assimilated in financial markets and is incorporated to the price of assets, hence there is less chance to take the informational advantage in the market, Fama (1965), Samuelson (1965).On the other hand, financial markets (especially developing / emerging) are inefficient and the information are not timely incorporated for price adjustments. Investors often act irrationally and their emotions lead them to erroneous decisions. Hence, ignoring human elements in decision making will make the judgments incomplete.

Market reflects the sentiments of investors and any challenge taken to quantify the emotional content of the market will add value to the researches in financial market. Recognising how investors behave in different market conditions and its allegation in the financial market will help in understanding the investor's decision making process as well as the regularity/irregularities in the market. The irrationality of the investors in decision making raises many behavioural issues in the market. It has been empirically and theoretically proved that, many anomalies of the market are because of the irrational behaviour of the investors, Thaler (1991). Number of

[29] For example up and down, high and low states of the market

researches offer behavioural explanations to many of the anomalies in the market and has been documented by the researchers in different contexts. For example, Tversky and Kahneman (1972), Heuristics and biases, Delong and et al. (1990), noise traders risk, Thaler (1991), Fama and French (1998), Market efficiency - long term returns and behavioural finance, Odean (1998), overconfidence are some of them.

The behaviour of investors is often irrational and these factors often play a significant role in financial market. Herding is one of such behaviour found in both developed and developing markets and is often used to describe the correlation in trades, which comes out of the interaction among investors or simply mimicking others in their actions or decisions. A stock market with increased level of herding will infuriate the market and raise the level of inefficiency. *Bikhchandani and Sharma (2001), Hwang and Salmon (2004)* noted that, the herding can be unintentional or intentional and the unintentional herding contribute to the efficient reallocation of assets, whereas later leads to market inefficiency and may further results to long-term/ short-term mispricing of assets or in spreading crisis or formation of bubbles.

The existence of an efficient financial markets itself is a symbol of economic stability, where it is biased, less sophisticated and led by irrational investors, who ultimately makes investment costly and thereby unattractive, uncompetitive and more risky. An efficient market incorporates the information available in the market and accordingly adjust price of the assets to their fundamental values. Whereas, when it is driven by herding, the price will deviate from the fundamentals and leads to inefficiency.

The behavioural researchers as well as the researchers in finance in general have raised the issue of intentional herding by the investors continuously over the last 20 years. It is true that academic work on herding behaviour is very few until recently. However since 1990's there have been attempts by many researchers and practitioners to analyses the various ramifications of herding behaviour and its impact on different markets and market situations throughout the world. This is an attempt to explore the various researches related to the herding behaviour and is organized to bring the different issues discussed in the literature

The researches in herding behaviour can be estranged into different heads. This chapter correlates various antecedents of different studies on herding behaviour, the important methods developed to the date to measure the herding behaviour, the influence of herding behaviour in the market, the factors controlling the herding behaviour, institutional or individual investors herding behaviour, the reputational herding and the role of herding behaviour in spreading crisis and the last part highlights the research gaps.

2.2 Measures of Herding Behaviour

There are several approaches to measure the herding behaviour in stock markets. Some of them theoretically explains the herding behaviour where as some others empirically proves the existence/absence of herding behaviour in different markets. The theoretical approaches on herding behaviour have been developed by the researchers like *Scharfstein and Stein (1990), Bikchandani and et al. (1992), Banerjee (1992), Devenow and Welch (1996), Avery and Zemsky (1998)*, and so on. *Shiller and Pound (1986)* used a survey approach to measure the institutional and individual investors herding behaviour. *Cote and Sanders (1997)* utilized the field experiment to analyze the herding behaviour of forecasters and *Gonzales and et al. (2006)* used an experimental study by stimulating the behaviour of managers and directors. Applying a new method *D-Bondt and Forbes (1999)* analysed the behaviour of analyst's disagreement in decision making.

Lakonishok and et al. (1992), known as (LSV) measure, the measure proposed by the *Wermer* in *(1995)* based on the portfolio changes, the measure developed by *Christie and Huang (1995)*, the method extended by *Chang and et al. (2000)*, the measure proposed by the *Hwang and Salmon (2001,2004,2006), Hachicha and et al. (2008)*, and *Hachicha (2010)*, are some of the measures developed or extended to empirically explain the existence of herding behavior in the stock markets. These methods are widely used to explain the market wide herding or the behaviour of different group of investors such as individual or institutional, analysts or the fund managers. This section recapitulates different methods used to explain the herding behavior and will concentrate mainly on the empirical methods of herding measure available in the literature.

The seminal papers of *Scharfstein and Stein (1990), Banerjee (1992), Bikhchandani et al. (1992)* and *Welch (1992), Barberis and Shleifer (2001)*, etc., explained the herding behaviour in the context of cascades, payoff externalities, reputational concerns and fads, where as *Froot and et al. (1992), Hirshleifer and et al. (1994)* explained about the investigative herding, which arises when investors follow the same signal or the same source for the information and as a result it is found that the actions of the investors are positively cross-sectionally correlated. *Del-Guercio (1996), Falkenstein (1996)* noted another important sign of herding, known as characteristic herding, that arise when the investors have preferences to securities with certain characteristics.

Shiller (2001) explained the social psychological theory of herding and some of his studies also explained the social aspects of stock market bubbles and fads. *Scharfstein and Stein(1990)* introduced a reputational model and explained the herding behaviour with the case of managers who make individual investment decisions, where they are motivated with implicit incentive rather than the pay off. The reputational herding arises when managers face a reputational cost by acting differently from the crowd.

Banerjee (1992) developed a simple sequential decision model of herd behaviour by examining the rationale behind the decision making and its implications. In his experiment the subjects were provided with three information states, a correct, wrong and no information and also used three tie breaking rules in the decision making process and found that, if the first two players choose the same action, the subsequent players will also follow them without considering their own available information.

Bikchandani and et al. (1992) and Welch (2000) introduced a model based on the informational cascade and considered a settings with a continuous signal space, "were people follow the actions of others and rationally ignore own private information. This happens when there are finite limits to agent's private information and possible actions", *Avery and Zemsky (1998), Welch (2000)* used a sequential trading model to show that, herding in the market depend on the uncertainty in fundamental values of the assets as well as the proportion of the informed traders, i.e. the occurrence of an information event in the market and is found, eventually if the prices are correctly set as per the order flow, that the investor will not herd in the market.

Bikhchandani and et al. (1998) explained that information precision, preference and payoff, changing tastes and payoff, costly information may lead to informational cascades. The study pointed out how learning by observing the past decisions of others can help in explaining the convergence of human thoughts and show similar behaviour and illustrate how mass behaviour prone to errors and fads. *Morone (2012)* extended the model proposed by Banerjee (1992), by introducing a new assumption, "Whenever the first decision maker has no signal, he/she chooses randomly an action from the set of all possible actions and observes the changes in the subjects decisions" instead of the first assumption of Banerjee in his work "Whenever a decision maker has no signal and everyone else has chosen zero, he/she always chooses zero". Their test introduced a different proposition and found that herding model under the two assumption sets was identical and player's strategies are parameter dependent, even if the equilibrium is characterized by extensive herd behaviour and a breaking in herd behaviour is thus possible. Further private information will not be systematically ignored in the presence of a queue and concluded that an incorrect herd could be reversed and a correct herd is irreversible

Lakonishok and et al. (1992) developed a new approach based on the trades carried out by portfolio holdings and other trade related information of institutional money managers of US market. *Wermer (1995)* designed a portfolio change measure (PCM), based on the changes in portfolios, where the intensity of market participant's beliefs was captured by the percentage change in the fraction accounted by a stock in a fund portfolio. For this, he considered factors like direction and intensity of trades and the method is helpful in understanding both the direction and intensity of trading by investors and capable to found a significant level of herding behaviour by mutual fund managers. *Nofsinger and Sias (1999)* examined herding behaviour based on the ownership change in portfolio. The above studies considered the trading information of investors and the details of the changes in the investor's portfolios to measure the herding behaviour.

In addition to the above studies *Christie and Huang (1995)* developed a new measure to explain the market wide herding behavior. For this he compared the portfolio return with the magnitude of cross-sectional dispersion of individual stock returns and explained that herding will be more prevalent during the period of market stress or during the period of high volatility. By using a least squares estimators, it is narrated as a negative coefficient of the squared market return, that suggests the existence of herding behaviour in the market, where "the dispersion should increase at a decreasing rate", i.e. the dispersion of return (cross-sectional standard deviation) will be relatively less when the individual investors show herding behaviour towards the market consensus. Their argument is in contrast with the theories of rational asset pricing models, which explains that, there will be an increase in dispersion with the absolute value of the market return during the period of high price movements or market stress and this is explained by the theory as, during periods of large price movements, the investors ignore their beliefs and solely depend on the market consensus.

Chang and et al. (2000) extended the method proposed by Christie and Huang (1995), by using the absolute mean deviation of return instead of cross sectional standard deviation of return and beta of assets to measure the herding behaviour. The model explained the non linear relationship between the dispersion of individual stock return and return of an equally weighted market portfolio and was explained with the conditional CAPM. The above two methods explain that, during the period of market stress or high volatile period, investors tend to suppress their own beliefs and try to follow others in the market. Hence, the decisions of the investors are likely to be based on the collective actions in the market. As a result, the individual stock returns tend to cluster around the overall market return. Hence, herding will be more prevalent and stronger under extreme market conditions or the periods of market stress.

Hwang and salmon (2001) developed a new measure, to examine the herding behaviour based on a linear factor model similar to the measure developed by the Christie and Huang (1995), which is capable of accessing market wide herding. The proposed method is based on the variability of factor sensitivities of assets rather than the individual returns of the assets and is capable to examine the information content in the cross-sectional market movements. The model also explained that if the investors show herding behaviour toward the market portfolio, then the cross-sectional variance of the estimated betas would decrease. Hwang and Salmon (2004) analysed the herding behaviour using cross sectional dispersion of market betas of individual assets. They used the concept of disequilibrium CAPM to measure herding behaviour based on the cross sectional variance of factor sensitivities of individual securities in the market, which controls the effects that might occur due to changes in fundamental variables but it considers the expectations on the market as given and hence helps to account spurious herding behaviour.

Gleason and et al. (2004) extended the methodology proposed by the Chang and et al. (2000), and used absolute deviation of return by suspecting the accuracy of beta proposed by Chang and et al. (2000). Based on the changes in correlation on the institutional holdings, *Sias (2003)* addressed the question whether the institutional investors herd in the market.

Hachicha and et al. (2008) proposed a new measure to examine the herding behaviour based on the concept used by Hwang and Salmon (2004), the cross sectional dispersion of the beta. The new model, employed the cross sectional standard deviation of market volatility instead of using the beta. *Amirat and Bouri (2009[a])* developed a herding measure based on the cross sectional dispersion factor sensitivity of volume and justified it by stating that “If the investors are behaviourally biased, their perception on the risk-volume relationship of asset may be distorted”. The method can be further explained thus; if there is herding behaviour towards the market consensus, the trading volume of individual asset may follow the direction of the market and the betas will deviate from their equilibrium values. Hence, the cross sectional dispersion of the asset beta can be expected to be smaller.

Yalamova (2009) demonstrated a scale dependent topological structure of trader's network in the stock market, which helps to follow the dynamics of self organization in the market and enable it to quantify the connectivity and herding patterns among traders which ultimately leads to bubble and crash in extreme market conditions. *Hachicha (2010)* developed a new measure based on trading volume, which is capable to measure herding based on the cross sectional dispersion of factor sensitivity of volume. Their model explain that, if the investors herd towards the market movements, it will affect equilibrium relationship between the risk and volume that exists in the conventional Capital asset pricing model and explain that if there is herding in the market, shift of the investors belief to follow the market will be more pronounced and this will cause the betas and the expected stock value to become biased.

Cipriani and Guarino (2012) developed a structural model of herd behaviour in financial markets based on the market microstructure. They estimated the model parameters through maximum likelihood and used Nelder Mead simplex and the Genetic Algorithm and identified the days on which the informed traders herd. *Bhaduri and Mahapatra (2013)* introduced a threshold regression approach to examine the herding behaviour. They extended the method proposed by Chang and et al. (2000), to capture a nonlinear effect of extreme market movement based on the investors trading behaviour in Indian stock market. This method is based on return dispersions among a group of securities and used symmetric properties of the cross sectional return distribution to find out the existence of herding behaviour in the selected market. The study used the difference of cross-sectional absolute mean and median (CSMMD) to capture the symmetry in the aggregate return distribution and is explained through the cross-sectional average and median of the returns of aggregate market portfolio at time t.

In addition to the above methods, there are number of measures which are used to explain the herding behaviour in different markets. The method developed by *Wermer (1999), Cont and Bouchaud's (1997),* the percolation model, to examine the herding of noise traders, which considers the fundamental value of the traded object as well as the behaviour of other traders. The stylized model introduced by *Abreu and Brunnermeier (2003),*the method explained by *Caetano and Yoneyama (2011),* using the allegory of interacting particle to elucidate the contagion and herding behaviour of financial agents leading to the formation of clusters are some other models used to explain the herding behaviour in the financial market.

While analysing the literature one can see that there are many criticism about these models. As a common limitation, most of the model explained have failed to distinguish the rational and irrational herding behaviour in the market; i.e. to distinguish the mimicking behaviour of investors from the price movements due to change in fundamentals. While considering the LSV model, *Bikhchandani and Sharma (2000)* pointed out two limitations and is explained as it considered only the number of managers on the buy and sell side of the market and did not consider the stocks they buy or sell to measure the extent of herding behaviour in the market. The second limitation as noted by their study is that the measure cannot be used to examine whether the managers constantly be inclined to herd others over time. Some other authors have pointed out further limitations, like, the measure (LSV) does not explain whether the herding results from the imitation or else it arises when the traders use the same source or same type of information. It is also noted that, the measure will be biased when there are limitations to short selling strategies, in such situations the measure overestimates true herding and the method need a very detailed records of different sets of data.

The measures proposed by *Christie and Huang (1995), Chang et al. (2000)* and *Gleason and et al. (2004)*, explains that herding behaviour among investors may be more during the periods of market stress. *Hachicha and et al. (2008)* noted that, the method of Christie and Huang (1995) was criticized for using dummy variable and it failed in defining the market stress, since it does not necessarily show either negative or positive return. In addition, some other important criticism raised by different authors against the measure are; it does not take in to account the movements in fundamentals, generally considered as the reason for the change in price and the measure used in the model; the cross-sectional standard deviation of individual return is not independent of time series volatility, *Hwang and Salmon (2001), Hachicha and et al. (2008)*. The results provided by the methods under discussion are static and allow examining for specific periods and there by one cannot explain the evolutionary nature of herding behaviour. *Khan and et al. (2011)* noted that, "the absence of control mechanisms of the different movements in fundamentals makes detection of herding difficult".

Hwang and Salmon (2001) criticized the Chang and et al. (2000), methodology by explaining that, the measure neither considers the time varying properties of beta in the CAPM nor the herding towards the other factors which might influence the assets return. In addition the study also pointed out that most of the studies like Lakonishok and et al. (1992); Christie and Huang (1995), Wermer (1995), Chang and et al. (2000) have tried to identify herding in absolute terms.

Another important limitation which is pointed out in the literature is the use of dummy variable to differentiate the extreme market condition since these methods does not control for movements in fundamentals. *Hwang and Salmon (2004)* and *Hachicha and et al. (2008)* noted that, "it is difficult to conclude that whether it is herding or independent adjustment to fundamentals". Based on the studies of Hwang and Satchell (2002) and Goyal and Santa Clara (2003), *Hwang and Salmon (2004)* argued that, "even a negative relationship between the cross sectional standard deviation of individual stock return and the dummy variable, one cannot surely say that the variations are due to the changes in volatility or due to herding".

The method introduced by Hwang and Salmon (2004) was criticized by the joint hypothesis they used in their measure, for the measure they based the concept capital asset pricing model, developed on the principle of efficiency of the market, whereas the herding shows the market inefficiency. In addition, there are many factors, such as market microstructure, which cause the systematic risk of the market and may result a deviation of the market risk from unity in addition to the herding behaviour *Hachicha and et al. (2008) and Hachicha (2010)*. This can be explained as, if market wide herding exists, the cross-sectional dispersion of the stock betas would tend towards the market beta, unity.

The measure proposed by *Hachicha and et al. (2010)* is also not free from criticism. It has been argued that the measure used, "trading volume", in the model is not necessarily a proxy for herding behaviour because of the reasons that herding behaviour denotes the asymmetry in buy and sell, rather than the fluctuations in the trading volume. Secondly the herding is more during the overreaction phase and the variation in trading volume may be higher in the under reaction phase based on the behavioural influence and the variations in trading volume may be used to explain the discrepancy from the efficient pricing and may not likely contribute to herding.

While analysing the different measures, it is clear that, none of the models are free from criticism. This study plans to use the method proposed by Hwang and Salmon

(2004) to detect the herding behaviour in Indian market, since as explained by Hwang and Salmon (2004), this method is able to consider herding due to the market sentiment from the movements or adjustment to fundamentals news and to extract the latent herding component in the asset returns. In addition, the concept used in this method, the linear factor models can also explain that the market may herd in addition to the market factor and hence the measure can control the information about the fundamentals by explaining the herding behaviour through the cross sectional movements in the betas rather than the factor return themselves as it is used by the Christie and Huang (1995), or Chang and et al. (2000). In addition to the above measure the study will also use the extended measure of Chang and et al. (2000) proposed by Gleason and et al. (2004) to examine the herding behavior in the studied market.

2.3 Rational and Irrational Herding Behaviour

The cannon concept of herding behaviour asserts that, it is driven by the rationality / irrationality of the investors and it can seriously influence and create chaotic situations in the market. In the literature, one can see two types of herding behaviour, one based on the rational decision and the other on irrational decisions, *Devenow and Welch (1996)*. The intentional herding arises when the investors tend to herd with a view to protect their own interest and the investors follow others to benefit from the market and is inefficient. Unintentional herding (spurious) arises when group of investors faces similar decision problem and accordingly end up with similar decision. *Scharfstein and Stein (1990), Bikhchandani and et al. (1992), Banerjee (1992), Devenow and Welch (1996), (Christie and Huang (1995), Nofsinger and Sias, (1999), Shiller (2000))* are few among those who explained this fact. It also noted that many studies pointed out the difficulties in differentiating the spurious herding from intentional herding behaviour. *Bikhchandani and Sharma (2001)* noted that this might be possible to separate unintentional herding by explicitly allowing changes in fundamentals. At the same time, he also noted that it is hard to do so because of two reasons, i.e. in defining and quantifying the fundamentals.

2.4 Herding Behaviour in Literature

Banerjee (1992) explained herding behaviour in the context of inefficiencies of information externalities and examined the rationale behind the decision making in the context of social learning and showed that investors will base their decisions largely on the observed decisions of other agents. Whereas *Bikhchandani et al. (1992)* noted that the herding is driven by the actions of first few decision makers and explained that informational cascade occurs when the investor avoid own private information and try to follow others in their action or when follows a 'fashion leader' (fads) instead of a group by believing that the former have better information than others. The irrationality of the investors, information cost, *Scharfstein and Stein (1990),* speed of information assimilation, *Sullivan (1999)* or the effect of changing signal precision, reputational reasons, *Scharfstein and Stein (1990),Trueman (1994),* market performance, volatility, investor psychology and the sense of security, certain events in the market such as bubbles, *Khan and et al. (2011*), informational cascade, *Becker (1991), Bikhchandani et al. (1992),* investors preference towards a stock of with certain characteristics, transactional or search costs, *Scharfstein and Stein (1990),* consumption externalities and social influence on pricing, *Khan and et al. (2011)*,information asymmetry, *Kermer and Nautz (2011)* prior beliefs of investors are some of the reasons which lead to herding behaviour.

Literature also shows that the sentiments may be driven by the statistics of ups and downs in the market, news, lack of information, fear, speculation, rumors, crashes and expectation of another crash in the markets, changes in the international markets, Shocks in the market, the bear counts and the sentiments. All these play important roles in the decisions of investors and hence may lead to herding behaviour. Further, the low transparency, low credibility and informational uncertainty in public information will also lead to herd behaviour and often it is attributed to the variation in the cognitive abilities of individuals.

Devenow and Welch (1996) noted that investors may tend to herd in anticipation of informational payoffs and the herding may be based on the same external information or on the coordination among individuals acting in the same direction by following the mass without adequate analysis. *Drehmann and et al.(2005)* examined the herding behaviour based on the theory of informational cascade through an internet experiment by using a sample of more than 6,400 subjects from different groups of different discipline and profession and explained that presence of flexible market price prevents herding. *Kulttiy and Miettinen(2006)*, applying Sgroi's (2002) approach, compared the results in the situations where the information was provided for cost as well as at cost free and found that results are not robust to small changes in the cost of observing other agents' actions. If the incentives are sufficient to pay the observation cost, then a herd gets started after the third agent with probability one and if there was no sufficient incentives for the third agent to exist, then all agents will go for independent decision.

Carbone (2010) analysed the ownership (social) herding and informational herding with the help of an experiment by using the measure proposed Bikhchandani et al. (1992) and the design proposed by Anderson and Holt (1997), by adding the acceptance decision. The study examined whether the betas of the players are a function of the number of previous acceptances and found that social herding was vital, but it does not induce more herding, but lack of ownership induces less herding.

Blasco and et al.(2012[b]) used intraday trading information over the period from Jan.1997 to Dec. 2003, and applied the method proposed by Patterson and Sharma (2006) and found increase in the intensity of herding during the down market conditions and high intensity of herding leading to greater volatility. The study also noted that, it is same in the case of historical and realized volatility but for implied volatility, where the influence of herding effect was closely related to the expiration dates in option markets as well as the option trader's behavior n Spanish market.

2.4.1 Herding Towards Market Consensus

Christie and Huang (1995) developed a new model and used daily data of NYSE and Amex for the period from July 1962 to 1988, and monthly data of NYSE from Dec. 1925 to Dec. 1988. Both data sets did not show herding during periods of large price movements or market stress. *Chang and et al. (2000)* using an extended methodology proposed by Christie and Huang (1995) and using daily data (the period varies 1963 to 1997 for different countries) found that herding behaviour was not present in US and Hong Kong markets during periods of extreme price movements but found significant herding for South Korea, Taiwan and partial evidence of herding in Japan.

Hwang and Salmon (2001), using a new approach, found herding behaviour towards the market portfolio and explained that herding behaviour is more prominent in emerging market (South Korea)as compared to the developed markets like US and UK and herding was more before a crisis and it became weaker during the crisis period. *Lin and Swanson (2003)* used daily data of 60 large sized firms of Taiwan's equity market over the period from Dec.1996 to Jun. 2003, but did not find evidence for herding towards market consensus. Where as in another study Hwang *and Salmon (2004)*,using the cross-sectional dispersion of monthly CAPM and Fama French betas of S&P 500 and KOSPI index data from1993 to Nov 2002,found existence of herding towards the market consensus in both bull and bear market conditions. The study found less herding during the Asian and Russian crisis and was less pronounced while comparing with the other periods and suggests that efficient pricing may helped by market stress.

Caperrelli and et al.(2004) applied the measures of Christie and Huang (1995), Chang and et al. (2000), Hwang and salmon (2001) and used the Italian stocks data from Sept. 1988 to Jan. 2001, the study found presence of herding during extreme market conditions. *Demirer and Kuttan (2006)* used firm level and sector level data from May.1993 to Nov. 2001and applied the method of Christie and Huang (1995), but did not find evidence of herding behaviour at firm level as well as sector level in Chinese market.

Hachicha and et al.(2008) used monthly stocks data of two Tunisian stock exchanges BVMT and TUNINDEX over the period from 1999 to 2005 and by applying a newly developed measure based on volatility in addition to the methods of Christie and Huang (1995), Chang and et al. (2000), Hwang and Salmon (2004) and found evidence of herding with the first and fourth measures. The study noted that the return causes the herding phenomenon for the two indexes, and the herding behaviour occurred as result of increased risk and trading volume. *Tan and et al. (2008),* using the extended methodology of Gleason and et al. (2004) found herding present in A-share and B-share markets of Shanghai and Shenzhen stock market during rising and falling markets. It is also noted that both institutional and individual investors herd in the market but the weekly and monthly data showed weaker evidence suggesting that herding was confined to short periods. *Zhou and Lai (2008)* used the method proposed by Lakonishok et al. (1992) to test the herd behaviour and compared the effect in property stocks and non property stocks by using inter day and intraday data. The study used stock data of the HSCI over the period from Jun. 2004 to Dec. 2005 and for intraday tests used a similar approach to Ghysels and Seon (2005) and found that both the inter day and intraday investors herd less in property stocks relative to other sectors.

Amirat and Bouri (2009[a]) examined the presence of individual investors herding behaviour in Toronto stock exchange by using 60 large, liquid Canadian stocks of S&P/TSX60 and the data covers from Jan 2000 to Dec 2006. The study applied the models proposed by Lakonishok and et al. (1992), Hwang and Salmon (2004), Christie and Huang (1995), Chang and et.al (2000) and the first two models showed evidence of herding while the other two did not exhibit herding effect. *Balsco and et al.(2010)* examined the intentional herding behaviour of Spanish equity market participants through a modified methodology by Blasco and Ferreruela (2008) in addition to different measures of herding and used the intraday trades carried out from Jan.1996 to Dec. 2003. The study also repeated the test with daily data of (10%), heavily traded stocks and found different results for different measures and suggested that herding is better revealed with intraday data. *Barber and et al. (2009)*, using tick-by-tick transaction data for US stock markets over the period 1983–2001, used the herding measure of Lakonishok and et.al (1992) and found strong herding by individual investors. The study also observed that trading preferences of individual investors are more persistent and coordinated.

Naoui (2010) analysed whether investors in Dow Jones index suppress their own prediction of stock’s future price and base their opinions on market consensus during extreme fluctuation periods in US stock market. Using the data of 25companies over the period from Jan.1987 to Dec.11, 2009 and applying the method suggested by Christie and Huang (1995) and the model proposed by Chang and et al. (2000) found that herding was present in the studied market. *Houda and Abdelfettah (2010)* used 10 years weekly data ranging from1996 to 2006 and methods proposed by Christie and Huang (1995), Chang and et al. (2000),Hachicha and et.al (2008) and found herding with the third measure in the Tunisian market. The study also verified the predictability of the CAPM model by including herding as an additional variable. Using weekly data of 101 stocks over the period 1990-2009, *Fernandez (2010)* examined the existence of herding in different industrial sectors of Chilean stock market by applying a similar measure of Christie and Huang (1995), Gleason et al. (2003,2004) found existence of herding behaviour in individual stocks in the studied market.

Chiang and Zheng (2010) used daily data from May 1988 to April 2009 and the methods proposed by Christie and Huang (1995) and Chang et al. (2000) and found that herding was present in advanced markets except US and Latin American markets out of 7 developed markets, 4 Latin American and 7Asian markets studied. *Chiang and et al. (2010)* investigated herding behaviour on aggregate market with dual listed shares and also for A & B markets at different market conditions by using daily return data of 1618 firms listed on the Shanghai and Shenzhen stock exchange for the period Jan.1996 to April. 2007. Applying the methodology of Chang et.al (2000) and a quantile regression approach, found herding behaviour in both the Shanghai and Shenzhen A-share markets but no evidence for herding found in B-share markets and dual listed firms. *Belhoula and Naoui (2011)*, applying the methods proposed by Christie and Huang (1995) and Gleason and Lee (2003) used the weekly data of American companies listed on the Dow Jones index for the period from Jan 1987 to Dec 2011 and found the presence of herding and opined that the investors tend to suppress their private information to follow average market behaviour. *Lao and Singh (2011)*, using the Chinese and Indian data for the period Jul.1999 to Jun. 2009,used the approach of Tan and et al. (2008) found that herding behaviour was greater in the Chinese stock market than Indian stock market and this behaviour was more visible for both markets during large market movements. The test for the presence of herding during the crisis period (1st Jan -2008 to 31st Dec-2008) showed that significant herding in Chinese market but no herding found in Indian stock market.

Khanna and Mathews (2011) used a multi stage model of herding with endogenous information production and multistage decisions and showed that herding behaviour can in fact improve the quality of information that inferred at a given time from a previous decision, particularly while decision makers are considering entry into a market characterized by significant product innovation, where future investments in effort, monitoring, advising, or capital are likely to have significant value consequences.

Khoshsirat and Salari (2011) examined the presence of herding at aggregate market level as well as within nine selected industries of Tehran Stock Exchange by applying the method of Christie and Huang (1995), Chang et al. (2000) from April 2001 to July 2009, but did not find enough empirical evidence for herding in the aggregate market and were able to find herding only in automobile and mineral industries. *Holmes and et al. (2011)* examined the existence of herding behaviour and window dressing using monthly holdings of individual funds in the Portuguese market at different market conditions over the period of 1998-2005 and found herding when the market is declining. In addition, the herding coefficient was found to be significant during the post regulation period and during the second month of each quarter, but not during the first or third month within a quarter. *Economou and et al. (2011),* using a survivor bias free data set of daily stock returns for the period Jan.1998 to Dec.2008 and applying the methodology of *Chang and et al. (2000)* found presence of herding behaviour in Greece and Italian markets but no evidence found for spain and found mixed result for Portugal. The financial crisis did not induce more intense herding behaviour in any of the four markets studied.

My and Troung (2011) examined the existence of investor's herding behaviour in Vietnamese market by adopting the methodology used by Tan and et.al (2008) and used the measure of Christie and Huang (1995) for robustness tests. Based on the market development the test were conducted for the whole period and also for two sub periods covering March 2002 to Jan. 2006 and from Jan.2006 to July 2007 and found the presence of herding regardless of the periods tested and the models used. *Khan and et al. (2011)* examined the herd behaviour using the models advocated by Hwang and Salmon in (2001,2004 and 2008) by using securities market data of France, United Kingdom, Germany and Italy (four European) and the result showed the existence of herding behaviour around the market performance in all countries except during the periods of market turmoil and crisis. *Prosad and et al.* (2012) analysed the existence and the nature of herding behaviour in Indian stock market by applying the methodology adopted by Christie and Huang (19950 and Chang et al. (2000) and find low level of herding in Indian market and opined that Indian market is efficient.

Mixed result of herding behaviour was found through the literature. Further, it is also noted that the developed markets like US and Japan showed either less herding or no herding behaviour, whereas most of the developing markets showed herding behaviour in almost all the cases with some exception. Studies by Chang and et.al (2000) on the stock markets of South Korea and Taiwan, Chen, Hwang and Salmon (2004) on South Korea, Kallinterakis and Kratunova (2007), Duasa and Kassim (2008) on Malaysia stock market, Lao and sing (2011) on China and India are some of the studies which found herding behaviour in different developing markets. In addition, Degirmen and et al. (2012) noted that rational herding is more in developing countries. While many authors who examined the presence of herding behaviour in developed markets often fail to found the herding behaviour in such markets. Christie and Huang (1995), Chiang et al. (2000), Hwang and Salmon (2004), on US market and Henker et al. (2006), on Australian market are some of the studies which found no herding or a very low herding behaviour in developed markets.

In addition to this, in most of the cases the measure proposed by the Christie and Huang (1995), and in few cases the measure proposed by the Chang and et al. (2000) failed to find herding behaviour in the tested markets. The tests, by considering the crisis period and other sub periods also showed mixed results, raises the need for testing the existence of herding behaviour in each market before predicting the possibility of herding behaviour in a particular market.

2.4.2 Pattern of Herding Behaviour

The behavioural finance help us to look from a different angle to understand the financial theories in the context of varied number of human behaviour, which arise out of the interactions of human beings. Behavioural asymmetry has been observed in human being and his decisions and actions often depends on his thoughts, the surroundings, experience and the availability of information for decision making. Understanding investor’s behaviour and decision making process will help in understanding many regularity/ irregularities in the market.

In herding literature many studies pointed out the asymmetries in the pattern and the variation in the intensity of herding behaviour based on different periods, policies and different states of the market, say for example high or low states of return, volume or volatility, the crisis and non crisis period and so on. The theoretical base of these concepts was explained by the studies Christie and Huang (1995) and Chang et al (2000), who explained that the herding behaviour may be observed more during the period market of stress. In addition the asymmetry explains that herding was more prevalent in the extreme down markets when compared to the extreme up market conditions. The literature explains the fact that investors get panic in extreme down market conditions. This section will recapitulate evidence from the available literature explaining asymmetries in the pattern of herding behaviour, the nature of asymmetry reported, the tools and method used in the previous studies and reproduces the logic they explained for this. It is believed that these can greatly support the understanding how people react to the diverse situations and the pattern of herding behaviour based on the different market condition or the states of the market.

While analysing the literature on the pattern of herding behaviour, one can see mixed evidence and often the results varies for different markets. Lakonishok and et al. (1992) examined herding conditional on past performance of the stocks, which revealed week indication for more herding in better performed stocks and less herding at industry level than at individual stock level. Using monthly and daily data of NYSE and AMEX, Christie and Huang (1995) reported asymmetry in herding behaviour and found a relatively high herding during extreme up markets and the results are inconsistent with the presence of herding during down market. Hwang and Salmon (2001) pointed the asymmetry in herding behaviour between the developed and emerging markets and the intensity of herding behaviour appeared to be relatively low for United States, United Kingdom whereas as it was high for South Korea during the Asian and Russian financial crises of 1997 and 1998, respectively. Further, the intensity of herding was more before a crisis and it became weaker during the crisis period.

Gleason and et al. (2004), using 15 minutes tick by tick data over the period Jan. 1999 to Sept. 2002, found that market reaction to news was not symmetric for up markets and down markets for the EFTs traded on the American Stock Exchange. *Bowe and Domuta (2004)* examined herding behaviour for pre crisis, during and post periods of 1997 Asian crisis and found that herding was more during the crisis period. Applying the Christie and Huang (1995) method, *Lai and Lau (2004)*found existence of herding behaviour during the Asian financial crisis and during extreme lower market stress conditions but not in upper market stress conditions for Malaysian stock market during the period Jan.1992 to Dec. 2001. *Caparelli and et al. (2004)* used a data set from Sept. 1988 to Jan 2001, adopted the methodology of Christie and Huang (1995), Chang and et al. (2000) and showed that herding is present in both up and down market conditions and was lower for small capitalized companies than for large capitalized companies in Italian stock market. Applying the state space model,

Lin and et al. (2007) used daily trading data of actively traded stocks by domestic and foreign institutional investors in the Taiwan Stock Exchange for the period from Dec. 2000 to Oct. 2006, and used the approach of Christie and Huang (1995) and found herding tendency in up markets for both the category of investors. *Tan and et al. (2008)* examined the asymmetry in the pattern of herding behaviour in the up and down market condition and high and low volatility, volume and return states of A share and B share markets in Shanghai and Shenzhen Stock market. The study found asymmetry in herding behaviour based on market return, trading volume, and volatility. For the Shanghai 'A' share market, the herding reaction was stronger in rising market and when volume and volatility are high but in Shenzhen market herding was stronger when volatility was high and no such asymmetry found in B share market.

Guoa and Shih (2008) examined herding during extreme up and down market conditions and the herd behaviour in high tech stocks in Taiwan market using the data from Jan. 1996 to Dec. 2000 and found a higher degree of directional co-movement in high-tech industries when compared with traditional industries during the time of extreme market movement and herding showed greater significance in extreme up market conditions. Using the intraday data of 200 stocks in the Hang Seng Composite Index from 2003 to 2004, *Zhou and Lai (2009)* looked in to the asymmetric nature of herding behaviour in Hong Kong market and found herding tendency differ in stocks based on geographic and industrial classification and investors herd more in financial sector, property and construction sectors. Further, investors herd more while selling rather than buying stocks and was more common with small capitalized stocks and when market sentiment was poor.

Amirat and Bouri (2009[a]), by using monthly data from 2000 to 2002, showed that herding was more significant when the market becomes riskier and was falling when compared to the extreme up markets in Toronto stock exchange. *Goodfellow and et al. (2009*) applied the methods of Christie and Huang (1995), and Chang et al. (2000) and tested Individual and institutional investor's trading behaviour in Warsaw Stock market during up and downswings of the market. By using the data from Jul 1996 to Nov 2000, it was found that, in single price auction, individuals herd more during bear phases and they are prone to sentiment driven investment decisions when the market return declines and there are some indication of herding in up markets. On the other hand they did not find any symptoms of institution's herding regardless of the state of the market.

Lao and Singh (2011) found that asymmetric herding behaviour in Chinese stock markets was greater during market stress and when trading volume was high whereas the Indian market showed herding mainly during market upswings and found to be unrelated to the volume of trade. The study also conducted the robustness test by considering the size of the firm was relevant in Chinese market in all the categories of stocks but in Indian market herding was present in medium sized stocks. *Chiang and Zheng (2010)* observed that the tendency to herd was more during the period of crisis and herding was present in both up and down markets except in US and Latin American markets and herding asymmetry was more visible in the selected five Asian countries in up markets and no asymmetry exists in advanced markets except those in Japan and Hong Kong.

Fu and Lin (2010), using monthly data of listed stocks and market index for the period from Jan. 2004 to Jun. 2009, tested investor's asymmetric reactions to good and bad news, herding in market stress and ups and found that investors tend to herd more with bad news and herding was more likely to happen during downward market. *Economou and et al. (2011)* examined the asymmetry in herding behaviour in four Mediterranean countries (Greece, Italy, Portugal and Spain) based on volume and volatility and observed that herding was stronger in Portugal during bear markets and was more prevalent in Greece and Italy during bull markets. The results based on the volume and volatility explains asymmetry in herding but does not prove that herding exists in all the studied states. *Fernandez (2010)* found herding in individual stocks and was more visible during extreme down markets. *Naoui (2010)*, using weekly data of 25 American companies listed on the Dow Jones index found more herding during the time of large price movements. *Chiang and et al. (2010)* examined herding behaviour during the period Jan.1996 to April 2007 and found that aggregate market and dual listed shares in up and down market displayed herding behaviour in the Shanghai and Shenzhen stock exchange, but the B share markets showed herding only in down turns. *Demirer and et al. (2010)*, by using firm level daily returns of stocks from 18 sectors of Taiwanese stock market, found that herding effect was more prominent during periods of market stress.

