STUDIES ON INDIAN CAPITAL MARKET UPHEAVALS:
A BEHAVIOURAL FINANCE APPROACH

SUBMITTED BY:

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No part of this thesis has the basis for award of any degree or fellowship previously.

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I. Acknowledgements:

During the post graduation days I used to be a stunned listener to various thought provoking lectures on financial economics delivered by our respectable teachers. Especially lectures on the market failures and efficiency theory by Dr. Hirak Roy(Associate Professor , Department of Commerce, University of North Bengal) and Dr. Malay K. Roy (Former Associate Professor , Department of Commerce, University of North Bengal) attracted me the most to engage myself in the research work in Behavioural finance after completion of my post graduation.

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Now at this jubilant moment of submitting the thesis I remember my father Late Narayan Chandra Ghosh who departed long before at the initial stage of my academic life. But his academic commitments and ideologies have inspired me the most in my life. I am now expressing heartiest gratitude towards his soul and want to dedicate this piece of work to him. I am finding very hard to locate my words to express my gratitude towards my mother. She left no stone unturned to fight against all odds to provide me enough scope to pursue this study. I also admit the enthusiastic companionship of my elder brother and sister – in – law.

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Needless to add, any errors and omissions in the thesis is entirely my responsibility and I will be extremely grateful if they are pointed out to me.

Above all I must bow my head to the Almighty, nothing can happen in this world without His will.

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II. Abstract:

Consecutive market crashes around the globe appeared to have systematically characterized the dynamics of speculative markets. These apparent high valuations in the aggregate market followed by devastating crashes cannot be attributed fully under the traditional dictum of market efficiency. Especially after nineteen eighties the intellectual dominance of efficient market theory has started to become far less universal. Many financial economists and financial mathematicians have started to believe that dynamics of speculative markets cannot be sufficiently explained in the backdrop of rational expectations. Going by these experiences a consensus for a new school of thought has started to grow among the financial economists to explain the market upheavals in the back drop of behavioural finance. Recently, theories from the fields of other social sciences like sociology, psychology etc. have been used widely in thre literature to exhibit strong influence of greed, fear and envy in shaping investors' behaviour. However, literatures on explaining upheavals in Indian equity market in the backdrop of behavioural biases are weak and scanty. Rather several scholars have identified patterns of price movements in Indian markets and its distributional shape that cannot be explained with the notions of random walk hypothesis. In such a backdrop, the present thesis is our humble approach to identify the presence of various behavioural biases of human decision making in Indian equity market and explain its upheavals.

In the current study we have followed the emerging trend in research in behavioural finance to analyse market dynamics in the structural heterogeneous agent model in multi agent framework. Market upheavals have been modeled in this new direction as an endogenous phenomenon arises quite naturally under the assumptions of bounded rationality.

In the empirical part of the present thesis we have studied the predictions of heterogeneous market model especially in the context of the patterns of price changes to offer coherent explanations of behavioural biases towards market upheavals. We have estimated the extreme returns , mean excess returns, Hill points and volatility of the Indian equity market considering the returns for the period ranging from 01.07.1997 to 30.8.2013 using some tools like EVT, GARCH etc. Empirical evidences of patterns in price changes In Indian equity market nicely confirm the predictions of heterogeneous market framework. Investors' decision making in the equity market appears as context specific. Their decisions in the

market can be modeled to have guided by an evolutionary force, generating adaptive belief in favour of price to price channels and ultimately results into bubble formation. These findings in turn attest the role of social and psychological biases in decision making in the backdrop of bounded rationality.

III. Preface:

In the literature of finance, determinants of asset prices are at the heart of grand debate for the last few decades. Rationality driven theories of market efficiency dominated for long, presumed it as an unchallengeable truth, immaculate description of market behaviour. Prices that emerge out of an efficient market *ought to incorporate all available information efficiently and can be regarded as optimal estimate of true investment values at all times,* thus promises *parato optimal allocation* of resources. If market truly behaves according to this standard of excellence how can we account for speculative upheavals around the globe (see Appendix IA and IB). the eventuality that does not fit in perfect foresight environment. Indian equity market is also not an exception. Skyrocketing rise in prices followed by massive falls in several consecutive occasions especially in the last couple of decades seems to have systematically characterized dynamics in Indian market (see Appendix IB). These findings however point towards some intrinsic dynamic forces of speculative market that are not fully captured in the existing paradigm of rationality. There seems to be some crucial dimensions missing, which if ignored, may lead to a constant repetition of same major errors and inevitably poorer market results. In this backdrop, very natural questions are how the corrective action of the market fails, irrationality prevails and bubble grows. Undeniably the events of market failure are wasteful, destructive, and inherently undesirable which belies the hope of market economists that their ideological prescriptions can deliver a stable and prosperous society.

Driven by the experiences of irregularities even in this era of financial acumen, consensus among the researchers has evolved towards developing a more comprehensive framework emphasizing socio-psychological underpinnings of human decision making. Much recent empirical works in the backdrop of human behaviour especially from psychology, sociology, anthropology etc. have been motivated for analysing the market upheavals. But a unified theory of behavioural finance in analysing stock price dynamics in speculative markets is yet to be developed. So far, most emphasis in the literature has been on identifying behavioural decision making attributes that are likely to have systematic effects on financial market behaviour.

However, in the last couple of decades, a rapidly increasing number of structural heterogeneous agent models in multi agent framework have been introduced in the financial literature to offer a more coherent analysis of psychological underpinnings behind market

upheavals. These approaches draw heavily from a new school of thought widely emphasized in literature by the Santa Fe Institute of New Mexico. The major emphasis in this new direction is on applying the bottom up approach, focusing on micro level of the agents' interaction but aiming at studying the behavioural macro effects on asset price dynamics. Most of these major theoretical developments in this front of behavioural analysis towards speculative price movements have evolved considering developed economies. So far the data available, no such significant efforts have been given in analysing upheavals in emerging markets like India. From the socio psychological end, we can expect considerable differences in investors' behavioural pattern in developing economies especially in the 'East', due to cultural deviations from developed countries – the 'West'.

In this backdrop, it is our humble attempt to identify, in Indian context, the impact of same socio psychological issues in decision making that are documented in studying markets of developed economies. .Following the recent trends in this new direction, we will try to apply non linear structural equilibrium models in multi agent framework. In this approach price changes are driven by a combination of exogenous random news about fundamentals and also the evolutionary forces underlying the trading process itself.

Our study is organized as follows. The chapter one contains a brief introduction of the topic followed by a brief survey of literature in chapter two. Chapter three presents a theoretical approach to model investor's behaviour to analyse market upheavals in the backdrop of non linear heterogeneous structural equilibrium model under the assumption of bounded rationality. Then the chapter presents research hypothesis, the objectives, data , time period and methodologies of the study of the study. In chapter four and five, we have attempted to identify objectively behavioural implications of Indian investors in asset market decisions using some tools like EVT, GARCH etc.Chapter six presents some concluding remarks.