My and Truong (2011) examined the asymmetric effect of herding conditioned to the up and down markets in Hochiminh stock trading centre over the period March 2002 to Jan. 2006 and from Jan. 2006 to Jul. 2007. Their study applied the methods of Chang and et.al (2000), Tan and et al. (2008) and the measure of Christie and Huang (1995) for robustness tests and found that herding was present only in rising market and was found significantly lower than that of downward market in the second period, where it was more pronounced in extreme upward market for the whole period and very low for the first sub period. Herding was present in upward markets in the second sub period and the results for rising and declining market showed that herding present in both phase of the market conditions in the first period, but not present in neither of the market states for the whole period.

Khan and et al. (2011) explained the asymmetric pattern of herding behaviour based on the dotcom bubble and the subprime crisis by selecting four European countries and found herding except during the periods of market turmoil and crisis. The test of herding with Fama and French factors showed that herding were more prevalent around the market return and was more common for all the countries during periods of normal fluctuation than during the situation of turbulence.

Khoshsirat and Salari (2011) selected six distinct stress periods; found none of them have significant effect on herding behaviour in rising and declining periods, except the stress period caused by the first UN Security Council resolution in 2006 against Iran nuclear activities, which had significant negative impact on return dispersion measure. *Economou and et al. (2011)* found that there are significant asymmetries in herding behaviour based on market ups and downs, with trading volume and volatility. Further, the financial crisis did not induce a more intense herding behaviour in any of the four markets studied. *Khaliliaraghi and et al. (2011),*using daily data over the period from 2006 to 2009 of Tehran stock exchange and adopting the methodology used by *Tan and et al.(2007)* found that, there exist herding behaviour during extreme upward and downward market movement, while market return rises or declines and also with high and low trading volume, but they couldn't find such relation with high and low volatility and the intensity of herding behaviour was more during the periods of rising market and with high trading volume.

Park (2011) examined whether asymmetric herding exists in Forex markets and how it was associated with asymmetric volatility. By using the daily closing spot prices data from 2003 to 2009 of USD/EUR, USD/GBP, USD/JPY and USD/KRW, study observed time varying herding behaviour in the studied markets. In addition, it is also noticed that the global financial crisis further magnifies the asymmetry in herding and volatility in South Korea.

Al-Shboul (2012) investigated the asymmetric herding behaviour using the daily and monthly data of the companies of two Australian indices from 2003-2010. Using the methodology of Chang and et al. (2000), herding was detected only in high volume state for both indices and found herding with high volatility states in one of the market studied with monthly returns, but did not find asymmetric herding in terms of fundamentals. *Prosad and et al*. (2012) considered the data from 2006 to 2011 and found herding in bull phases Indian market, i.e. when market was up.

Seetharam and Britten (2013) examined the existence of herding behaviour by using the monthly data of JSE and All share indices in South African market using the data from1995 to 2011. Applying the methods of Christie and Huang (1995), Chang and et al. (2000) and Hachicha and et al. (2008) found that herding behaviour appears to be asymmetric and were more during bear markets and opined that asymmetry may be due to a loss in investor confidence during bear markets. *Ouarda and et al. (2013)* based their study on return, volatility and volume of transaction in different sectors by using the data over the period 1998 to 2010 and applying the Chiang et al. (2010), methodology the study documented evidence for asymmetric herding behaviour in up and down markets and also with volume and volatility in most of the studied sectors in European market. In addition, the study also found that the herding was more during the crisis period and found intense herding behaviour in finance and the technology sectors. *Bhaduri and Mahapatra (2013)*, by using the daily data on stock prices for all the firms listed on BSE-500 for April 2003 to March 2008 in Indian stock market, found herding was more pronounced during the 2007 crash and the rate of increase in security return dispersion was relatively higher during down market days when compared to the up market days.

Examination of the pattern of herding behaviour helps one to explain the conflicting empirical results in different market conditions. *Chang et al. (2000)* extended the approach developed by Christie and Huang (1995) and used a nonlinear function between the cross-sectional absolute deviations of returns and examined the asymmetric effect of herding behaviour in US, Hong Kong, Japan, Taiwan and South Korean markets and found asymmetry in the pattern of herding behaviour in some of the market examined. *Amirat and Bouri (2009b)* noted that herding behaviour increased when the market is falling and also with high trading volume and low volatility. *Cajueiro and Tabak (2009)* in Japanese market find herding with small stocks and investors are likely to herd more when selling rather than buying stocks. *Zhou and Lai (2009), Chiang and Zheng (2010)* also provide evidence for asymmetry in the pattern of herding during different crisis periods in most of the examined markets. *Gebka and Wohar (2010)* noted that one can expect herding when there is "high level of information asymmetry, volatility and uncertainty". *Park (2011)* explained that asymmetric herding effect became more acute during the period of the global financial crisis.

Applying the measure developed by the Chang and et al. (2000), it is possible to check the pattern of herding behaviour in different market situations. The study followed the assumption that, during the periods of market stress cross-sectional absolute deviation of returns will increase at decreasing rate. *Tan et al (2008)*, by following the extended version of the model developed by Chang and et al. (2000) in four markets with Chinese data and found the asymmetry in the pattern of herding behaviour in some of the markets examined and explained that asymmetric effects exist in the Shanghai A-Share market, where it is driven mainly during higher trading volume and when market is more volatile and in B-share market no difference found in the pattern of herding behaviour.

While analyzing the literature it is clear that a number of factors are controlling herding behaviour and the states of the market or the market direction could have certain role in deciding the herding behavior. It is also noted that out of the above studies, most of them found existence of asymmetry in the pattern of herding behaviour when the market is in down swing but the results are mixed.

Many empirical studies examined investors herding asymmetry with high and low states volatility and the results are mixed, but in many case the studies found that asymmetry exist in most of the studied market. For example, *Tan and et.al (2008)* examined the asymmetric effect of volatility and found that herding is present during the period of high volatility in the four selected Chinese markets, where as *Khaliliaraghi and et al. (2011)* did not find any asymmetry in herding behaviour with high and low states of volatility.

Number of studies discussed the asymmetric pattern of herding behaviour and established that there exists asymmetry in the pattern of herding behaviour based on different market conditions. At the same time it is also noted that different studies conducted in the same market found different results and the intensity of herding behaviour varied over time. This may be because of the fact that these experiments deal with human behaviour and due to the difference in data, number of sample constituents and the period selected for the analysis may also matter. Investors may perform differently and his decisions are influenced by factors like his expectation, the surroundings, his mental condition, risk tolerance and risk aversion and so on. From the literature, it is clear that the majority of the studies reported asymmetries in the pattern of herding behaviour in different markets studied.

2.4.3 Thin Trading and Herding Behaviour

A market is said to be thinly traded if the trading volume is low. In addition, a thinly traded market is featured with low trade frequency, low transparency, illiquidity and low number of buyers and sellers. As a result, the market will be more volatile and there is chance for larger spread between the two quotes with a material impact on asset prices and violation of market efficiency.

Antoniou et al. (1997) noted thin trading as one of the attribute of emerging markets and failure in considering thin trading may lead to biased explanations of the estimated results. Based on the concepts of thin trading by Lo and Macckinley (1990), Miller and et al. (1994), Ha (2007), *Kallinterakis and Kratunova (2007)*, examined the herding behaviour on thinly traded Bulgarian market and found an adverse effect of thin trading on the estimates of herding behaviour and explained that thin trading will produce underestimated herding results.

Kallinterakis (2009), noted that thin trading always do not produce adverse effect over herding behaviour. Using the data of all listed stocks of Vietnamese market from 2002 to 2007 and applying the Hwang and Salmon (2004), approach he found that thin trading caused for a positive bias over herding and failed to find the effect after adjusting for thin trading. In another study, with the same methodology, Andronikidi and Kallinterakis (2010) used data from Jan.1997 to Dec. 2006 of Israeli stock market and found that correcting for thin trading renders more persistent and smoothened evolution of herding. Using the methods of Christie and Huang (1995) and Chang and et al. (2000) and using data from 2004 to 2009, *Kallinterakis and et al. (2010[a])* tested the thin trading effect in Banja Luka, a newly established stock exchange and observed that adjusting for thin trading largely refute the herding hypothesis.

The research on the effect of thin trading on herding behaviour is still scanty and only few people and papers discussed this issue in the herding context. The study was conducted only in few markets. The results of *Kallinterakis (2009), Andronikidi and Kallinterakis (2010)* confirm that thin trading have certain effect and encourage herding tendencies of the investors and it has a positive effect on herding behaviour, were *as Kallinterakis and et al. (2010[a])* showed that extreme periods do not always experience market wide herding in illiquid markets and opined that order book data is more appropriate to get an exact measure of herd behaviour in similar market conditions. While analysing the available studies, it is clear that the results are mixed and a comparative study using different markets and samples are virtually essential to get a clear and detailed picture about this issue, since the number of studies are very few.

2.4.4 Institutional and Individual Herding Behaviour

A few number of studies investigated the herding behaviour of institutional and individual investors. The literature on the herding behavior of different investment groups systematically explores how this group behaves and it can explain the important facts about how these groups differ from each other.

Lakonishok and et al. (1992), using the trade details of the end of quarter portfolio holdings of 341 institutional money managers and the details of 769 tax exempted funds of all NYSE, AMEX stocks of US market from the first quarter of 1985 through the last quarter of 1989 and find herding and positive feedback trading in large stocks but a relatively higher level of herding and strong positive feedback trading in small capitalized stocks. *Nofsinger and Sias (1999)* investigated herding and feedback trading by institutional and individual investors in NYSE stock by using the data for the period from 1977 to 1996 and found strong positive correlation between changes in institutional ownership and returns and Institutional herding has greater impact on returns than individual investor's herding.

Voronkova and Bohl (2005) used the measure suggested by Lakonishok and et.al (1992) and used the semi-annual and annual details of pension funds for the period 1999-2002, found that there was substantial herding by Polish pension fund managers towards small size stocks and industries, like computer services, banking, metal production and conditional on the past return performance, substantial herding found in both past winners and past extreme losers. *Chang and Dong (2006)* used the change in institutional ownership of individual stocks data from Jan.1975 to Dec. 2002and showed that both institutional herding and fundamental factors are positively related to variation in firm's idiosyncratic volatility.

Lin and et al. (2007) applied the approach of Christie and Huang (1995) and investigated the price co-movement of stocks using daily trading data of actively traded stocks by domestic and foreign institutional investors and security dealers in the Taiwan Stock Exchange and found herding tendency in up markets for both types of investors and suggested that it was related to firm characteristics and market conditions. *Hsieh and et al. (2008)* examined whether herding behaviour and feedback trading in the international private capital inflows and the causes of such behaviour by considering 12 Asian and 7 Latin American markets, used monthly and quarterly aggregate mutual fund data over the period from Jan. 1996 to Oct. 2004 and found that there was feedback trading and also for the two lagged periods in Asia but they couldn't find herding behaviour in Asia markets but found in Latin American markets.

Sehgal and Tripathi (2008) by using firm level and at aggregate level data of BSE SENSEX companies over the period from Jan.2000 to Dec. 2006 and using the measure proposed by Lakonishok and et al. (1992) and based on quarterly data; find that FIIs exhibits strong herding behaviour. The intensity of the behaviour was more at the aggregate level than at the individual stock level and opined that FII's use fundamentals of the stocks besides mimicking each other's investment behaviour.

Applying the methodology of Sias (2004) and the data of all firms listed in the Taiwan Securities Exchange Corporation and Gretai Securities Market (OTCE) from Jan. 2002, to Dec. 2006, *Chen and et al. (2008)* found there was investigative herding from the part of QFIIs of Taiwan stock market and they are industry specific, prefer stocks with high past returns and firms with large size. The study also found that QFIIs follow each other into and out of the same securities and characteristic herding and investigative herding explain QFIIs' trading behaviour.

Lu and et al. (2009), using an extended method of Lakonishok et al. (1992), Wermers (1999) and Borensztein and Gaston (2003) approaches showed that QFIIs herding effects are resulting from the price impact of herding. Their study did not find over sold herding or any causation between the average herding values of the long, mid, and short term sell herding measure and the corresponding average return. *Goodfellow and et al. (2009)* contributed empirical evidence on herding behaviour of different group of investors by examining two trading mechanisms with different investor models during market up and down swings in Warsaw Stock market. The study used data from Jul. 1996 to Nov. 2000, applied the method of Christie and Huang (1995), Chang et al. (2000) and found that in single price auction, individuals herd more during bear phases and are being prone to sentiment driven investment decisions when the market return declines. Further, the studies found some indication of herding in up markets whereas institutions' trading does not exhibit flocking behaviour regardless of the state of the market.

Andreu and et al.(2009) examined the intensity of herding, the informational cascades and inter temporal herding behaviour among Spanish equity pension fund managers by analyzing the changes in the strategic asset allocations of pension funds. Using data over the period 2000 to 2007 and applied the method of Lakonishok and et.al. (1992) to detect the herding, the study found there was higher level of herding in the Spanish market but did not find any joint effect on size or investment company size. Analysis of inter-temporal herding and informational cascade showed that there was significant number of pension plans with convergent behavior which stress the herding behaviour.

Barber and et al. (2009) found that trade behaviours of individual investors are not mainly caused by passive reactions to institutional herding and the correlations mostly derived out from psychologically motivated trading behaviour like the representativeness heuristic, the desire to post pone, regret and limited attention. *Hsu and Huang (2010)* by comparing the extent of variation in herding during pre and post full liberalization policies (before and after Jan. 2001) investigated how foreign investment behavior affects the movement of Taiwan stock market. Through a sector wise analysis of industries based on the FII's investment, the study showed that impacts from foreign investment have asymmetric responses and prior to full market liberalization, market participants herd only in down market conditions were as investors herd in both up and down markets after the full market liberalization.

Li and Wang (2010) using the daily stock transaction records of the Shanghai Stock Index-180 from Jul. 2002 to Dec. 2004 and applying the measures of Lakonishok et.al (1992), *Chordia and Subrahmanyam (2004)* found that Institutional Investors herd in their present trading but do not systematically engage in positive feedback trading and they herd mainly on large stocks. *Jeon and Moffett (2010)*, using data of Korean firms for the period from 1992 to 2003 (excluding the year 1998) and applying Nofsinger and Sias (1999) approach, found that neither foreign nor domestic institutional herding was consistent with information cascades and ownership changes during the herding year was not positively correlated with those during the pre herding year. *Chang (2010)* used weekly order flow data from Dec. 2000 to 2005, found that foreign institutions lead others and their trading are closely interrelated despite controls for return and trading momentum while considering the dealers, margin traders, and mutual funds in Taiwan stock market.

Chen and Ma (2011) examined the informational and behavioural cause of cascading by using the investors trading account data. Study used the method of *Bernhard et al. (2006)* to separate the real herding from the informational herding, which explains the effect of behavioural factors on trading performances and informational cascades. With intraday samples for the period from April 1999 to Dec. 1999 of Taiwan stock market, found that informed trading, overconfidence and herding behaviours have influential effect under informational cascades. Further, noted that informational cascade was due to informational herding instead of overconfidence. *Venezia and et al. (2011)* analysed the micro herding and showed that herding of amateur investors are higher than that of professionals.

Another important factor used in the study is the role of Institutional investors in deciding the herding behaviour. The institutional investors generally considered as informed investors with their own investment policies and techniques. The Globalisation and the liberalized policies of the governments attracted these types of investments and it increased the cross border fund flows. If we consider the developing economies, the role of institutional investors is very important and many studies noted that institutional investor's especially foreign institutional investors are playing important role in the market movements. The statistics show that the participation of institutional investors in Indian stock market is increasing year by year. Large number of studies narrated the different aspects institutional investors and their perception is negative especially in the case of foreign institutional investors. *Sias and et al. (2001) Gompers and Metrick (2001), Chiyachantana et al. (2004) Kallinterakis and Ferreira (2005)* are some of the examples who noted the influence of institutional investors in stock market. *ko and et al. (2007)* found that foreign investors prefer large capitalization stocks and low book-to-market ratio and their investment preference based on the return on equity changes from country to country when compared with domestic institutional investors.

Dennis and Strickland (2002) found institutions react stronger than individuals do when the absolute value of the return on the market is large on a given day. *Barber and Odean (2008)* found that individual investors are net buyers of certain stocks, which are in news, like high trading volume or extreme return. All these shows the different characteristics of different types of investors and the analysis by including the institutional inventors may add value to this study and will bring more information about the herding behaviour.

While analysing the literature, most of the studies showed that both institutional and individual investors show herding behaviour in the market. At the same time a few studies found that institutional investors showed less herding behaviour, some others showed that institution herd among themselves and some others did not find herding behaviour among the foreign institutional investors. While analysing these studies one can see mixed results and the behaviour varies from market to market or even different sub periods.

2.4.5 Reputational Herding

The concept of reputation based herding model was developed by *Scharfstein and Stein (1990)*.The model explains that institutions or professional investors may follow their leaders subject to reputational risk, i.e. losing their reputation or pay off, if they fail to win while acting differently from others. Since the aim of the study is not testing the reputational herding, this study concentrated only on a few selected studies to give a brief idea about the reputational herding behaviour and included the studies related with fund managers.

Walter and Weber (2006) examined whether German mutual fund managers are engaged in herding and the effect of correlated trading on stock prices by using data of 60 mutual funds over the period from 1997 to 2002. The study employed the measure designed by Lakonishok et al. (1992) and Wermers (1999) and the results for different sub periods revealed that there was herding behaviour and high geographic concentration of funds are associated with increased levels of herding.

Villatoro (2009) examined reputational herding among financial intermediaries in the context of delegated portfolios management problem of US mutual fund manager's and found that financial intermediaries with high reputation use private information efficiently and those with poor reputation will tend to herd the other financial intermediaries portfolio decisions. *Bedke and et al. (2009)* experimented the rational and irrational herding in the context of reputational herding and uncovered experimental evidence for analysts reputational herding by using 138 individuals from different discipline. The experiment was designed in such a way that a positive pay off is offered if a decision maker stands alone in making a correct forecast and an incentives to follow the herd but also to risk an individual forecast and the findings confirm that the theory of reputational herding can be used to explain the herd behaviour.

Lutje (2009) with a survey method, tested the existence of reputational herding behaviour in the German asset management industry and their attitudes, perceptions and investment behaviour while herding and found that herding managers show less working effort, focus on shorter investment horizons and prefer the use of non-fundamental information. They are generally more risk averse, but in short term, they are willing to take more risk as they apparently fear falling out of the herd.

2.4.6 Factors Controlling Herding Behaviour

The investors are different and similarly the perceptions, the information availability, attitude, the risk tolerance are different for different investors. Further, a number of factors directly or indirectly affect the investment decision, since the motives behind the investment varies.

Lakonishok and et al. (1992) investigated whether herding and positive-feedback trading behaviour was present among institutional money managers and find herding and positive feedback trading in large stocks and a relatively higher level of herding and strong positive feedback trading in small capitalized stocks. *Olsen (1996)* found that low return and the perceived stock risk varies directly with the dispersion of analysts' earnings forecasts and herding increased with the level of earnings unpredictability.

Chang and et al. (2000) found that there was no size effect on herd behaviour and concluded that macroeconomic information has more significant impact on investor behaviour than firm specific information in markets. The study also examined the pre and post liberalization effect and found daily price limits have no impact on the herding behaviour of Taiwan and South Korean investors were as price limits show impact during up market condition in South Korean market.

Bowe and Domuta (2004), by analysing the trading patterns of both local and foreign investors and examined herding conditioned on firm size to address the possibility that liquidity deficiencies among smaller stocks could explain group trading patterns. The study did not find significant correlation between herding and size of the firm. Domestic herding appears positively related to firm size but there was very little evidence of size-based foreign herding. *Caparrelli and et al. (2004)* found that herding was lower for small cap companies than for large cap companies in Italian stock market. *Li and Yung (2004)* used the log size and the market momentum factor of Carhart (1997) and found that institutional herding in the ADR market was related to momentum trading and was not with positive feedback trading. Further, the study also opined that lack of accurate information about the market was another reason for the herding behaviour of the US ADR investors in the market.

The study conducted by *Hwang and salmon (2004)* and (2006) noted that stock return and herding behaviour are affected by fundamental factors and examined the effect of dividend price ratio, Treasury bill rate, term spread and default spread in both developed and developing markets like US, United Kingdom and South Korea. Further, the study found that during market stress investors considered stock fundamentals rather than market movements while herding. The study also examined herding towards size and value factors and found significant evidence of herding towards value at different periods in the sample within the US market. Researchers also found that instead of the market condition, the government's interventions also play important role in shaping the behaviour of investors. For instance, Mei and et al.

(2004) noted the interventions of Chinese government in the stock market affected the behaviour of investors.

Voronkova and Bohl (2005) found that there was substantial herding by Polish pension fund managers towards small size stocks and industries, like computer services, banking and metal production and opined that this may be due to the specific regulatory framework in the country and conditional on the past return performance, substantial herding found in both past winners and past extreme losers. *Walter and Weber (2006)* found that benchmark index composition as an important driver of herding behaviour. Further, for stocks which did accounting according to international standards found higher values of herding measure but no relationship between fund size and the propensity to exhibit herding behaviour.

Kulttiy and Miettinen (2006) experimented how the cost of third agent to pay for the information for the predecessors' actions and its effect on agent's herd behaviour and found results are not robust to small changes in the cost of observing other agents' actions and the incentive for the third agent was important in the formation of herd behaviour. *Lin and et al. (2007)* tested herding behaviour of domestic and foreign institutional investors and security dealers in the Taiwan's stock market and found that herding tendencies are related to firm characteristics and market conditions and found almost similar result in both type of investors. After controlling for return volatility, study found that institutional investors avoid high volatility stocks in extremely down markets, but prefer high volatility stocks in extremely up markets.

Agudo and et al. (2008) found herding phenomenon in value stocks, growth stocks and cash for the whole time horizon from Jul.1997 to Jun.2002 and Value Style was the most imitated, with levels higher than 16% for both buying and selling in Spanish market. *Zhou and Lai (2008)*, using the inter-day and intra-day data of Hang Seng Composite Index found that announcement of interest rate increased the herd behaviour. *Tan and et al. (2008)* tested effect of the Asian financial crisis (July 1997 to Nov. 1997) by adding a dummy variable and found that herding behaviour was not significantly influenced by the Asian crisis. In addition the study also tested the effect of macro and firm fundamental variables, risk free rate represented by Chinese demand deposit rate, earnings yield for each firm, are significant, supported the evidence of herding behaviour.

Zhou and Lai (2009) used the intraday data of stocks in the Hang Seng Composite Index from Jan. 2003 to Dec. 2004. The study found that herding behaviour was more common with small capitalized stocks and during the time of poor market sentiment. Further, herding tendency differs in stocks based on geographical and industrial classification and investors have clear preference to certain sectors while herding.*Villatoro (2009)* found a negative relationship between herding behaviour and the intermediary's reputation and a positive relation between the fees and reputation. *Bedke and et al.(2009)* found gender or group of subjects do not influence the herding behaviour but the success or failure of the previous decision affects their decisions and suggest that the individual behaviour of subjects follows reputational herding hypothesis of Keynes (1936).

Lao and Singh (2011) found size of the firm was irrelevant in Chinese market in all the categories of stocks but in Indian market herding was present only in medium sized stocks. *Fu and Lin (2010)* examined the herding behaviour in Shanghai and Shenzhen Equity Market and found that Investors tend to herd more with bad news and herding is more likely to happen during downward market. Further, the study found that herding is more in low turnover stocks than the high turnover stock. *Hachicha (2010)* found that the market returns and the trading volume factors increases when herding is more relevant and a large trading volume is a necessary for the existence of herding behaviour, but the volatility is very low when herding exists.

Blasco and et al. (2012[a]) found past return causes herding behaviour and it drive sentiment. The test for the joint link between the herding intensity, stock return and sentiment showed that stock return and market sentiments are the key factors underlying the level of herding behaviour and are inter related. *Kremer and Nautz (2011)* found that daily data do not show more pronounced short term herding than quarterly data during market stress in small capitalized stocks in German stock market. *Khan and et al. (2011)*, using securities market data of France, United Kingdom, Germany and Italy, compared the size and value factor and found herding around the size factor and value factor. Value factor does not appear to play a crucial role but while considering all the studied market the effect of the value factor is higher than the size factor.

Venezia and et al. (2011) found that herding depends on the firm's systematic risk and size and the professionals are less sensitive to these variables. The study also used total market volume, volatility, and market returns to examine the macro herding and found hat herding was positively and significantly correlated with stock market volatility, especially amateurs, causes market volatility in the Granger causality sense. Further, the study found a negative relation between size and herding but a positive relation between herding and market return.

Blasco and et al. (2012[b]), their results based on the volume, size and volatility as variables showed that firms with larger capitalization and high trading volume increase herding behaviour in investors. Further, the study also found that even if the intensity of herding was different, herding has a direct linear impact over the realized and historical volatility, but not on implied volatility.

Kremer, Nautz (2013) found that intensity of herding behaviour depends on stock characteristics including past returns and volatility in short term and noted that small capitalized stocks are less vulnerable to herding behaviour and increase in stock volatility leads to an increased sell herding were as it leads to a decrease in buy herding and return reversals have a destabilizing impact on herds in German stock market. *Kurz and Kim (2013)* explained that absolute excess return can be an important measure of herding behaviour by investors on stock markets and opined that "short run investment was determined mainly by the investors herding behaviour and was not necessarily be fundamental driven and argued that the level of the stock price and stock market volatility decides the herding dynamics in stock markets".

Literature provides varying evidence on different factors causing herding behaviour. Chang and et al. (2000) examined the role of macroeconomic variables and US firm specific information in South Korean and Taiwan markets and examined the role of systematic risk in herding behaviour and found strong evidence in favor of herding. Further the study also conducted size based portfolio tests, test for shift in behaviour due to the liberalization policies and also based on the price limits and concluded that size factor and the liberalization have no important role but the price limits may cause herding behaviour.

Tan and et al. (2008) used risk free rate represented by Chinese demand deposit, the earning yield of each firm and found evidence of herd behaviour with these factors in some of the studied markets. *Kallinterakis (2009)* found market volatility have certain controlling effect on herding behaviour in Vietnamese market. *Fu and Lin (2010)* evaluated the effect of turnover effect and found that the results partly agree the turn over effect in Chinese market. The study also analysed the asymmetric effect of news (good & bad) and found that Shanghai and Shenzhen investors herd more when there is bad news. *Chiang and Zheng (2010)* analysed the role of US market in herding behaviour in eighteen markets, includes developed markets, Latin American markets and emerging markets from Asia and opined that one cannot rule out the role of US market in analyzing the herding activity and is more pronounced in Asian markets. *Chiang and et al. (2011)* found time-varying herding behaviour in Pacific Basin equity markets and a positive relation between current stock returns, conditional stock-return variance and herding but it was negatively related to market volatility. The study explains that increase in stock return leads to a corresponding increase in the herding measure, where as the stock-return volatility decreases the herding tendency of the investors.

Jeon and Moffet (2010) investigated the effect of herding behaviour of foreign institutional investors in Korean market and used a number of variable, includes firm characteristics, (beta-proxy for systematic risk, size-the log value of sales, the market to book ratio, dividend yield, leverage and a proxy for profitability), macroeconomic variables like (interest rate volatility and Exchange rate volatility) variables of interest and six potential instruments of foreign ownership. Their study found that the foreign investors are herding towards the firms with greater abnormal return and changes in foreign ownership significantly affect abnormal herd year return. Further firm size and exchange rate volatility also affect the herding behaviour of the institutional investors. *Basu and et al (2011)* tested the possible impact of market return, market volatility, net FII investment and net mutual fund investment on herding behaviour by using Indian stock market data and found the volatility and Net mutual fund have significant impact on herding behaviour.

Al-Shboul (2012) used dividend yield, earning per share, price earnings ratio, Treasury bill rate and the government bond yield and found that the Australian investors affected neither by firm level nor by market level fundamental variables. *Kremer and Nautz (2013)* found that herding intensity depends on stock characteristics including past returns and volatility".

2.4.7 Herding Behaviour and Contagion Effect

Contagion is the ripple effect of certain event happened in a country/economy which causes for the setting off a chain of events in some other countries/economies. The adverse effect of one event happened in one country may spread to other country even if it does not share any common macroeconomic fundamentals or beyond the fact it is linked in any other sort. Today the financial markets are globally interlinked and studying contagion effect has greater scope and importance since the shock to one market can cause changes and instability in another market. It is also important to note that it is not necessary that the countries need not be linked directly through fundamental or through any trade linkage in order to spread a shock from one country to another. This section reviews the related literature about the contagion effect in general and the role of herding behaviour in spreading crisis.

The literature provides different definition and there exists a disagreement in defining contagion. *Caporale et al. (2005)* noted that there is no consensus among the economist in defining contagion and what really cause for contagion. *Eichengreen and et.al (1995)*, given the basic definition, explains contagion as a shift in shocks or the transmission of shocks internationally. One aspect of contagion is that the proliferation or propagation of shocks in excess of normal due to the fundamental linkages between countries. Another view explains transmission of crisis through the irrational behaviour of the investors. A broader definition identifies contagion as any channels, which links the countries and cause the markets to move together; Forbes and *Rigobon (2001)*. A restrictive definition for contagion is given by Forbes and *Rigobon (2002)*, as "significant increase in cross market linkage after a shock to one country (or more countries)" and explained as, if two markets shows higher degree of co-movements during a stable period and continue to show a higher degree of correlation after a shock to one market may not be considered as contagion and is because of inter dependence and it can be considered as contagion only if there exists significant increase in the cross market movement after the shock. *Khan and Park (2009)* explained that if the correlations of residuals are significantly higher than the historical correlations, then there is reason to believe that market sentiments have shifted from the crisis country to the other country.

Literature explains different types contagion effect based on the channel, which include the fundamental based contagion, the common cause contagion and the pure contagion, *Kaminsky and Reinhart (2000)*. The fundamental based contagion spread through the bilateral trade, through an indirect market or through the financial linkages. Another channel of contagion as explained, the financial institutions and the global diversification of the portfolios and portfolio re balancing. The explanation of pure contagion focus on the herding behaviour, defined as the tendency to mimic others by simply observing the activity of other investors, which also cause spreading the crisis. *Baig and et al. (1998)* reported (cited Christiansen (2000)that cross-country correlations among currencies and sovereign spreads in the Asian region increase significantly during crisis periods, whereas equity market correlations offer mixed evidence. *Choe and et al.(1999)* noted that domestic investors will engage in herding behaviour by looking to what other investors are doing or what they are expected to do. Based on the definition of contagion given by Mishkin (2003), *Zhu and Yang (2008)* opined that behavioural approach might be capable to provide an alternative explanation to the herding behaviour of investors during the crisis period.

Large number of empirical researches confirmed that herding tendency of investors could generate bubbles, which in turn can leads to financial contagion. *Calvo and Reinhart(1996),*explains herding contagion is independent of economic fundamentals. *Kaminsky et al. (2004)* used Latin America's mutual fund data and found contagion trading, where investors either buy or sell assets from one country when asset prices rise or fall in another country. A questionnaire survey based on worldwide stock market crash in 1987, Shiller[30] found that both the Japanese investors and U S investors respond similarly and concluded that price movements driven by investors herding behaviour might be transmittable across borders (cited in Kaizoji (2001))[31].

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[30] Shiller, R.,J. Market Volatility, MIT Press, Cambridge, MA, 1989.

[31] Kaizoji, T. (2001). A model of international financial crises. Physica A, 299, 279–293

Hernandez and Valdes (2001) explained four ways of contagion and pointed, "Information asymmetries and herding behaviour produce co-movement across countries". *Pericoli and et al. (2003)* noted that "contagion also include discontinuity in the behaviour of economic variables due to the learning processes or by informational cascades and herding by market participants". Another reason explained for the herding contagion is the informational limitations of investors and *Frenkell and Menkhoff (2004)* opined that information limitation may lead to herding behaviour and then leads to contagion. *Khan and et al. (2011)* presents empirical evidence for herding contagion in the stock markets during the Asian financial crisis (1997).

Chiang and Zheng (2010) noted that "crisis triggers herding activity in the crisis origin country and then produces a contagion effect". *Kenourgiosa and et al. (2011)* found that time varying correlation dynamics among the developed and Balkan markets increased during 2008 crisis and supported the herding driven contagion effect. *Zhu and Yang (2008)* noted that the cross market herding behaviour (pure contagion) was not related to a country's macroeconomic fundamentals but the driving factor was the changes in expectations due to the lack of information and their study confirms the role of psychological perceptions of investors in spreading the crisis and concluded that herding behaviour based on perceived similarities among countries made crisis contagious. *Chiang and Zheng (2010)* analysed the role of financial crisis and the significance of the US market in herding behaviour by using the data of 18 markets (include developed and developing) from Asia, Latin America and USA with the daily data over the period from 1988 to 2009 and found that tendency to herd was more during the period of crisis and investors in the tested markets are herding around the US market.

One of the important explanations about the contagion effect is that, it is rooted in factors that are independent of economic fundamentals and "is more likely to happen when common shocks or all channels of interdependence are not present or controlled", *Calvo and Reinhart (1996)*. Following are some of the studies which discussed the contagion effect in different markets.

Eichengreen and et al. (1995) examined the role of contagion by using Probit model and annual data of macro and financial indicator of 20 industrialised countries and concluded that trade links and macroeconomic similarities boosted contagion effect. *Edwards (1998)*, considering monthly data of short term interest rate for the years 1992 to 1998, found strong support for the contagion effect from Mexico to Argentina but did not find supports for the contagion effect from Mexico to Chile.

Kaminsky and Schmukler (1999) explained that large portion of the market movements during the Asian crisis (1997) cannot be explained by economic or political factors alone but was driven by the herding behaviour of investors. *Yang and Lim (2004)* inspected the extent of contagion effect on the east Asian stock markets, Hong Kong, Indonesia, Korea, Malaysia, Thailand, Philippines, less affected economy Singapore and Taiwan and a developed market Japan by considering the Asian financial Crisis. Dividing the data in to Pre-crisis and post crisis, their correlation analysis showed a contagion effect in the region and suggests that capital controls may have an impact on the role of short term relations between East Asian stock markets and opined that contagion effects may also be related to the levels of economic development since Japan has no influence during post crisis and pre crisis period.

Using monthly data and seemingly unrelated bivariate probit models, *Fazio (2007)* analysed the contagion and inter dependence of currency crises in fourteen emerging economies and found that herding contagion was limited between only few countries belonging to the same region and found that common macroeconomic weakness or perceived similarity and the cost of information affected investor’s decisions and opined that crises in emerging markets can be generated by sudden shifts in investor’s confidence.

Chiang and et al. (2007) analysed presence of contagion effect among nine Asian countries during the period of Asian financial crisis of 1997 using daily un-adjusted index return data over the period from Jan.1990 to March. 2003. Applying dynamic multivariate GARCH model, the study found contagion effect in the first phase and consistently higher correlation in the second phase due to herding behaviour among the studied countries. Further, the correlation coefficients are found to be significantly influenced by news about changes in foreign-currency sovereign credit ratings in its own and foreign markets and opined that both international investors and financial credit rating agencies play an influential role in shaping the dynamic correlations in the Asian markets and the shifts in the level as well as in the variance of correlations doubt the benefit of international portfolio diversification during the crises.

Khan and Park (2009) examined the existence of herding contagion during the period from Jan.1994 to Dec.1999 among Thailand, Malaysia, Korea, Indonesia and Philippines and analyzed the cross country time varying correlation dynamics of stocks prices by controlling the macroeconomic fundamentals during crisis and normal periods. The study noted the role of market sentiment and argues that sentiments are very important in capturing herding contagion and suggests that if the correlations of residuals are significantly higher than the historical correlations, then there is reason to believe that market sentiment has played an important role.

Chiang and Zheng (2010) investigated the investor's herding behaviour by testing the cross-sectional stock return dispersions and used daily data of 7 developed markets, 4 Latin American and 7-Asian markets. Using data for the period from 25th May-1988 to 24th April- 2009 and applying the method proposed by Christie and Huang (1995), and Chang et al. (2000) found that, crisis prompted herding activity in the crisis country of origin and then produces a contagion effect, which spreads the crisis to neighboring countries. *Gallegati (2010)* found that there was financial contagion from the US to other markets during the US subprime crisis but the effects are not uniform except for Japan and Brazil, a week transmission between US and Hong Kong and the pattern was similar for all European countries, explain that crisis may affect differently for different countries.

Rose and Spiegel (2012) made an attempt to model the causes of the subprime crisis and examined the role of financial and real channels through which the crisis was spread to the other countries. The study selected a sample of 85 countries and compared with a cross country multiple indicator using multiple cause (MIMIC) model of Goldberger (1972) but failed to find strong evidence of contagion. Further none of the tested channels showed statistically noticeable effects on crisis intensity for contagion except the financial channel.

Ulku (2011) investigated the information transmission and contagion effects among the Budapest and Istanbul markets and tested the time variation in the degree of co movement between the markets. The study used both monthly and daily data for the period from May 1998 to Dec. 2009 and found the existence of co movements between the markets and was more during the crisis period and opined that trading patterns of international institutional investors may cause the bilateral short-term correlations between these two countries and this may be a factor for contagion effect in the tested markets.

Kim and Kim(2013) made an attempt to examine whether the subprime crisis in July 2007,the bankruptcy of 'Bear Stearns' in Mar. 2008, the collapse of Lehman Brothers in Sept. 2008 and the deterioration in market stability in Feb. 2009 was contagious or interdependence. By using the data of thirteen countries for the period 2005 to 2009, found that there was contagion effect and the regime shifts in correlations occurred mainly during the collapse of Lehman brothers.

Using data over the period 2000–2009 and applying AG-DCC multivariate GARCH model, *Kenourgios and Samitas (2011)* found that there was contagion effect among five Balkan stock markets during stable and crisis periods (Romania, Serbia, Croatia, Turkey and Bulgaria), the US and three developed European markets (UK, Germany, Greece) from the crisis originated country and pointed the role of herding tendency in spreading crisis during 2008 stock market crash period and noted that dependence or herding tendency among the developed and the Balkan stock markets increased during the crash period. *Kenourgios and et al. (2011)* examined the stock market contagion in BRIC countries, US and UK markets during five crisis periods. By applying an extended multivariate regime-switching Gaussian copula model, found evidence of behaviour based contagion effect rather than macro fundamental based from the crisis originating country to the studied countries.

Based on the time-varying correlation dynamics during the stock market crash 2007–2009 and applying the dynamic conditional correlation analysis *Syllignakis and Kouretas (2011)* examined the correlation pattern of the Korea with other selected financial markets and found substantial evidence for the herding driven contagion effect during the 2007 -2009 crisis period in the central eastern European markets.

Celık (2012) used the DCC-GARCH model of Engle (2002) found evidence for herding driven contagion effect for most of the studied market during global financial crisis (2007-2009).

Fenzl and Pelzmann (2012) explained how individually unintended aggregate outcomes such as financial market booms and panics are shaped by collective dynamics in the participant's behaviour and how the behavioural mechanism works in spreading speculative crashes and bubbles. The study addressed the question why different market players are ignorant to mass psychological dynamics and explained the role of herding in spreading shocks in complex market situations in the financial market. Further the study viewed that a detailed examination of social dynamics rather than individual psychology will be helpful to explain the financial market behaviour.

Beirne and Fratzscher (2013) analysed the pricing of sovereign risk and contagion during the European sovereign debt crisis and found that the regional spillovers and contagion have less importance for the studied countries and found evidence for short lived herding contagion based on the simultaneous increases in sovereign yields among few countries during the crisis and was concentrated based on time and location of the countries.

While analyzing the literature one can see that the tests on contagion effect using the data of emerging markets are very scanty and an attempt to examine the role of herding behaviour will give clearer picture about the contagion effect and the role of human behaviour in spreading crisis. From literature, it can be concluded that the important factors which may lead to contagion effects includes the common shocks which may affect the global stock markets, the fundamentals, the trade linkage, financial linkage, interest rate volatility and the shifts in investors sentiments (pure contagion).The behaviour driven contagion was due to the changes in the sentiments of international and domestic investor's behaviour and was explained as the shift in market expectations lead by an observable structural break in the correlation between the markets resulting from herding behaviour of investors.

By analysing the conditional correlation coefficients, during the 1997-1998 crisis period *Eichengreen et al (1996)* and *Gallegati (2010)* explains that pure contagion generally related to investors' behaviour such as herding, financial panic, loss of confidence, etc and this leads to excessive co-movements. *Khan and Park (2011)* found strong evidence of herding contagion in the selected stock markets of East Asian countries during the financial crisis of 1997. *Kenourgiosa and Samitas (2011[a])* found increased dependence among the Balkan stock markets during the period of financial crisis of 2007–2009 and supported the herding behaviour during the crisis period. Celik (2012), *Belke and Setzer (2004)* noted that the theoretical focus on pure contagion centers around herding and Celik (2012) found contagion effect in most of the countries tested and explained that it was driven by herding behaviour.

There are a number of reasons to examine the contagion effect in the selected markets. First *Caporale et al. (2005)* pointed that, it is necessary to find out how the shock of one country spread to other countries through some transmission mechanism such as herding or irrational investor behaviour. Second, *Baur (2006)* explained that the global market association has increased in recent years and there are asymmetric effects of jointly positive and negative shocks. Thirdly, the Indian capital market is linked to other developed market, *Ahmad and et al. (2005)* noted that there was short term causal influence between NASDAQ and Nifty and SENSEX for the period 1999 to 2004. Studies like *Copeland and Copeland (1998), Jeon (1999)*, explained the relation between international stock markets and the role of the US market.

Dunis and Shannon (2005) found long run relationship between Indian markets with US over the period 1999 to 2003 and are attributed to the trade links. *Bose (2005)* noted that Indian stock market was not in isolation and returns in India were highly correlated with returns of international markets and was led by returns in the US and Japan as well as other Asian markets. So it was expected that the developments in the US market can potentially influence the Indian market and can generate herding behaviour among the investors and that can spread the evil effect of crisis.

Since, India is one of the fastest developing economies, institutional investors, both foreign and domestic investors are much interested in this market and their influence will be more in these markets. Fifthly, the information asymmetry, the type of investors, investor ability to analyse the market, transparency, and the stability of the economy matters and this may also induce herding tendencies among the market participants to follow the consensus of market. "Financial liberalization and the globalization policies given an open up for the financial intermediaries from the developed countries and the speculative attacks during turbulent periods may sometimes raise serious potential hazards for developing countries", *Sornette (2003)*. Hence it is decided to examine the contagion effect from US to India during the period of financial crisis (2007-2009).

While analysing the studies one can see that different methods and statistical tools are used to explain contagion effect. For explaining the herding driven contagion effect, a number of studies used dynamic conditional correlations measure (DCC- GARCH (1, 1)) to investigate possible herding behaviour in emerging financial markets during crises periods. The advantage of this tool is that it is useful to find out the dynamic conditional correlation between the tested countries. The models are largely acknowledged because it can adjust for volatility effect. Boyer and et al. (2006) noted that the dynamic correlation coefficients provided substantial evidence of the existence of contagion effects due to herding behaviour. In addition number of empirical studies *Corsetti and et al. (2005), Boyer and et al. (2006), Chiang et al. (2007), Syllignakis and Kouretas (2011), Jeon and Moffett (2010), Khan and Batteau (2011), Celık (2012), Moore and Wang (2013)* are some of the studies used this tool to explain the dynamic conditional correlation to explain the contagion effect during the crisis period in the context of herding behavior.

One can see that the research which examines the contagion effect in herding context are very few and it is hard to find studies which consider the Indian market which examined the contagion effect in the herding context. However, one of the important limitations in analyzing this pure contagion is that, it is difficult to distinguish between the fundamental based contagion and the pure contagion. In addition a number of factors contribute to contagion of crisis.

2.5 Research Gap

While analysing the literature one can find that there are not many studies which examined the herding behaviour in Indian market till recently. The studies which explain the herding behaviour in Indian market showed different results in the pattern of herding behavior in different states of the market. For example see Lao and Sing and Prosad and et al. (2012). In addition to this, the test of herding behaviour in Indian stock market is done with the extended method of Chang and et al. (2000) adopted by Tan and et al. (2008). The present study will use the method proposed by Hwang and salmon (2004), which is considered as the better measure since it take in to account the changes in asset fundamentals. The model will also help the researcher to check the herding towards the other factors like size or value factors, which are hardly tested in Indian stock market so far. In addition to this, the tests will be carried out for different periods, say the whole period, pre-crisis period, crisis period and post-crisis period and is rare to see such detailed analysis in Indian stock market and is difficult to find such a study in Indian stock market.

The factors controlling the herding behaviour are not tested by many studies and it is very hard to find such studies in Indian stock market. This study will examine the herding behaviour by controlling effect of variables like return of the market, market volatility, market trading volume, Net FII investment, Net mutual fund investment and the net investment of FII and Mutual fund, the size factor and value factor and such detailed analysis cannot find in Indian stock market so far. The literature gives mixed and varied results for the controlling effect of these factors in different markets and hence, this must be tested to get a clear picture about the herding behaviour in the Indian stock market

Literature clearly shows that the pattern of herding behaviour varies based on the prevailing market conditions and the pattern is asymmetric. Literature on herding is restricted to explain the pattern of herding behaviour in the context of market return, trading volume, market volatility and period of crisis. In addition, the herding behaviour of institutional investors was examined by the studies like Grinblatt and et al. (1995), Falkenstein (1996), Gompers and Metrick (2001), Bennett and et al. (2003), but the pattern of herding behaviour based on the high and low states of FII has been hardly tested so far. In addition, it is hard to find a study, which examined the pattern of herding behaviour based on the volatility and the net FII investment in the equities in Indian stock market. Hence, this study planned to analyze the pattern of herding behaviour in high and low states of volume, volatility and the net FII investment of FII in the selected equity market. Further the study tests empirically, the pattern of herding behaviour for different sub periods divided based on the Subprime crisis.

The contagion effect is one of the widely discussed topics in the finance history. The researchers and academicians showed keen interest on this issue because the effect of crisis or booms often spread over the boundaries of the continents. If we analyse the literature, one can see that the literature on herding driven contagion effect is very scanty and there are not many studies examined the role of herding behaviour on contagion effect by considering Indian market. In addition, it is rare to find a single study based on the US subprime crisis, which explains the herding driven contagion effect by using Indian stock market data and this study makes an attempt to fill this gaps.

CHAPTER - III

METHODOLOGY

3.1. Introduction

In India, the stock market has witnessed strong growth in the last few decades due to the keen interest from both foreign as well as domestic investors. Investing in stock market is a complex process and has to consider many factors before the investment decisions and these includes the fundamentals, social, psychological, cognitive and emotional factors. The traditional finance theories emphasize the belief that investors are rational and unbiased agents and the market is efficient in different forms. The portfolio theory explains that investors are risk averse and they construct their portfolio to optimize the expected return on an accepted level of systematic risk. Based on the information assimilation, the efficient market hypothesis explains that stock prices reflect all the information available about the stocks at any point of time. The behavioural finance challenges the traditional theories with theoretical and empirical evidence and explained number of anomalies and behavioural biases, which cause for mispricing of assets and led to market instability and inefficiency.

Belsky and Gilovich (2000) explained that the behavioural economics combines psychology and economics and explain why and how investors make seemingly irrational or illogical decisions in their financial dealings. (i.e. when they borrow, spend, save and invest money). The behavioural finance explain about the psychological phenomena permeate in the financial markets. It systematically explains how men deviate from the traditional economic assumption and how the market forces and the investor behaviour mould the investment decision and hence pricing of the asset. It covers researches, that drop the traditional theoretical assumptions and challenges the efficient market theory with the irrational behaviours of investors in the market. This explains that, the emotions and psychological biases in decision making play an important role, which dilutes the efficiency of the market and excessive transition of certain behaviour, spread the issues, led to instability, and even collapse of the market.

The market offers a fruitful arena, where it could be possible for one to observe a number of individual's as well as group behaviour or behaviours and the confluence or convergence of such actions. Adequate researches and knowledge about these factors definitely add value to investment decision process. In addition, this study is an attempt to examine the presence of herding behaviour, determinants of herding behaviour, and the pattern of herding behaviour in different market conditions in Indian stock market especially Bombay Stock Exchange, (BSE). The study also investigates the role of herding on spreading crisis by considering BSE during the period of US subprime crisis.

3.2. Scope of the Study

This empirical study throws light on the existence herding behaviour in Indian stock market, the controlling effect of different variables on herding behaviour and the pattern of this behaviour at different market conditions (say high and low states of market volatility, market volume and net FII investment) in the selected stock market. Further, the study will also examine the role of herding on contagion effect based on the crisis period. To examine the herding behaviour, the study will use ten years daily data and two approaches, a static measure and a time varying measure. This study is an attempt to explore different issues related to the herd behaviour in Indian stock market. For building up the objectives of the study, the basic models are extended by adding few more variable which are not yet studied in Indian market, say the net Investment by Foreign Institutional Investors (FIIs) and Institutional investors (Mutual Funds-(MF)) and the US variable (the market return of S&P 500).

In the first measure (Static Measure), the study will use cross sectional absolute deviation of daily return while the second method (Time Varying Measure) will use time varying beta(monthly), which will help one to understand the time varying nature of herding behaviour. Large number of issues related with herding behaviour has been discussed in the literature by using different methodologies and data sets and this study does not cover all these methods and are beyond the scope of this study. In addition the study only considered 243 companies of BSE-500 due to the non availability of data and considered only 10 year data from 01-04-2004 to 28-03-2012. Further, this study is an attempt to contribute new evidence that will add to better understanding about the existence, determinants of herding behaviour and the pattern in particular using the data of whole period and dividing the data in to crisis, pre and post crisis periods.

3.3. Significance of the Study

As per behavioural finance theories, a large number of social, behavioural and cognitive factors affect investor's decision making process. Investor's decision can be either rational or irrational and often the decisions viewed as the outcomes of behavioural or cognitive perspectives of investors. A clear picture about the market and the investor sentiments will help one to evaluate the market and for a fair decision making. Identifying emergence, understanding the existence and knowing the determinants of different behaviour in the stock market helps an investor in many ways and is necessary for formulating his decisions, for self discipline, to advance his knowledge and to guide others actions.

Bikhchandani and et al. (1992) noted that for less developed markets, lower will be the information efficiency and hence the investors may rely more on the trades of their peers for their decisions. Since herding behaviour is a common trait of almost all developing and emerging markets, it is utmost important for one to understand about this behaviour in judging the efficiency of the stock market and hence it is imperative to examine how far the herding behaviour is prevalent in Indian stock market. Further it makes good sense to exert efforts to understand about these behaviour and its frictions in the market, because an in depth understanding of this behaviour and the underlying factors will help one to effectively deal with his negative emotions, to understand why people react like this and what cause for such reaction.

It is also important to note that herding behaviour potentially affect the market and create fluctuation in return. Since understanding, the basis of herding behaviour will help one to analyse the price variation in the market. Information about the herding behaviour will help the individual investors, fund managers and the analysts, and policy makers to comprehend the various motives behind this behaviour and facilitate them to deal with it more pragmatically and to take proper decisions accordingly. There for this study is an attempt to examine different aspects of herd behaviour and to examine the role of herding on contagion effect during crisis period in Indian stock market.

3.4. Objectives of the Study

The overall objective of this study is to assess the dynamics of Herding Behaviour in Indian stock market but it specifically intended

1. To examine the existence of Herding Behaviour in Indian Stock Market.
2. To find out the determinants of Herding Behaviour in Indian Stock Market.
3. To identify the pattern of Herding Behaviour in Indian Stock Market.
4. To check the role of Herding Behaviour on Contagion effect in Indian Stock Market.

3.5. Hypothesis

To examine the existence of herding behaviour, the pattern of herding behaviour and the determinants of herding behaviour in Indian stock market, the following hypotheses were tested.

3.5.1. To Test the Existence of Herding Behaviour

$H_1$1: The stock market investors exhibit herding behaviour towards market Consensus.

$H_1$2: The stock market investors exhibit herding behaviour towards the size factor.

$H_1$3: The stock market investors exhibit herding behaviour towards the Value factor.

$H_1$4: The Indian stock market investors exhibit herding behaviour during the whole study period.

$H_1$5: The Indian stock market investors exhibit herding behaviour during the pre crisis period.

$H_1$6: The Indian stock market investors exhibit herding behaviour during the period of crisis.

H_17: The Indian stock market investors exhibit herding behaviour during the post crisis period.

3.5.2. To Examine the Determinants of Herding Behaviour in Indian Stock Market

H_18: Market return has controlling effect on herding behaviour.

H_19: Market volatility has controlling effect on herding behaviour.

H_110: Market trading volume has controlling effect on herding behaviour.

H_111: Size factor has controlling effect on herding behaviour.

H_112: Value factor has controlling effect on herding behaviour.

H_113: Net FII investment has controlling effect on herding behaviour.

H_114: Net Mutual fund has controlling effect on herding behaviour.

H_115: Net Institutional Investments has controlling effect on herding behaviour.

H_116: Return- US (S&P-500) has controlling effect on herding behaviour.

3.5.3 To Identify the Pattern of Herding Behaviour in Different Market Conditions

H_117: There is asymmetry in the pattern of herding behaviour during the high and low states of Trading volume.

H_118: There is asymmetry in the pattern herding behaviour during the high and low states of market volatility

H_119: There is asymmetry in the pattern of herding behaviour during the high and low states Net FII Investment.

3.5.4. To Examine the Contagion Effect and the Role of Herding

H_120: There exist contagion effect in the studied market and is driven by herding behaviour.

3.6. Data: Source, Period and Methodology

3.6.1. Source of Data

In this study, the test is organised to examine the existence of herding behaviour, its pattern at different states of the market and the determinants of herding behaviour in Indian stock Market by considering 10 years daily data. This study uses daily stock price of 242 companies, from BSE- 500. BSE-500 index is a broad-based index as the base year 1998-99 (February 1, 1999), launched in 1989. The data for this study is taken from four different sources viz, the official web site of Reserve Bank of India (RBI), CMIE-data base; (Center for Monitoring Indian Economy).

The data comprises individual stock return of the sample companies, market return, and market trading volume; market capitalization of the index; book value and market value of the selected companies, market capitalization of sample stocks, net foreign institutional investment and net mutual fund investment, 91days Treasury bill rate. Puckett and Yan (2008) argued that a destabilizing effect of herding is more likely to be detected in the short horizon and Walter and Weber (2006) noted that in highly developed financial markets, herding might be occurred within shorter time intervals.

The empirical study on herding behaviour with different data frequency provides mixed results and thereby felt to use daily data, will be helpful to capture the short term herding behaviour prevailing in the market. In addition to this, many studies like Christie and Huang (1995), Henker, and et al. (2006), Christoffersen and Tang (2009), Zhou and Lai (2009) explained that herding is a short lived phenomena and high frequency data will provide better results. Further, the 91 day Treasury bill is specifically chosen because it will better reflects the short term changes in the financial market and a number of studies have been conducted using the same.

To examine the role of herding behaviour on contagion effect, the study used adjusted daily closing price of the selected markets[32], India (BSE), and USA (S&P 500) as the crisis originating country and the required data collected from yahoo finance, one of top financial news and research site provides financial news as well as other information. In addition, the official website of BSE was used for some statistical information about the selected market.

32 The study also used adjusted daily closing price of China (HIS), Malaysia (FTSE), Indonesia (JKSE), Taiwan (TWI), South Korea (KOSPI), and Singapore (STI) for the analysis.

3.6.2. Period of Study

To examine the herding behaviour, the sample for the study covers 10 years daily data comprises the period from 01-04-2002 to 28-03-2012.Further the data is divided in to three sub periods say post crisis, crisis and pre -crisis periods and the details are explained below.

- Period of data: 01-04-2002 to 28-03-20012.
- Pre- crisis period: 01-04-2002 to 30-11-2007.
- Crisis period: 01-12-2007 to 31-01-2009.
- Post-crisis period: 01-02-2009 to 28-03-2012.

To examine the contagion effect and the role of herding behaviour in contagion effect of the crisis, the study uses data from 01-01-2004 to 31-01- 2009 and the study period is divided again in to three sub period as pre-crisis, first phase of the crisis and second phase of the crisis.

- Post Crisis period : 01-01-2004 to 30-11-2007
- First Phase of the Crisis: 01-12-2007 to 13-07-2008
- Second Phase of the Crisis:15-07-2009 to 31-01-2009

The study divided whole period into three sub periods based on the crisis period in order to get a better understanding about the herding behaviour. The study based the NBER –USA (National Bureau of Economic Research) in order to fix the crisis period. Further the whole period (10 years is a long period) and there are many changes to these markets in market capitalization, trading volume, sophistication and many important incidence like crisis happened during this period. Herding is mostly a sentiment driven behaviour, the researchers expect some difference in intensity in herding behaviour. Hence, the whole period has divided into different sub periods to examine the difference in the pattern and intensity of herding behaviour.

3.6.3. The Measures Used in this Study

The study will use two measures to examine the herding behaviour a static measure (extended version of Chang Cheng and Khorana (2000)) and a time varying measure (the state space model proposed by Hwang and salmon (2004)). The study restricted the sample to 242, in order to satisfy the condition that the sample companies should trade regularly from the beginning to the end of the study period. The study also used Multivariate Dynamic Conditional Correlation GARCH (M DCC-GARCH) to extract the dynamitic conditional correlation between the selected countries and the post-hoc ANOVA to compare the difference in the mean correlation over the different period under study. The analysis of the study followed through the steps explained below.

This study used adjusted closing price series of the index and of the selected individual securities

1. Preliminary analysis is done through line graph and descriptive statistics
2. Used Augmented Dickey fuller (ADF) test and Phillips-Perron (PP) test to examine the presence of unit root.
3. Used various models for different objectives.

The time series data having special characteristics and these will be analysed and used suitable tools for analyzing the data to satisfy the objectives. Stationarity characteristics are checked and with ADF and PP tests. Further, the study also used the Fama French Model to calculate monthly betas of market, size and value factors and used the book value, market value and the market capitalization of the individual sample stocks for sorting scrips in this stage of analysis. To calculate the monthly volatility the study followed the methodology of Schwert (1989).

3.7. Limitation of the Study

The method proposed by Chang and et al. (2000), examines the herding behaviour for extreme market movements and argues that traders are more likely to herd during extreme market conditions. Though the theoretical models provide sufficient explanation, most of the empirical models of herding suffer from the subjectivity involved in defining the extreme market movements. This study also suffers with the same problem. Further, like other researches of herding, this study does not distinguish spurious herding empirically. It is also noted that few studies focused on intraday data because it has been found that herding is more prevalent in short term and is able to catch up with intraday data and this study is able to track only business day level herding(not intraday level herding). In addition to the above the study has all the limitation which is beard by the secondary data and the limitations of the models used in this study. Further the study used only 242 companies from BSE even though the selected index covers 500 companies and did not considered other aspects of herding like reputational herding or informational herding individually and the factors like cost of information, different class of investors, macro economic factors like growth rate, GDP, IIP etc. Even though the researcher does not consider some of the issues discussed in the literature, this study is novel and many of these issues are not been discussed in Indian context and thereby it is expected that the study will end up with good results and research implications.

3.8. Econometrics Models Used

3.8.1 Stationarity (Unit Root)

Unit root tests examine stationarity of data using an autoregressive model. There will be serious mistakes in the inferences if we use non-stationary data for the analysis. Brooks (2008) defined a stationary series as "one with a constant mean, constant variance and constant auto covariances for each given lag". It can be explained as, a series is said to be stationary if it has a time independent, mean, variance and auto correlation, which are consistent over time. For example, the simplest case is the AR (1) model, the distribution of the OLS estimator of the parameter in the simple first order process and is denoted as,

$$y_t = a + y_{t-1} + e_t$$

For testing the unit root null hypothesis is defined as "there is unit root", i.e. $y_{t,}$, is trend stationary and on process the coefficient estimates will converge in probability to the true values (0 and 1) as *t* gets large. Further in an AR (1) process coefficient on lagged variable will be "1" and if a series has a unit root, it is said that the series is non-stationary; hence the mean and variance are changing over time. In this study the existence of unit root is tested with ADF test and PP test. "The PP test is likely to be more robust to wide range of serial correlation and time dependent heteroskedasticity", Kenourgios (2005).

3.8.2. Regression

Regression analysis is one of the most important and common tool used in the econometrics analysis and is concerned with explaining and evaluating the relationship between a given dependent variable and one or more exogenous variables. The regression explains the movements in a variable with reference to the movements in one or more other variables and the tool is used to examine the determinants of herding behaviour as well as to check the pattern of herding behaviour in the studied market. The commonly used method in econometric model estimation to explain the relationship between the variable is Ordinary Least Squares (OLS).

3.8.3. State Space Model

In general, a state space model is any model that includes an, observation process and a state process. The equations may be nonlinear or non-Gaussian. The state space model consists of two equations a transition equation and a measurement (observation) equation. The transition equation is one that explains the dynamics of the un-observed variable and the later explain the relationship between observed and unobserved (state) variables. A linear state-space model hypothesize that an observed time series is a linear function of a (often unobserved) state vector and the law of motion for the state vector is first-order vector auto regression. The model defined as

$$y_t = b^{'}\alpha_t + u_t$$

$$\alpha_t = A\alpha_{t-1} + v_t$$

Where the scalar u_t,v_t are mean zero, white noise process independent of each other and the first equation is called the measurement equation and the second is called the transition equation and a higher order system can also possible by adding additional state variable. The State space model allows unobserved variables to be incorporated into and estimated along with the observable variables. It can also be analyzed using a powerful recursive algorithm known as the Kalman (Bucy) filter. The state space models been used to capture the unobserved variable, which may be missing observations, (rational) expectations, or an unobserved component (cycles and trends).

Kalman Filter is a recursive algorithm, used to solve state space models in the linear case, first derived by Kalman (1960). It provides an optimal estimate of the coefficient conditional on an information set and knowledge of the parameters of the state space.

In this study, the model is defined as

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + V_{mt},$$
$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt} \ ,$$

Where $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, a standard state space model and is estimated by using Kalman filter. The detail of the model explained in a separate head below.

3.8.4. Multivariate GARCH Model

Multivariate GARCH models are developed by Engle (2001), and Engle (2002) and M-GARCH provides estimators for three different conditional correlation models, the constant (CCC), dynamic (DCC), varying conditional correlation (VCC) models. The Multivariate Generalized Autoregressive Conditional Heteroskedasticity Model proposed by Engle (2002), can be used to examine the time-varying correlation coefficients and it offer the flexibility of univariate GARCH models.The model is useful to explain the parametric correlation and can be used to examine multiple asset returns. In this study the model has been used to estimate dynamic conditional correlations (DCC) and in the first stage the model will estimate the correlation coefficients of the standardized residuals and then accounts for Heteroskedasticity directly. Further, it is also possible to include explanatory variables in the mean equation of the model to measure the common factor. The model gives a flexible approach in the estimation of correlation and it work on the principle that when two assets move together in the same direction, the correlation will be increased slightly and if it moves in opposite direction the correlation will decrease and the effect will be more in down market than in the up market. Further it is to be noted that often the assumed correlations are only to deviate temporarily from a long run mean and if both the returns are negative in the first period, then correlations will be higher and it will lead to lower tail dependence.

3.9. Static Measure

In the literature, one can see many methods used to explain the market wide herding behaviour. Christie and Huang (1995), one of the first who used the cross sectional standard deviation (CSSD) of individual stock return with respect to the market returns to measure the herding behaviour. Chang and et al. (2000) extended this model (CSSD) (model-(1)) and used the cross sectional absolute deviations of return with market return to examine the herding behaviour.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{Nt} R_{it} - R_{mt})^2}{(N-1)}} \qquad \text{………. (1)}$$

Where N is the number of companies in aggregate portfolio and R_{it} is the observed percentage return of individual security for day t and R_{mt} is the cross sectional average of N return for the day t. Their study used the following model to explain the herding behaviour.

$$S_t = \alpha + \beta^l D_t^l + \beta_t^u D_t^u + \varepsilon_t \qquad \text{……….. (2)}$$

Where S_t is the calculated return dispersion at time t, D_t^l ,D_t^u are the dummy variables when market return lies in the extreme lower tail of the distribution and upper tail respectively and which take the value unity otherwise zero. The model explain the herding behaviour based on the concept that the security return will not be far away from the overall market return, if there exists herding behaviour in the market. Christie and Huang pointed out that, if there is herding in the market towards the market consensus, the dispersion of equity return from the market will be significantly lower than the average return of the market because the investors will mould their own belief in favor of the market consensus. Further, the literature explains many limitations to this model[33].

Chang and et al. (2000) extended the Christie and Huang (1995) model and examined the herding behaviour in several markets like US, Honk Kong, developing market like South Korea, Taiwan and found the existence of herding behaviour in developing markets. This study will use the extended model of Chang and et al.

33 Explained in detail in chapter two: review of literature.

(2000) and is similar to the model used by Gleason et al. (2004). The same method is used by many studies like Tan and et al. (2008) in Chinese stock market, Shboul (2011) Australian stock market, khaliliaraghi and et al. (2011) Iranian stock market and many others to explain the herding behaviour. The advantage of the extended version is that it does not need to find out beta for measuring the herding behaviour. The model specification explained below.

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \qquad \text{............. (3)}$$

$$CSAD_t = \alpha + \gamma_1|R_{mt}| + \gamma_2 R_{mt}^2 + \varepsilon_t \qquad \text{............. (4)}$$

The cross-sectional absolute deviation of return *($CSAD_t$)*, explain the measure of return dispersion of individual securities R_{it} from R_{mt}, the calculated market return. Here the study used the relationship between the cross sectional absolute deviation of return (CSAD) and the calculated market return R_{mt} to explain the existence of herding behaviour in the selected stock market.

Tan et al. (2008) explained that, as the absolute market return increases, the dispersion in individual return also increases. Their study further explained that, theories of rational asset pricing models imply a linear relation between the dispersion in individual asset return and the return on the market portfolio. Further, they also noted that, when market is under stress or if there is large market movements, the investors may act in a similar manner. As a result, the return dispersion will be less or at least increase at a less than proportionate rate while comparing with market return. For this reason, a non linear market return R_{mt}^2 is included in the equation (4).

Here the test will use the relationship between the cross sectional absolute deviation of return $CSAD_t$ in the equation (4) used to explain the herding behaviour in the market. A statistically significant γ_2 with a negative coefficient explains the presence of herding behaviour in the market and a linear relationship with an increase in the relation shows the absence of herding behaviour, were the proportion of dispersion increases with the increase in return of the market. If there exists herding behaviour in the market, there will be a less than proportionate increase or decrease in the cross sectional absolute standard deviation of return.

3.10. Models Applied to Test the Pattern of Herding Behaviour

In addition, to examine the pattern of herding behaviour with respect to different market conditions, the study used the static measure and the herding pattern is checked with high and low states of market volatility, high and low states of market volume and also with the high and low states of net Foreign Institutional investment. In all the three cases, thirty days moving average is calculated and compared with the daily values. If the daily value is greater than the thirty days moving average, it is considered as the high state and else as low state. The following models are used to examine the pattern of herding behaviour in different states of the market.

3.10.1. Association of Herding with Trading Volume

$$CSAD_t^{Vh} = \alpha + \gamma_1^{Vh}\left|R_{mt}^{Vh}\right| + \gamma_2^{Vh}(R_{mt}^{Vh})^2 + \varepsilon_t \qquad \text{……………… (5)}$$

$$CSAD_t^{Vl} = \alpha + \gamma_1^{Vl}\left|R_{mt}^{Vl}\right| + \gamma_2^{Vh}(R_{mt}^{Vl})^2 + \varepsilon_t \qquad \text{……………… (6)}$$

Here Vh denotes the high volume state and Vl denotes the low volume states of the market. The trading volume of the day considered as high if the volume of the day t is greater than the previous 30 day moving average trading volume and the trading volume is considered as low if the volume of the day t is less than the previous 30 day moving average and the expected pattern of herding behaviour is checked with models (5) and (6).

3.10.2. Association of Herding with Volatility

$$CSAD_t^{\sigma^{2l}} = \alpha + \gamma_1^{\sigma^{2l}}\left|R_{mt}^{\sigma^{2l}}\right| + \gamma_2^{\sigma^{2l}}(R_{mt}^{\sigma^{2l}})^2 + \varepsilon_t \qquad \text{…………… (7)}$$

$$CSAD_t^{\sigma^{2h}} = \alpha + \gamma_1^{\sigma^{2h}}\left|R_{mt}^{\sigma^{2h}}\right| + \gamma_2^{\sigma^{2h}}(R_{mt}^{\sigma^{2h}})^2 + \varepsilon_t \qquad \text{…………… (8)}$$

Here $\sigma^2 h$ denotes the high volatility state and $\sigma^2 l$ denotes the low volatility states of the market. The volatility of the day is considered as high, if the volatility of the day t is greater than the previous 30 day moving average volatility and the volatility is considered as low, if the volatility of the day t is less than the previous 30 day moving average volatility and the expected pattern of herding behaviour is checked with models (7) and (8).

3.10.3. Association of Herding with Net Foreign Institutional Investment

$$CSAD_t^{FIIh} = \alpha + \gamma_1^{FIIh} \left| R_{mt}^{FIIh} \right| + \gamma_2^{FIIh} (R_{mt}^{FIIh})^2 + \varepsilon_t \qquad \text{…………….} (9)$$

$$CSAD_t^{FIIL} = \alpha + \gamma_1^{FIIL} \left| R_{mt}^{FIIL} \right| + \gamma_2^{FIIL} (R_{mt}^{FIIL})^2 + \varepsilon_t \qquad \text{…………….} (10)$$

Here $FIIh$ denotes the state of the market were the FII investment is high and $FIIl$ denotes the state of the market were the foreign investment is low. The FII investment of the day is considered as high, if the net investment of the day t is greater than the previous 30 day moving average Foreign institutional investment and the Foreign institutional investment is considered as low, if the Foreign Institutional investment of the day t is less than the previous 30 day moving average Foreign Institutional Investment and the expected pattern of herding behaviour is checked with models (9) and (10).

3.11. Time Varying Measure[34]

To analyse the herding behaviour, in addition to the static measure the study also used a time varying measure to examine the herding behaviour in Indian stock market. For this, the study followed the method followed by Hwang and salmon (2004), which used a state space model based on the Kalman filter. This measure examines the herding behaviour based on cross sectional dispersion of the factor sensitivity of assets. The model presumes that when the investors are behaviourally biased their perception of risk return relationship of the asset may distorted and the investor herds towards the market consensus, then the individual asset return follow the direction of the market and the CAPM beta will deviate from their equilibrium values.

If the herding exists in the market, the crosses sectional dispersion of the stock betas would expect to be smaller and it will tend towards the market beta. i.e. if the investors herd towards the market consensus, then the individual asset return may follow the direction of the market. Further, it is noted that the beta is time varying, Harvey (1989), Ferson and Harvey ((1991), Ang and Chen (2005) are some of the

[34] Source: Hwang, S., and Salmon, M. (2004). Market Stress and Herding. Journal of Empirical Finance, 11(4), 585–616.

studies explained the time varying nature of beta. The beta of stock not expected to remain constant and fluctuate with investor's sentiment.

The study used time varying beta and the beta estimated by using the Fama French model (11). In the second step, the cross-sectional standard deviations of the betas are calculated and used this in the state space model in its log form. Hwang and Salmon in their study assumes that if there is behavioural biases from the part of investors their perception of risk return relationship of assets may distorted and if the investors herd towards the market then the individual asset return may follow the market direction and their CAPM beta will deviate from the equilibrium values. The study used the following model (11) (Fama and French) to find the betas to find out herding behaviour in the market.

$$r_{itd} = \alpha_{it}^{b} + \beta_{imt}^{b} r_{mtd} + \beta_{iSt}^{b} SMB_{td} + \beta_{iHt}^{b} HML_{td} + \varepsilon_{itd} \text{ ……….}(11)$$

Where r_{mtd} is the market factor, SMB_{td} is the size factor and the HML_{td} value factor. If herding exists in the market, the cross sectional dispersion of beta of individual stocks would be smaller, i.e. the asset beta would tend towards the value of the market beta. By taking this in to account Hwang and Salmon (2004) formulate herding measure. By assuming this they explained the following relationship to hold between the equilibrium beta (β_{imt}) and the behaviourally biased equivalent (β_{imt}^{b}). Considering the following CAPM equilibrium and is modeled as

$$\frac{E_t^b r_{it}}{E_t r_{mt}} = \beta_{imt}^{b} = \beta_{imt} - h_{mt}(\beta_{imt} - 1)$$

Where $E_t^b r_{it}$ and are the market biased conditional short run expectation on the excess return on the asset *i* and its beta at time *t*, $E_t r_{mt}$ conditional expectation of excess return of market at time *t* andh_{mt} is a latent herding parameter that changes over time, $h_{mt} \leq 1$, and conditional on market fundamentals. Here the magnitude of h_{mt} can be used to explain the existence of herding behaviour and one can say if $0 < h_{mt} < 1$, some degree of herding exists in the market.

This study examines the market wide herding behaviour and assumes to hold for all assets in the market, the level of herding estimated using all assets[35] in the market rather than a single asset, thereby removing the effects of idiosyncratic movements in any individual β_{imt}^{b} then the stand deviation β_{imt}^{b} is then formulated as

$$Std_c(\beta_{imt}) = \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1)^2}$$

$$= \sqrt{E_c((\beta_{imt} - 1)^2)}\,(1 - h_{mt})$$

$$= Std_c(\beta_{imt}^{b})(1 - h_{mt}) \qquad \text{………. (12)}$$

To extract H_{mt} from $Std_c(\beta_{imt}^{b})$ the study took the logarithms of equation (12) and following Hwang and Salmon (2004) also as per the requirement for this study, herding parameters follow an AR (1) process and the model is written as

$$\log\ [Std_c(\beta_{imt}^{b})] = \log[Std_c\beta_{imt}] + \log(1 - h_{mt})$$

Using this assumption on $Std_c(\beta_{imt})$ this may written as

$$\log\ [Std_c(\beta_{imt}^{b})] = \mu_m + V_{mt}$$

Where µm = E[log[$Std_c(\beta_{imt})$]] and$V_{mt} \sim iid(0, \sigma_{mv}^2)$, and then

$$\log\ [Std_c(\beta_{imt}^{b})] = \mu_m + H_{mt+}V_{mt}$$

Here, $H_{mt} = \log(1 - h_{mt})$ and assuming a mean zero AR (1) process, gives model the model

$$\log[Std_c(\beta_{imt}^{b})] = \mu_m + H_{mt+}V_{mt}$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt} \qquad \text{………….. (13)}$$

Where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$, this is now a standard state space model with Kalman filter estimation. Here the dynamic pattern of movements in the latent state variables,H_{mt} , the state equation when $\sigma_{m\eta}^2 = 0$, then the model becomes

$$\log[Std_c(\beta_{imt}^{b})] = \mu_m + V_{mt}$$

35.Sample restricted to the condition stated previously

As the model explains, the absence of herding will give the value $H_{mt} = 0$ for all t, and a significant value of $\sigma^2_{m\eta}$ will explain the existence of herding behaviour. In addition to this a significant Φ the AR-1 coefficient, supports the auto regressive structure of the series. For herding is said o be significant both $\sigma^2_{m\eta}$ and Φ to be significant and absence of significance of either means no herding. To explain the herding behaviour, we expect $|\Phi_m| \leq 1$, since it explain the explosiveness of the process and low value explain the smoothness of the herding process.