During the course of my study I have defended one research paper titled Extreme Value Theory : Lessons from Indian Capital Market (co authored with Dr. M.K.Roy and Dr.Hirak Roy) at the International Finance Conference organised by IIM Calcutta in December,2009 and published two research papers: (i) Estimating the Tails: Application of EVT in Indian Capital Market (Co authored with Dr. Hirak Roy and Dr. Malay Roy, PRAJNAN Journal of Social and Management Sciences,National Institute of Bank Management ISSN : 0970-8448,Vol XL, No.03, October – December 2011), (ii)Measurement of Catastrophic Failure: Application of EVT, Hill Estimation in Indian

Capital Market, Co authored with Dr. Hirak Roy and Dr. Malay Roy, International Research Journal of Finance and Economics, Euro Journals, ISSN : 1450-2887,Issue No.95, August' 2012.

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Chapter -I

Introduction

Introduction:

Truth underlying the stock price movements is yet to be established. For many years this has been a source of continuing controversy, a fertile ground for research in both the academic and in professional financial world.

According to the conventional paradigm financial prices efficiently incorporate available information and that prices can be regarded as optimal estimate of true investment values at all times. This efficiency theory has developed in the backdrop of "rational expectations" revolution in economic theory at around 1960s (Muth 1961). The idea behind the market efficiency is in fact based on such notions of rationality where agents are able to process all available information , update their belief correctly following the Bayesian Paradigm and make unbiased choices that are normatively acceptable and consistent with the Savage's Notion of "Subjective Expected Utility"(Savage 1954). Investors always exhibit non satiation, more terminal wealth to less terminal wealth and they are risk averse i.e. they reject fair gamble. Investor's utility function in general is increasing but concave shape towards origin satisfies law of diminishing marginal utility. Expectations in this framework are made on the basis of all available information, where relevant information is not ignored, and systematic errors are not made. Security prices are determined subject to the maintenance of a perfect relation between risk and return. Prices 'fully reflect all available information' making it to be always at levels consistent with fundamentals(Fama 1991, 1965). Informationally efficient prices respond only on the arrival of genuinely new information and as the arrival of information cannot be predicted, movement of asset prices also becomes random (Shiller 2002). Variability of prices is equal with the variability of information. Thus histories of asset prices do not have any predictive power for future asset returns. At any point of time, market value reflects the cumulative knowledge of all participating investors. Although each individual investor may err about his opinion of future value, but if the number of opinions is large and if the opinions are developed through independent thinking, the thousands or perhaps millions of individual errors will largely cancel out, so that the resulting consensus becomes a powerful

predictor of future value. Moreover, there remains no free lunch in an efficient market: no investment strategy can earn excess risk adjusted returns, or average returns greater than are warranted for its risk. As soon as there is any deviation from fundamental value (more simply, a mispricing) an attractive investment opportunity is created and rational traders will immediately snap up the opportunity (Friedman 1953). As information arrives in the market infrequently, efficient market theorists suggests, large movement in prices will also be rare. Ordinarily, price will move within a narrow band due to investors' liquidity needs or portfolio rebalancing consideration. Prices may exhibit trends over time; fluctuations in price away from trend will be unpredictable. This strong version of hypothesis can only be literally true if 'all available information' is costless to obtain. If information is instead costly, there must be a financial incentive to obtain it . There would not be a financial incentive if the information is already "fully reflected" in asset prices (Grossman and Stigliz'1980).A weaker, but economically more realistic, version of the hypothesis is therefore that prices reflect information up to the point where the marginal benefits of acting on the information do not exceed the marginal cost of collecting it (Jensen 1978).

Despite the widespread allegiance to the notion of market efficiency, a number of authors have suggested that certain periodic movements in asset prices can not related to economic realities. Browsing through the finance journals especially from 1970's one can easily find evidences of numerous numbers of furious market failures. If the market truly behaves according to the prescription of rationality driven efficient market hypothesis then, how can we account for the consecutive market bubbles and its devastating crashes around the globe. These findings however, question the basic underpinnings of expectation formation, and thereby rendering the existing paradigm to a much more controversial proposition.

The observed deviations from the prediction of rational expectation often been belittled as worst small departures from fundamental truth. A 'bad model' problem, that with greater diligence in seeking out better data and subjecting it to more sophisticated statistical tests, the anomalies will disappear(Fama 1998). While this may be a logical possibility, it presumably

applies with progressively less force and the violations remain unexplained using models based on rational paradigm. Longer-run asset price misalignments almost certainly represent the most serious manifestation of the failure of the efficient market hypothesis. Thus, urgency has been felt among economic researchers especially after eighties to look beyond the existing paradigm in an attempt to find a more comprehensive and satisfactory explanations of empirical evidences. However, it is a formidable challenge to question basic underpinnings of market efficiency.

In market efficiency, upheavals[1] in prices is an explosive path that increasingly deviates from the fundamental, and continue to satisfy the no-arbitrage condition. Clearly such a definition of upheavals is not interesting in a perfect foresight environment. Either it goes on indefinitely, or if a crash is expected at some future date, it cannot start (because of backward induction). The insight provided by Blanchard and Watson was to formulate a bubble or a price upheavals theory in a stochastic environment, and to assume that when the asset price is on an explosive bubble path, rational agents expect a future crash but do not know its exact timing (see Blanchard1979, Blanchard and Watson1982). This analysis came to the conclusion that a bubble, defined as an explosive path of the asset prices, is a theoretical possibility. The analysis of Blanchard and Watson has spurred a large literature extending this initial insight and analyzing the conditions for the emergence of upheavals in rational expectations models. The discovery that bubbles can arise in rational expectations models is important. Yet this "rational bubble" theory is not all together satisfactory. The weak part of the rational bubble theory is in the modeling for crashes. The latter is introduced in an ad-hoc fashion, i.e. agents are assumed to expect a crash, although this expectation does not come from the structure of the model itself. It is based on some "reasonable" but model-exogenous assumption that bubbles cannot go on forever. A further extension of the rational bubble theory consisted in allowing for heterogeneity of traders. Models were developed with the assumption that rational traders interact with 'noise traders' (DeLong, Bradford,Shleifer and

[1] the term upheavals and bubble are used interchangeably throughout the thesis.