3.11.1 Cross-Sectional Standard Deviation of Betas

The study will calculate the OLS estimates of the betas using the daily return data for each month over the study period using the Fama and French three factor model. After estimating $\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}}$, the cross-sectional standard deviation of the betas on the market portfolio $\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}}$ as

$$Std_c(\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}}) = \sqrt{\frac{\sum_{i=1}^{nt}(\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}} - \overline{\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}}})^2}{Nt}}$$

Where $\overline{\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}}} = \frac{1}{\mathrm{N_t}}\sum_{i=1}^{nt}\hat{\beta}^{\mathrm{b}}_{\mathrm{imt}}$ and Nt is the number of companies in the respective month t. we could write the equation as

$$\log[std_c(\hat{\beta}^{b}_{imt})] = \square_\delta + \log[\mathrm{std_c}(\beta^{b}_{imt})] + \delta_{mt}$$

Where $\delta_{mt} \sim iid(0, \sigma^2_{m\delta})$, though, the estimation error should not be serious when the estimation error is random and uncorrelated with the V_{mt} and H_{mt}, and the state space becomes

$$\log[std_c(\hat{\beta}^{b}_{imt})] = \square^{\mathrm{s}}_{\mathrm{m}} + H_{mt} + V^{s}_{mt}$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt} \qquad \text{............ (13)}$$

Where, $\square^{\mathrm{s}}_{\mathrm{m}} = \mathrm{E}\left[\log\left[std_c\left(\beta^{b}_{imt}\right)\right]\right] + \square_\delta$ and $V^{s}_{mt} \sim iid(0, \sigma^2_{mv} + \sigma^2_{m\delta})$. This suggests that $\square^{\mathrm{s}}_{\mathrm{m}} \neq \square_{\mathrm{m}}$ and $\mathrm{Var}(V^{s}_{mt}) > Var(V_{mt})$ and we cannot identify the true $\square_{\mathrm{m}}$.

As Hwang and Salmon noted, the herding variable H_{mt}, is designed in such a way that it could be able to capture the relative variations in the herding behaviour over time. Similarly the method assume that the estimation error (δ_{mt}) is not correlated with the error term in the measurement equation (V_{mt})andH_{mt}. Further, it is also noted that the measure used in this study, H_{mt} the term mean zero herding, is not itself affected by the estimation error.

3.12. Models used for identifying the Determinants of Herding Behaviour

To examine the controlling effect of different variables on the herding behaviour, the study used the time varying measure and used different variables reflecting the state of the market. To examine this the study used the degree of market volatility, the market return, market trading volume, Net investment of foreign and institutional investment, Net FII investment, Net mutual fund investment, size factor (SMB) and value factor (HML) factor and market return of US,S&P -500.

To examine the controlling effect of these variables on herding behaviour the study considered log market volatility and market return, log market trading volume as independent variables and tested individually and jointly in the measurement equation, thus the models become (Model 14,15,16,17 and18).

$$\log[Std_c(\beta_{imt}^b)] = \alpha_m + H_{mt} + C_{m1} r_{mtBSEt} + V_{mt} \quad \ldots\ldots\ldots\ldots (14)$$

$$\log[Std_c(\beta_{imt}^b)] = \alpha_m + H_{mt} + C_{m2} log\ \sigma_{mt} + V_{mt} \quad \ldots\ldots\ldots\ldots (15)$$

$$\log[Std_c(\beta_{imt}^b)] = \alpha_m + H_{mt} + C_{m3} logvol_{BSEt} + V_{mt} \quad \ldots\ldots\ldots\ldots (16)$$

$$\log[Std_c(\beta_{imt}^b)] = \alpha_m + H_{mt} + C_{m1} log(\sigma_{mt}) + C_{m2} r_{mtBSEt} + C_{m3} logvol_{BSEt} + V_{mt} \quad \ldots\ldots\ldots\ldots (17)$$

$$\log[Std_c(\beta_{imt}^b)] = \alpha_m + H_{mt} + C_{m1} log(\sigma_{mt}) + C_{m2} r_{mtBSEt} + C_{m3} logvol_{BSEt} + C_{m4} S\&P_{500\,t} + V_{mt} \quad \ldots\ldots\ldots\ldots (18)$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt}$$

Where, r_{mtBSEt} is the index return (Model-14) σ_{mt} is the log market volatility of the Index (Model-15) at time *t*. of time *t*, defined as the percentage log differenced return of the BSE SENSEX, vol_{BSEt} is the log market volume and $S\&P_{500\,t}$ is the return of the us market (S&P-500). Here the index volatility calculated using the index return of BSE SENSEX by following the methodology adopted in French and et al (1987) Schwert (1989), model (19) and is as follows.

$$\sigma(Rt) = \left[\sum_{i=1}^{N_t} (R_{it} - \overline{R_i})^2 + 2\sum_{i=1}^{N_t-1} (R_{it} - \overline{R_i})(R_{it+1t} - \overline{R_i})^{1/2} \right]$$

$$\sigma_{mt}^2 = \sum_{i=1}^{Nt} R_{it}^2 + 2\sum_{i=1}^{Nt-1} R_{it} R_{i+1,t} \qquad \text{.......... (19)}$$

Where R_{it} is the return of the index on day t, and $\overline{R_i}$ is the 30 day's average returns. The study estimated the variance of the monthly return to the BSE portfolio as the sum of the squared daily returns plus twice the sum of the products of adjacent return.

In addition to this, the study will investigate the role of net foreign institutional investment, net mutual fund investment and the net of institutional investment on herding behaviour. In order to normalize the data the study used market capitalization of the index and the models are explained below, Model (20), (21), (22) below.

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m1} NetFII_t + \mathrm{V}_{mt} \qquad \text{.......... (20)}$$

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m2} NetMFI_{\,t} + \mathrm{V}_{mt} \qquad \text{.......... (21)}$$

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m3} NetII_{\,t} + \mathrm{V}_{mt} \qquad \text{.......... (22)}$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt}$$

Where , $NetFII_t$, $NetMFI_{\,t}$, $NetII_{\,t}$ is the net of foreign institutional investment, net of mutual fund investment and net of institutional investments respectively on time *t*.

The study also tested the size effect and value effect (Small Minus Big: SMB) and (High Minus Low: HML) factors of Fama and French (1993) as independent variables, the model is then written as; model (23), (24), (25) below.

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m1} SMB_t + \mathrm{V}_{mt} \qquad \text{.......... (23)}$$

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m2} HML_t + \mathrm{V}_{mt} \qquad \text{.......... (24)}$$

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m1} SMB_t + C_{m2} HML_t + \mathrm{V}_{mt} \qquad \text{........ (25)}$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt}$$

Finally the study also tested the combined effect of all the variables and examined the effect on herding behaviour and the model (27) below.

$$\log\left[Std_c(\beta^b_{imt}\right) = \alpha_m + H_{mt} + C_{m1}\log\sigma_{mt} + C_{m2}r_{mtBSEt} + C_{m3}NetFII_t + C_{m4}NetMFI_t + C_{m5}logVOl_t + C_{m6}SMB_t + C_{m7}HML_t + C_{m8}USS\&P_t + V_{mt}$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt} \qquad \ldots\ldots\ldots (27)$$

The study also examined the combined effect of all the variables excluding net FII and Net mutual fund investment the model is (28) below

$$\log\left[Std_c(\beta^b_{imt}\right) = \alpha_m + H_{mt} + C_{m1}\log\sigma_{mt} + C_{m2}r_{mtBSEt} + C_{m3}Net_t + C_{m4}VOl_t + C_{m5}SMB_t + C_{m6}HML_t + C_{m7}USS\&P_t + V_{mt}$$

$$H_{mt} = \Phi_m H_{mt-1} + \eta_{mt} \qquad \ldots\ldots\ldots (28)$$

To test the robustness the study examined the power of various factors by using regression and used the herding measure extracted as the dependent variable and the volatility, volume and FII investment as the independent variables. The regression equation is explained below.

$$Herd_t = \alpha + \beta_1 Vol_t + \beta_2 Volm_t + \beta_3 NetFII_t + \varepsilon_t \qquad \ldots\ldots..\ ..\ (29)$$

Where $Herd_t$ is the herding measure extracted through the state space model kalman filter, Vol_t is the log volatility factor of the market $Volm_t$ is the log market volume $NetFII$ is the net foreign institutional investment in the studied market.

3.13. Models used for Determining the Role of Herding on Contagion Effect

Dynamic conditional GARCH (1,1) of Engle (2002) will use to examine the existence of contagion effect during the period of subprime crisis of 2007. The study will extract the conditional correlation and this will help the researcher to identify the dynamic nature of the investor's behaviour during the study period. In the next step, the study will apply a post-hoc ANOVA tests to examine the changes in mean correlation during different sub periods say the pre crisis period and first and second phase of the crisis period and the models are explained as follows. As noted by Chiang and et al. (2007), the model can accounts the problems of heteroskedasticity directly, since the model estimates correlation coefficients of the standardized residuals. In addition one can also include additional explanatory variables in the mean equation.

The DCC-GARCH (1,1) include two equations, a mean equation, a variance equation and a mean equation (30), is explained as follows.

$$r_1 = \gamma_0 + \gamma_1 r_t + \gamma_2 r_{t-1}^{US} + \varepsilon_t \qquad \text{……… (30)}$$

Where, $r_t = (r_{1t}, r_{2t}, ...r_{nt})$; and

$$\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t,}, \dots \dots \dots, \varepsilon_{nt}) \text{ and } \varepsilon_t(\digamma_{t-1} \sim N(0, H_t),$$

Number of empirical studies noted that "U.S. stock returns influence Asian markets. Further, Asian stock returns have no significant dynamic effect on U.S. stock returns", see Chiang and et al. (2007). The AR (1) term is used to account for the auto correlation and used the one day lagged US stock return (S&P500), in the mean equation, to control the effect of US market in the studied markets. To adjust the time difference between the Indian market and the US market one day lagged U.S. stock return are used in the mean equation and the multivariate conditional variance is defined as

$$H_t = S_t R_t D_t;$$

Where, the term S_t is an (n X n) diagonal matrix of time-varying standard deviations obtained from a univariate GARCH models with $\sqrt{h_{ii,t}}$ on the i_{th} diagonal, i = 1,2, ……,n; R_t is an (n x n) time-varying correlation matrix.

The approach followed by Engle (2002) include a process of two-stage estimation of the conditional covariance matrix Ht .In the first step, estimates of $\sqrt{h_{ii,t}}$ are obtained by fitting a univariate volatility models for each of the selected stock returns and for the second step, the residuals for each stock returns are changed by their estimated standard deviations obtained through the first step. Thus it can be noted as, $u_{it} = {}^{\varepsilon_{i,t}}\!/\!_{\sqrt{h_{ii,t}}}$, where u_{it} is then used to estimate the parameters of the conditional correlation

The DCC model specification is defined as follows

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1}, \qquad \text{……… (31)}$$

Here $Q_t = (q_{ij,t})$ is the (n x n) time-varying covariance matrix of ut, the standardized residuals, $\overline{Q} = E[u_t u_t^{'}]$ is the (n x n) unconditional variance matrix of ut and α and β are nonnegative scalar parameters satisfying $\alpha + \beta < 1$ and

$$R_t = \left(diag(Q_t)\right)^{-1/2} Q_t \left(diag(Q_t)\right)^{-1/2}, \qquad \text{………. (32)}$$

$$\text{Where} \quad \left(diag(Q_t)\right)^{-1/2} = diag\left(\frac{1}{\sqrt{q_{ii,t}}}, \ldots \ldots \frac{1}{\sqrt{q_{nn,t}}}\right),$$

The R_t in equation (31) is a correlation matrix with ones on the diagonal and off-diagonal elements less than one in absolute value and $\sqrt{q_{ii,t}}$ is a diagonal matrix with square root of i_{th} diagonal element of Q_t on its i_{th} diagonal position.

Hence, the conditional correlation for the markets (the country and the crisis originating country) be defined as

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}, \qquad i,j = 1,2, \ldots\ldots, nandi \neq j$$

and the correlation coefficient in a bi-variate case is expressed as

$$\rho_{ij,t} = \frac{(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{1,t}\, u_{2,t-1} + \beta q_{ij,t-1}}{\sqrt{[(1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{1,t-1}^2 + \beta q_{ii,t-1}]}\sqrt{[(1-\alpha-\beta)\bar{q}_{jj} + \alpha u_{2,t-1}^2 + \beta q_{jj,t-1}]}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots (33)$$

Where $q_{ij,t}$ is the element on the i_{th} line and j_{th} column of the matrix Q_t.

Engle (2002) suggested the DCC can be estimated by using a two-stage approach to maximize the log-likelihood function. By assuming the parameters Let, ϑ denote the parameters in D_t and φ the parameters in R_t, then the log-likelihood function is

$$l_t(\vartheta\varphi) = \left[-\tfrac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|Dt|^2 + E_t' D_t^{-2} E_t)\right] + \left[-\tfrac{1}{2}\sum_{t=1}^{T}(\log|Rt| + u_t' R_t^{-1} u_t - u_t' u_t\right] \qquad \ldots\ldots\ldots\ldots\ldots\ldots (34)$$

The first part of the equation (34) explains the volatility, given by the sum of individual GARCH likelihoods. As noted by Chiang and et al. (2007), "the log likely hood function can be maximized in the first stage over the parameters in D_t and based on the estimated parameters in the first stage, the correlation parameters of the likelihood function in the second stage can be maximized to estimate the correlation coefficient".

To check the contagion effect and the role of herding behaviour in Indian stock market the study will use a Post-hoc ANOVA test, which will help to check the consistency in the mean dynamic conditional correlation between India and the crisis originated country during different periods under study, say the pre crisis, first phase of the crisis and second phase of the crisis. The Post-hoc test will help to determine or to compare each condition with all other conditions where significance exists. The study selected “Hochberg” Post-hoc test and “Scheffe” Post-hoc test and these tests designed to compare each of the groups to every other group. These Post-hoc tests will compare the pre crisis correlation with the correlation in the pre Lehman period and the correlation between the period after the Lehman collapse, and a significant result shows that there is significant difference in the mean correlation during the periods compared.

3.14. Organization of the study

Chapter I: Deal with a brief back ground of Indian stock market (BSE), important theories of finance and the development of behavioural finance as a subject of interest in the finance paradigm, Herding Behaviour and Contagion effect and role of Herding on Contagion effect.

Chapter II: This chapter presents a description about the different dimensions of available literature on herding behaviour and the research gaps.

Chapter III: This chapter summarizes the objectives, methodology, models used in this study, data, sample and period of the study, limitations and the various terms and explanation about the required theoretical support for this study.

Chapter IV: Presents empirical evidence of different tests to examine the Existence of Herding Behaviour and the findings.

Chapter V: Presents empirical evidence for the determinants of Herding Behaviour in Indian stock market.

Chapter VI: Examines the pattern of Herding Behaviour or the existence any asymmetries in Herding Behaviour and their empirical results in different market conditions.

Chapter VII: Examines the role of Herding Behaviour on Contagion and the explanations.

Chapter VIII: Finding, suggestion and the Scope for Future Research.

CHAPTER IV

HERDING BEHAVIOUR IN INDIAN STOCK MARKET

4.1 Introduction

The behavioural finance tries to figure out how investors behave in the market, considers the individual characteristics as well as different attributes of the market or market conditions and explains how and why this factors influence the market movements. The behaviour shown by the investors may be rational or irrational and herding is one such common behaviour found in almost all type of investors[36]. Generally, an investor may take his decision based on the action of his predecessors or based on his private signals or information. Herding behaviour is innate and these we can see in almost all creatures. It can be described as the tendency of an investor to imitate or mimic others or follow the movement of others or the market in their actions, even besides the available information or their own beliefs. Literature, explains that this behaviour is more visible in developing and under developed markets than the developed markets.

There are attempts by researchers to examine the existence of this behaviour in different capital markets throughout the world and the number of works in this area is very limited. One of the noted and important empirical works in stock market for verifying the herding behaviour towards the market consensus is the work of Christie and Huang (1995), which examined the presence of herding behaviour in normal and extreme market conditions by considering the US stock market information. As per the theory, herding is more pronounced during extreme market condition than the normal conditions, i.e. the chance for showing irrationality is more during extreme market conditions because the investors are obsessed to emotions than reasons and follow the crowd in their actions in such market condition.

The modern portfolio theory explains that there exists a linear relationship between the return of asset and its beta and the systematic risk and if the cross sectional standard deviation of return (CSSD), derived out of the individual stock return is low, it is considered as the sign of herding behaviour. It is also noted that CSSD may be

[36] Individual or institutional, informed, uninformed and so on

low because of the changes in fundamentals. By using the cross sectional standard deviations of stocks return to explain the presence of herding, Christie and Huang (1995) noted that if there is herding from the part of investors, the value of cross sectional standard deviation will increase at a decreasing rate and it will fall in the case of extreme herding.

Further, Chang and et al. (2000) extended Christie and Huang (1995) measure and used a cross sectional absolute deviation of return, a mean based measure and the model allows us to test the herding behaviour based on the assumption that during the period of market stress the cross-sectional absolute deviation would increase at decreasing rate and is explained as the presence of herding behaviour. The relationship will be a non linear function and will be decreasing or the dispersion of return will be decreasing if there is herding in the market. Later on this model was extended by many including Gleason and et al. (2004).

Another issue in testing herding behaviour is the spurious herding. The spurious herding arises when investors rationally follow others and it does not conflict with the theory of efficient market hypothesis. Hwang and Salmon (2001, 2004)disagreed with the concepts of characterizing herding based on the market conditions and argued that herding may be observed in the normal market conditions also. The methodology proposed by Hwang and Salmon used time varying beta (the variability of beta over time) instead of estimating variability of return in the earlier models. Their study explain that there will be intentional herding, if there is significant difference in the cross sectional variance of beta.

While analyzing the literature, one could see many attempts by researchers to check the existence of herding behaviour and to explain how people behave in different market conditions. This study used both of the methodologies discussed above and daily stock return of 243 stocks, which are the part BSE-500. The study is for the recent time period, 1st April 2002 to 28th March 2012, the period was specifically chosen because the growth and expansion of Indian stock market is greater during this period.

This chapter is designed to check the existence of herding behaviour and the aim is to analyse the investors herding behaviour towards the market consensus (towards the market portfolio) in Indian stock market. In addition, the study also examined the herding towards the size and value factor in Indian stock market. To examine the existence of herding behaviour two methodologies are used, one is proposed by Chang and et al. (2000) and extended by Gleason and et al. (2004) and this methodology has been used in many other studies, for instance by Tan and et al. (2008), and Demirer and et al. (2010), Lao and Singh (2011), Khaliliaraghi and et al. (2011) etc. The second is the state space model (kalman filter), the method proposed by Hwang and Salmon (2004).The later is capable to adjust for the spurious herding methodically and also capable to identify herding towards a particular sector or style in the market including market index itself[37]. The state space model is used (used the market beta of CAPM) by Kallinterakis and Ferriera (2007), Portuguese market, Kallinterakis (2009) in Vietnamese market, Andronikidi and Kallinterakis (2010) in Israeli market, Demirer and et al. (2010)Taiwanese market, Basu and et al (2011) in Indian market, Chiang and et al. (2011) in pacific-basin equity market to identify the herding behaviour. In addition, this study also checks the presence of herding behaviour by dividing the whole period in to pre crisis period, post crisis period and the crisis period. The extended static measure is used for all the periods and the time varying measure is used only for the whole period.

4.2. Variables and Methodology

The study uses the daily individual stock return data of the selected companies, which are the constituents of BSE-500 index and the data cover the period from 01-04-2002 to 23-03-2012. Further, the study also uses daily return data of the BSE–SENSEX as the proxy for market portfolio. To calculate the return, the study used the adjusted closing price series of the individual stocks as well as the index and calculated the daily return by taking the first difference of the log value of the corresponding series. The study uses the details of 243 companies for analysis from BSE, which fulfil our criteria[38]. Further, the study will also use the implicit cut of yield of 91 days Government of India Treasury Bill (T-Bill) as proxy for the risk free return, which is available on weekly basis. This data is converted in to daily format and used to calculate the excess return available to the investors. Based on the

37. As noted by Hwang and Salmon (2004).
38. The sample companies should be traded regularly during the study period.

National Bureau of Economic Research, the study period is divided in to three different sub periods and these include the pre crisis period, (01-04-2002 to 30-11-2007), the crisis period from (01-12-2007 to 30-01-2009) and the (01-02-2009 to 28-03-2012) as the post crisis period. For the time varying measure the study uses the variables, log cross sectional standard deviation of beta calculated using the Fama French model and this include the beta of the market factor, size factor and value factor.

To examine the presence of herding behaviour at market level the study uses two methodologies, a static measure, proposed by Chang and et al.(2000) and later extended by Gleason and et al. (2004) and a time varying measure proposed by Hwang and salmon (2004). The first one is based on the daily cross sectional absolute deviation of return and the later is based on the monthly logarithmic cross sectional standard deviation of time varying equity betas. The second methodology follows the concept of Christie and Huang (1995) and contends that the cross section of asset return could be used to explain the herding behaviour.

The primary examination of data is done through line graph and used summary statistics, mean, standard deviation, skewness, kurtosis etc. The ADF test and PP test showed that the return series are stationary. In the next stage, the study used different measures by following the steps prescribed by the models. The detail of the various steps in the analysis is below.

4.2.1 General Procedure for the Analysis

To find out the existence of herding behaviour, the study applies two measures and following steps are used for different methods at different stages of the analysis.

1. Collect adjusted daily closing price of the individual stocks, the adjusted daily closing price of the selected indices and the Implicit cut of yield of 91 day Treasury bill as proxy for risk free return.
2. Do Preliminary analysis of the closing price series.
3. Convert the daily index series and stock price series into a daily return series by taking the first difference of the log value of the closing price of the individual series.

4. Check the stationarity properties of the series through ADF test and PP test.
5. Convert weekly implicit yield of Treasury bill in to daily series.
6. To find out the presence of herding behaviour in the market apply the proposed methods.

4.2.2. Procedure Adopted Under Static Measure

The method applied in this study was developed by Chang and et al. in (2000) and extended by Gleason et al. in (2004) and used the following procedure.

7 To find out the cross sectional absolute deviation of return (CSAD) for the sample 243 stocks from BSE 500.
   a. Find out the daily individual stock return.
   b. Find out the daily market return (denoted by $R_{m,t}$).
   c. Deduct Calculated value (R_{mt}) from each individual stock return series.
   d. Find the absolute value (without Sign) of series obtained in the above step (c).
   e. Find the average of the step (d) by dividing with the number of companies in the sample to get the CSAD series.

8 To examine the presence of herding

   a. Find the absolute value (without sign) of the calculated market return ($|R_{m,t}|$).
   b. Square the value obtained in the above steps ($R_{m,t}^2$) .
   c. Regress the value of CSAD (as dependent variable) with the $|R_{m,t}|$, ($R_{m,t}^2$), along with the error term.
   d. Check the coefficient of ($R_{m,t}^2$) to explain the existence of herding behaviour and a significant negative coefficient explains the existence of herding behaviour in the market.

8 Repeat the same steps for different study periods.

4.2.3. Time varying Measure

For the time varying measure, the study adopted the following procedure. This model is based on the cross sectional variability of factor sensitivity of assets i.e. beta of individual security. The study calculated monthly beta of securities using Fama French method and then calculated the standard deviation of these betas of securities, thus building a monthly time series of the cross sectional standard deviation of equity betas to use in the state space model.

4.2.3.1. Procedure Adopted under Time Varying Measure

1. Use Fama French model and extract beta of market factor, value factor and size factor on monthly basis.
2. Calculate the cross sectional standard deviation the betas and construct monthly cross sectional time series of beta.
3. Check and ensure the series does not exhibit departures from normality and confirm significant skewness, kurtosis, Jarque-Bera test-statistics etc.
4. Convert into log form as per the requirement.
5. Apply Kalman filter to extract herding out of the logarithmic cross sectional standard deviation of betas.

4.3. Rationale of the Study

Identifying the existence of herding behaviour in stock market is important in many respects. Jo and Kim (2008) noted that irrationality of the investor have a substantial and long lived impact on prices. Herding is a common behaviour found in most of the markets, which leads to mispricing of assets and a better understanding of this behaviour helps an investor to frame his decisions more accurately. This will also help an investor to understand about the investor's behaviour in the markets and will give a better insight about the market movements. In Indian context, there are not many studies, which analysed this behavioural effect and are very less in number.

Out of the available studies, only few studies, examined specifically the intentional herding (rational herding) behaviour in Indian stock market. Since different studies showed different results in emerging markets, examining and confirming the existence of this behaviour is important for domestic as well as for international investors in decision making. Studies that examined the herding behaviour of investors towards the market consensus by using Indian stock market data and those specifically examine and compare herding behaviour in crisis period with the normal period are scanty. In addition, this study will give a detailed picture about the existence of herding behaviour in Indian stock market and the results can help in explaining the efficiency of the market in behavioural context. The study is important since previous researches suggests that heard behaviour increases as the size of the group increases and as herding increases, the chance of mispricing of asset will increase and hence reduce the efficiency of the market and the diversification benefit. Analysing the herding behaviour is important to financial policy makers, investors and wealth managers to understand better about this behaviour, to cope up the ensuing changes in the market and to take appropriate decisions. Further the knowledge about the existence of herding behaviour in the studied market may help the investors to manage their portfolios since herding is usually associated with sudden swings in the market.

4.4. Descriptive Statistics and Stationarity

The Table IV.I explains the descriptive statistics of the variables used in static measure as well as time varying measure under study. The data is for the period 01-04-2002 to 28-03-2012 and the table shows the details of the daily data for the static measure and monthly information for the time varying measure since monthly betas used for time varying measure. The CSADBSE denotes cross-sectional absolute deviation of returns, calculated as per the equation[39] (3), ABSRMBSE: which is the absolute value of the market return and SQRMBSE: is the square of the market return used in this study. MRBSE, SMBBSE and HMLBSE are the cross-sectional standard deviation of beta of market factor, size factor and value factor, calculated through the Fama French model.

The Table IV.I shows that the average CSADBSE for the whole study period is (0.433) and the standard deviation is (0.8313). The standard deviation will be higher if the market had a higher level of cross sectional variation due to unexpected news

[39] See the methodology chapter for the equation.

or shocks and explain a higher volatility in the market and as Barclay and et al. (2003) noted this can also be attributed to higher information asymmetry existed in the market. The average returns for the markets for the whole period and is nearly (0.45). The mean value of the estimated cross sectional standard deviation of beta (β) shows that it is significantly different from zero. Further, the summary shows that for BSE, the cross sectional standard deviation of betas are skewed positively in all the cases as expected like any other volatility series. Jarque-Bera shows the asymmetry (non-Gaussian) in the series and thereby log values of cross sectional standard deviation of betas are used, which improved the Jarque-Bera statistics. Hence as explained by Hwang and Salmon (2004) one can apply Kalman filter to extract herding behaviour by using the state space model.

Table IV.I
Descriptive Statistics and Stationarity Tests of Different Variables Used in this Study for the Whole Study Period

BSE	Static Measure			Time varying measure (Fama French Betas)		
	CSAD BSE	ABSRMT BSE	SQRMT BSE	MRBSE	SMBBSE	HMLBSE
Mean	0.4333	0.4544	0.4122	0.087049	0.523069	0.63667
Std. Dev.	0.8313	0.4537	1.1979	0.048407	0.0483	0.052113
Skewness	5.5759	2.9898	10.3171	1.27804	1.207687	0.991421
Kurtosis	55.5625	18.8832	153.1730	4.4111	6.3835	4.7773
Jarque-Bera	300266.6	29955.18	2389680	42.6237	86.4097	35.4536
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2496	2496	2496	120	120	120
ADF	-9.749*	-16.141*	-23.635*	-8.838 *	-9.225*	-6.559*
PP	-46.393*	-47.311*	-37.081*	-8.896*	-9.706*	-7.509*

Note: * denotes significant at 1% level, The study calculated betas for BSE socks by using the Fama French Model. To extract beta the study used daily data and calculated beta for each month on the market return, size and value factor and used the calculated betas to obtain cross sectional standard deviation of beta in each case. The summary statistics presented Table IV.I is not for the data in log form.

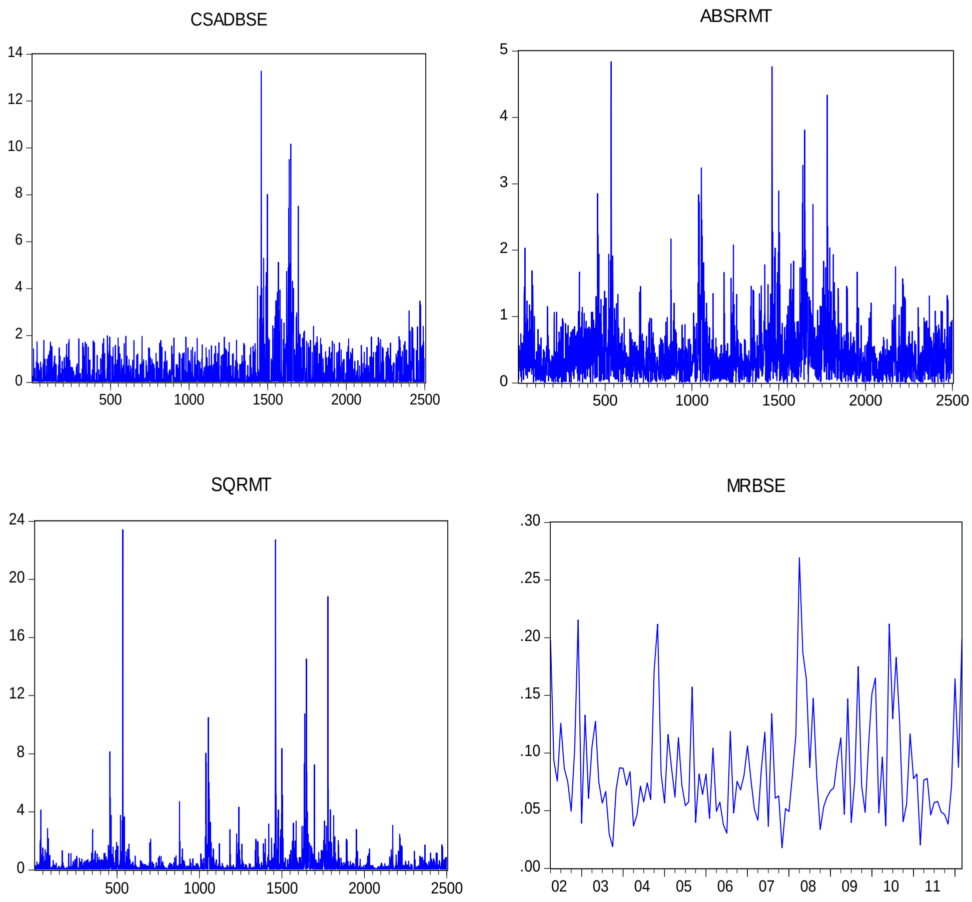
Stationarity is an important feature of time series data, since it shows the ability of the data series to explain the long term and short term information. If the statistical properties such as mean, variance and auto correlation are constant over time, that series is said to be stationary. As preliminary analysis, the Stationarity of the data series are tested using Augmented Dickey Fuller test (ADF) and Philip Peron (PP) unit root tests. The results from Table IV.I show that, the series are stationary at the level itself. The significant results show that there is possibility of rejecting the null hypothesis that there is unit root in the selected variable. The result showed that there is no unit root and hence the series is stationary.

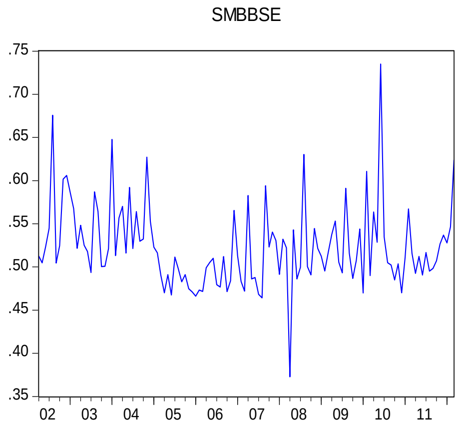
4.4.1 Line Graph

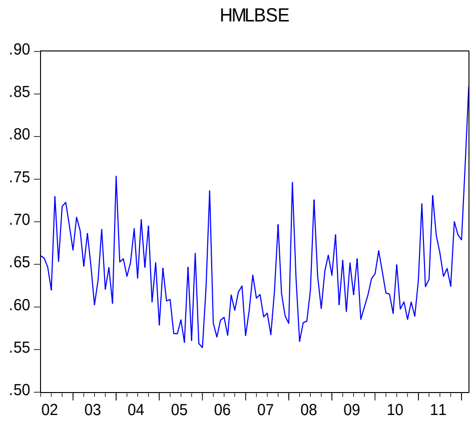
Figure VI.I below shows the line graph of the cross-sectional absolute deviation of returns BSE (CSADBSE) calculated from the individual stock return, the absolute deviation of calculated market return (ABSRMT) and the square of the market return (SQRMT) and the log cross sectional standard deviation of the market beta (MRBSE), size factor (SMBBSE) and the value factor (HMLBSE).

Figure IV.I.

Line Graph of Different Variables Used in this Study







While analysing the figure one can see that there higher variation in the series during the crisis period (approximately 1500 to1700) in the case of CSADBSE, ABSRMT, SQRMT and MRBSE , where as the deviation is not that much visible in the case of SMBBSE.

4.5. Estimation of Herding Behaviour in Indian Stock Market

4.5.1. Herding Behaviour through Static Measure

Table IV.II shows the estimation of the equation based on the static measure used in this study. The study runs regressions by selecting the specified variables in model[40] no. (4) For each of the selected periods; say the whole study period, the pre crisis period, the crisis period and for the post crisis period. The table shows the regression coefficients of the nonlinear relationship between CSAD and the market return. The analysis showed that the series are auto correlated and this may produce spurious results and inaccurate inferences. To avoid this issue, the study added an Ar (1) term, a lagged dependent variable where ever necessary since the higher order data did not provide improved results. All the estimations are undergone an Ar (1) process because of the auto correlation and low Durbin Watson test statistics find in the first analysis. Lao and Sing (2011) used the same method and Chiang and Tan (2010)[41] used longer lagged 'Ar' term and find the results significant.

40 See Chapter No.3: methodology.

41. Cited: Lao, P., and Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics*, 22(6), 495–506.

The study used the data over the period 1st April 2002 to 28th March 2012 and found evidence of herding behaviour in the market for the whole study period, suggesting that herding behaviour exists in the Indian stock market. Further estimates of the pre-crisis period and crisis period also show the existence of herding behaviour in the market. However, the study fails to find the presence of herd behaviour during the post crisis period. For all the study periods, except the post crisis period γ_2, the coefficient of R_{mt}^2 is negative and the estimates are highly significant (at1% levels) providing support for the existence of herd behaviour during these periods. For the post crisis period the estimates of R_{mt}^2 is negative but it is insignificant, do not support the presence of herding behaviour. This indicates that equity return dispersions increase during this period, were as a significant negative coefficient of γ_2 explain that the equity dispersion has decreased over the study period and it happen, when people herd towards the market. Further, it is noted that the magnitude of the herding behaviour is higher during the crisis period and it is less during pre-crisis period while comparing to the whole study period or the crisis period. The low level during the pre-crisis may be attributed to the fact that a majority of this period was bullish and investors may have good opportunity to get a better return from the market than what normally expected and hence, investors may keep away from herding others in their investment decisions.

Table IV.II

Estimates of Herding Behaviour through Static Measure for Different Study Periods

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
C	0.29857*** (9.2146)	0.222815*** (10.998)	0.913888*** (3.9739)	0.341613*** (9.0512)
γ_1	0.421168*** (6.4375)	0.232125*** (4.5368)	0.841731** (2.4939)	0.175772** (1.8878)
γ_2	-0.137316*** (-5.3614)	-0.068646*** (-3.2854)	-0.311842*** (-2.8974)	-0.047249 (-1.1484)
AR(1)	0.354354*** (18.565)	0.082492*** (3.1108)	0.377706*** (6.5561)	0.163808*** (4.6275)
F Value	133.3648	10.5530	15.5645	7.9987
Prob. (F Stat)	0.00000	0.000001	0.00000	0.00003

Note: ***Denotes significance at 1% level, **denotes 5% level. Table shows the estimated coefficients of regression with the equation, $CSAD_t = \alpha + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \varepsilon_t$, CSAD is the independent variable and R_{mt}, R_{mt}^2 are the independent variables, the calculated market return and the squared market return respectively. if γ_2 is significantly negative it is an indication of herding behaviour

The finding is consistent with many other studies which found evidence for herding behaviour in developing markets in similar market conditions. Chang and et.al (2000) in the stock markets of South Korea and Taiwan, Chen and et al. (2003) in the Chinese market, Hwang and Salmon (2004) in South Korea, Kassim (2008) in Malaysia, Lao and sing (2011) China and India, Demirer and et al. (2010) on Taiwan market Basu and et al. (2011) in Indian market, Degirmen (2012) in developing markets are some of the studies which found herding behaviour in developing markets. Further, the result raises an important question, why herding is not present during the post crisis period in the Indian stock market. One possible reason is that in BSE, the individual investors are more than the institutional investors. The panic experience from the market during the crisis period might have forced many of the investors to withdraw from this market or shift to some other better investment opportunities as they believe. Further, there is a decrease in trading volume[42], shows a declining trend after crisis and this may be another reason for this result. Another possible reason may be that, the overall herding behaviour in the studied market, is comparatively less when compared to China or some other emerging markets[43].

The existence of herding behaviour does not mean that all the investors in the market herd towards the market consensus and there is enough possibility to believe that majority of the investors who herd in the studied market may be shifted to some other market like NSE, the leader and fastest growing competitor to the BSE and comparison of these two markets may give better explanation of this issue. There is possibility to think in this line, because of two reasons, first, the trading volume in BSE showed a decreasing trend and secondly, the people who show the herding may have the tendency to herd towards a market which is flourishing. Thus, it may be concluded that the people who show herd behaviour shifted to some other market or to some other investment opportunities.

4.5.2. Herding Behaviour through Time Varying Measure

The study also examined the herding behaviour by using the time varying measure given by Hwang and Salmon (2004) by using log cross sectional standard deviation

42. See the figure A-I and AII in appendix, compare the trading volume in NSE and BSE, there is a decrease in trading volume in both the market, but it is more in BSE.
43. See the studies Tan et al. (2008), Lao and sing (2011).

of betas to extract the herding component. The estimates of the model are given in table IV.III.

4.5.2.1. Herding towards the Market Portfolio

The study examined the herding behaviour towards the market consensus based on the log cross sectional standard deviation of beta calculated on market portfolio by using Fama French model. The study extracted the H_{mt} by using the Kalman filter and the Table IV.III explains that the persistent parameter ϕ_m and $\sigma_{m,n}$ are statistically significant and this indicates the presence of significant herding behaviour towards the index during the sample period. It is seen that H_{mt} is persistent with significant ϕ_m (0.44394390) and with a proportion of signal nearly 54% indicate that herding explains around 54% of the total variability in (β_{im}^b). Further, the estimates of $\sigma_{mn,}$ (SD of η_{mt}, the state space equation error term) is non zero and is (at 1% level) highly significant, confirms that there is herding behaviour towards the market portfolio in Indian stock market. The persistent factor $\phi_{m,}$ explains the smoothness of the evolution of herding in the market and the value nearly (0.44). Further, the term (μ_m) used to denote the mean level of the log $std_c(\beta_{im}^b)$ adjusted through herding expressed as H_{mt}, is also significant and hence, conclude that there exists herding behaviour in the market and investors of BSE showed herding behaviour towards the market.

Table IV.III.
Results of Time Varying Measure of Herding Behaviour in Indian Stock Market

Estimates	Herding Towards Market Factor	Herding Towards Size Factor	Herding Towards Value Factor
$\Phi_{(m,s,v)}$	0.44394390*** (2.6472)	0.90941722*** (11.9934)	0.97638471*** (40.8111)
μ	-2.57565130*** (-42.2375)	-0.64566234*** (-35.3342)	-0.41203703*** (-14.2546)
$\sigma_{(m,s,v),n}$	0.28880340*** (2.7802)	0.01691854 (1.1313)	0.01604360* (1.8728)
$\sigma_{(m,s,v,)v}$	0.42462731 *** (5.3060)	0.07936420 *** (7.0354)	0.062252373*** (6.9311)
Proportion of Signal	0.53990705	0.19005616	0.20196501

***Denotes significance at 1% level, **, * denotes 5% level and 10% level respectively .The study used log cross sectional standard deviation of beta obtained through Fama French Model. The proportion of signal is given by the equation $\sigma_{m,n/SD}$ of time series standard deviation of log cross sectional standard deviation of beta(LCSSDB). The table explain the estimates of the model, $\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt+}V_{mt},, H_{mt} = \Phi_m, H_{mt-1} - \eta_{m,s,v\,t}$ by using the (LCSSDB) of Fama French betas.

4.5.2.2. Herding towards the Size Factor (SMB)

The study also examined the investors herding behaviour towards the size factor by considering the log cross sectional standard deviation of beta of the size factor calculated with the Fama French model. The result in Table IV.III shows that ϕ_s (0.90941722) is higher than ϕ_m and is statistically significant at 1% level. The $\sigma_{sn,}$ the herding error term (η_{st}), (0.01691854) of the state space model is non zero but it is insignificant. As a basic condition, the persistent parameter ϕ_m and the $\sigma_{m,n}$ should be significant to say there exists herding behaviour towards the size factor, hence concluded that the result is not in support to explain the existence of herding behaviour towards the size factor in the studied market, explain that investors in BSE do not herd towards the size factor of the firms.

4.5.2.3. Herding towards the Value Factor (HML)

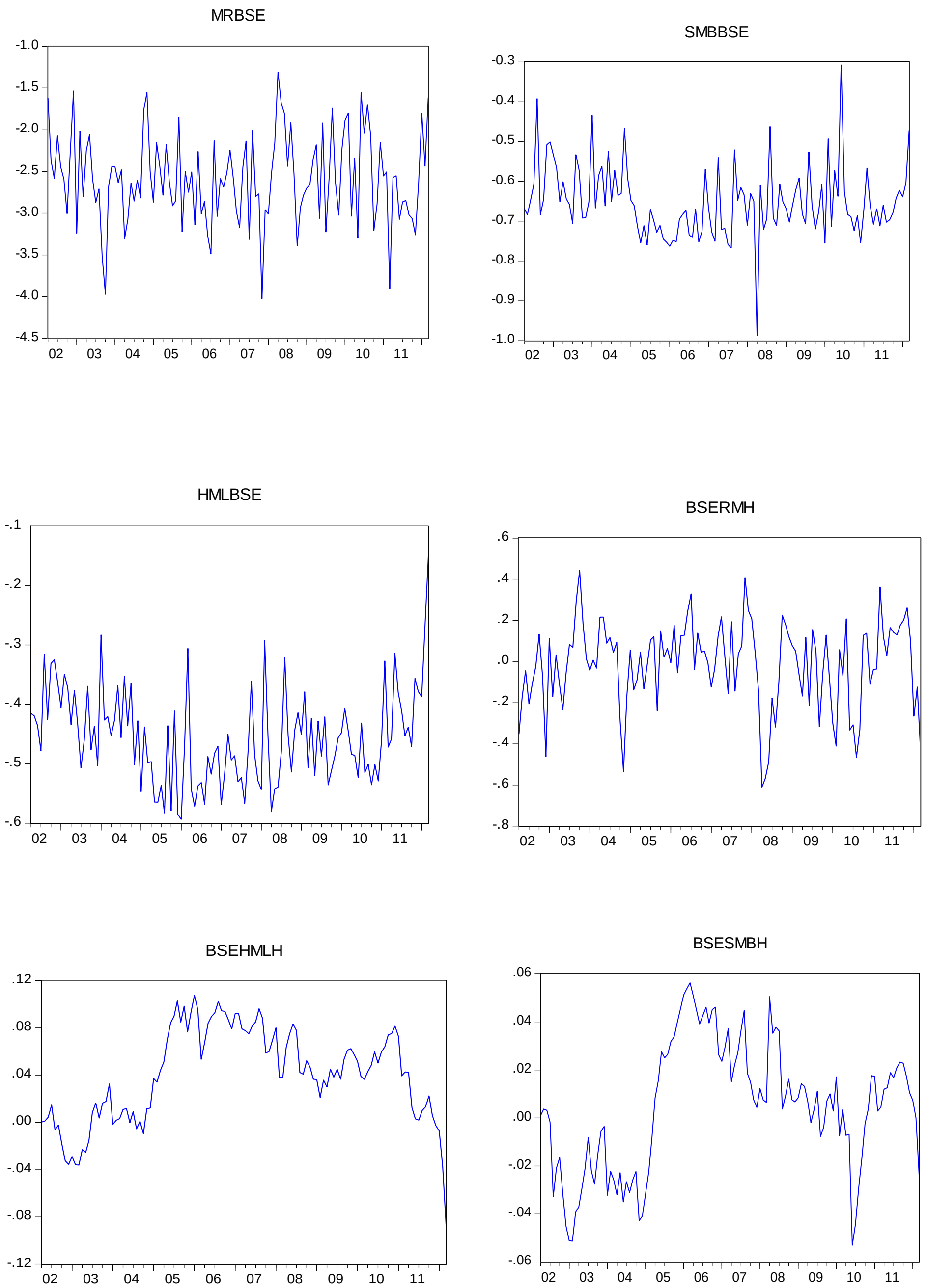
The study also investigated the herding behaviour towards the value factor by using the same model. The analysis showed in Table IV.III H_{vt} is persistent with significant ϕ_v (0.97638471) and with a proportion of signal nearly 20% indicate that herding explains nearly 20% of the total variability in (β_{iv}^{b}). Further, the estimates of $\sigma_{vn,}$ is non-zero (0.01604360) and is significant at 1% level confirms that there is herding behaviour towards the value factor in the studied market. In addition, it is also noted from the table that H_{vt} is more persistent and smoother than H_{mt} , and the proportion of signal is nearly 20%. In addition the term (μ_v) used to denote the mean level of the log $std_c(\beta_{iv}^{b})$ adjusted through herding expressed H_{vt} is also significant and hence it is concluded that there is herding behaviour towards the value factor in Indian market and the intensity is lesser than with the market factor during the studied period.

4.5.3. Line Graph

The above findings can also be explained with the help of line graph prepared out of the result extracted through the kalman filter using the state space model. Figure IV.II shows the line graph of the individual series MRBSE, SMBBSE and HMLBSE, the log cross sectional standard deviation of beta based on the market factor, size factor and value factor respectively, estimated using the Fama French model and

BSERMH, SMBBSEH and HMLBSEH are the herding behaviour extracted from the respective log cross sectional standard deviation of betas. Figure IV.III shows the line graphs of log cross sectional Standard deviation of the beta estimates along with the herding behaviour throughout the study period.

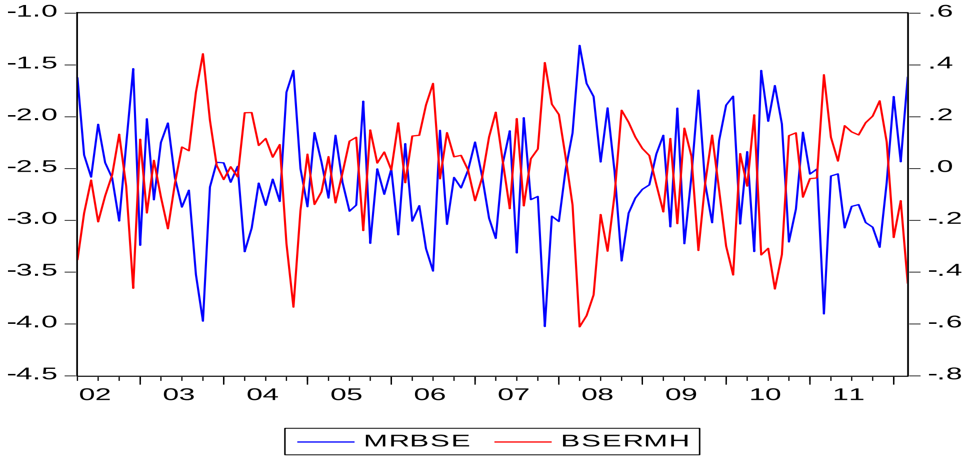
Figure IV.II.
Line Graph of Log Cross-sectional Standard Deviation of Beta and
The Pattern of Herding Behaviour throughout the Study Period



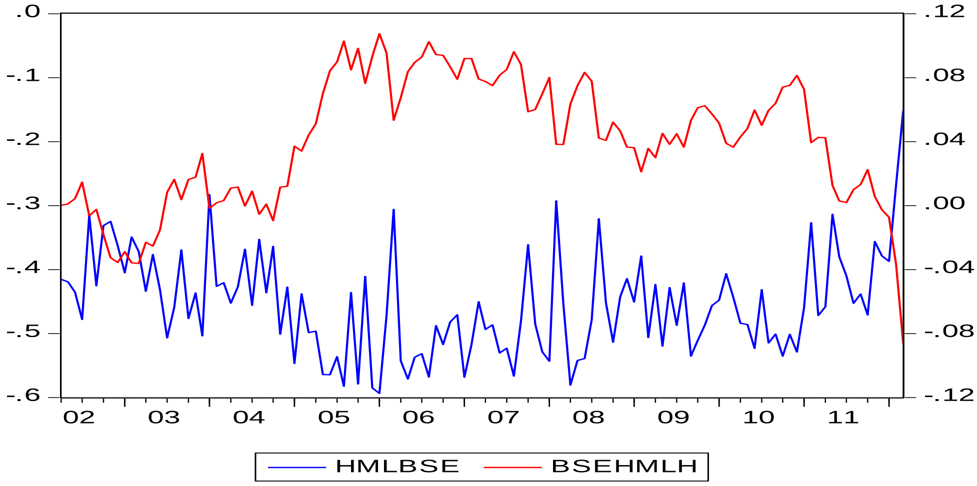
The variation in herding behaviour can be observed from the Figure IV.II. Analysing the figure one can compare the evolution and the time varying nature of the BSERMH and HMLBSEH. The figure shows that (BSERMH) herding towards the market factor shows that there is variation in the herding behaviour in Indian stock market. During the period 2003 to 2004 the investors showed moderately higher herding tendencies while it swing around zero during the period 2004 to 2007 and it showed the higher level of herding during the crisis period. The post crisis period also showed almost similar trend like the pre crisis period. While analysing investors herding behaviour towards the value factor, investors showed a higher level of herding during the bullish period and one cannot see any particular trend or pattern in the herding behaviour. The figure BSESMBH clearly shows that investor herding towards the value factor was more during 2005 to 2007, the bullish period and is as expected since the individual investors, (are more when compared to institutional investors) who often look at the value factor than any other factor in bullish period.

Figure IV.III. Show the evolution of herding behaviour throughout the study period. BSERMH, SMBBSEH and HMLBSEH denote the herding measure extracted through State Space model using Kalman filter. The analysis finds existence of herding behaviour in the studied market during the study period. At the same time from the figure it can be seen that the highest value of h_{mt} is nearly 0.60 (in the case of herding towards the market factor), explain that there was no extreme degree of herding behaviour in the market. If h_{mt} = 1, we say there was perfect herding or extreme herding in the market and form the figure IV.III and figure IV.IV can see that herding was highest during the end of 2007. Further, from the Figure IV.III, one could see many cycles of herding and there was no adverse herding towards the market portfolio except few periods during the study period and these may attribute to the various events, which have happened in the economy as well as in the stock market during these periods. It is also noted that herding shows its peak (0.6) during the end of 2007.

Figure IV.III
Line Graph of Log Cross Sectional Standard Deviation of Market Beta and the Pattern of Herding Behaviour throughout the Study Period



Line Graph of Log Cross Sectional Standard Deviation of Beta of the HML Factor and the Pattern of Herding Behaviour throughout the Study Period



Further analysing the graph one can see that the evolution of herding behaviour is smooth in the case of herding towards the value factor (BSEHMLH) while comparing with the herding pattern towards the market factor. As noted by Hwang and Salmon (2004) the higher the signal to noise ratio, the pattern of herding behaviour will be less smooth over time it evolves. This can be found from the Figures IV.III, IV.IV and IV.V. These figures show that the herding evolution is smoother in the case BSEHMLH while compared with BSERMH, the herding towards the market portfolio.

Figure IV.IV.
Herding Pattern towards Market Factor, Size Factor and Value Factor

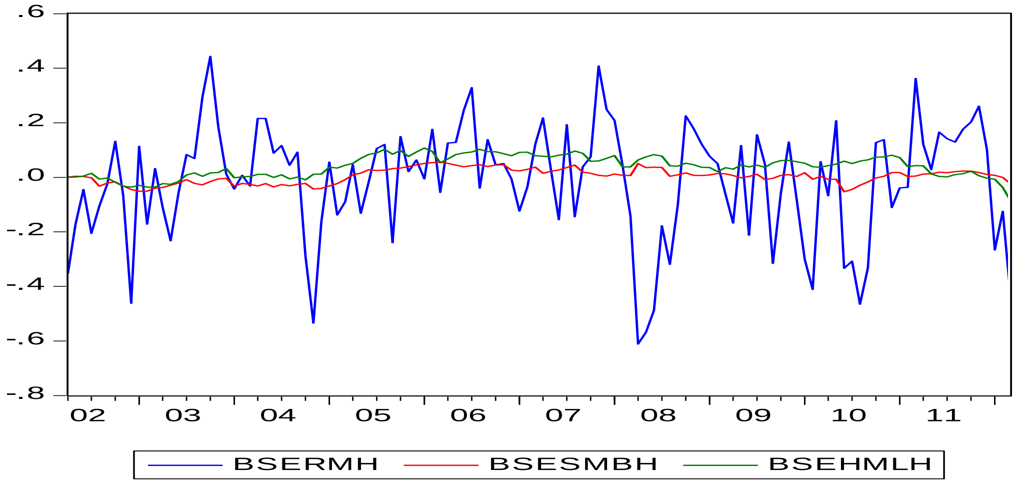


Figure IV.IV shows the evolution of herding behaviour towards Market return, SMB and HML factors.

Figure IV. V
Herding Pattern towards Market Factor, Size Factor and Value Factor Along With The Log Cross Sectional Standard Deviation of Fama French Betas

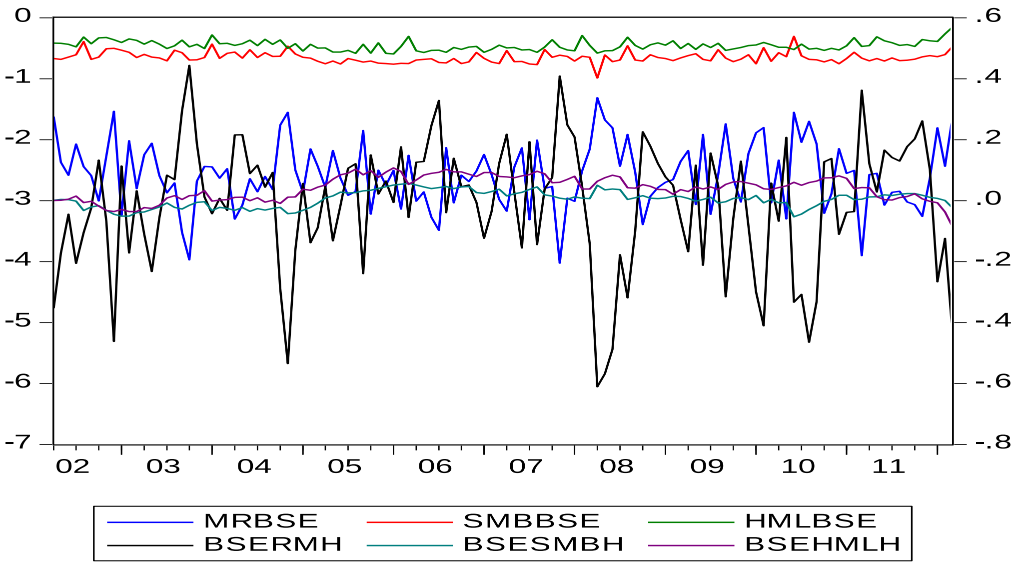


Figure IV.V shows the evolution of herding behaviour with the Fama French factors

4.5.4 Comparison of the Two Measures

Two measures are used in this study to examine the existence of herding behaviour in Indian stock market. The first one is a static measure (a non linear measure) while the second is a time varying measure based on the state space model proposed by Hwang and Salmon (2004). Even though the methods and the variables are different and the comparison of results makes valid sense (not methodically) in explaining the herding behaviour in the studied market. Through both methods, the study finds herding behaviour towards the market portfolio in the studied market. The static measure used daily data and the results showed herding behaviour in the whole period, the pre crisis period and during the crisis period but fail to find herding during the post crisis period. The second method used the monthly log cross-sectional standard deviation of Fama French betas and found herding behaviour in the studied market throughout the study period

While comparing the two measures the study found a very low level of herding during the post crisis period with the static measure and one could see almost similar result in the time varying measure, where Figure IV.III., IV.IV shows that mostly herding swing around zero during this period. Further, the static measure find a higher level of herding nearly (0.35) during the crisis period, where as one can find similar result in the case of time varying measure, where it records the highest (nearly (0.6) during the crisis period. It is also noted that there is moderate level of herding during the post-crisis period while using the time varying measure and find an insignificant negative coefficient while applying the static measure. It shows the absence of herding behaviour and this may happen since different variables and different methods are used for the analysis. The difference in the result is in line with the previous research, like Hachicha and et al. (2008), Amirat and Bouri(2009a), Balsco and et al. (2010), who found different results while applying static measure (no herding) as well as time varying measure (found herding) in Tunisian market. Hence, one could see that the results are almost similar and explain that there was moderate level of herding behaviour in Indian stock market and was higher during the crisis period.

Table No. IV. IV.
Summary Findings Using the Static and Time varying Measures

specifics	Static Measure	Time varying Measure
Period of Study	01-04-2002 to 28-03-2013	01-04-2002 to 28-03-2013
Data Considered	Daily	Monthly*
Whole Study Period	Found existence of herding behaviour	Found existence of herding behaviour
Pre crisis Period	Found existence of herding behaviour and the intensity is low	Found existence of herding behaviour and the intensity was low and mostly swing around zero
Crisis Period	Found existence of herding behaviour and is higher during this period	Found existence of herding behaviour and is higher during this period
Post Crisis Period	No herding	Found herding
Market Factor	-	Found herding towards Market factor
Size Factor	-	No herding towards Size factor
Value factor	-	Found herding towards Value factor
Conclusion	There exists herding behavior in the studied market and there was moderate level of herding	There exists herding behavior in the studied market and there was moderate level of herding

*Beta calculated from daily data using Fama French Approach

4.6. Summary and Conclusion

4.6.1. Summary

The dynamics of developing stock markets are complex and it differs from country to country based on number of factors. BSE is one of the important stock markets in India. This chapter empirically analysed the degree of herding behaviour in Indian stock market (BSE) by using daily data of the 243 constituent scrips of BSE 500, a major index of BSE. Many models have been proposed over the years to measure herding behaviour and the study adopted two methods, a static measure (extended version of Chang et al. (2000) and a time varying measure, developed by Hwang and

Salmon (2004). By using the first measure, the study carried out the tests for the whole period and different sub periods while the second method used monthly time varying beta to measure the herding behaviour for the whole period. This study used the return of the individual stocks as well as the markets and the log cross sectional standard deviation of betas calculated by using the Fama French model for calculating the different constituents of the applied models. The study used Fama French model because it can incorporate the effect of three factors while comparing with one factor model or two factor model of CAPM.

From the analysis, the study found the existence of herding behaviour in Indian stock market with difference in the degree of herding towards the market consensus during the study period. The intensity of herding is more during the crisis period and is less during the pre crisis period. The reason for such result is that during crisis, the investors may be more panicked and might have followed others. In addition the study also examined the herding towards the size factor and value factor by using the time varying measure and found that the there is no herding towards the size factor but there is herding behaviour towards the value factor (investors considered the value of the firm). While comparing the herding behaviour towards the market factor as well as the value factor the proportion of signal is higher, nearly 54%, for market factor while it is nearly 20% in the case of value factor. The reason for this observed result may be because of the type of investors in Bombay Stock Exchange, has more number of individual investors than the institutional investors, who generally less informed and less sophisticated while comparing with institutional investors. Further, individual investors often look at the market movements as well as the value of stocks where as institution often look at the size and liquidity factors.

4.6.2 Conclusion

Analysing the herding behaviour in a rapidly developing market like Indian stock market is important to financial policy makers, investors and wealth managers to understand this behaviour and the ensuing changes in the market to take appropriate decisions. Further, the actions of investors in the market based on this behaviour may typically affect market movement, lead to mispricing of assets and hence lead to market inefficiency. Through the applied methods, it is found that herding behaviour throughout the studied period and is more during the period of crisis. Overall this study found a moderate level of herding in Indian stock market. In the light of these, policy measures must be taken by the concerned authorities like SEBI and Stock exchanges to educate the investors, since the herding behaviour create damage to the market and lead to mispricing of assets and hence affect the efficiency of the market. Further lack of information is one of the important reasons for herding behaviour and transparency and easy availability of the necessary information may reduce the herding behaviour in the market.

CHAPTER V

DETERMINANTS OF HERDING BEHAVIOUR IN INDIAN STOCK MARKET

5.1. Introduction

The growth and potentials of Indian stock market attracted many investors during the last decades. The investors show herding behaviour in the stock market and often try to follow others in their actions or decisions. Most of the empirical examination on herding behaviour in developing stock markets found existence of herding behaviour at least in different states[44] of the market. Identifying the determinants of herding behaviour will help one to explain a number of behavioural issues exist among the investors and the analysis will give more clarification and shed light in explaining the characteristics of herding behaviour in Indian stock markets. There are adequate evidences in the literature to show that many factors influence the investors herding behaviour. The objective of this chapter is to identify and demonstrate the different factors controlling the herding behaviour in Indian stock market during the period of study. Further, it also helps to understand the destabilizing facts of the market and explains how investors process the available information and frame their investment decisions accordingly. Indian stock market as a developing market, this study assumes the influence of both firm fundamentals as well as market factors as the controlling source of herding behaviour.

Herding behaviour in the market seems to be one of the common behaviour found in stock market especially in developing markets with depressing characteristics[45]. The literature well established the fact that herding behaviour is likely to be influenced by different factors like firm fundamentals, macroeconomic factor or psychological factors and so on. One of the established factors is the information asymmetry and varied number of literature pointed out this fact. Lakonishok et al. (1992), Wermers (1999), pointed out the role of market capitalization of firms, generally reflects varied number information about the stocks and thereby can expect higher levels of herding towards size factor and showed trading in small capitalized stocks as evidence for intentional herding. Chang and et al. (2000) noted that in the absence of efficient

44 During high or low states of volatility, return, crisis period and so on.
45 Leads to mispricing of assets and inefficiency of the market

information, the market participants may not have the information about the fundamental factors and hence they may follow the signals of others in their trade decisions. In addition, it is also important to ensure these factors do not cause herding behaviour. As explained in the previous chapters herding behavior will lead to market inefficiency, hence examining the various factors controlling herding behavior is important in many aspects.

5.2. Rationale of the Study

The existence of association between herding behaviour and different factors has been documented in a number of empirical studies. Few studies examined the role of macroeconomic factors in the stock market in deciding herding behaviour. Further one can see that the firms with small size are less transparent while comparing with the large firms because of the limited information disclosure of small firms. But it is also noted that literature on herding behaviour provide mixed result on the size factor and one could see herding towards both small as well as large stocks. Further, while comparing the developed and developing countries it is found that the factors affecting the herd behaviour are different. It is also noted that the results in developing market itself differ from one another. A thorough analysis of the herding behaviour in Indian stock market will help the investors and practitioners in many ways and one can better understand about the destabilizing effects of these factors in the markets and can also provide further insight on the driving sources behind herd behaviour. Analysis by using different factors are essential to establish the determinants of herding behaviour in Indian stock market and thus the sources of herding, by considering different variables explained in the next section.

5.3. Variables and Methodology

The study used a multifactor time varying measure followed by Hwang and salmon (2004), who explained that the return of stock as well as herding may be affected by fundamental factors and this study used both firm fundamentals as well as market fundamentals to analyse the controlling effect of variable on herding behavior in the selected market. The analysis will help to assess the relative importance of these factors in determining the herding behaviour and planned to use market return, market volatility, market trading volume, Size factor (SMB), Value Factor (HML), net Institutional Investment, net foreign institutional investment, net mutual fund investment and the US index return (S&P-500), In addition, the study also tested the joint effect of market volatility, market return and market trading volume and Us return (S&P500), MFI and Institutional investment, and the joint effect of all variables together (including net institutional investment and excluding net FII investment and net mutual fund investment) in determining the herding behaviour. Out of the selected variables, two are firm specific factors while the remaining are market related factors.

The monthly volatility of the index is calculated by following the methodology adopted by Schwert (1989)[46]. In this stage the daily time series of the index return of BSE-SENSEX was used to find the monthly volatility time series. All other data required for the study are taken from Prowess-CMIE data base, official website of BSE and the analysis is carried out by using monthly data.

To investigate the controlling effect of different variables on herding behaviour the study carried out analysis for the whole period. To examine the role of different variables, study uses the state space model, (Kalman filter) and considers different alternative models to explain the effects. The study specifically selected the role of foreign institutional Investors (FII) because a number of studies stressed the role of FIIs in Indian stock market and there is a perception that FII have dominative power in Indian stock market and it is very visible with the statistics that the percentage trade by foreign institutional investors and domestic institutional investors has increased very much during the last decades. The study uses the data over the period 1st April 2002 to 28th March 2012 and the time varying beta of the sample companies (243 Companies) to check the various determinants of herding behaviour while herding towards the market portfolio. In addition to check the robustness of the results, the study used the time varying herding measure extracted through the state space model and the series is regressed with selected independent variables jointly. The adopted methodology will provide necessary information about the controlling effect of various selected factors on herding behaviour in the studied market.

[46] See French, Schwert and Stambaugh (1987) for further reading.

5.3.1. Procedure for Analysis

To check the role of various factors on herding behaviour the study followed the following procedure.

1. Extract the herding measure by using the state space model from the log cross-sectional standard deviation of beta of the market factor (using the kalman filter approach).
2. Collect the required variables under study.
3. Calculate monthly return of the Indices BSE –SENSEX and S&P 500 by using the first difference of the log value of the corresponding series
4. Calculate the monthly market volatility by following the procedure adopted by Schwert (1989) methodology.
5. Convert the series in to log form.
6. Divide the net Institutional Investment, Net of foreign institutional investment and the net domestic institutional investment with market capitalization of BSE to normalize the data.
7. Convert the Data (volume) in to log form.
8. Do Preliminary analysis through descriptive statistics and line graph.
9. Check the Stationarity of the variables individually through ADF and PP tests.
10. Apply the state space model and find the controlling effect of the selected variable on herding measure.(individually and jointly)
11. Regress, the extracted herding measure with selected variables to check the robustness.

5.4. Analysis of Determinants of Herding Behaviour

5.4.1. Summary Statistics and Stationarity Tests

Table VI.I explains the summary statistics of the different variable used in this study. The mean value and standard deviation of cross sectional standard deviation of beta on market factor are positive in the Indian stock market. It also shows the peakedness of the data.

Table V.I
Summary Statistics and Results of Stationarity Tests for Different Variables

Description	**Variables Used**										
	Market Beta (FF Model) (Log)	Market Return	Market Volatility (Log)	Market Volume (Log)	US Index Return (S&P-500)	Net Investment (Normalized)			Size Factor (SMB)	Value Factor (HML)	Time varying Herding Measure
						FIIs	MFIs	IIs			
Mean	-2.58181	1.343954	1.741862	9.9272	0.002174	0.000129	0.005894	0.123414	0.005352	-0.03611	-0.016055
Median	-2.58773	1.509622	1.638835	9.8702	0.010274	0.000104	-0.0004	0.099483	-0.01218	-0.03559	0.028217
Std. Dev.	0.534913	7.70185	0.451331	0.4057	0.046462	0.000493	0.056721	0.187909	0.203317	0.200958	0.209578
Skewness	-0.03502	-0.55032	0.797559	0.5593	-0.8861	-0.20931	1.376175	0.417081	0.548693	-0.02823	-0.63965
Kurtosis	2.961079	4.403678	3.279323	2.9684	4.777583	5.581522	6.617869	3.671011	4.832521	4.303998	3.236053
Jarque-Bera	0.03210	15.9087*	13.1121*	6.2624**	31.5026*	34.1974*	103.3221*	5.7304***	22.8119*	8.5180**	8.4616**
Observations	120	120	120	120	120	120	120	120	120	120	120
ADF	-9.2567*	-9.6870*	-5.7550*	-2.9997**	-8.7032*	-3.2323**	-8.2684*	-6.7426*	-9.3845*	-3.7851*	-6.5088*
PP	-9.2922*	-9.7616*	-9.3845*	-3.0157**	-8.7909*	-3.2323**	-8.3003*	-7.1312*	-9.3165*	-10.3676*	-6.5088*

Note: * denotes significance at 1%level and **, *** denotes significance at 5% and 10% respectively. FII, MFI and IIS are net foreign institutional investment, net mutual fund investment and institutional investments respectively and all are normalized by dividing with the market capitalization of the index. The All the series are in monthly time interval. CSSD: cross sectional standard deviation. Time varying herding measure extracted through the state space model.

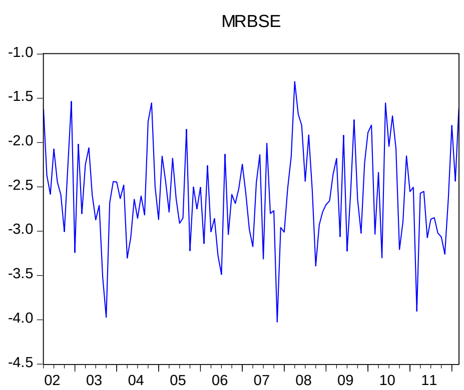
The Jarque-Bera shows departure from normality and shows that most of the series depart from normality (non-Gaussian). To explain the effect of different variables on herding behaviour in Indian stock market the study uses log cross sectional standard deviation of market beta extracted through Fama French model and used the state space model, Kalman filter.

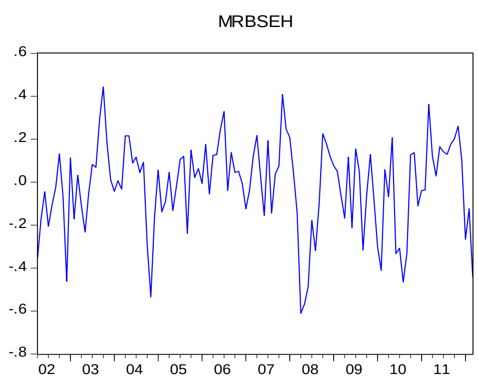
5.4.2. Line Graphs of Variables Included in the Study

Figure V.I. shows the line graph of different variables considered in the study. RBSE is the market return of the index; VOLBSE is the log volatility of the Index, volume BSE is the log volume of BSE and S&P-500 representing the US stock market returns. EQFIIBSE, EQMFIBSE and NETBSE are net foreign institutional investment; net mutual fund investment and Net institutional investments (FII+ MFI) normalized by dividing with market capitalization of the index of the month *t*. SMBBSE and HMLBSE are the size factor and value factor and MRBSE and MRBSEH represent the log cross sectional standard deviation of market beta (Fama- French) and the herding measure extracted through the state space model.

The figures VI.I gives a brief sketch of each variable used in the study for the period April -2002 March-2012. It helps to analyse the movement of variable over the study period and data converted into log form for smoothening. The line graphs clearly show the variations due to different events in the markets, especially the crisis.

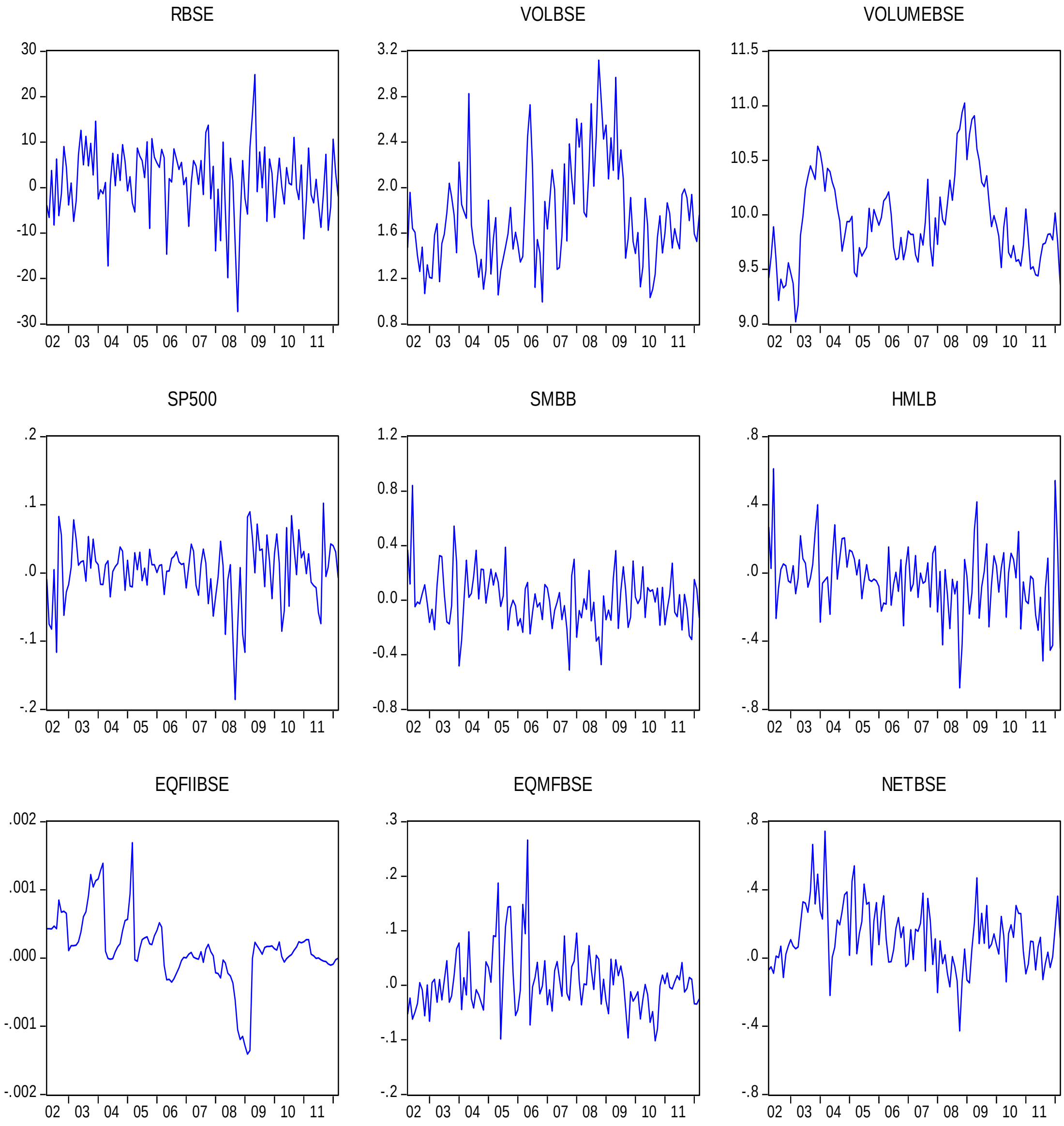
Figure V.I.
Line Graphs of Different Variables Used in this Study





MRBSE represents the log cross sectional standard deviation of beta and MRBSEH represents the herding series extracted through the kalman filter. The graph shows that the variation is more during the crisis period 2007-2008 (07-08, in the graph) in both of the cases.