Summers,1990),;Shleifer and Vishny,1997). The essence of these models is that some constraints exist on the capacity of the rational traders to exploit the profit opportunities generated by the bubble. These limits to arbitrage arise because of risk aversion or capital constraints. More recently, Abreu and Brunnermeier(2003) have developed models in which the arbitrage failure by rational traders arises because they have different views about the timing of the crash and fail to synchronize their exit strategies. Moreover, further developments in this direction have occurred in the recent past. An increasing number of non linear heterogeneous multi agent equilibrium models have been introduced in the literature which sharply contradicts the rational bubble theory by way of not dividing the market agents in between rational and noise traders. Moreover, the recent models have been developed on more generalized notions of bounded rationality. In these models it is assumed that individual agents have limited capacities to process and to analyse the available information and they select simple forecasting rules. These agents, however, exhibit rational behaviour in the sense that they check the profitability of these rules and are willing to switch to more profitable one. Thus they use the best possible strategy within the confines of their limited ability. This more recent extensions in this field of study have been posited to offer a more parsimonious explanations of socio psychological dynamics of human behaviour towards bubble formation(Hommes and Gounresdorfer ,2007. Gounresdorfer ,2001. Johansen and Sornette 2010,Lux, 1998 .Lux and Marchesi 2000, Broke and Hommes 1998,1997 etc.)

Going by these recent empirical advancements, in our study of Indian Capital market upheavals, we will try to model it in the backdrop of heterogeneous market framework with bounded rational agents. Simply speaking, our target is to analyse the influences of various psychological antecedents in capital market decisions that restricts rationality and bubble grows in a more cohesive way.Now in the next chapter, we would like to navigate through the literature in behavioural finance that would enrich us more to model investor's behaviour in India.

References:

Abreu, D. and Brunnermeier, M., (2003), "Bubbles and Crashes", *Econometrica*,71(1), 173-204.

Broke ,W.A. and Hommes, C.H. (1997), "A rational route to randomness",*Econometrica*,55, 1059-1095.

Broke ,W.A. and Hommes, C.H. (1998), "Heterogeneous Belief and routes to chaos in a simple pricing Model", *Journal of Economic Dynamics and Control*,22,1235-1274.

Blanchard, O.J., and Watson, M.W, (1982), "Bubbles, rational expectations and speculative markets", in Wachtel, P., eds., Crisis in economic and financial structure: bubbles, bursts, and shocks. Lexington books: Lexington.

Blanchard ,O.J., (1979), "Speculative bubbles, crashes and rational expectations", *Economics Letters*, 3, 387-389.

De Long, J., Bradford, B., Schleiffer and Summers, L.,(1990), "Noise Trader Risk in Financial Markets", *Journal of Political Economy*.

Fama, Eugene F.(1991), "Efficient Capital Markets II." *Journal of Finance* ,46, no. 5 ,*PP.*1575–1617.

Fama, Eugene F. (1965), "The Behavior of Stock Market Prices." *Journal of Business* ,38, *PP.* 34–105.

Fama, Eugene F, (1998), "Market efficiency, long-term returns, and behavioral finance", *Journal of Financial Economics* ,49, *pp.*283-306.

Friedman, M., (1953). "The case of flexible exchange rates". In: Essays in positive economics. University of Chicago Press: Chicago, 157–203.

Grossman, Sanford J., and Joseph E. Stiglitz, (1980). "On the Impossibility of Informationally Efficient Markets." *American Economic Review*, 7, *pp.*393–408.

Goundersdorfer, A.(2001). "Adaptive Belief and Volatility of Asset Prices, Central European "*Journal of Operation Resaearch*, 9,5-30.

Gaunersdorfer A., Hommes C.H.,(2007). "A nonlinear structural model for volatility clustering. In:Teyssiere, G., Kirman, A. (Eds.), Long Memory in Economics". Springer: Berlin/Heidelberg, 265– `288.

Hommes, C. H. (2007), "Bounded Rationality and Learning in Complex Markets", CeNDEF School of Economics, University of Amsterdam.. (http://dare.uva.nl/document/110509, Last accessed on 15.06.2014)

Johansen, A and Sornette,D, (2010); "Shocks, Crashes and Bubbles in Financial Markets," *Brussels Economic Review,* vol. 53, issue 2, pages 201-253

Jensen M. (1978) ,"Some anomalous evidence regarding market efficiency," *Journal of Financial Economics*, Elsevier, vol. 6(2-3), pp. 95-101.

Lux T. (1998), "The socio-economic dynamics of speculative markets: interacting agents, chaos, and fat tails of return distributions", *Journal of Economic Behaviour and Organisation*, vol.33, 143-165

Lux, T. and Marchesi, M.(2000). "Volatility Clustering in Financial Markets:A Microsimulation of Interacting Agents",*International Journal of Theoritical and Applied Finance,* 3,675-702.

Muth, J.F. (1961), "Rational Expectations and Theory of Price Movements", *Econometrica* 29,315-335

Savage, L.J. (1954). "The Foundations of Statistics". New York: John Wiley.

Shiller, R.J. (2002) ,"Bubbles, human judgment, and expert opinion". *Financial Analysts Journal.* 58, 18–26

Shleifer,A; Robert W. Vishny, (1997), "The Limits of Arbitrage", *The Journal of Finance*, Vol. 52(1)., 35-55.

Chapter – II

Survey of Literature

2.1. Introduction:

Efficient Market Hypothesis reached its height of dominance at around 1970, the time "rational expectations revolution was in its first blush of enthusiasm". Recently economists began to accept anomalies as counter examples that could not be permanently ignored and developments in the field of psychology have identified promising directions for a new theory. Models of human behaviour, especially the theories of human behaviour from psychology, sociology, anthropology etc. have helped motivate much recent empirical research on behaviour of financial markets. While behavioral economics appeared as a relatively new field of study, most of its ideas are not new; indeed, they return to the roots of neoclassical economics after a century-long detour. Beginning at around 1980s academic research once again started to be dominated by the application of socio – psychological and cultural factors in financial decision making. Behavioural finance has been started to be identified as a promising direction with better explanatory power in order to supplement the missing link of the existing robust theory of market behaviour. Currently no unified theory of behavioural finance exists. So far, most emphasis in the literature has been on identifying behavioural decision making attributes that are likely to have systematic effects on financial market behaviour. The review presented below is a synthesis of major empirical findings confirming systematic departures from the predictions of rationality driven theories of market efficiency.

2.2. Definition of Behavioural Finance:

The major emphasis of Behavioural finance is to replace the behavioually incomplete theory of finance now often referred to as standard or modern finance. It is a part of science, in that it starts from fundamental axioms and asks whether a theory built on these axioms can explain behaviour in the financial market place. Contrary to some assertions, this new paradigm does not try to define "rational" behaviour or label decision making as biased or faulty. Rather, it seeks to understand and predict systematic financial market implications of psychological decision processes (Olsen 1998). The main focus is on the application of psychological and economic principles for the improvement of financial decision making. Especially, behavioural finance theorists have identified a number of potential psychological decision attributes with overarching potential axiomatic status. These mainly include the following:

1. Decision maker's preferences tend to be multifaceted, open to change, and often formed only during the decision process itself.

2. Decision makers appear to be adaptive, in the sense that the nature of the decision and the environment in which the decision is made contribute to their selection of a decision process or technique.

3. Decision makers seek satisfactory rather than optimal solution.

Basically behavioural finance increases the explanatory power of economics by providing it with more realistic psychological foundations. Such an approach from a broader social science perspective including psychology and sociology is appearing as the most fertile ground of research. Its findings often stand in sharp contradiction to much of the efficient market hypothesis.

The field of behavioural finance is far too vast and it is impossible to cite every known work. Therefore, some subjective choices are to be made to mention scholarly works .In the forth coming survey, our major emphasis would be on

presenting socio psychological biases highly influenced in the in the heterogeneous market framework.Especially we will present the theories that have been widely acknowledged in explaining self fulfilling prophesies in asset price dynamics in speculative markets.

2.3. Theories of Behavioural Finance:

(a) Prospect Theory[2]:

Prospect theory is perhaps the most influential findings so far in the development of Behavioural finance literature(Kahneman and Tversky 1979, Tversky and Kahneman,1992). It is a mathematically-formulated alternative to the theory of expected utility maximization, an alternative that is supposed to capture decision making more realistically under uncertainty.

The points of departure from the expected utility maximization are cited below:

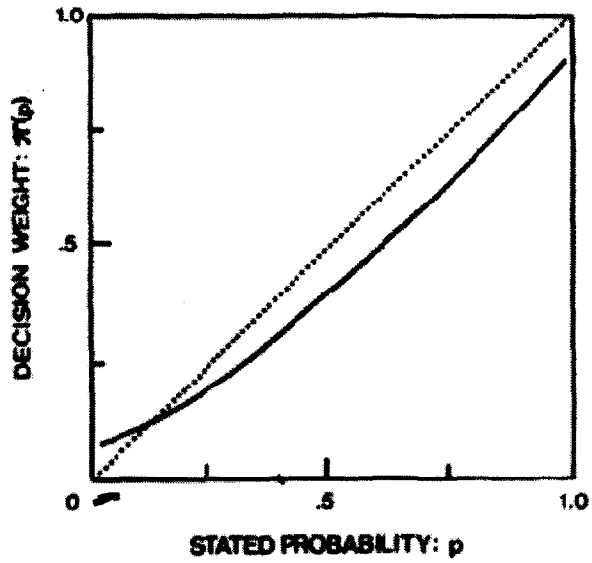
(1) Certainty Effect and Weighting Function:

According to the Prospect Theory, individuals are represented as maximizing a weighted sum of "utilities," although the weights are not the same as probabilities and the "utilities" are determined by what they call a "value function" rather than a utility function. The weights are, according to Kahneman and Tversky (1979) determined by a function of true probabilities which gives zero weight to extremely low probabilities and a weight of one to extremely high probabilities. That is, people behave as if they regard extremely improbable events as impossible and extremely probable events as certain. However, events that are just very improbable (not extremely improbable) are given too much weight; people behave as if they exaggerate the probability. Events that are very probable (not extremely probable) are given too little weight; people behave as if they underestimate the probability. What constitutes an extremely low (rather than very low) probability or an extremely high (rather than very high) probability is determined by individuals' subjective impression and prospect theory is not precise about this. Between the very low and very high probabilities, the weighting function (weights as a function of true probabilities) has a slope of less than one (see figure 2.1).

[2] The Theory has been incorporated from the Cowels Foundation Paper No.1025, titled "Human Behaviour and the Efficiency of the Financial System" by Robert J. Shiller in 2001, available at Cowels Foundation For Research In Economics, Yale University.

Figure: 2.1

(Weighting Function)



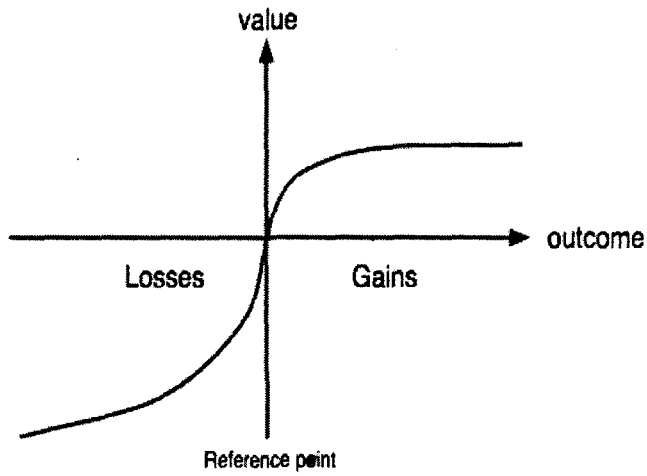
(Source : Kahneman.D and Tversky.A,1979,Prospect Theory : An Analysis of Decision under Risk,Econometrica, Vol .47,No.02,(March 1979),263-292)

If we modify expected utility function by substituting the Kahneman and Tversky weights for the probabilities in expected utility theory, it might help explain a number of puzzling phenomena in observed human behavior toward risk. For a familiar example, such a modification could explain the apparent public enthusiasm for high-prize lotteries, even though the probability of winning is so low that expected payout of the lottery is not high (Shiller 2002). It could also explain such phenomenon as the observed tendency for overpaying for airline flight insurance that has coverage only during the flight (Eisner and Strotz (1961,Shiller 2001).

(2)Value Function:

We now turn to another foundation of prospect theory, the Kahneman and Tversky (1979) value function (see figure :2.2).

Figure:2.2



(Source : Kahneman.D and Tversky.A,1979,Prospect Theory : An Analysis of Decision under Risk,Econometrica, Vol .47,No.02,(March 1979),263-292)

The value function differs from the utility function in expected utility theory in a very critical respect: the function (of wealth or payout) has a kink in it at a point, the "reference point," the location of which is determined by the subjective impressions of the individual. The reference point is the individual's point of comparison, the "status quo" against which alternative scenarios are contrasted. Taking value as a function of wealth, the Kahneman-Tversky (1979) value function is upward sloping everywhere, but with an abrupt decline in slope at the reference point, that is, that may be today's wealth or whatever measure of wealth that is psychologically important to the subject. For wealth levels above the reference point, the value function is concave downward, just as are conventional utility functions. At the reference point, the value function may be regarded, from the fact that its slope changes abruptly there, as infinitely concave downward. For wealth levels below the reference point, Kahneman and Tversky found evidence that the value function is concave upward, not downward. Thus people behave as risk lovers for losses.

Prospect theory does not nail down accurately what determines the location of the reference point. The experimental evidence has not produced any systematic patterns of behavior in this respect that can be codified in a general

theory. However, the reference point is thought to be determined by some point of comparison that the subject finds convenient, something readily visible or suggested by the wording of a question. This discontinuity in the value function has another implication. In making choices between risky outcomes, kink is always relevant, no matter how small the amounts at stake are. The reference point always moves with wealth to stay at the perceived current level of wealth or the current point of reference.