Line Graphs of Different Variables Used in this Study



RBSE represents the market return of BSE, VOLBSE and VOLUMEBSE denotes the log market volatility and log market volume, shows more variation during the crisis period. SMBB and HMLB represent the SMB and HML factor found through the Fama French factors. EQFII, EQMFBSE, NET BSE are the normalized net FII investment, net mutual fund investment and net institutional investments respectively and EQFII did not show any trend while EQMFI and NETBSE showed almost similar pattern but there is greater variation during the 2004-06 period and the withdrawal of FII during the crisis is more visible from the graph.

5.5. Determinants of Herding Behaviour in Indian Stock Market

5.5.1. Herding Behaviour with Market Return, Market Volatility, Market Volume and Return of S&P -500.

The study examined the effect of market return and market volatility and market volume independently and all these factors jointly as control variable to examine the effect on herding behaviour. Table V.II expounds the estimation results of the state space model (14), (15) and (16)[47] for the tested market and help to analyse how these factors affect herding behaviour for a given market condition. The Table V.II below explains the role of different variables on herding behaviour and it provides valuable insight in explaining the herding behaviour. The estimates of the model ϕ_m, $\sigma_{m,n}$ is significant in all the cases, which shows that there is herding behaviour in Indian stock market. While analyzing the Table V.II, it can be seen that the coefficients of the monthly return on BSE (r_{mtBSEt}) is insignificant, (model 14) which explains that market return is not sensitive factor to the herding behaviour of investors or herding is not affected by the changes in market return.

[47] See the methodology chapter for the model

Table V.II.
Estimations of State Space Model after Controlling Market Volume, Market Return, Market Volatility and Return of S&P500

Estimates	Market Return(14)	Market Volatility(15)	Market Volume(16)	Market Return Volatility & Volume, (17)	Volume, Volatility, Return & S-P500(18)
ϕ_m	0.48891516*** (3.0722)	0.83521301*** (11.1373)	0.437472** (2.49507)	0.727277*** (6.56821)	0.742739*** (7.01883)
μ	-2.58276175*** (41.3335)	-1.6299996*** (-19.6576)	-1.83374*** (30.5852)	-3.61692*** (-52.2695)	-3.6123*** (-51.2076)
$\sigma_{m,n}$	0.2749923*** (2.67203)	0.1377388* (1.83689)	0.281292 (2.65425)	0.173953** (2.00974)	0.169037** (1.9867)
$\sigma_{m,v}$	0.4286441*** (5.4790)	0.4454245*** (6.7701)	0.429704*** (5.41674)	0.433354*** (6.45241)	0.434589*** (6.49718)
Log Volume	-	-	-0.07481*** (12.3937)	0.207279*** (29.73775)	0.207713*** (29.22479)
Log Volatility	-	- 0.5310682*** (-11.9726)	-	-0.57492*** (-15.2821)	-0.57942*** (-15.1299)
r_{mtBSEt}	0.00632154 (1.0180)		-	-0.00273 (-0.46962)	-0.00272 (-0.46872)
SP-500	-	-	-	-	0.18814 (0.19031)
Proportion of Signal	0.5140877	0.2574975	0.525865	0.325198	0.316007
Maximum Likely Hood Values	17.7509	25.0937	17.3916	25.8232	25.8395

Note: ***,* denotes the significance at1% and 10% respectively, table shows the estimates of the state space models, $\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m2} r_{mtBSEt} + V_{mt}$, $\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m1} \log \sigma_{mt} + V_{mt}$, model (14). And (15), $\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m2} vol_{BSEt} + V_{mt}$, model (16), $\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m1} log \sigma_{mt} + C_{m2} r_{mtBSEt} + C_{m1} vol_{BSEt} + V_{mt}$, model(17) $\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + C_{m1} \log \sigma_{mt} + C_{m2} r_{mtBSEt} + C_{m3} \log Vol_{mt} + C_{m4} r_{mSP\,500} + V_{mt}$, model (18). $and\ H_{mt} = \Phi_m H_{mt-1} + \eta_{mt}$. To calculate the volatility model (19) is used. $\sigma_{mt}^2 = \sum_{i=1}^{N_t} R_{it}^2 + 2\sum_{i=1}^{N_t-1} R_{it} R_{i+1,t}$ (19).

The results of the model (15), explain the effect of market volatility on herding behaviour. The study used log volatility of the market calculated through the Schwert (1989) methodology and one can see that the estimates of the herding measures are significant at1% level and the coefficient of the volatility factor also significant at 1% level and the negative sign explain that the log cross sectional dispersion of the beta increases (decreases) as market volatility decreases (increases). The results also suggest that herding is still significant even after controlling the volatility. Further, it is important to note that the value of $\sigma_{m,n}$ decreased to (0.13) from (0.27), and the negative coefficient showed that $Std_c(\beta_{imt}^b)$ decreases when the market volatility rises, explain that herding increases with volatility factor. Further the ϕ_m coefficient is significant and the value of the persistent factor is high when compared to the market return. There is an increase in the estimated ϕ_m while comparing with the model no 14. With all these it is possible to conclude that $Std_c(\beta_{imt}^b)$ decreases when the market is more risky.

While examining the market trading volume (model-16), we can also see a similar result, but it is important to note that the value of σ_{mn} increased to (0.28), and the ϕ_m decreased to 0.43 and there is decrease in the μ while comparing with the volatility factor, shows that $Std_c(\beta_{imt}^b)$ increased while controlling volume, explains herding is decreased when compared to the volatility factor, means that the influence of volume is comparatively less when compared to the market volatility.

The model 17 analysed the combined effect of all the three factors (market return, log market volatility and log market volume) together and the result we can see in table V.II. While controlling these factors it can be observed that the estimates of the coefficients are still significant except r_{mtBSEt}. It is also noted that ϕ_m and μ increased 0.72 and μ decreased to -3.61.means the significant factors influence herding behaviour in Indian stock market.

The model (18) explains the degree of herding behaviour while using the log market volatility and market return and log market volume and SP-500 jointly as predictor[48]

[48].variable used in a relationship to explain or to predict changes in the values of another variable, independent variable

variables. From the table II, it is seen that the term H_{mt} is significant; explain the presence of herding behavior in the studied market. While analyzing the influence of different factors and their joint effect, one can see ϕm increased from 0.4 to 0.7, shows that the inclusion of volatility and other variable increased the persistence. It is also noted that there is not much difference in the results of model 17 while comparing with the results of the model (16). Further the S&P-500, the additional variable used in this model is insignificant; explain that it has no influence or impact on herding behaviour. The results of this analysis is similar to the studies of Hwang and Salmon (2004), by using US and Korean market data, Demirer and et al. (2010) for Taiwan market, Chiang and et al. (2011), and Basu and et al. (2011) for Indian market, Kermer and Nautz(2013) they found volatility is an important factor , which increases herding behaviour.

The Figure V.I. below shows the evolution of herding behaviour with different tested variables. Figure V.II shows the evolution of herding behaviour with market volatility and market volume VOLBSE is the log volatility of the market and VOLBSEH is the herding measure extracted through the state space model (15). Here VOLUMEBSE is the log market volume and VOLUMEBSEH is the herding measure extracted through model (16).

The figures above show the evolution herding behaviour with different factors. While analysing the graphs it is clear that during the crisis period[49], in most of the cases there is higher degree of herding. During the post crisis period, figures do not show a particular trend and it is difficult to explain the pattern of herding behaviour. In the case of volatility, it is difficult to find a particular pattern, but it is seen that herding mostly moves near to the 0.2 during the pre crisis period but there is extreme herding during the crisis period. Further it is also noted that the common convention is that investors show higher level of herding behaviour during market stress and this result is in line and consistent with the previous studies, like, Hwang and Salmon (2004), Andronikidi and Kallinterakis (2010), Demirer and et al. (2010) and Basu and et al. (2011) and Chiang (2011), who found that volatility impact herding behavior in the tested markets.

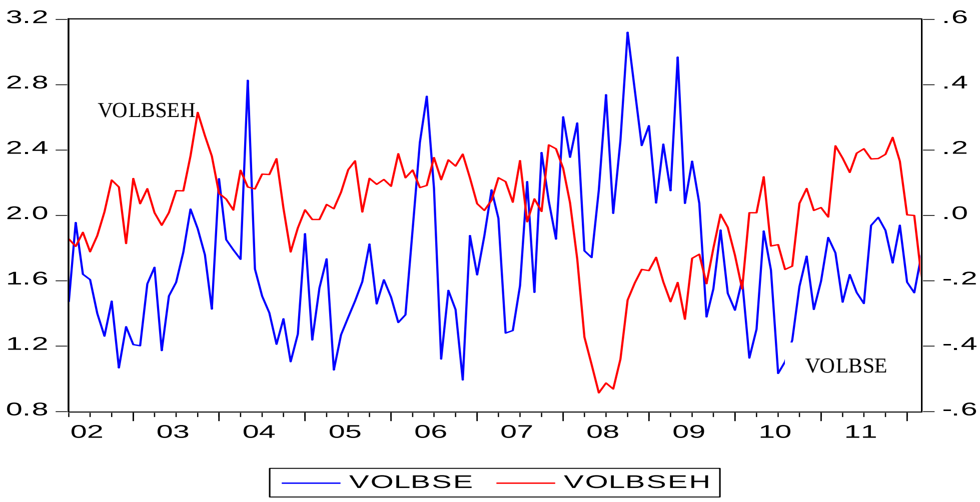
[49] Used crisis period, pre and post crisis period as defined in the methodology chapter for analysing the herding measure by using the static measure. The periods explained here are approximate since it is difficult to plot the exact date in the graph.

Figure V.II.

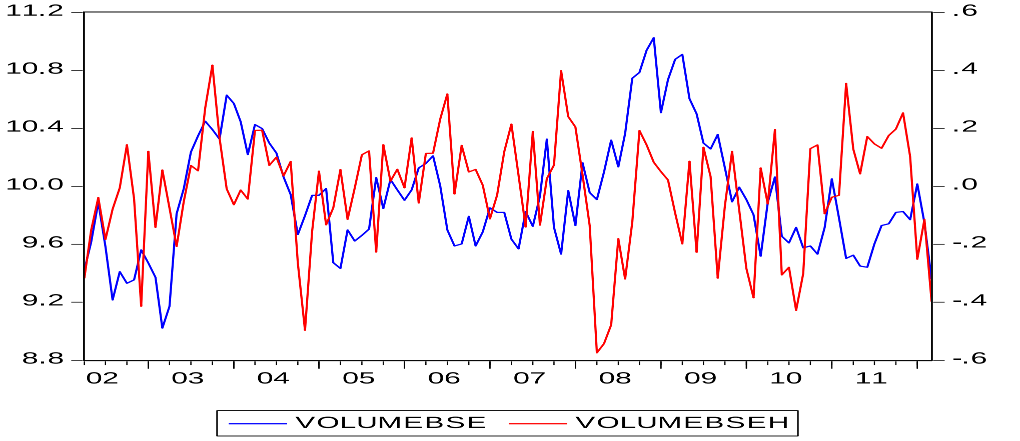
Evolution of Herding Behaviour with Market Volatility and Market Volume

Figure V.III.

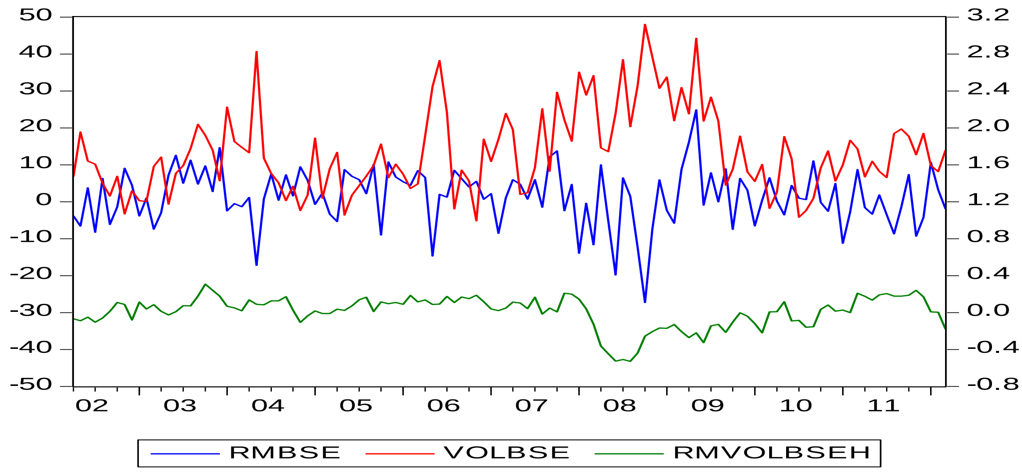
Evolution of Herding Behaviour with Market Volatility



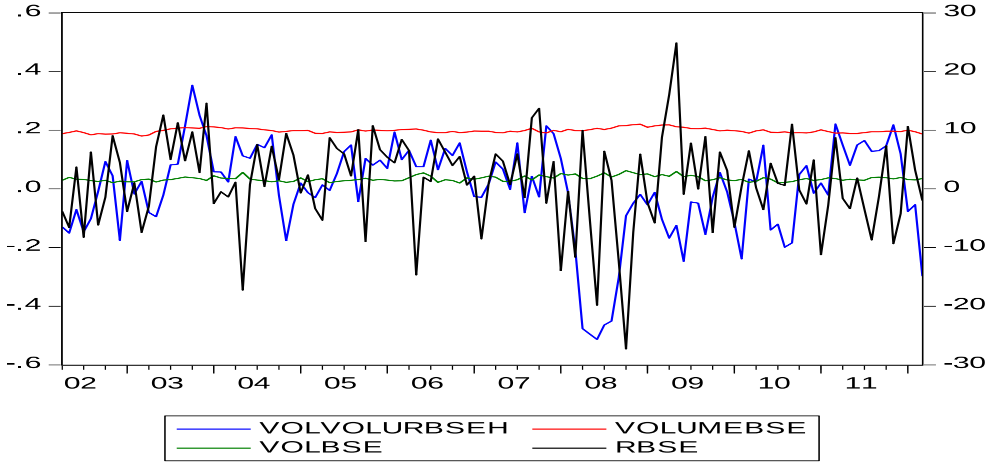
Evolution of Herding Behaviour with Market Volume



Evolution of Herding Behaviour with Volatility and Market Return



Evolution of Herding Behaviour with Market Volatility, Market Volume and Market Return



While considering the volume one can observe certain pattern till 2007, but there after one cannot see any particular trend in the evolution of herding behaviour and the figure shows many cycles. The VOVOLURBSEH shows the evolution of herding behaviour while using all the three variables jointly.

5.5.2. Herding Measure with FII and MFI

The study also analysed the effect of foreign institutional investment, the role of mutual fund investment and the effect of both together in driving the herding behaviour in Indian stock market. The study used the monthly net investment flows and used the model (19), (20), (21) and the analysis is done with the net FII flow and net mutual fund flow to the market (both the factors are normalized by dividing with market capitalization of the index). The study also tested the role of net institutional investment and the estimates of different model (19), (20) and (21), are presented in Table V.III. The table shows that herding exists in the Indian stock market, since both ϕ_m and $\sigma_{m,n}$ are highly significant (at 1% level) with a proportion of signal equal to nearly 54%. The significant persistence factor, ϕ_m explain that there is herding behaviour in the studied markets and the estimate of the mutual fund is negative(insignificant) but it is positive in the case of FII Investment and is significant, shows that FII influences herding behavior. While comparing $\sigma_{m,n}$, ϕ_m and μ it is clear that there is not much variation in $Std_c(\beta^b_{imt})$, explains that the effect FII movement on herding behaviour is less in the studied market. Further the positive coefficient of the net FII investment explains that $Std_c(\beta^b_{imt})$, increases with the level of net FII flow, points that herding decreases when net FII flow increases. Hence it can be concluded that the net foreign Institutional investment has very limited controlling effect on herding behaviour. Further, it can be found that the net flow of institutional investment (NET) is positive and insignificant, which means that net institutional investment have no controlling effect on the herding behaviour in the studied market. Hence, concluded that the institutional investors do not have a major influential power on herding behaviour in Indian stock market.

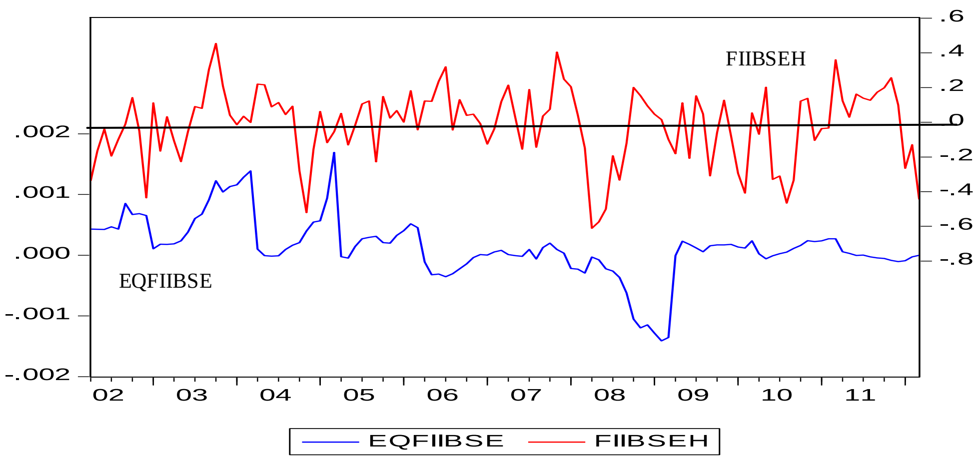
Table V.III.
Estimations of State Space Model after Controlling Different Institutional Investors

Estimates	FII (20)	MFI (21)	NET (MFI+FII) (22)
ϕ_m	0.457701*** (2.7484)	0.43410311** (2.5070)	0.4467915*** (2.6756)
μ	-2.58193*** (-41.9962)	-2.574814*** (-42.7592)	-2.577532*** (-42.2069)
$\sigma_{m,n}$	0.2850109*** (2.7490)	0.2865274*** (2.7268)	0.2877671*** (2.7699)
$\sigma_{m,v}$	0.42590773*** (5.3536)	0.42677267*** (5.3426)	0.4251709*** (5.3211)
FII_{net}	5.76323*** (6.0514)	-	-
MFI_{net}		-0.2245571 (-0.2561)	-
NET_{ii}	-	-	0.015814 (0.0656)
Proportion of Signal	0.532817	0.537969	0.534792
Maximum Likely Hood Values	17.351	17.3755	17.2590

Note:*** denotes significance at1%level, table shows the estimates of the state space models, $\log[Std_c(\beta^b_{imt})] = \square_m + H_{mt} + C_{m1}NetFII_t + V_{mt}$(20), $\log[Std_c(\beta^b_{imt})] = \square_m + H_{mt} + C_{m2}NetMFI_t + V_{mt}$,(21), $\log[Std_c(\beta^b_{imt})] = \square_m + H_{mt} + C_{m3}NetII_t + V_{mt}$(22), $H_{mt} = \Phi_m H_{mt-1} + \eta_{mt}$ The variables are normalized with market capitalization.

Figure V.III, shows the evolution of herding behavior with net FII flow in to the studied market. EQFIIBSE is the net flow (Normalized with market capitalization of the index) in the left axis and FIIBSEH, the extracted herding measure in the right axis, from the figure it is difficult to find and a specific trend or pattern of herding behavior and shows very low level of herding on an average.

Figure V.IV
Evolution of Herding Behaviour with Net FII Flow



5.5.3. Herding Measure with Size and Value Factors

The study also carried out the analysis by using the Fama French factors SMB and HML as explanatory variable. The study used the style approach followed by Fama and French (1993) & (1995) and Table V.IV explains the relationship between the herding by using SMB factor and HML factor, the size factor and value factor respectively.

The study found that, none of the factor showed significant result to explain that the factors, both HML and SMB have no controlling effect on herding behaviour in Indian stock market. The study also examined the joint effect of SMB and HML based on the size and value factor and found the same result and confirms that the tested variables have no influence.

Table V.IV.
Estimations of State Space Model after Controlling Size and Value Factor

Estimates	SMB (23)	HML (24)	SMB,HML (25)
ϕ_m	0.419666** (2.2654)	0.461649*** (2.6110)	0.436862** (2.37084)
μ	-2.57916*** (-44.177)	-2.56359*** (-42.9332)	-2.57231*** (-43.9072)
$\sigma_{m,n}$	0.172116*** (2.6041)	0.168357** (2.4823)	0.269257 ** (2.50636)
$\sigma_{m,v}$	0.183373*** (5.4353)	0.18335*** (5.6109)	0.431574*** (5.55216)
SMB	0.378694 (1.605)	-	0.263435 (1.1198)
HML	-	0.346982 (1.4845)	0.166333 (0.71272)
Proportion of Signal	0.321765	0.314736	0.321765
Maximum likely hood values	18.5072	18.3149	18.6364

Note:***,** denotes significance at1%level and 5 % level respectively. Table shows the estimates of the state space models, $\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + C_{m1}SMB_t + V_{mt}$(23), $\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + C_{m2}HML_t + V_{mt}$,(24), $\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + C_{m1}SMB_t + C_{m2}NHML_t + V_{mt}$(25), $H_{mt} = \Phi_m H_{mt-1} + \eta_{mt}$ are used..SMB and HML are derived using the Fama French approach.

5.5.2. The Joint Effect of Various Factors

The study also tested the joint effect and the results are shown in Table V.V. The analysis using all the variables together excluding the net institutional investment (to avoid auto correlation between the factors) showed that only volatility, volume and foreign institutional have control effect on herding behaviour. The analysis also repeated with all variable together excluding the FII_{net} (net FII) and MFI_{net} (net MFI) and by including net institutional investment (to avoid auto correlation between the factors), denoted by NET_{ii}, showed that only volatility, volume and Net institutional investment has controlling effect on herding behaviour, confirms the previous results and explains that the institutional investors together can also influence the herding. It is also noted that the joint effect may be because of the influence of FII in the market since net mutual fund was insignificant when tested individually and jointly. At the same time the volatility factor is still significant at 1% level, shows the controlling effect of this factor in Indian stock market. Further, the value of μ decreased from -3.3 to -4 shows these factor jointly increased the herding behaviour in Indian Stock market.

The results are almost similar to our previous findings with the models (14), (15), (16), (18) and (21) the MFI_{net} shows insignificant results, explain that it has no control over the herding behaviour in the studied market. Based on the previous analysis and considering the variations in $Std_c(\beta^b_{imt})$, from the found results it can be concluded that volatility is the major factor which control the herding behavior in the studied market along with volume, and net FII investment .Further the study also tested the robustness of the result by using regression and found that the volatility is the most significant factor which controls herding behavior in Indian stock market.

Table V.V.
Estimations of State Space Model after Controlling
Tested Factors Jointly

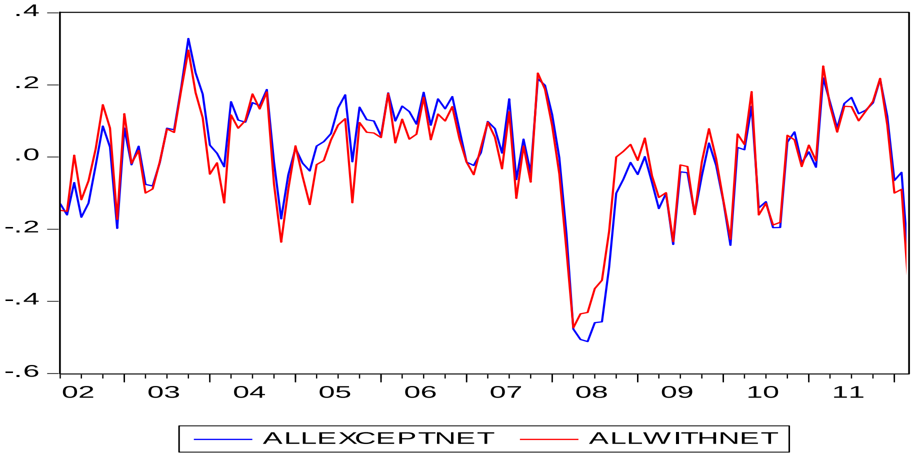
Variables / Estimates	Estimates	Estimates
ϕ	0.729518*** (6.6720)	0.605061*** (3.9821)
μ	-3.30313*** (-47.7665)	-4.00247*** (-67.4243)
$\sigma_{m,n}$	0.173033** (2.0174)	0.198528** (2.0749)
$\sigma_{m,v}$	0.430655*** (6.4508)	0.420541*** (6.1930)
MFI_{net}	0.702463 (0.8703)	-
FII_{net}	-7.8695*** (-22.154)	-
VOLUME	0.180057*** (25.8398)	0.260854*** (43.6411)
VOLATILITY	-0.59396*** (-15.8008)	-0.61969*** (-19.0186)
RETURN	-0.00297 (-0.5143)	0.003008 (0.5259)
SMBB	0.037751 (0.1728)	0.060619 (0.2791)
HML	0.119701 (0.5467)	0.096432 (0.4456)
SP-500	0.250635 (0.2570)	0.300151 (0.3190)
NET_{ii}	-	-0.66519** (-2.9468)
Proportion of signal	0.323478	0.37114
Maximum likely hood values	28.138	27.817

Note:***,** denotes significant at 1%level and 5 % level , respectively, the study used model no 27 and 28 for the analysis

Figure V.IV explain the evolution of herding while using the selected factors. ALLEXCEPTNET, explain the herding behaviour when the net institutional investment is excluded, where as ALLWITHNET explain the evolution of herding behaviour when Net FII flow and Net Mutual fund flow is excluded. The result shows similar and there is not much variation in the evolution of herding while comparing the two cases and herding is more during the period 2007-2008, the crisis period.

Figure V. V

Evolution of Herding Behaviour with all the Factors



5.6. Conclusion

The existing literature clearly explains that different market fundamentals and Asset fundamentals like size, value of the stocks etc. affect the herding behaviour. The primary factors that shape the herding behaviour in Indian capital market are not firm specific factors like size or values, since these factors found insignificant in the analysis. From the results it can be found that market factors like volume, volatility and the foreign institutional investments have controlling effect on herding behaviour in Indian stock market.

This evidence also provides the explanations for how different factors affect the Indian investors while they are herding towards the market. Indian investors generally herd less when compared to the other emerging market investors (like China or Taiwan (comparing the available literature, for instance. Lao and Sing (2011), enjoy better investment atmosphere when compared to other developing markets. It is also noted that while considering the net institutional investment along with the other factors as explained in the previous section, it is found significant, explains the role of net institutional investment in controlling herding behavior in Indian stock market.

Despite this evidence, there have been many research papers who found similar results in similar market, for example Demirer and et al. (2010) in Taiwan market Chiang and et al. (2011) in Pacific Basin market, the study of Basu and et al. (2011) with the Nifty -50 Companies with the same methodology (used CAPM beta , where as this study used Fama French beta, which has more explanatory power than the CAPM beta) also showed similar result and found volatility is one of the important factor which influence herding behaviour in Indian stock market. Basu and et al.[50] (2011) found that volatility and net mutual fund influenced the herding behavior in NSE were as this study find volatility, volume and net FII investment cause the herding behavior. Dissimilarity in result can be expected since the types of investors are differing in the studied market. In addition the data used, the period and the beta used for the analysis are different. In NSE institutional investors are more where as individual investors are more in BSE, who often characterised as more prone to herding behavior, because the institutional investors are considered to be informed investors while comparing with the individual investors. The experience in the Indian market cannot be used to explain the effects in similar markets because the condition, the risk tolerance, the sophistication, the nature and type of the investors may be different.

[50] Not tested the effect of volume and net institutional investment.

CHAPTER – VI

PATTERN OF HERDING BEHAVIOUR IN INDIAN STOCK MARKET

6.1 Introduction

A growing body of literature on herding behaviour explains that there exist asymmetries in the pattern of herding behaviour at different states of the market[51]. Number of studies examined this issue with the factors like trading volume; volatility and market return in different conditions viz; up and down or high and low states of the market. Many of the studies pointed out that the pattern of herding behaviour differ with the different states of the market and it can be conclude that these factors play certain role in the intensity of herding behaviour. It is also noted that the results are mixed and some of the studies did not find any asymmetry in the pattern of herding behaviour based on the tested states of the markets. In this chapter the study intend to examine the asymmetry in the pattern of herding behaviour (if exists) during high and low states of volatility, trading volume and net foreign institutional investment.

To examine the pattern of herding behaviour in the selected market, the study followed the extended version of the methodology proposed by Chang and et al. (2000) the methodology adopted by Tan and et al. (2008) .The study used separate models for both up and down market conditions and checked the pattern of herding behaviour in Indian stock market for the whole period and also for different sub periods.

6.2 Rationale for the Study

As mentioned in the previous chapters the study of herding behaviour is important in many aspects for practitioners, investors, wealth mangers and many other interested groups. The excessive herding will hoist many issues in the markets and ultimately leads to inefficiency in the market. One could find number of researches, which

51. See, for example, Christie and Huang (1995), Tan and et al.(2008),Amirat and Bouri (2009), Lao and Sing (2011) ,Al-Shboul (2012).

substantiate the asymmetric pattern of herding behaviour in number of markets in different market conditions, were people react differently to a rising as well as falling markets. Similarly, these are found with variation in volume and volatility.

Gallant and et al. (1992) found large price movements are associated with high trading volume. Chen and et al (2003) noted that "a large trading volume is a necessary condition for the existence of herding behaviour and the volume signal has to be large enough to persuade investors to herd others and ignore their own priors". Al-Shboul (2012) noted that, the herding behaviours of Australian investors are affected by the decisions of foreign investors from China, US and UK. In this context, this chapter designed to check the pattern of herding behaviour in different states of the market based on the selected factors to get better understanding about the pattern of herding behaviour in the selected market. It is expect that the results will help in understanding the herding behavior in Indian stock market and may be helpful to explain the distortion in the market, the market movement, reduced or excess volatility of the market.

6.3 Variables and Methodology

A careful examination of the literature explain that market return, trading volume and volatility are important factors which can influence the investor behaviour and herding may be associated with these factors. Further, it is widely believed that the foreign institutional investors (FII), their investments and the withdrawal from the market have an important role in the market movement. Based on these facts the study examined the pattern of herding behaviour on the high and low states volume, volatility and Net FII investments. Employing the methodology adopted by Tan and et al. (2008), this study examined the hypothesis listed below and by using cross sectional absolute deviations of stock return of individual firms, the squared market return and the absolute market return, market trading volume, market volatility and the Net FII investment of the market. The study also checked the pattern of herding behavior for different study period and compared the differences in coefficients (herding) to explain the intensity of herding behaviour in Indian market for different study periods.

Here to define the high and low states, the previous thirty days moving average of daily market trading volume (V_{mt}) is calculated and compared with daily trading volume. If the volume of the day (V_t) is high it is considered as high and if volume of the day is less than that of the 30 days moving average it is considered as the low state. Similar procedure is adopted in the case of market volatility and net FII investment .The methodology adopted by Tan and et al.(2008),a non linear model was used for trading volume, market volatility and FII investment to examine the asymmetric pattern of herding behaviour and the specification of the models are explained in the methodology chapter: models (5), (6), (7), (8), (9) and (10).

6.3.1. Hypothesis

To examine the pattern of herding behaviour during different states of the market with respect to trading volume, market volatility and the net FII investment, the following hypothesis are framed.

$H_1$17: There is asymmetry in the pattern of herding behaviour during the high and low states of trading volume.

$H_1$18: There is asymmetry in the pattern herding behaviour during the high and low states of market volatility

$H_1$19: There is asymmetry in the pattern of herding behaviour during the high and low states net FII Investment.

6.3.2. Procedure for Analysis

To examine the pattern of herding behaviour based on different market conditon the study followed the following procedure .

1. Collect the daily trading volume and find out the average monthly trading volume and group the data based on the high and low state of trading volume (condition: if the daily trading volume is higher than the average monthly trading volume it is considered as high and else low: used moving average to calculate the monthly volume).
2. Group the dependent and independent variables based on the above information and run regression for different study periods.
3. Find out the daily volatility series using market return.

4. Find out the average monthly volatility and group the data based on the high and low volatility condition (condition: if the daily market volatility is higher than the average monthly volatility it is considered as high and else low volatility, used moving average to calculate the monthly volatility).
5. Group the dependent and independent variables based on the above information and run regression for different study periods.
6. Collect the daily net foreign institutional investment (net FII)data
7. Find out the average monthly net foreign institutional investment and group the data based on the high and low state of net foreign institutional investment (condition: if the daily net FII is higher than the average monthly net FII it is considered as high and else low, used moving average to calculate the monthly net FII).
8. Run regression for different states of the market and compare the results.

6.4. Summary Statistics

Table VI.I shows the summary statistics of the cross-sectional absolute deviations of stock return for the market, sorted for different states of the conditional factors selected for the study. The variables CSADFIIUP, CSADVOLUMEUP CSADVOL UP, CSADFIIDOWN, CSADVOLUMEDOWN are the Cross-sectional absolute deviation of return, RMTVOLUP, RMTFIIUP, RMTVOLUMEUP, RMTVOL DOWN, RMTFIIDOWN, RMTVOLUMEDOWN are the absolute value of the market return, based on the high and low states of market volatility, net foreign institutional investment and trading volume respectively. SRMTVOLDOWN, SRMT VOLUMEDOWN, SRMTFIIDOWN,SRMTVOLUP, SRMTVOLUMEUP, SRMT FIIUP are the squared value the market return at different states of the market, say low and high conditions of market volatility, volume and net FII investment in the market. The table shows the mean, median, standard deviation, skewness and other relevant detail.

Table VI.I, showed a smaller variation in the mean among the group of variables and the mean values of all the variables are high when the volatility is in up condition. As expected, this indicates the uncertainty and higher fluctuation in the market and unpredictability and the higher risk associated with this market condition. The variance explains how far a set of numbers spread out and it describes how far the values lie away from the mean or from the expected value. The table shows there is difference in the values for each group of variables and is above one in the case of SRMTFIIDOWN, SRMTVOLUMEUP, SRMTVOLUP. Further, as shown in the table, that the series are positively skewed and the series SRMTVOLUME DOWN, SRMTVOLUMEUP, SRMTFIIDOWN are highly skewed when compare with the other series. The Jarque-Bera value shows that the selected series are not normal. The ADF and PP tests showed that there is no unit root and all the series are stationary at its level.

Table VI.I
Summary Statistics and Stationarity of Different Variables Used in this Study

Variables	Mean	Median	Std. Dev.	Skewness	Jarque-Bera	Observa-tions	ADF	PP
RMTFIIDOWN	0.4752	0.3507	0.5034	3.3295	19124.95***	1260	-16.7962	-29.1248
RMTVOLDOWN	0.3942	0.3092	0.3556	2.5693	15291.18***	1516	-13.9764	-41.1986
RMTVOLUMEDOWN	0.4214	0.3095	0.4071	2.5193	8484.937***	1302	-13.3665	-30.8381
CSAD FIIDOWN	0.5082	0.1041	0.95	5.5351	128706.9***	1260	-16.5068	-23.5135
CSADVOLDOWN	0.3553	0.0570	0.5362	1.7452	729.12***	948	-26.3844	-27.700
CSAD VOLUMEDOWN	0.4513	0.0822	0.8766	6.1922	220287.1***	1302	-8.47309	-29.0788
SRMTFIIDOWN	0.4791	0.123	1.5207	9.2773	650006.9***	1260	-17.4982	-23.4004
SRMTVOL DOWN	0.2817	0.0956	0.7262	3.6418	5641933***	1516	-14.6577	-40.6212
SRMTVOLUP	0.6294	0.1581	1.6911	7.6187	254661.3***	948	-11.8905	-22.2962
SRMTVOLUMEDOWN	0.3432	0.0958	0.8792	9.9714	1489581***	1302	-12.6407	-31.4561
SRMTVOLUMEUP	0.4937	0.1341	1.4776	9.2644	640857.1***	1173	-18.2109	-18.6789
RMTFIIUP	0.4357	0.3258	0.3991	2.0005	2586.341***	1207	-11.1422	-30.9098
RMTVOLUP	0.5545	0.3977	0.5678	2.6811	6137.557***	948	-11.8905	-22.2962
RMTVOLMEUP	0.4934	0.3662	0.5005	3.1521	15251.24***	1173	-13.6248	-29.3544
CSAD FIIUP	0.3605	0.0613	0.6877	4.8122	96908.43***	1207	-8.18576	-30.4185
CSAD VOLUP	0.4735	0.0722	0.9141	4.6337	44497.45***	948	-5.33323	-25.7294
CSAD VOLUMEUP	0.4172	0.0688	0.7841	4.5071	55119.43***	1173	-10.7944	-32.3662
SRMTFIIUP	0.3489	0.1061	0.7374	5.6355	120208.1***	1207	-10.8759	-26.3917

Note *** denotes the significance at1%level

6.5. Pattern of Herding Behavior under Different States of the Market

The study investigated the pattern (asymmetry) of herding formation under different market conditions, particularly high and low state of trading volume, volatility and the net FII investment. The results of the different tests are explained below.

6.5.1. Pattern of Herding Behaviour Based on Trading Volume

Many studies examined the association or the pattern of herding behaviour based on trading volume. Table VI.II and VI.III below presents the test results of the pattern of herding behaviour during high and low states of trading volume (as defined in the previous section) in the selected market for different study periods.

Table VI.II
Herding Behaviour When Trading Volume is High

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
α	0.31603*** (7.3140)	0.21810*** (7.8196)	0.87834*** (2.8126)	0.34957*** (5.3054)
γ_1^{Vh}	0.27990*** (3.0530)	0.15103** (2.2390)	0.50122 (0.9598)	0.29366 (1.4222)
γ_2^{Vh}	-0.07378** (-2.3388)	-0.03877* (-1.6675)	-0.14808 (-1.0575)	-0.13324 (-0.9922)
AR(1)	0.20479*** (7.0652)	-	0.11758 (1.2971)	0.18540*** (3.6705)
F	22.4378	2.6380	0.0257	4.9489
Prob. (F Stat)	0.00000	0.07227	1.12514	0.00221

Note:***,**,*denotes significance at 1%, 5% and 10% respectively. $CSAD_t^{Vh} = \alpha + \gamma_1^{Vh}|R_{mt}^{Vh}| + \gamma_2{}^{Vh}(R_{mt}^{Vh})^2 + \varepsilon_t$.

The estimates of the regression model (During high market trading volume) are shown in the Table VI.II. A significantly negative coefficient (γ_2^{Vh}) explain the presence of herding behaviour and a positive or insignificant (γ_2^{Vh}) shows the absence of herding behaviour, Huang and et al. (1995), Chang and et al. (2000), Tan et al. (2008). The results from the table VI.II suggests that during the period of high trading volume investors showed herding behaviour. Theoretically the results explain that, there is a negative and significant relationship between the levels of firms return and cross sectional absolute deviation of return and coefficients of (γ_2^{Vh}) are significantly negative at 5% and 10 % for the whole period and pre-crisis period in Indian stock market. This indicates that there is herding behaviour during these periods. At the same time the study could not find significant herding behaviour during the period of crisis and the post crisis period based on high trading volume in the studied market. It is also noted that during the tested period the intensity of herding behaviour is very low and it is nearly (0.07) and (0.04) respectively for the whole study period and pre crisis period.

Table VI.III

Herding Behaviour When Trading Volume is Low

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
α	0.35501*** (7.4807)	0.20016*** (6.5371)	0.88446*** (4.1364)	0.28037*** (4.2704)
γ_1^{Vl}	0.00073 (0.0150)	-0.18275*** (-3.3788)	0.07271 (0.5983)	-0.43473 (-1.2365)
γ_2^{Vl}	0.22828** (2.1372)	0.44073*** (4.5976)	0.04369 (0.1279)	0.42426 (1.2610)
AR(1)	0.3525*** (13.2804)	0.0770* (2.0789)	0.3868*** (6.3820)	0.0858 (1.4795)
F	77.0078	9.0292	16.3879	0.0131
Prob. (F Stat)	0.00000	0.00001	0.00000	0.00313

Note: ***, **,*denotes significance at 1%, 5% and 10% respectively. $CSAD_t^{Vl} = \alpha + \gamma_1^{Vl} |R_{mt}^{Vl}| + \gamma_2^{Vl} (R_{mt}^{Vl})^2 + \varepsilon_t$.

Table VI.III, shows the result of herding behaviour during the period of low trading volume. Like the previous analysis the study examined the herding behaviour by using the whole period data, for the pre-crisis period, crisis period and the post-crisis period but not able to find herding behaviour in any of the tested periods.

While analyzing the results presented in Table VI.II and VI.III, it can be concluded that herding behaviour is present only during whole period and pre crisis period during the period of high trading volume, where as no herding behaviour found with low trading volume during this period. The crisis and post crisis period, shows the symmetry in the behaviour of the investors during high and low states of the trading volume. This also supports the earlier findings that the effect of trading volume has very low influence on herding behaviour in Indian stock market. In addition, one can see that herding is comparatively more prevalent when the trading volume is high. It is also noted that the intensity of herding bahaviour is very less, 0.07 and 0.03, and in crisis period. For the post crisis period the study could not find such behavior either in high or low state of trading volume. Thus with caution, it can be concluded that high trading volume may lead to common consensus and leads to herding behaviour in Indian stock market and there is asymmetry in herding behaviour with the different states of volume. Thus, concluded that the results partially support the effect of trading volume on herding behaviour and concluded that the investors acted more rationally during the states of low trading volume.

6.5.2 Pattern of Herding Behaviour Based on Volatility

Literature explains that there exists asymmetry in herding behaviour based on different states of volatility. The herding behaviour may differ with the high and low states of volatility. These are tested and the results explained in Table VI.IV below. The volatility of the market are calculated as the variance of the error terms of the regression of the lagged market returns in period t and the study used thirty days moving average of the volatility for sorting data for the analysis.

Table VI.IV
Herding Behaviour When Market Volatility is High

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
α	36510*** (6.1631)	0.255262*** (7.5654)	1.21487*** (3.1005)	0.36287*** (5.3613)
γ_1^{Volh}	0.34302*** (3.3442)	0.170104** (2.2473)	0.62285** (1.9075)	0.07150 (0.3405)
γ_2^{Volh}	-0.13261*** (-3.7564)	-0.049203* (-1.9151)	-0.26068* (-1.8897)	-0.07069 (-0.5454)
AR(1)	0.36815*** (11.8378)	0.023073 (0.5257)	0.36068*** (4.0400)	0.12443* (2.1336)
F	49.60221	2.67636	5.52633	1.88169
Prob. (F Stat)	0.00000	0.06975	0.00137	0.13275

Note: ***, **,*denotes significance at 1%, 5% and 10% respectively. $CSAD_t^{Volh} = \alpha + \gamma_1^{Vl} |R_{mt}^{Volh}| + \gamma_2^{Vl}(R_{mt}^{Volh})^2 + \varepsilon_t$.

By comparing with the daily volatility measure, the study fixed the volatility as low when it is below the calculated thirty days average, whereas it considered as high when volatility measure is greater than the thirty days average. Like the previous section, here also the study used a similar non linear regression model to examine the pattern of herding behaviour. As found in Table VI.IV there is negative and statistically significant relation between cross sectional absolute deviation of return and the market return during the whole study period, pre-crisis period and crisis period, where as the results shows absence of herding behavior during the post crisis period. It is also noted that the herding behaviour is more during the crisis period, where it is less during the pre crisis period, the bullish period.

Table VI.V explain the estimated results during the low volatility state of the market for different study periods

Table VI.V
Herding Behaviour When Market Volatility is Low

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
α	0.26928*** (7.0287)	0.17588*** (5.9899)	0.84408*** (2.8149)	0.30426*** (6.3545)
γ_1^{Voll}	0.38439*** (7.0370)	0.42679*** (3.8845)	0.20541 (0.3058)	0.36247*** (2.9727)
γ_2^{Voll}	-0.03147 (-0.6905)	-0.20569** (-2.5197)	0.16348 (0.5461)	-0.08032* (-1.7637)
AR(1)	0.27627*** (11.1237)	0.10710*** (3.1488)	0.26381*** (3.4029)	0.15901*** (3.5387)
F	58.76588	9.3406	5.91791	7.05169
Prob. (F Stat)	0.00000	0.0000	0.00075	0.04188

Note: ***, **,*denotes significance at 1%, 5% and 10% respectively. $CSAD_t^{Voll} = \alpha + \gamma_1^{Vl}|R_{mt}^{voll}| + \gamma_2^{Vl}(R_{mt}^{voll})^2 + \varepsilon_t$.

The results show that herding exists only pre-crisis period and post-crisis period but not in the crisis period or during the whole study period.

Table VI.IV and VI.V reveals that the pattern of herding behaviour is asymmetric based on the high and low volatility. Table VI.IV present the existence of herding behaviour in Indian market during post-crisis period and crisis period and during the period of high volatility and the results are significant at 10 % level, whereas the study found significant herding behaviour during whole period, pre-crisis period and post-crisis period with low volatility. This explains that there exist asymmetries in the pattern of herding behaviour in Indian stock market with the high and low states of volatility during some of the study period. In addition it can be seen that the intensity of herding behaviour is different during different study periods, for example the post crisis period, where the study found herding behaviour in both states of the market and the intensity of herding is very high in low volatility when compared to the high volatility state, showed the asymmetric pattern of herding behaviour. This may be because the investors who herd in the market may stay away from the market during the high volatility state, because chance for losing money is more in such market.

6.5.3 Pattern of Herding Behavior based on Net Foreign Institutional Investments

There is wide belief that the foreign institutional investors drive the stock market and their investment and withdrawal from the market can influence the behaviour of the investors. This may happen because the institutional investor's actions may influence individual investor's decisions since they are considered as better informed investors with sophisticated methods and analysis.

Table VI.VI
Herding Behaviour When Net FII Flow is High

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
α	0.27631*** (6.8443)	0.19903*** (6.4942)	0.79447*** (2.5524)	0.38998 (1.6673)
γ_1^{FIIh}	0.22654** (2.0411)	0.17765** (1.9605)	0.37913 (0.5080)	0.11514 (0.1780)
γ_2^{FIIh}	-0.04189 (-0.6746)	-0.06594 (-1.4251)	-0.10410 (-0.2808)	-0.08286 (-0.2250)
AR(1)	0.28451*** (10.1922)	0.05002 (1.3075)	0.29731*** (3.2870)	0.02892 (0.1666)
F	43.3220	2.0962	4.8911	3.980
Prob. (F Stat)	0.00000	0.09943	0.10815	0.008479

Note: ***, **, denotes significance at 1%, 5% respectively, $CSAD_t^{FIIh} = \alpha + \gamma_1^{FIIh} \left|R_{mt}^{FIIh}\right| + \gamma_2^{FIIh} (R_{mt}^{FIIh})^2 + \varepsilon_t$,

Table VI.VI, shows the estimates of the model (9) for different study periods and explains the relationship between cross sectional absolute deviation of return and the squared value of the market return as shown in the equation. It is clear from the table that none of the coefficients (γ_2^{FIIh}) are significant for Indian stock market; it indicates that herding behaviour does not exist in the BSE during the period of high FII flow into the market. However, during the period of low FII investment the results shows that the coefficient (γ_2^{FIIl})is negative and significant at 1% level, 5 %

level and 10% level respectively during the whole study period, pre- crisis period and crisis period, Whereas, similar to the previous results the study did not find herding behaviour during the period of post-crisis period. Hence, conclude that there exists asymmetry in the pattern of herding behaviour based on the FII investment in Indian stock market. While comparing the results, it is found that herding exists when FII is low. This may be because; if there is high level of FII participation the price will be up and the other investors may not be able to buy shares when FII withdraw from the market and the negative sentiments of the investors of losing money from the market may lead them to follow others.

Table VI.VII
Herding Behaviour When Net FII Flow is Low

Estimates	Whole Period	Pre-Crisis Period	Crisis period	Post-Crisis period
α	0.39586*** (7.6151)	0.25978*** (8.9567)	1.43785*** (3.8027)	0.40136*** (7.3103)
γ_1^{FIIl}	0.37436*** (3.8082)	0.26028*** (3.6875)	0.41720 (0.8130)	0.12996 (0.9828)
γ_2^{FIIl}	-0.13949*** (-4.1521)	-0.07091** (-2.8007)	-0.25233* (-1.7658)	-0.05181 (-1.0470)
AR(1)	0.35728* (13.0278)	0.05346 (1.4295)	0.39720*** (4.7539)	0.09152* (1.8081)
F	64.1160	0.0228	7.1549	1.5495
Prob. (F Stat)	0.00000	5.52601	0.00016	0.20125

Note: ***, **,*denotes significance at 1%, 5% and 10% respectively. $CSAD_t^{FIIL} = \alpha + \gamma_1^{FIIl} |R_{mt}^{FIIl}| + \gamma_2^{FIIl} (R_{mt}^{FIIl})^2 + \varepsilon_t$,

This may happen because the withdrawal of FII_S from the market will lead the market go down and there by other investors may get panic lead others also to follow the market. Thus conclude that the asymmetric pattern of herding exists in the studied markets.

6.6. Conclusion

The study examined the existence of the asymmetry in the pattern of herding behaviour in the Indian stock market by selecting the data over the period 01-04-2002 to 28-03-2012. The study used the daily individual stock return data of 243 companies of BSE-500. Analysis of the pattern of herding behaviour in Bombay

Stock Exchange (BSE) based on high and low states of trading volume of the market, volatility of the market and net foreign institutional investment flow to the market. It is noted that the results are interpreted with caution, as the definition of high and low state is subjective and influences the results. By taking daily data the study intends to reduce the estimation error where as the division of sub periods helps the researcher to closely analyse the changes in herding behaviour, its nature and pattern of herding behaviour and to provide a detailed picture of the behaviour in different states of the market. In addition, it is also note that chance for overlapping data while comparing the different states of the market may make the interpretation complex and create difficulties in interpreting the results.

Based on the analysis, the results are mixed and there is significant difference in the intensity of herding behaviour. While analysing the results, in general one can see there is asymmetry in the pattern of herding behaviour in Indian market. In addition, the behaviour is more visible in the case of low FII investment flow and at high volume states. While comparing the intensity of herding behaviour, one can see that it is more during the high volatile period during crisis and this may be attributed to the investor's sentiment, where people may be panic more in such situations. From the results, it can be find that there exist asymmetries in herding behaviour, where the study find herding behaviour based on high trading volume and the market is more prone to herding in such situation. Further it is noted that in some of the cases the coefficient γ_2 is positive, which shows that absence of herding behaviour in such market conditions, explains that the investor's acted rationality in their decision process.

In addition the analysis revealed that during the period of financial crisis, the coefficients are negative and highly significant with volatility, shows the existence of herding behaviour in the studied market during the period of stress, shows the influence of the crisis and the shocks and sentiments, made the investors irrational, but in many cases the study could not find evidence of herding behaviour and is in line with the rational asset pricing theory. In addition, volume and low FII investment explains that, market is inconsistent and not in line with the rational asset pricing theory, which explains that the return dispersion decreased in the period of stress. Another interesting aspect is that during the pre-crisis (bullish) period, even though the level of herding is less, people tend to herd more during low volatility period than the high volatility period where as during the crisis period people are more irrational and the study could not find herding behaviour in low volatile period. These may be because; the post crisis period gave enormous opportunities for a diversified investment and it provided a higher rate of average return to the investors. The study conclude that investors showed less herding and the investors often showed rational behaviour in many of the studied market conditions and the tendency of herding is very low when compared to other studied market like China, Vietnam etc.

Consistent with the available literature this study also found asymmetry in the pattern of herding behaviour in Indian stock market and the results are mixed. Mostly the return dispersion is less in the downside market conditions, points the tendency of investors to mimic others in their investment decisions. Even though the degree of herding is less except during the crisis period and the results are mostly in line with the theory. This explains that the herding behaviour is most likely visible during the period of market stress or extreme market conditions, where investors adhere with the market consensus during these periods.

Based on the findings, the study suggests that herding may arise because of informational asymmetry and the introduction of informational monitoring system about the scrip's listed in the exchange may help to further reduce herding behaviour in the market to a greater extent. The result further show that the herding is more prone during the period of crisis especially during high volatility, where people may react more to bad news than good news[52]. It is also note that the excessive herding may further amplify the volatility, but not examined here.

The policy implication that could be taken in to care is that herding behaviour is more visible where net FII flow is low except in the post crisis period, it points that profit booking or withdrawal of FII in the market affects the sentiments of the investors and SEBI should think about this fact seriously. In addition to this result could be interpreted with at most care because the low FII flow does not always means the withdrawal of FII from the market and a further detailed analysis is suggested in this matter[53]. Further, investors tend to herd more during the state of

52. See Fu and Lin (2010), for more details.
53. The study used the Net FII investment for the analysis.

high volatility and the state of high volume and there is no herding in low volume state of the market, there for some measures by SEBI in this matter to provide the required information may reduce the herding behaviour in Indian stock market.

CHAPTER VII

Herding Behaviour on Contagion Effect

7.1 Introduction

The emerging business order and the changes in the financial arena increased the inter linkage between different economies and interconnection between the countries in many aspects. Emerging markets and their financial system plays an important role and are the frontiers of these changes. The impressive growth rates, the attempts form FIIs and FDI's[54] to seize the existing opportunities, the trade relations, the converging effect of these emerging markets towards the developed markets and bilateral trades from both these economies increased the inter linkage between the countries. The new business order, globalization - that integrates the markets, the economic policies of the countries also acted as a catalyst in this process.

Further, the advances in technology and the rapidity in information transmission made an increased level of integration as well as an immediate reaction towards favorable and unfavorable market environment. In addition to this, many authors noted that there is significant increase in the cross market correlation during the period of crisis when compared to the stable periods. Analyzing the literature one could see many factors behind this inter linkage and spreads, which includes investors flow, the liquidity benefits, capital flows, trade relation, psychic distance[55] and the behavioural factors of investors in the markets. The purpose of this chapter is to examine the contagion effect and the role of herding on contagion effect during US 'Subprime crisis' where USA[56] is the origin.

Generally, a number of distresses affect the financial markets and often they spread from one country to another very rapidly. In history, there are many examples for such incidents in financial markets and it mainly occurred during financial crunch or crisis. It has been established by number of studies that, emerging markets, especially Asian markets are largely linked and coupled and apparently reacts very strongly

54. FII and FDI- foreign institutional investors and foreign direct investment.
55. The perception of self and other investors operating across international markets.
56. USA : United States of America.

towards the changes and developments of the US financial markets, see for example Cheung and Ng (1993) and this often cause for spreading shocks and leads to contagion effect.

The literature provides various definitions for contagion but so far no general consensus in defining contagion and there exists a disagreement between different researchers. The basic definition explains contagion as a shift in shocks or the transmission of shocks internationally, Eichengreen and et al. (1995). One aspect of contagion is that, the proliferation or propagation of shocks in excess of normal due to the fundamental linkages between countries. Another view explains transmission of crisis through the irrational behaviour of the investor. A broader definition identifies contagion as any channels, which links the countries and cause the markets to move together, Forbes and Rigobon (2001).

This study follows the more restrictive definition given by Forbes and Rigobon (2002),who defined contagion as "significant increase in cross market linkage after a shock to one country (or more countries)" and explained as, if two markets show a higher degree of co movements during a stable period and continue to show a higher degree of correlation after a shock to one market may not be considered as contagion and it is because of interdependence and it can be considered as contagion only if there exists significant increase in the cross market movement after the shock.

This chapter analyses the conditional and unconditional correlation and examines the variability in the correlation measures during the crisis periods. The study considered the period from 01-01-2004 to 30-01-2009 and examined the variation in correlation during the study period. The study used the data of Index Return of India (BSE)[57]and the crisis origin countries USA (S&P-500). This study examined the existence of contagion effect on the emerging stock market in India with the Multivariate DCC-GARCH model. It is the maiden attempt to analyze the role of herding on contagion effect in Indian Stock market in the context of herding behaviour based on the US financial crisis. The Indian stock market is one of the major emerging markets in Asia and the results will be helpful in explaining the variability in dynamic conditional correlation during crisis. Further, this will also be helpful in explaining

[57] The study also used six markets from Asia, in addition to India, (BSE) and this include , Malaysia (FTSE), China(HIS), Taiwan(TWI), South Korea(KOSPI), Indonesia(JKSE) and Singapore(STI). The presented results are only for India.

how this crisis may in turn reshape the investment decisions in these markets and will answer the scope of portfolio diversification and whether it provides hedging opportunities to the international investors.

7.2. Data, Variables and Methodology

A large number of studies explain the mechanism and the situations in which a crisis may happen and its transmission across the markets over and above the fundamental risk factors. The study intends to check the role of herding on contagion effect during the US subprime crisis in Indian market (BSE) towards the crisis originated country. The study examines the hypothesis on contagion effect and uses the stock market index return series (difference of log prices of the closing Index series) of the selected markets in log form as variable. In the second stage, the study uses the multivariate dynamic conditional correlation (M-DCC) extracted in the first step to run Post-hoc ANOVA test to examine the variation in during different periods. Based on the literature the study hypothesized that there is no difference in the dynamic conditional correlation between the indices of crises originated country and the Indian market during stable and crisis periods.

A multivariate GARCH Model proposed by Engle (2002) is applied and this will enable to estimate the conditional correlation between the crisis origin country and other selected countries. The proposed model estimates correlation coefficients of the standardized residuals and hence considers the Heteroskedasticity issues directly. Further, the model can also be examined using multiple asset returns without adding too many parameters, Chiang et.al. (2007). The model will also consider the issue of volatility, usually it moves together more or less closely over time across the markets and taking in to consideration all these features of a multivariate model will help for more relevant empirical results than running separate univariate models[58]. The estimates of the time varying correlation coefficients will help to analyse the dynamic relations between the selected stock indices in a multivariate setting and to analyse the relationship in response to the crisis or shocks. Further, the study calculated the unconditional correlation and compared the results for the different

58The inclusion of other markets in this study is justified by the above fact.

stages of the crisis. The data used were the daily price series of the selected indices from 02-04-2004 to 30-01-2009.

The selection of Indian market as an emerging market is justified, as the testing of contagion effect will be very much helpful in portfolio diversification view and is one of the major markets in this region. The required data for the study sourced from yahoo finance and used adjusted closing price of the indices for further analysis. For the US Subprime crisis the study will consider two phases of the crisis, the first started from Dec.-2007 and the second phase started on 15th Sept. -2008, based on the collapse of the Lehman Brothers Holdings Inc, One of the largest investment banks in USA. For deciding the first phase, the study used the US business cycle period proposed by National Bureau of Economic Research (NBER), USA. NBER defines[59] recession as a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. The primary analysis of the data is done through line graphs, summery statistics. The stationarity properties of the data checked with Augmented Dickey Fuller (ADF) and Phillips–Perron (PP) tests and used Multivariate DCC–GARCH model to extract correlation coefficients of the standardized residuals. The study used daily data because high frequency data may provide broader evidence and room for testing different combination of data sets.

7.3. Procedure for Analysis

The various steps below will explain the proposed methodology used in examining the role of herding behaviour on contagion effect.

1. The adjusted daily closing prices of the selected indices are collected.
2. Convert the daily index series in to daily return series by taking the first difference of the log value of the corresponding series.
3. Do Preliminary analysis with line graph and summary statistics
4. Check the Stationarity properties of the series through ADF tests and PP tests.
5. Find the unconditional correlation between the selected index return series for the study periods.

59. http://www. nber. org /cycles.html

6. Apply multivariate DCC- GARCH model to extract conditional correlation coefficients of the standardized residuals and the estimates of mean and variance equations.
7. Use one way ANOVA Post-hoc test to compare the difference in mean dynamic conditional correlation in different periods and its statistical significance.
8. Calculate the percentage difference in unconditional correlation and conditional correlations for different periods say pre crisis, and different phases of the crisis for further explanation and comparison.

7.4. Rationale of the Study

Investigating the relationship between the stock markets and crisis origin market by using this methodology will help in understanding the inter linkage between the markets and in explaining the role of investor's sentiments in spreading crisis. It is expect that the study will bring out valuable results, which will be helpful for understanding about the contagion effect, the role herding behavior in spreading crisis. It is also expects that the findings will help for appropriate policy formulation and to the investors especially for portfolio diversification.

7.5 Analysis and Interpretation

7.5.1 Descriptive Statistics

Here the descriptive statistics used to describe the various properties and the basic features of the individual data series. The summary statistics and other properties of the return series of the selected indices are shown in table below. The properties of the different series are described for the whole study period, showed in table VII.I. While analyzing the Table VII.I, it is clear that the mean return during the whole study period (01-04-2004 to 30-01-2009) is positive for India and negative for USA(S&P-500) and the positive mean and median indicates that returns from the indices are positive. Further, the standard deviation explains the average difference between observed values from their mean.

Table VII.I

Descriptive Statics of Index Return Series for the Whole Study Period

Indices	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
S&P-500	-0.02426	1.36809	-0.34644	16.9273	9933.128***	1226
BSE	0.03905	1.90757	-0.73223	8.4419	1622.368***	1226

Note: *** denotes significance at1%level

BSE shows a higher volatility as measured by standard deviation. The return series are negatively skewed for both the countries. The kurtosis explains the peakedness of the series and S&P showed the highest value. For both the cases, it is much higher than the standard value (3).The Jarque-Bera value confirms that the series is asymmetric. The summary statistics shows the asymmetry in the return series, which is similar to a number of studies. Park (2010), pointed out that, return series of Asian markets used in his study are asymmetric and are fat tailed. Further, the negatively skewed indices explain that the market is in backwardation and hence the market offers significant arbitrage opportunities to the investors (Vipul 2005).

7.5.2 Line Graph

The following figure shows the line graphs of the return series of different indices during different periods, through which one can easily understand the behaviour of the return series. The line graphs show the pattern of the return of each index price series at its first difference. Generally, the return series are near to mean and the reverting behaviour is visible from the graph. Both of the series move near to its mean value and for further analysis the Stationarity properties of the series is checked.

Figure VII.I
Line Graph of Returns Series of the Selected Indices for the Whole Study Period

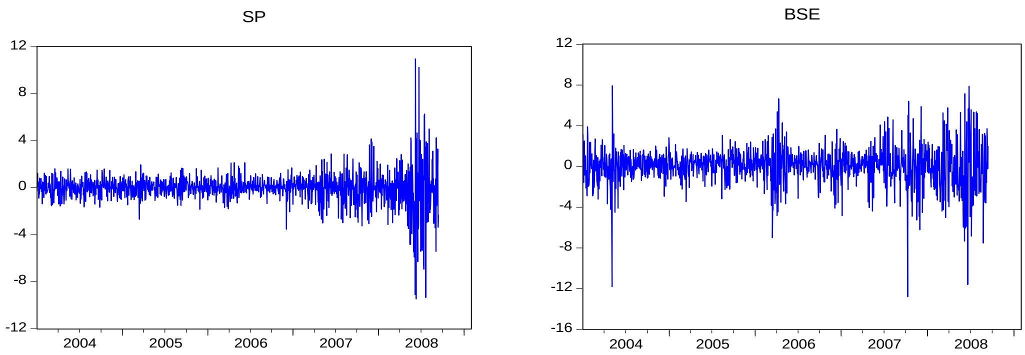
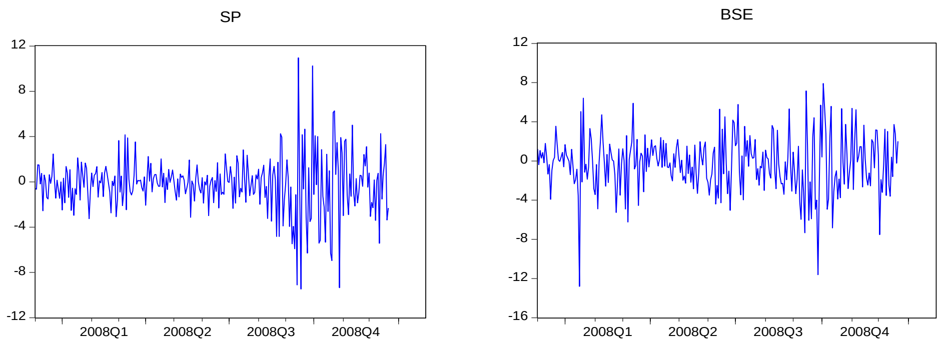


Figure VII.II
Line Graph of Returns Series of the Selected Indices for the Subprime Crisis Period



7.5.3. Stationarity of the Variables

The Stationarity of the variable is an essential property to run econometric models in a time series data. The issue of unit root arises when the variables are non stationary. A non stationary series have time dependent mean or variance or both, i.e. the returns time series is stationary, if the distribution parameters like mean, variance etc. are constant over a period. Further, the covariance between lag values depends only on the lag length and the theoretical auto-correlation coefficient decay fast as lag length increases. To check the Stationarity, unit root tests like ADF and PP tests are applied. One can check the unit root through three methods, with constant and trend, with constant but not trend and without constant and trend and is customary to consider the first difference and the differencing will help to eliminate the unit root involved. Here the index returns taken as the first difference of the index price series for examining the presence of unit root. Here all the three methods are tested but presented the result at level with intercept. The table VII.II shows that the series used in the study is stationary in its level form for both the ADF and PP tests. All the data series are stationary, hence explain that the data exhibits deterministic and stochastic trend.

Table VII.II
Results of Stationarity Tests for the Whole Study Period

Indices	ADF	PP
S&P	-28.91066***	-41.34370***
BSE	-33.15515***	-33.10855***

Note: *** Denote significance at 1% level

7.5.4. Karl Pearson Correlation Analysis

With the help of correlation results, one can evaluate interdependence of the selected stock markets. Table VI. III presents the correlation coefficients for the whole study period and for the two sub periods for the selected markets. From the result, one can see that the correlation increased and the results are significant. Further the correlation for different periods and the result in general shows an average correlation around (0.28) between US and the selected market over the period 2004 to 2007, i.e. during pre crisis period.

Table VII.III.
Correlation Coefficients across the Selected Stock Markets during Different Study Periods

Countries	Whole Study Period	Pre -Crisis	Subprime Crisis		
			Whole Period	Phase-I	Phase-II
US & BSE	0.28222	0.14593	0.364930	0.10194	0.52787

Note :all the results are significant

However, while comparing with the pre-crisis and subprime crisis periods, correlation increased during the subprime crisis period. While analyzing the first phase of the crisis, the correlation decreased for BSE with the US market. During the second phase of the crisis (after Lehman collapse) the result showed a notable increase in correlation and the rate of correlation was very high between India and

US shows the high risk associated with these markets during this period and it reduces the portfolio diversification opportunities.

The correlation analysis gives a different view and there are arguments against using the simple correlation for explaining contagion effect. It is noted that simple correlation as a proxy as contagion is misleading[60]. Further, Boyer et al. (1997) opined that testing in correlation is not straight forward and explained that "splitting a sample of data according to the ex post realizations of a series", can be misleading and is explained as "such a procedure is likely to suggest correlation breakdown regardless of whether the correlation coefficient have changed". Based on this, Bekiros and Georgoutsos(2008) also argued that that usage of "correlation index on different sub-periods in order to establish a possible breakdown between two markets is wrong". Further, Boyer et al. (1999), Chiang et al. (2007) also opined that one could expect higher degree of correlations during high volatile periods. Hence, the correlation of the returns of these markets might not be the appropriate for measuring contagion effect and therefore this study used multivariate dynamic conditional correlation GARCH, (M-DCC GARCH) which is capable to adjust volatility related changes to analyse the contagion effect of the selected markets.

7.5.5. Estimation of M-DCC GARCH Model: US-Subprime Crisis

The global economies have witnessed great depression during the period 2007-2009, which started in the US subprime mortgage market and gradually spread throughout the world. During this period, some countries experienced sharp decline in the equity market but for some others the effect was not that much severe and for a few the effect was moderate. Based on the impact on their economy some countries named it as crisis and for some it was meltdown. In this context, examining the contagion effect and the role of herding is fruitful and as mentioned in above sections it will be helpful in many aspects. As mentioned in the previous sections examining the contagion effect and the role of herding in the Indian market during crisis is the prime objective of this chapter. Many authors like Chiang (2007), Boyer and et al. (2006) explained the role of behavioural influence in explaining contagion and is attribute to the herding behaviour of investors, which is happens when investors mimic others in their decision making. This study will check contagion effect from

60. Chan-Lau, J. A., Mathieson, D. J., and Yao, J. Y. (2004). Extreme contagion in equity markets. IMF Staff Papers, 386-408.

the US market during the US subprime crisis. Many researchers explained the herding driven contagion effect in both developing and developed markets by applying the MDCC- GARCH model. The estimation of the selected model include two steps a univariate GARCH model and the calculation of time varying conditional correlation coefficients by the model, which helps to detect the contagion effect led by herding behaviour. Corsetti and et al. (2005) Chiang and et al. (2007), Syllignakis and Kouretas (2011), Celik (2012) and many others used this model to explain the contagious effect in both developed and emerging markets in herding context.

After the preliminary investigation of the data the empirical analysis, begin by running MDCC- GARCH over the selected countries by following the steps outlined by Chiang (2007). By running the model, the study extracted the time varying conditional correlation coefficients for the selected countries and the estimates of the mean equation and variance equation. The study worked out the model for the whole study period and the estimates of the of the MDCC- GARCH model are shown in Table VII.IV.

Table VII.IV.
Estimations of the DCC- GARCH Model

Panel	USA	India
γ (M)	0.05014** (2.440)	0.14969*** (4.403)
$US_{(t-1)}$(M)	-0.0877*** (-3.588)	0.31473*** (7.080)
C (V)	0.01358** (2.231)	0.05218** (2.490)
α_1 (Alpha1)	0.08103*** (6.051)	0.15502*** (3.695)
β_1(Beta1)	0.90850*** (63.660)	0.83939*** (24.110)
Persistence	0.98953	0.99442
Estimates of Multivariate DCC Equation	α= 0.022554*** (t_{value}= 5.418) β = 0.920290*** (t_{value}= 43.15)	

Note:The values in the parentheses shows the t-statistics, ***, ** and * explains the statistical significance at 1%, 5% and at 10% levels with respective critical values 2.58, 1.96 and 1.65.The persistence level is calculated as the sum of the coefficients in the variance equation (α_1+ $\beta 1$), (M), (V), denotes the mean and variance equation.

One can find the results from the table and the constant terms in the mean equations is significant and are positive in almost all the cases during the study period. Further, it can be seen that the constants of the variance equation are significant for India. Further, the highly significant $\propto_1$ term in the variance equation explains the substantial time varying co movement during the study period. While analyzing the term (β_1), the coefficient of the shock squared term is highly significant and the highly significant coefficients of both the lagged conditional volatility and the shock squared term showed the consistency of the model and explains the suitability of GARCH (1, 1) specification in the model. The persistence of the model (sum of $\propto_1$ and β_1) is important factors that explain how quickly or slowly the prediction goes to the unconditional volatility or the variance reverts towards the long run average. Normally the sum of $\propto_1$ and β_1 will be less than one and if it is more than one it explains that the volatility are explosive and is abnormal. Generally, a low persistence explains a rapid decay and fast reversion towards the mean. The results shows that the persistence in all the case is near to one, indicates that the existence of reversion to the mean and explain that volatility is highly persistent.

7.5.6 Examination of Contagion Effect and the Role of Herding

In the next step, to examine the contagion effect and the role of herding during US subprime crisis the study employed a post- hoc analysis to examine the effect in multiple comparisons of different sets of data. The study planned to compare three sets of data in order to examine the effect of contagion and the role of herding and this include the crisis and pre crisis period, the first phase of the crisis and the second Phase of the crisis. The test will help to compare the difference in mean of the conditional correlation in the pre crisis with the mean correlation with the first phase of the crisis and the first and second phase of the crisis period.

The study performed a One-way ANOVA -Post-hoc test to examine the difference in mean between the different sample periods and hypothesized that there is no significant difference between the mean correlations during different study periods. The test of homogeneity of variances, which tests for similarity of variances and found insignificant means that there is similar variance. From the analysis, it can be seen that there is significant difference in the mean value under the specified condition .The details of the results are shown in the table below.

H120: There is significant difference between the mean dynamic conditional correlations during different study periods.

From the table, it is clear that the results are significant for India and concluded that there is significant difference in mean hence the null hypothesis rejected. Further, it should be noted that the results are not enough to explain which of the specific groups differed and these can be found out with the multiple comparisons table of the post-hoc tests.

Table VII.V.
Test Result of ANOVA- US Subprime Crisis

Country	Relation	Sum of Squares	Degrees of Freedom	Mean Square	F. Value	Significance P. Value
BSE	Between Groups	0.945	(2,1223)	0.473	186.483	0.0000
	Within Groups	3.100		0.003		
	Within Groups	4.770		0.004		

*Note: Condition, for instance [F (2,978) = 557.009,P = 0.000] for the first case.

7.5.7. Results of the Post-hoc Analysis

Since the significant value obtained in a one way ANOVA does not explain everything and the objective of the study is to examine the significant difference in conditional correlation. The Post-hoc analysis Table (VII.VI) will help to explain whether there is significant difference between the mean of conditional correlation during the different study periods. The Post-hoc test will help to determine or to compare each condition with all other conditions where significance exists. The study selected “Hochberg” Post-hoc test and “Scheffe” post-hoc test and the test is designed to compare each of the groups to every other groups. This Post-hoc tests will compare the pre crisis correlation with the correlation in the pre Lehman period and the correlation between the period after the Lehman period. The results of the “Scheffe” Post-hoc test and Hochberg Post-hoc results tabled below.

A number of comparisons are shown in the table below. In the first row, one can see the comparison between pre crisis period (1) and the first phase (2) of the crisis while in the second row explain the details of the first (2) and second phase (3) of the crisis period. The fourth column (I-J) explains the difference between the means and two of them are statistically significant.