(b)Loss aversion:

Another important dimension of the kink or discontinuity in the value function is the psychology that "losses loom larger than corresponding gains". Abrupt changes in the slope of value function indicate the tendency for people to strongly prefer avoiding losses than acquiring gains. Some studies suggest that losses are as much as twice as psychologically powerful as gains (Kahneman and Tversky 1979)". "The central assumption of the theory is that losses and disadvantages have greater impact on preferences than gains and advantages (Tversky and Kahneman 1992).Moreover the concave shape of the value function in the domain of losses in terms of reference point indicates people to be risk lover to avoid mental penalty associated with given amount of losses.

This tendency of loss aversion under the reference dependent decision making has been extensively studied in a wide range of literatures. The term *"equity premium puzzle,"* coined by Mehra and Prescott (1985), is widely used to refer to the puzzlingly high historical average returns of stocks relative to bonds (Siegel,1994). Benartzi and Thaler(1995) show that if people use a one-year horizon to evaluate investments in the stock market, then the high equity premium is explained by *myopic loss aversion.* Moreover, prospect theory does not suggest that in this case riskless real interest rates need be particularly high. Thus, if we accept prospect theory and that people frame stock market returns as short-term, the equity premium puzzle is solved (Siegel and Thaler ,1997).The failures to accept many bets when one considers them individually has been called as myopic loss aversion by Benartzi and Thaler (1995). They

demonstrated the issue nicely.In their experiment when subjects are asked to allocate their defined contribution of pension plans between stocks and fixed incomes, their responses differed sharply depending on how historical returns were presented to them. If they were shown thirty individual 'one-year' returns, their median allocation to stocks was 40%, but if they were shown 30-year return their median allocation to stocks was 90%(Thaler, Tversky, Kahneman and Schwartz ,1997).

While Benartzi and Thaler's (1996) hypothesis is viewed by many as a plausible explanation of the equity premium puzzle, there are few direct empirical tests about it. The work that has followed their paper has instead focused on formalizing their original argument (see, Barberis, Huang, and Santos 2001, Andries 2012, Pagel 2012). There is, however, some evidence for the related idea that loss aversion and narrow framing can explain the *non-participation puzzle*: the fact that, historically, most households did not participate in the stock market. Dimmock and Kouwenberg (2010), for example, find that survey-based measures of loss aversion predict stock market participation in a cross-section of households.

Another set of application of Prospect Theory aims at understanding how people trade financial assets over time. One target of interest is the *'disposition effect'*,which is nothing but buying the losers and selling the winners. This empirical findings of Odean 1998; Frazzini 2006 state that both individual investors and mutual fund managers have a greater propensity to sell stocks that have risen in value since purchase, rather than stocks that have fallen in value . This behavior is puzzling because, over the horizon that these investors trade, stock returns exhibit *"momentum"*: stocks that have recently done well continue to outperform, on average, while those that have done poorly continue to lag. Interistingly, investors concentrate their selling stocks with poor past performance—but they do the opposite. This apparent unwillingness to sell stocks at a loss relative to purchase price has an important counterpart in the real estate market (Genesove and Mayer 2001,Shefrin and Statman 1985). The intuition is that, if a stock (or a piece of real estate) performs poorly, this brings its owner into the loss region of the value function, where, because of the

convexity, the owner becomes risk-seeking. As a result, this investor holds on to the stock (or the real estate) in the hope of breaking even later on. A number of recent papers have tried to formalize this intuition but that task turns out to be harder than expected. In particular, some researchers have argued that, for the argument to work, the value function needs to be much more convex over losses than the experimental evidence suggests issue still continues to be a hot topic to debate (Barberis and Xiong 2009). Meanwhile, some authors have argued that the disposition effect in both the stock market and the real estate market can be better understood as a consequence of *"realization utility,"* the idea that people derive utility directly from selling an asset at a gain relative to purchase price -- and disutility from selling at a loss -- perhaps because they think that selling assets at a gain relative to purchase price is a good recipe for long term wealth accumulation or conversely, that selling assets at a loss relative to purchase price is a poor recipe for wealth accumulation. If the time discount rate is sufficiently positive, even linear realization utility can generate a strong disposition effect, as well as other empirically-observed trading patterns (Barberis and Xiong ,2012) . While this explanation for the disposition effect differs from that based on the convexity of the prospect theory value function, it is ultimately still rooted in prospect theory, in that it relies on the investor deriving utility from gains and losses rather than from absolute wealth levels.

(c)Bounded Rationality[3]:

It is the idea that in decision-making, rationality of individuals is limited by the information they have, the cognitive limitations of their minds, and the finite amount of time they have to make a decision. It was proposed by Herbert A.Simon in 1955 as an alternative basis for the mathematical modeling of decision making, as used in economics, political science and related disciplines. It complements rationality as optimization, which views decision-making as a fully rational process of finding an optimal choice given the information

[3] See "A Behavioral Model of Rational Choice" by Herbert A. Simon , The Quarterly Journal of Economics, Vol. 69, No. 1. (Feb., 1955), pp. 99-118

available. Another way to look at bounded rationality is that, because decision-makers lack the ability and resources to arrive at the optimal solution, they instead apply their rationality only after having greatly simplified the choices available. Thus the decision-maker is a satisfier one, seeking a satisfactory solution rather than the optimal one. This concept of bounds on rationality has been successfully applied in wide ranges of literature as a root cause for imposing limits on arbitrage operation generating adaptive behaviour and bubble grows (see Broke and Hommes 1997,1998, Goundersdorfer 2001, Woodford 2000, Munier 2010)

(d) Regret Theory:

There is a human tendency to feel the pain of regret at having made errors, even small errors, not putting such errors into a larger perspective. One kicks oneself at having done something foolish. If one wishes to avoid the pain of regret, one may alter one's behaviour in ways that would in some cases be irrational unless account is taken of the pain of regret. For the purpose of investment decisions regret theory may play role by deferring selling stocks that has gone down in value and accelerate the selling of stocks that have gone up in value (Shefrin and Statman 1985, Ferris , Haugen and Makhija 1988. Odean 1998).

(e) Cognitive Dissonance:

It is a mental conflict that people experience when they are presented with evidences that their beliefs or assumptions are wrong .It may be termed as pain of mistaken belief.In order to reduce cognitive dissonance people are found to avoid new information and develop contorted arguments to maintain the statusquo (Festinger 1957, Erlich, Guttman , Schopenback and Mills 1957).Cognitive dissonance may restrict the arbitrage operation whereby investors in loosing funds have been found unwilling to confront the evidences that they made a bad decision.(Goetzmann and Peles 1997).