The multiple comparison tables of the Post-hoc tests of “Hochberg” and “Scheffe” explain which groups differed from each other. We can see from the Table VII.VI that there is no significant difference in mean of dynamic conditional correlation in the cases of BSE while comparing the pre crisis and first phase of the crisis while the results shows significant difference in the DCC while comparing the pre crisis and post Lehman period (2 and 3). The comparison of the crisis periods, pre Lehman and post Lehman period showed that, the results are highly significant at 1% level, for the selected market, shows that there is difference in correlation between the pre Lehman and Lehman Periods. This shows that the correlation has either increased or decreased during the tested periods.

Table VII.VI.
Multiple Comparisons of the M-DCC for Different Study Period

Dependent Variable		(I) Period	(J) Period	Mean Difference (I-J)	Std. Error	Significance
BSE	Scheffe	1	2	-0.005109	0.004019	**.4460**
		2	3	-0.103084	0.006503	.0000
	Hochberg	1	2	-0.005109	0.004019	**.4950**
		2	3	-0.103084	0.006503	.0000

*The table shows the results of only two sets, (1, 2) and (2, 3), 1- for pre crisis period, 2 for pre Lehman period and 3- for during Lehman period.

Further, the descriptive statistics, while comparing the pre crisis and crisis period Table VII.VII shows that there is no notable increase in the conditional correlation in the case of BSE during the first phase of the crisis. It is also noted that the change in DCC is nominal and one could not explain it as contagion as per the definition of Forbes and Rigobon (2002). This shows that there is no contagion effect from the crisis originating country to the Indian market during the first phase of the US subprime crisis.

Table VII.VII.
Table showing the M-DCC during Different Study Period

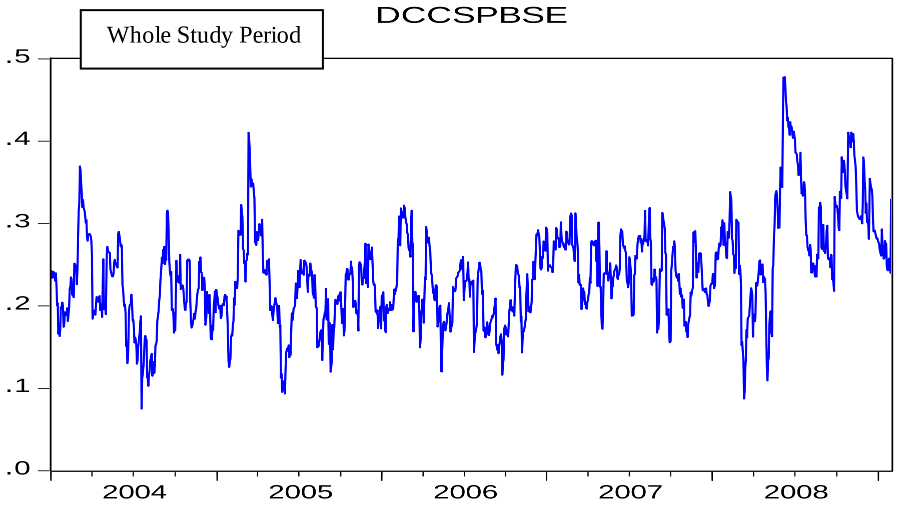
Country	Correlation			Std. Deviation		
	Pre-crisis	Crisis: Phase I	Crisis: Phase II	Pre-crisis	Crisis: Phase I	Crisis: Phase II
BSE	0.223067	0.228176	0.331259	0.048969	0.047764	0.067619

Note: Pre- Crisis: 01-01-2004 to 30-11-2007,Phase I:01-12-2007 to 14-09-2008, Phase II:15-09-2008 to 30-01-2009.

While comparing the change in DCC during the second phase of the crisis, i.e. after the collapse of Lehman Brothers Holdings Inc the DCC has increased significantly for India, showed nearly 50% increase in the dynamic conditional correlation. This shows that for India herding behaviour increased after the collapse of Lehman Brothers Holdings inc. and other companies, which drive the sentiments of the investors and showed more during the second phase of the crisis.

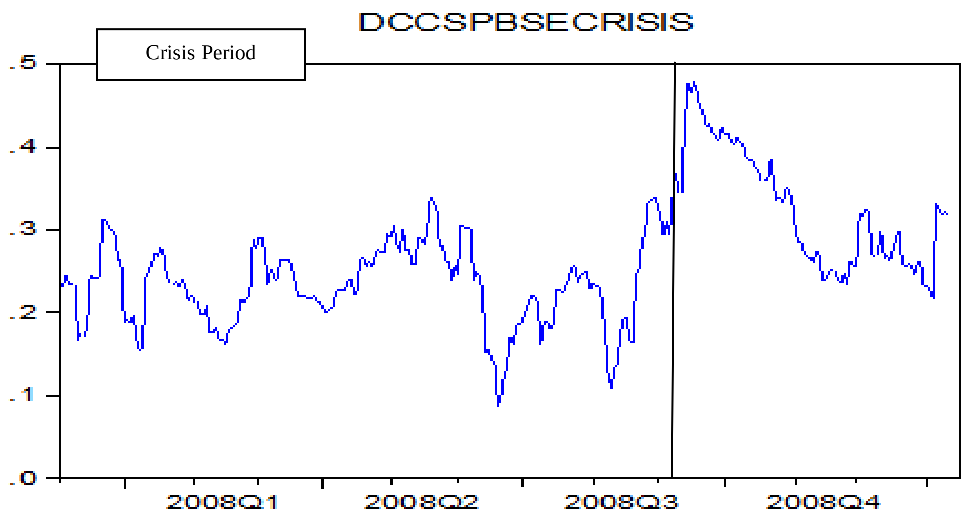
7.5.8 Line Graph Showing Dynamic Conditional Correlation

Figure VII.III
Dynamic Conditional Correlation between USA and Indian
Stock Markets during Whole Study Period



The Figure VII.III and Figure VII.IV (below) show the Dynamic Conditional Correlation between USA and India during Whole Study Period. The time series pattern of the conditional correlation series shows many cycle and the DCC is all time high during the last quarter of 2008. This shows that there is shift in GARCH corrected correlation between US and Indian Stock Market during the last quarter of 2008. In the first phase, the correlation among the selected market showed similar trend whereas in the second phase showed an increase in the beginning and tend to decrease later. The comparisons of the results in the stage two explain that the dynamic conditional correlation has changed, shows the extreme contagion led by the herding behaviour

Figure VII.IV
Dynamic Conditional Correlation between US and Indian
Stock Markets during Crisis Period



In short, while comparing the pre crisis and first phase of the crisis, the study showed that there is no contagion effect during the first phase of the crisis for the tested countries and there is steep increase in the mean correlation during the second period of the crisis. Further. TableVII.VII shows the magnitude of changes in the conditional correlation during the second phase and the pre crisis period, which confirm that the percentage of change in the conditional correlation is high (nearly 50% increase) during the second phase of the crisis period. This confirms the presence of contagion effect among the selected markets and point to the fact that high correlation arises when investors herd in the market.

7.5.9. Comparison of Results for the Two Phases of the Crisis

The comparison of the results will be informative in many aspects. It will help for better understanding of the different phases of the crises and its effect on Indian market. Interestingly the results seem to be quite different with the two phases of the crisis periods and there is no evidence to prove that the crisis driven contagion in Indian market during the first phase of the crisis. The adopted methodology is necessarily be able to explain the issue that has risen as the objective and it is evidenced that herding has played an important role in intensifying the crisis during the second phase of the crisis and caused for huge collapse especially in the equity markets during the US subprime crisis. The result is as expected since many studies pointed out that the contagion will be most influenced by emerging markets, and is due to their instability, shocks will affect and lead to harmful consequences in the emerging markets ((Celik)(2012). Further to confirm the results following Sylignakis (2011) the study examined the changes in the dynamic conditional correlation over time and the Table VII.VII explains the test results. From the table one can easily find the difference for the selected market over the periods.

The comparison of figures, which explain the conditional correlation, itself explain the difference. Further while analyzing the results one can see that spread, its intensity is more in the beginning of the second phase of the crisis, and later the correlation decreased. This may be attributed to the explanation given by Goldstein (1998), Goldstein et al. (2000) “that information that prompts investors to reassess the vulnerability of other market or countries,” and they act rationally in the later stage.

The different studies showed the effect of crisis contagion may be different in different countries based on many factors and studies like Celik (2012) showed negative correlation. Further, Fazio (2007) pointed out that, the crisis transmission in emerging markets may not always be alike and the transmission may be selective and tend to happen between specific pairs within and across the region. In short, concluded that the US subprime crisis seems to be contagious after Lehman collapse and it indiscriminately spread to Indian market. Thus, the results showed less chance for diversification during the second phase of the crisis. Further, the study also noted that the results might be different for the markets with similar characteristics and for the countries from the same region.

7.6 Conclusion

Bartram and Dufey (2001) pointed out that exploring opportunities and identifying the limits in portfolio diversification and asset pricing has important implications. The integration, interdependence and the contagion effect in different stock markets, especially emerging markets, because of its potentials for growth has been a great issue and subject of interest to a large number of groups such as financial analysts, economists, policy makers, local and international investors and researchers. Identifying contagion effect is one of the important issues because crises or bubbles are happening in a regularly irregular manner in different economies during these decades. Although there are exponentially large number of works in contagion research, but works that discuss the contagion effect in the context of herding behaviour on emerging markets especially Indian market is comparatively less. This led the present research. In addition, the study will help to characterize the impact of the US subprime crisis on Indian markets.

This study applied multivariate DCC – GARCH model to examine the short run inter relationship between the Indian market and the US market during the US subprime crisis. The study selected Indian market and used daily index return series by taking the first difference of the log value of the adjusted closing price series of the corresponding index for the period from 02-01-2004 to 30-01-2009. From the analysis, it is clear that the conditional correlation coefficients derived from the applied model shows significant and valid evidence for variation for Indian market during the second phase of the subprime crisis and an increased amount of correlation and this points towards the spread of crisis at the extreme point of subprime crisis, the collapse of Lehman brothers holdings inc. In addition, the results points that, during the peak of crisis, it reduces the diversification opportunities in India market. At the same time, noted that the high correlation found immediately after the Lehman collapse decreases while the time passes and one can see this from the figureVII.III, support the diversification opportunities to these markets.

This result supported by the findings of Hwang et al. (2010) and Celik (2012), they find evidence of contagion during US subprime crisis. Further, the results is also supported by the work of Syllignakis and Kouretas (2011), who confirmed evidence of herding driven contagion effect in the central eastern European emerging markets during the US financial crisis. Naoui and et al. (2010) also find the contagion effect and concluded that contagion is strong between the US and Brazil, Mexico, Argentina, India, Malaysia and Singapore during the subprime crisis. Further most of the emerging markets are found to be affected by contagion and this result points the fact that emerging markets are unstable than developed markets Ceilik (2012). Further, it is also confirms the argument that herding is an evanescent phenomenon and in particular, the result of figureVII.III, showed increases in the correlation in the second phase of the crisis and gradually the correlation showed a decreasing trend and can be concluded that this increase the probability of finding spurious short-term herding in the beginning of the second stage of the crisis.

In short, the study found evidence for contagion effect in Indian market during the second phase of the US subprime crisis. The results bring out many interesting conclusions and policy implications. First, the simple pair wise correlation and the results of the dynamic conditional correlation showed different results and it supports that the simple correlation is not an exact measure of reporting contagion, but as the Table VII.III, the simple correlation also shed light in predicting the relation. The investors and policymakers further analyse very thoroughly the other factors which may causes contagion. The policy makers can introduce an early warning systems, that can warn about the sentiment driven contagion effect in the market and educate the people regarding this issues and can introduce an international warning system to save the country which are not directly linked with the crisis affected country.

CHAPTER VIII

FINDINGS AND SUGGESTIONS

8.1. Introduction

The increased complexity, uncertainty, insufficient and asymmetric information, especially in developing markets made the investment arena tougher and raised many behavioural issues in the market. The liberalization process and the convolution in investment setting made the investment arena tougher and the investment decisions more complex. Further, emerging markets like India are being considered as a dome for investment, since it provides liquidity and comparatively higher return than the developed markets and this invited the attention of many to these markets. It is also noted by many studies that, different type of investors, say individuals or institutional investors act differently in the market. As noted by Aguilar (2013) commissioner, U.S. Securities and Exchange Commission, "the institutional investors itself not all the same, but they are in different forms with many different characteristics".[61]

Behavioural finance explains that there are many behavioural issues which can be observable in the market and it can seriously influence the price of an asset and the market. The link between asset mispricing and the behavioural issues in the market attracted much attention from the part of researchers and practitioners in both developed and developing markets and there is no consensus in the findings and the results are mixed. Herding behaviour in the stock market is one of the important but hardly discussed aspects in behavioural finance which has an exorbitant power to influence the market seriously and lead to mispricing of assets and hence causes market efficiency.

Contrary to investors in developed markets, the investors from the developing markets herd more and may imitate others because of many reasons. These include lack of information or unaffordable cost information or any other reasons like reputational or informational cascade. In the literature one can see many more reasons, which leads the investors to follow others in their investment decisions as

61. http://www.sec.gov/news/speech/2013/spch041913laa.htm.

noted in the previous chapters. Many researchers argued that herding behaviour is more prone during market stress but literature gives mixed results. One of the major roles of the researcher is to identify appropriate financial information about the effect or the consequence of this behaviour and communicating this to investors and decision makers; with this, they can avoid herding and follow informed judgments and decisions. Even though there are many studies, which examined the different aspects of herding behaviour in emerging markets, the studies in Indian market are rare and scanty and this study examined the dynamics of herding behaviour in Indian stock market and is an attempt to fill this gap.

This chapter is designed to analyze the conclusions drawn based on the empirical analysis on different objectives set to examine the different aspects of herding behaviour in the Indian stock market. This study addressed the issue of existence of herding behaviour, its determinants and the asymmetry in the pattern of herding behaviour based on high and low states of volatility, trading volume and net FII investments in Indian stock market. Further, the study also examined the role of herding behaviour on contagion effect during the crisis period. The study examined the existence of herding behaviour in Bombay stock exchange of India, BSE, by using 10 years daily data of 243 constituent scrips of BSE-500 and the data spans over the period from 01-04-2002 to 28-03-2012.

To test the existence herding behaviour, the study applied two methodologies a static measure and time varying measure and the tests are carried out for different sub periods using the static measure. In the second stage, the study examined the influence of different factors on herding behaviour and used factors such as market return, market volatility, and market trading volume, HML, SMB (Fama-French), net FII flow, net mutual fund flows and the net institutional investment. In the third stage, the study analysed the asymmetry in the pattern of herding behaviour on different factors using daily data and examines their effect on high or low market conditions of volatility, volume and net FII investment using the static measure. In the fourth stage the study analysed the role of herding behaviour on contagion effect during US subprime crisis by using US as the crisis origin country.

8.2 Findings

8.2.1. Herding Behaviour in Indian Stock Market

8.2.1.1 Existence of Herding Towards Market Consensus

This study examined whether there exist herding behaviour and if so the intensity of this behaviour in the selected stock market. Using the daily data of 243 constituents of the BSE-500, the study provides significant evidence for the existence of herding behaviour in the studied markets in the whole study period. For the second methodology, the study used log cross sectional standard deviation of Fama French betas and found significant results with market factor, which support the existence of herding behaviour in Indian market. This result stands in line with the earlier evidence of herding in emerging markets[62]. Further, the results also support partially the study made by Lao and Singh (2011), Prosad and et al. (2012), Bhaduri and Mahapatra (2013) examined the herding behaviour in Indian market and found evidence for herding behaviour towards the market consensus. It is also noted that the study could not find herding during the post crisis period by using the static measure.

8.2.1.2 Higher Intensity of Herding During the Crisis Period

While analyzing the herding towards the market consensus, the result showed a strong support in the case of BSE and the intensity of herding is more during the crisis period, which is also in line with theory and arguments of Christie and Huang (1995), Chang and et al. (2000), who explained the possibility for higher level of herding during the crisis period. It is also noted that it is against the findings of Lao and Singh (2011), in Indian market and the arguments of Hwang and salmon (2004), who found the tendency of herding is decreased during the crisis period. The study could not find herding behaviour during the post crisis period using the static measure. The panic experience of the investors during the crisis period, the fear of losing money, lack of sufficient and correct information, higher level of market volatility etc, may be the reason for showing higher level of herding during the crisis period.

62. See Chang and et al. (2000), Hwang and Salmon (2004),Tan and et al. (2008), Lao and Sing (2011).

Further the study also adopted the methodology proposed by Hwang and salmon (2004), gives time-varying estimates of the dynamic nature herding behaviour in the market which also showed highest level of herding during the crisis period and there after a decline in the herding behaviour. The analysis also showed that herding behaviour in the studied markets are time-varying based on market conditions or other factors. While analyzing the graph one can see many cycles in the evolution of herding behaviour in the studied market and is not smooth. The intensity of herding behaviour is at its peak during the crisis period and the tendency to herd towards the market consensus was relatively less during the bullish period and showed a declining trend during the second phase of the crisis period. The trend continues and there is variation in the intensity of herding behaviour after the crisis period. Comparing with the other two factors, the size and value factor, the study found more persistent herding towards the market factor, which is in line with the findings of khan and et al. (2011), who found that investment strategies of the investors focus more to the market factor than the size and value factors in the selected four markets, United Kingdome, Germany, Italy and France.

8.2.1.3. Non Existence of Herding Towards the Size Factor

The study also examined the herding behaviour towards the size factor in the selected markets by using the methodology followed by Hwang and salmon (2004).The study used the log cross sectional standard deviation of beta of the size factor extracted through the Fama French model and the analysis gives insignificant results explains that there is no herding behaviour towards the size factor in the studied market. This is in line with the study of khan and et al. (2011), who found the investors do not herd towards the size factor for United Kingdome, where as German investors herd more towards size factor when compared with Italy and France and concluded that the intensity of the herding varies over the countries.

8.2.1.4. Existence of Herding Towards the Value Factor

The results of herding behaviour towards the value factor in Indian stock market is tested by using the log cross sectional standard deviation of beta of the value factor (HML) extracted through the Fama French model. To examine the herd behaviour of investors towards the value factor the study used the methodology proposed by

Hwang and salmon (2004) and found significant result, showed the existence of herding behaviour towards value factor in the studied market. The result is as expected because the individual investors may usually look at the value factor than the size factor. In addition, based on the coefficients and the graph the evolution of herding behaviour is smooth when compared to the market factor. Further, noted that the study is in line with the studies Hwang and Salmon (2004), who found herding behaviour towards the value factor in South Korea. Khan and et al. (2011), who observed herding behaviour towards the value factor for France during the study period from 2002 to 2008, were as a less amount of herding for Germany, and Italy and for united Kingdome.

8.3. Determinants of Herding Behaviour

The study also analysed the influence of various factors both firm fundamental as well as market factors on herding behaviour. It also facilitates to account the effect of these factors for the robust measure of herding behaviour in the studied market. For this the study used the market volatility, market return, market trading volume, Size factor and Value factor (Fama-French), net FII flow, net mutual fund flow, the net institutional investors flow and return of S&P-500 to account for the possible control effect of these variables on herding behaviour in the studied market.

8.3.1. Market Volatility is the Controlling Factor of Herding Behavior

The analysis of the influence of various factors generally shows evidence in support of herding behaviour. The market volatility (log) found to have controlling effect on herd behaviour in BSE since it gives significant results and the variation in $Std_c(\beta_{imt}^{b})$ is higher and is decreasing. Further, the negative and significant coefficients of the volatility factor explain that the volatility of the factor sensitivities decreases when market volatility increases and the results are consistent with a number of studies, which explain that herding, is likely to be occurred during market stress. The test results suggest an increase in herding behaviour in Indian market when market volatility increases. One possible reason for this may be because of the type of investors participated in the market. Based on the results, concluded that herding increase when the market is volatile and market volatility leads to an increase in the intensity of herding behaviour in the BSE.

8.3.2. Trading Volume has Lesser Impact on Herding Behaviour

The study also found that market trading volume (log) has impact on herding behaviour in BSE since it gives significant results. Like volatility the volume also influence herding behaviour in Indian stock market where as the influence of volume is very low since the variation in $Std_c(\beta_{imt}^b)$ is low. The average $Std_c(\beta_{imt}^b)$ increased when volume is used as a controlling factor, explain a weaker influence of volume on herding behaviour. In addition, it is found that the coefficient of volume is negatively significant and the variation in $Std_c(\beta_{imt}^b)$ is comparatively less when compared the market volatility and the result show that herding increases as market volume increases and it does not contribute much to herding behaviour.

8.3.3. Market Return is not a Determinant of Herding Behaviour

The analysis revealed that market return and the US market return does not have any influence on herding behaviour in Indian stock market since the estimates are insignificant.

8.3.4. Size Factor and Value Factor do not Influence Herding Behaviour

Examining the relative influence of the size and value factor on herding behaviour will explain whether these factors have any influence on herding towards the market consensus. The size and value factors are insignificant while testing the herding behaviour towards the market consensuses in BSE; shows these factors do not have any controlling effect or have any impact on investors herding behaviour in Indian stock market.

8.3.5. Foreign Institutional Investment Impacts Herding Behaviour

There is much debate on the role of institutional investors in emerging markets and many studies found that institutional investors play important role in the stock market. Further a number of studies showed that institutional investors showed herding behaviour in the market but it is comparatively less when compared to the individual investors. While analyzing the net investment of institutional investors (net of FII and MFI together), one can see the result is significant, shows the institutional influence in the herding behaviour in the studied market. Further the variation in the herding coefficient is very low while including these variables, shows that their effect was very less on herding behaviour and based on the other analysis these may be attributed to the sell side herding[63]. This can be explained as investors herd when the institutional investors withdraw their investment from the market, or investors herd more when there is investment outflow in the studied market.

8.3.6. No Herding Based on Mutual Fund Investment

The study also examined the role of foreign institutional investors and the mutual funds investors separately and found that mutual fund do not have any influence in the studied market, since both the results showed insignificant results, this questions the dominance of the domestic institutional investors in the studied market. Thus, the study shows that dynamic herding behaviour significantly correlated with the said factor foreign institutional investment in the studied market even though their influence is very less.

8.4. Pattern of Herding Behaviour in Indian Stock Market

The examination of the factors influencing the herding behaviour in Indian stock market showed that volume, volatility and net FII investment flow influences herding behaviour of the investors. To examine the effect of these factors in detail, the study examined the pattern of herding behaviour at high and low states of market volatility, trading volume (market) and the net flow of FII and the test was carried out for different study periods. Further, the findings are interpreted with caution, since there is chance for overlapping data while sorting data based on different state of the market.

8.4.1. Existence of Asymmetric Pattern of Herding Behaviour Based on Trading Volume

The study examined the pattern of herding behaviour in high and low states of volume. In order to get more precise picture about the role of trading volume on herding behaviour, the study analysed the effect in the whole study period and also dividing the period in to three sub periods say pre crisis, crisis and post crisis periods. The study found different result for different period and found herding mostly in the

63. A detailed analysis required in this aspect, since the study considered only the net institutional investment. It is suggested to experiment with total investment inflow and outflow instead of using net investment for better understanding before concluding that it is sell side herding.

states of high trading volume, whereas test do not support the existence of herding behaviour in the low state of trading volume during the whole study period.

The results for different sub periods, showed evidence for the herding behaviour only during high state of volume during the pre-crisis period, whereas the study did not found herding behaviour during crisis period or post crisis period neither in high nor low states of trading volume. The evidence signify that the pattern of herding behaviour in the studied market is asymmetric based on trading volume, during the whole study period and pre crisis period since herding found only during the high states of trading volume. Where in few cases the coefficient is significant but positive, which shows lack of herding during such periods.

8.4.2. Existence of Asymmetric Pattern of Herding Behaviour Based on Market Volatility

The market volatility provides much information about the market movements and is one of the important factors, which may affect the sentiment of the investor. The analysis showed that volatility is influencing the herding behaviour in the studied market. Investigation of the asymmetric effect of herding with volatility in the studied market showed that the investors are prone to the volatility factor in the market. While analyzing the results of the different study period one could see that the results are different and we can see asymmetries in the pattern of herding behaviour. The result showed that there is no asymmetry in herding behaviour based on the volatility factor and showed significantly negative coefficient in both the cases during the pre crisis period, but there is difference in the intensity of herding behaviour. The study finds asymmetry in the pattern of herding behaviour with the whole period, crisis period and the post crisis period, where herding is present at high volatility state in the whole study period and pre-crisis period and crisis period, where as herding is present during the low volatility states during the pre-crisis and post crisis periods. Thus concluded that, the pattern of herding is different in Indian stock market based on the volatility states and it differs during different period based on the market condition

8.4.3. Existence of Asymmetric Pattern of Herding Behaviour Based on Net Foreign Institutional Investment

Based on the previous results the study also tested the pattern of herding behaviour based on the net FII investments to Indian stock market and found herding is present only when FII is low. Further the results for the different sub period also showed the same results, showed the asymmetries in the pattern of herding behaviour. It is also noted that the intensity of herding over the different period varies and herding is more visible during the crisis period. In certain period the coefficient of the term become positive and insignificant, shows the lack of herding during the period.

8.5. Herding Behaviour Leads to Contagion

The study examined the role of herding on contagion effect during crisis by using the daily data of the indices of the studied countries. The study examined the changes in dynamic conditional correlations during different study periods. The study used US subprime crisis to examine the role of herding and found that herding plays an important role in spreading contagion. The study found that crisis was contagious only during the second phase of the crisis. The result shows that the conditional correlation increased (nearly: 50%) during the second phase of the crisis when compared to the pre crisis period, confirms the role of herding behaviour in spreading crisis.

8.7. Suggestions

A large number of studies examined the existence and the asymmetric effect of herding behaviour in developed and emerging markets. For India, the studies are scanty and there are only few studies, which examined the herding behaviour. The general view is that, the herding tendency is more in the developing markets and literature explains many reasons like informational asymmetry, transparency, informational cascade and reputational reasons. From this study, it is clear that, there exists low/moderate level of herding behaviour among Indian investors and the evolution of the behaviour is not smooth and it varies from period to period. The authorities should consider this fact and take initiation to educate the investors about the herding behaviour and its consequence in the stock market since it leads to asset mispricing and to market inefficiency. The study brings the following suggestions for the policy perusal.

1. **Reduce information Asymmetry**

   Extreme herding behaviour will create market inefficiency and mispricing of assets and this ultimately leads to the loss of confidence of investors. Hence, the authorities should take necessary control measures to avoid herding in the market and take measures to encourage the rational investment concept among investor. These are possible by introducing more transparent market system and also by reducing information asymmetry. This is possible because investors in many of the developed markets do not show or showed a very low level of herding behaviour even in extreme market conditions.

2. **Controlling Over Withdrawal of FII Flow**

   The study found herding behaviour when the Net FII flow is low, one of the major investment group in the market; withdrawal of FII from the market enhance the possibility of herding behaviour in the studied market. Hence, the effective measure should be taken to control this group and should analyze the motive behind their behaviour and a detailed study is suggested in this aspect.

3. **Warning Signal by the Government to Investors**

   The study found that the crisis was contagious during the second phase of the crisis and it significantly affected the Indian stock market during its peak. The government can monitor such facts and warn or guide investors about the possibilities of the damage in the economy and provide better information about the scenario may help the investors to reduce mimetic behaviour in the market and is possible since crises are not happened all of a sudden.

4. **Sponsored Research on FII's Trade**

   Institutional investors are playing an important role in Indian stock market and it is found that there is herding behaviour when the net foreign institutional investment flow to the market is low and a detailed probe is suggested with the purchase as well as sales of these group, since the effect of their purchase as well as sales on herding behaviour is not differentiated in this study. Further it is also found that herding is more, when the net FII is low and this may happen when the FII's withdraw money from the market and introduction of appropriate regulatory measures to control such capital out flow may be useful for controlling herding behaviour in the market.

5. Up-Scaling Existing Investor Education (Training)

Individual investors are more prone[64] to herding behaviour than the institutional investors and their inexperience in the market may induce herding behaviour and this can be avoided by providing adequate training.

6. Measures to Control Contagion Effect

The existence of contagion effect in the second phase of the crisis explain that there is greater need for coordination of policy level actions from the part of government to control the contagion effect, since it brings heavy loss to the investors and reduce the investors confidences in the market .

7. Reduce the Vulnerability to Contagion

The contagion in the studied market is driven by the herding behaviour which is the outcome of certain emotions of the investors; if the fundamentals of the market and of country are stable it will give more confidence to the investors and thereby can reduce the effect. Thus it is crucial to ensure strengthening the stability of financial market and the economy and bring policies that reduce a country's vulnerability to contagion. Financial market is one of the most sensitive markets which respond and reflect immediately to the vulnerability of the economy. Most often the crisis spread into the developing countries because of the instability in country's economic fundamentals. A market which exhibit fundamental value efficiency will provide investors an efficient opportunity diversify the available resources and any attempt made to strengthen the countries fundamentals will foster stability of the economy and hence the confidence of the investors and will reduce the chance for contagion of crisis.

[64] Based on different studies

8 Mechanism to Provide Information at Affordable Cost

Though role of cost is not included in this study, the investors perception overweighed to suggest that Information cost is another important reason for herding behaviour and the authorities should take necessary steps to provide the information at affordable cost or free of cost. Since government is looking for more equity participation and involvement from the part of individual investors through different schemes like Rajiv Gandhi equity scheme, will attract more individual investors and the government should take necessary steps to teach such group and arrange facilities to make information available to the market about the scrips and other fundamentals. At present the market showed herding tendency and if an unsophisticated group join with the herd, it may increase the intensity of herding and this may led to market inefficiency.

9. Inclusion of Behavioural Factor in Assessing Risk

Further the study supports the role of herding on contagion effect and there is enough reason to believe that pure contagion contributed in spreading crises during the second phase of the Subprime crisis. Therefore the study stress the inclusion of behavioural factors especially during the period of market stress for assessing the risk associated with the assets. During the stress/ crisis the investment risk increases and the psychological bias may affect the entire financial system. Inclusion of the behavioural factor in assessing the risk will add value to the risk assessment and its management. Thus inclusion of herding variable in the model like CAPM may improve the predictability of security return and the predictability of the models.

8.8. Concluding Remarks

Behavioural finance became one of the talk factors in the recent history of finance. The importance of behavioural finance is increasingly growing in discussions and many researchers are showing keen interest in this area of finance and discuss many issues in the financial market, which arises due to different behaviour shown by the investors. The analysis of different behaviour and its consequences helps the investors, policy makers, wealth managers and other interested parties for a better understanding of the market and the asset, for pricing the risk associated with the assets and formulating and improving their decisions in the market.

As discussed in the previous chapters, examining herding behaviour in Indian stock market is important and this study contributes to the herding literature in many aspects. The study analysed the existence of herding behaviour in one of the important emerging market, India (BSE) and the various factors controlling herding behaviour, the asymmetric effect of herding behaviour in different market conditions. The study used two measures a static measure and a time varying measure to examine the herding behaviour and also the role of herding behaviour in making the crisis contagious. This study has analysed the persistence and evolution of herding behaviour during the study period. The analysed market is an emerging market and the study found almost similar results of the previous studies, which confirm the existence of herding behaviour in the studied market. While analyzing the herding behaviour towards the market, the study found that intensity of herding is more during the crisis period because the investors may be panic during such periods and may find more irrational. The finding is in line with Kim and Wei (2002[a]), Bikhchandani and Sharma (2001), Bowe and Domuta (2004), who found herding tendency increased during crisis period. In addition, the evolution of herding is not smooth and found many 'ups' and 'downs' in the pattern of herding behaviour in the studied market, may be explained by the influence of different factors in the Indian stock market. For the value factor, the behaviour is visible but no herding found towards the size factor in BSE.

Findings showed that there is herding behaviour in the studied market, explained as the uninformed trading in the Indian stock markets. Only volatility, volume and the net foreign institutional investment is found affected individually and jointly where as the other tested factors, net mutual fund investment, net institutional investment (jointly affect),market return, the size factor and value factor do not have any controlling influence on herding behaviour.

The pattern of herding behaviour based on the high and low states of market trading volume, market volatility and Net FII flow explain the asymmetric pattern of herding and these may be of the psychological effect during the extreme up and down market movements of the market. Similarly, the investors follow each other more intentionally and herd more during the period of market stress or crisis than when the market is calm or bullish. It is also noted that herding behaviour appears not only to the occurrence of large swings in market, but also to the state of low volatility. In addition the study found herding during the low sates of FII investment but do not found herding in the high states of FII investment.

This study empirically examined the existence of herding behaviour, its determinants, asymmetric effect of herding behaviour on BSE and examined the role of herding behaviour on contagion effect in Indian market. The study found that investors showed a moderate level of herding in the studied market. Further, the herding behaviour tends to be much evident and it is at its peak during the crisis period. However, it is noted that, the behaviour is found to be diminishing during the second phase of the crisis, say the collapse of Lehman Brothers Holdings Inc. and showed a declining trend. This sign that the investors tend to show this behaviour when the market is under stress rather in bullish condition.

8.9. Future Research

The behavioural finance explicates the psychological and cognitive aspects of human behaviour, which is extremely valuable in explaining many of the anomalies existed in the market and for decision making. The research on herding behaviour can be extended in the following ways

1. The intensity of individual herding and Institutional herding are different and such an analysis may provide better understanding about the herding behaviour in Indian stock market, since institutional investors are one of the major investors in Indian stock market and they are considered to be better informed investors than the individual investors.
2. Further one can check the bi-directional relationship between volatility and herding and the effect of herding driven volatility in the market and the same effect on volume can also be checked
3. This study found herding with low state of net foreign institutional investment; one can extend the study by considering the purchase and sale of foreign and institutional investment and Mutual fund investment in Indian market.

4. The present study tested the contagion effect based on the Subprime crisis. One can also test the role of herding behaviour in other crisis such as Euro crisis (2010-2012) or Asian crisis 1997.
5. Herding is more prevalent in short term and is able to catch up with intraday data and thereby one can test the intraday level herding behaviour of investors in the market.
6. There is no established clear-cut methodology to distinguish spurious herding from rational herding. Any empirical contribution to develop a tool to distinguish spurious and rational herding will be a highly appreciated contribution from the empirical finance.

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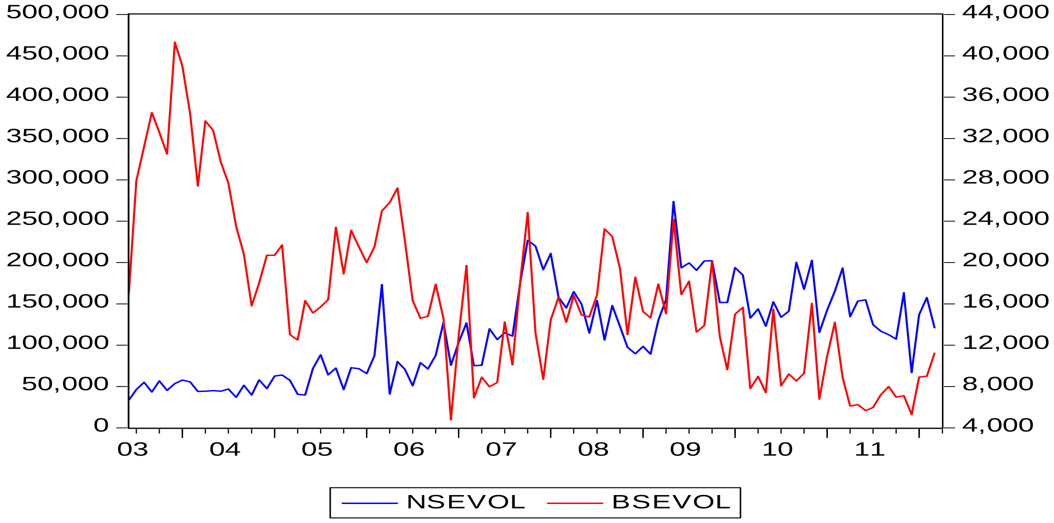
APPENDICES

Appendix: i

Figure A-I
Line Graph Showing the Monthly Trading Volume of
NSE and BSE over the year 2003 to 2012(Different Axis)



Appendix: ii

Figure A-II
Line Graph Showing the Monthly Trading Volume of
NSE and BSE over the year 2003 to 2012 (Same Axis)

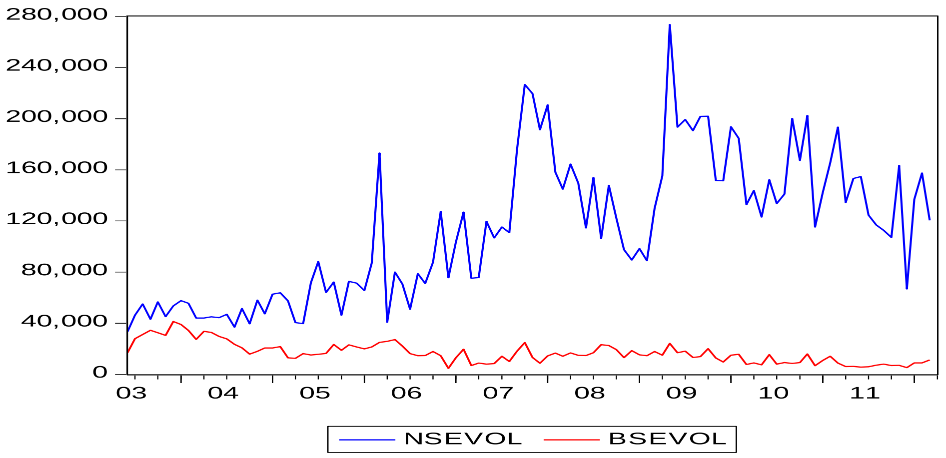


Figure A-I and A-II shows the trading volume of NSE and BSE for the period June 2003 to March 2012, BSE shows a declining trend in volume.