(f) Anchoring:

In making quantitative assessments people tend be influenced by suggestions i.e. the anchors. This tendency restricts people to form unbiased expectations purely on the basis of available information and sometimes

influence them to predict in many situations where there is no information. Two types of psychological anchors have been identified in the literature ,so far, in the context of speculative prediction. Firstly, the quantitative anchors which gives indication for the appropriate level of market. Secondly , there are moral anchors which operate by determining the strength of the reason that compels people to buy stocks , a reason that they must weigh against their other uses for the wealth they already have (or could have) invested in the market. With quantitative anchors, people are weighing numbers against prices when they decide whether stocks are priced right. In the absence of any better information where people has to come up with an estimate, decisions are found to be influenced by whatever available anchor at hand (Tversky and Kahneman ,1979).For example , past prices(or asking prices or prices of similar objects or other simple comparisons) are likely to be important determinant of today's price (Northcraft and Neale 1987). With moral anchors, people compare the intuitive or emotional strength of argument for investing in the market against their wealth and their perceived need for money to spend now. Here market is tied down by people's comparisons of the intuitive force of stories and reasons to hold their investment against their perceived need to consume the wealth that these investment represent.

(g) Overconfidence:

People often tend to show excessive confidence about their judgment (Fischof,Slovic,Lichtenstein, 1977).It is a broader difficulty with "situational construal", a difficulty in making adequate allowance for the uncertainty in one's own view of the broad situation. Obviously people do learn substantially in circumstances when the consequences of their errors are repeatedly presented to them but still there seems to be a common bias towards overconfidence (Ross 1987).Overconfidence may lead to the overreaction and biased self attribution on the part of decision makers. These phenomenon can be found in the literature of excess volatility of speculative prices (Shiller 1979,1981 a,Le Roy and Porter 1981).Psychologists have long wondered why it is that people seem to be overconfident. One theory has been that, in evaluating the soundness of their conclusions, people tend to evaluate the probability that they are right on only the

last step of their reasoning, forgetting how many other elements of their reasoning could be wrong (Shiller'2005).Another theory is that people make probability judgments by looking for similarities to other known observations , and they forget that there are many other possible observations with which they could compare.(Shiller,2005).

(h)Heuristic Simplifications:

1) Attention /Memory/ Ease of Processing Effects:

Limited attention, memory and processing capacities force a focus on subsets of available information.Uncocious associations also create selective focus.In many studies, priming subjects with (possibly irrelevant) verbal information triggers associations that influence judgements.

i. *Salience or availability effects:*

An information signal is salient if it has characteristics that are good at hooking our attention or at creating associations that facilitate recall. Items that are easy to recall are judged to be more common as they are noticed or reported more often making them easier to remember.Moreover people underweight the probabilities of contingencies that are not explicitly available for considerations. Availability heuristics has been posited as a prominent cause of "*negativity bias*[4]" in stock and future market returns (Akhtar, Faff ,Oliver,and Subrahmanyam,2012).The affect of salience or availability biases has also been studied widely in explaining decision making in consumer goods market (see Busse, Lacetera, Pope ,Jorge Silva-Risso, Justin R. Sydnor,2013)

ii. Representativeness Heuristics:

[4] An asymmetric reaction of US stock and futures market returns to the preliminary announcement of the monthly consumer sentiment index provided by Thomson Reuters/University of Michigan(see Shumi Akhtar,Robert Faff Barry Oliver,*Avanidhar Subrahmanyam)

People tend to make judgements in uncertain situations by looking for familiar patterns and assuming that future patterns will resemble past ones, often without sufficient consideration of the reasons for the patterns or the probability of the pattern repeating itself.(Tversky and kahneman 1991, Boussaidi, 2013;Luo,2012).

iii. Magical thinking:

It is the innermost thoughts that decision makers do not have to explain or justify to others.People have occasional feelings that certain actions will make them lucky even if they know logically that the actions cannot have an effect on their fortunes(Shiller 2005).

2) **Narrow framing/ mental accounting/ reference effects:**

(i)*Mental Accounting:*

It is a kind of narrow framing that involves keeping track of gains and losses related to decisions in separate mental accounts and to reexamine each account only intermittently when action relevant. This economic concept was established in the financial literature by economist Richard Thaler (2008), which contends that individuals divide their current and future assets into separate, non-transferable portions. The theory purports that individuals assign different levels of utility to each asset group, which affects their consumption decisions and other behaviors. The importance of this theory is illustrated in its application towards the economic behavior of individuals, and thus entire populations and markets. Rather than rationally viewing every dollar as identical, mental accounting helps explain why many investors designate some of their dollars as "safety" capital which they invest in low-risk investments, while at the same time treating their "risk capital" quite differently. play an important role in determining how people evaluate risky gambles.Experimental studies on behavioural finance suggests that ,an important feature of mental accounting is narrow framing,the idea that people do sometimes appears to derive utility from narrowly defined gains and losses.If one of an investor's many stock performs poorly, the investor may experience a

sense of regret over the specific past decision to buy that stock.In other words,individual stock gains or losses can be carriers of utility in their own right. Moreover ,narrow framing i.e. the tendency to focus on narrowly defined gains and losses with Loss aversion have been found to play an important role indetermining how people evaluate risky gambles (Berberis and Huang 2001).

(ii) House money effect:

A greater willingness to gamble with money that is recently own.The unpleasantness of a loss of recently own money may be diluted by aggregating it with earlier gains (Ackert and Deaves 2009).

(iii) Wishful thinking:

Wishful thinking is the formation of beliefs and making decisions according to what might be pleasing to imagine instead of by appealing to evidence, rationality, or reality. It is a product of resolving conflicts between belief and desire. Studies have consistently shown that holding all else equal, subjects will predict positive outcomes to be more likely than negative outcomes (Szyszka , 2013).

3) Updating of belief:

(i) Conservatism:

Under appropriate circumstances individuals do not change their beliefs as much as would a rational Bayesian in the face of new evidence.The more useful the evidence , the greater the shortfall between actual updating and rational updating (Szyszka , 2013).

(ii) *Statusquo bias :*

The status quo bias is a cognitive bias for the status quo; in other words, people tend to be biased towards doing nothing or maintaining their current or previous decision(Thaler et. al(1992) defines the bias as preference

for the current state that biases the economist against both buying and selling his wine.'Thaler et.al (1992).'One implication of loss aversion is that individuals have a strong tendency to remain at the status quo, because the disadvantages of leaving it loom larger than the advantages. (Kahneman et al., 1991).' Gal (2006). The status quo bias is a part of a more general issue known as ' loss aversion.'

(i)Theories of Social Learning:

Traditionally financial economists have borrowed more from individual psychology than from social psychology in explaining behaviour of speculative prices, its volume and related corporate actions. In the traditional framework, all trades are expected to take place as an outcome of independent analysis whereby "walrasian auctioneer" with their simultaneous execution of a large number of trades, tend to produce optimal outcomes and set prices correctly. As a challenge to this basic proposition of modern financial economics ,during the past decades, herding behaviour has received much attention from both academic researchers and practitioners. It has appeared as an alternative explanation of the way the investment choices are made by investors. Basically the literature recalls for a once prominent view of financial markets—as driven by "animal spirits," (Keynes 1935) where investors behave like imitative lemmings. While the rational actor approach has largely driven this view from mainstream research in financial economics, it is far from gone. Both influential market participants and financial economists reportedly still believe that imitative behavior is widespread in financial markets (Devenow and Welch, 1996). This has led some researchers to assert that market participants engage in non-rational herd behavior (e.g. Kirman, 1993, Shleifer and Summers, 1990). Herd mentality and herd behavior have been prevalent descriptors for human behavior since people began to form tribes, migrate in groups, and perform cooperative marketing and agricultural functions. The idea of a "group mind" or "mob behavior" was first put forward by 19th-century French social psychologists Gustave Le Bon in 1947. Herd behavior in human societies has also been studied by Wilfred Trotter (1914), whose book Herd Instincts in Peace and War is a

classic in the field of social psychology. Sociologist and Economist Thorstein Veblen's Theory (1953) of the Leisure Class illustrates how individuals imitate other group members of higher social status in their consumer behavior.

Intuitively, an individual can be said to be in herding if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so. Alternatively, she herds when knowledge that others are investing, changes her decision from not investing to making the investment. However for an investor to imitate others, she must be aware of and be influenced by others' actions. Basically, herding is a form of convergent social behaviour that can be broadly defined as the alignment of the thoughts or behaviours of individuals in a group (herd) through local interaction and without centralized coordination. It is an influential and well-documented feature of human behaviour in a number of domains, particularly in economics and finance [Sornette, D. et al. (2009), Shiller, R.J. (2000), Shiller, R.J. (2002)]. Although the current economic turmoil has revealed the depth of herding among financial institutions and individual investors [Shiller, R.J. (2008)] .This concept also has much broader relevance beyond the economic arena. Examples of phenomena that have been described as involving herd behaviour are diverse and varied, ranging from stock market bubbles and financial speculation to zealotry (e.g. the 2002 Gujarat mob violence (Kumar, M., 2007), political choice (Battaglini, M., 2005).Whereas the concepts behind herd mentality and herd behaviour have a rich history, the methods, techniques and approaches currently used to elucidate them are relatively recent. The process has also been investigated in social psychology and terms such as Fad, Fashion, Mass Hysteria, Bandwagon Effect, Groupthink and Herd Instinct have entered common parlance.

Literatures from behavioural finance have identified several reasons for an investor to be influenced in reversing a planned decision after observing the others. So far the theories of herding behavior are available in the financial literature, the key mechanisms underlying the behaviour are multifaceted. Let us start with the rationality driven theories of herd behaviour.

(j) Rationality driven theories of Herd Behavior:

These models on rational herding behavior concentrates on how utility maximizing investors not being influenced by their independent judgements, swayed away by the decisions of others and ultimately, true information about fundamental value fails to be disseminated and evaluated (see Banerjee 1992,Bickachandani , Hershleifier and Welch 1992, Avery and Zemsky 1998, Bickachandani and Sharma, 2001, Bulow and Klemperer ,1994, Caplin and Leahy 1993, Chamley and Gale 1992 etc.). Several potential reasons have been documented in favour of rational herding models and chief of them includes imperfect information, concern for reputation, and compensation structures. Let us discuss all these type of herding model in brief.

(1)Information-Based Herding and Cascades:

The central theme in this approach is herding by imperfect information. This approach is based on some structural assumptions about the information content of individual investor below:

(i) Individuals face similar investment decisions under uncertainty and have private (but imperfect) information about the correct course of action.

(ii) An investor's private information is the conclusions of her own research effort.

(iii) All information relevant to the investment is public but there is uncertainty about the quality of this information. An individual's assessment of the quality of publicly available information is only privately known to her.

(iv) Investors are not participating in the market simultaneously but they decide sequentially whether to invest in a particular stock or market.

Under such structural conditions individuals can observe only each other's actions but not the private information or signals that each player receives.

Each individual has some view about the appropriate course of action but inferences about a player's private information can only be derived from looking at his actions. Even if individuals communicate their private information to each other, the idea that "actions speak louder than words" provides justification for this assumption. In this context even a completely rational people can participate in herd behaviour when they take into account the judgments of others , even if they know that everyone else is behaving in a herd like manner. The behaviour , although individually rational, produces a group behaviour that is , in a well defined sense , irrational. This herdlike behaviour is said to arise from an information cascade. Once a cascade starts, an individual's action does not reflect her private information. Consequently, the private information of subsequent investors is never included in the pool of public knowledge. In the context of capital market decisions, another dimension is added to the underlying uncertainty of the basic model.It assumed that, there are two types of investors depending upon the quality of information they posses viz. H and L (see Avery and Zemsky ,1998) . Type H investors have very accurate information about the appropriate course of action and type L have very noisy information. Further, it is assumed that the proportion of the two types of investors in the population is not common knowledge among market participants (Avery and Zemsky ,1998). In particular, this proportion is not known to the market-makers. Hence, although at any point of time the price in the stock market reflects all public information, the price does not reveal the private information of all previous investors. A clustering of identical decisions may arise naturally in a well informed market (one in which most of the investors are of type H) because most of the investors have the same (very informative) private signal realization. Further, a clustering of identical decisions is also natural in a poorly informed market (one in which most of the investors are of type L). Because of herding by type L investors who mistakenly believe that most of the other investors are of type H. Thus, informationally inefficient herd behavior may occur and can lead to price bubbles and mispricing when the

accuracy (or lack thereof) of the information with market participants is not common knowledge. Traders may mimic the behavior of an initial group of investors in the erroneous belief that this group knows something. Thus, when the uncertainty is only about the value of the underlying investment, the stock market price is may be informationally efficient and herd behavior may not occur. But, when there is an additional dimension to the uncertainty, namely uncertainty about the accuracy of the information possessed by market participants, a one-dimensional stock price is no longer efficient and herd behavior can arise, even when investors are rational (Avery and Zemsky ,1998,Bikhachandani and Sharma 2001).Here people might be choosing rationally not to , as they see it, waste their time and effort in exercising their judgments, about the market, and thus choosing not to exert any independent impact on the market. It has been found in the literature that, an individual is in an "invest cascade" ("reject cascade") if and only if the number of predecessors who invest is greater (less) than the number of predecessors who do not invest by two or more (Bickachandani and Sharma, 2001, Andrea Devenow, Ivo Welch,1996, Bikhchandani, Hirshleifer, and Welch (1992).

(2).Reputation-Based Herding

Scharfstein and Stein (1990), Trueman (1994), Zweibel (1995), Prendergast and Stole (1996) provide another theory of herding based on the reputational concerns of fund managers or analysts. Reputation or, more broadly, career concerns arise because of uncertainty about the ability or skill of a particular manager. The basic idea is that if an investment manager and her employer are uncertain of the manager's ability to pick the right stocks, conformity with other investment professionals preserves the fog—that is, the uncertainty regarding the ability of the manager to manage the portfolio. This benefits the manager and if other investment professionals are in a similar situation then herding occurs.

Consider the decisions of two investment managers, I_1 and I_2, faced with an identical investment opportunity. Each manager I_i, $i = 1,2$, may be of high ability or low ability, and their type or ability level is chosen independently. A high ability manager receives informative signals about the return from an

investment, whereas a low ability manager's signal is pure noise. Neither the manager I_i nor her employer E_i knows whether the manager I_i is of low or high ability. Each manager and employer has an identical prior belief about the manager's type. This belief is updated after the decisions of the two managers and the return from the investment are observed.

If both managers are of high ability then they observe the same signal realization (good or bad) from an informative signal distribution (but neither manager observes the other's signal realization). If both managers are of low ability then they observe independent draws of a signal (either Good or Bad) from a distribution that is pure noise. If one manager is of high ability and the other of low ability, then they observe independent draws from the informative signal distribution and the noisy signal distribution respectively. The informative and noisy signal distributions are such that the ex ante probability of observing good signal is the same with either distribution. Thus, after observing her signal realization a manager does not update her prior beliefs about her own type.

I_1 makes her investment decisions first and then I_2 does so. I_1's decision is based only on her signal realization (which may either be informative or pure noise—I_1 does not know which it is). I_2's decision is based on her own signal realization and on I_1's decision. In the final period, the investments pay off and the two investors are rewarded based on an ex post assessment of their abilities.

This game has a herding equilibrium in which I_1 follows her own signal and I_2 imitates I_1 regardless of her own (I_2's) signal. The intuition behind this result is that since I_2 is uncertain about her own ability, she dare not take a decision contrary to I_1's decision and risk being considered dumb (in case her conflicting decision turns out to be incorrect). Thus, it is better for I_2 to imitate I_1 even if her own information tells her otherwise. If the common decision turns out to be incorrect it will be attributed to an unlucky draw of the same signal realization from an informative distribution, thus increasing the posterior beliefs of her employer that I_2 is of high ability. I_1 is happy to go

along with this arrangement as she too is unsure of her own abilities—I_2's imitation also provides I_1 with cover.

If there are several managers deciding in sequence, everyone imitates the decision of the first manager. Eventually there will be a preponderance of Good signals (Bad signals) if the investment is profitable (unprofitable). However, this private information will not be revealed because all subsequent managers, without regard to their information, imitate the first manager's decision. Thus, the herding is inefficient. Moreover, it is idiosyncratic because it is predicated on the first individual's signal realization and fragile since the herd behavior is based on very little information. Many of the implications of this theory are similar to that of informational herding with rigid prices.As in the papers by Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992), here too it is assumed that the investment opportunity is available to all individuals at the same price.

(3)Compensation-Based Herding:

If an investment manager's (i.e., an agent's) compensation depends on how her performance compares with that of other similar professionals, then this distorts the agent's incentives and she ends up with an inefficient portfolio (see Brennan (1993) and Roll (1992)). It may also lead to herd behavior.

Maug and Naik (1996) consider a risk-averse investor (the agent) whose compensation increases with her own performance and decreases in the performance of a benchmark (which may be the performance of a separate group of investors or the return of an appropriate index). Both the agent and her benchmark have imperfect private information about stock returns. The benchmark investor makes her investment decisions first and the agent chooses her portfolio after observing the benchmark's actions. Then, as argued in the section on information-based herding above, the agent has an incentive to imitate the benchmark in that her optimal investment portfolio moves closer to the benchmark's portfolio after the agent observes the benchmark's actions. Furthermore, the compensation scheme provides an additional reason to imitate the benchmark. The fact that her compensation decreases if she underperforms the benchmark causes the agent to skew her investments even more towards the benchmark's portfolio than if she were trading on her own account only.

It is optimal for the principal (the employer of the agent) to write such a relative performance contract when there is moral hazard or adverse selection. Any other efficient contract (i.e., any contract that maximizes a weighted sum of the principal's and the agent's utility) will also link the agent's compensation to the benchmark's performance. Thus herding may be constrained efficient (the constraints being imposed by moral hazard or adverse selection). However, the compensation scheme selected by an employer would seek to maximize the employer's profits rather than society's welfare.

Apart from the above, various other socio psychological causes have been identified in the literature generating convergence in opinion. Theories of social interactions, person to person and media contagion of ideas, factors of interpersonal communications etc. have been found to have profound influence in formation of herd like behaviour in speculative markets.

(K) Information Communication and Word of Mouth:

The human mind is the product of evolution almost entirely in the absence of any printed word, e mail, internet, or any other artificial means of communication. Human society has been able to conquer almost all habitats of this planet primarily because of its own innate information processing ability. A fundamental component of this information processing ability is the effective communication of important facts from one person to another. This superior ability to communicate knowledge has been made possible over past millions of year by evolutionary changes in human brain that have optimized the channel of communication and created an emotional drive to communicate effectively. It is because of this emotional drive that most people's favorite activity is conversation. The incessant exchange of information has become a fundamental characteristic of human species. The information that tends to flow most rapidly is the kind that would have helped society in centuries past in its everyday living: information about such things as food sources, dangers, or other member of the society. By analogy, in modern society there is likely to be rapidly spreading conversation about a buying opportunity for a hot stock, or about immediate threats to personal wealth, or about story of the people who run a company. These topics resemble the kind of things our ancestors have talked about since time immemorial. But conversation seems to flow less well about abstract topics, such as mathematics of finance, or statistics about asset returns or optimal level of savings for retirements (Shiller, 2005).The conventional media – print media, television, and radio- have a profound capability for spreading ideas, but their ability to generate active behaviour is still limited. Interpersonal and interactive communications, particularly face to face or word of mouth communications still have the most powerful behaviour (Shiller and Pound ,1986, Shiller ,2000).Word of mouth communication can proceed with great speed and across disparate social groups. The channels of human communication that we know today seem to favor the interpersonal face – to – face and word – of- mouth communication that developed over millions of years of evolution , during times when such communication was virtually the only form of interpersonal communication. The patterns of communication hard-wired into our

brains rely on there being another person;s voice , another person's facial expressions, another person's emotions, and an associated environment of trust, loyalty, and cooperation. Because these elements are missing from the written or electronic word, people find it somewhat more difficult to react to these sources of information. They cannot give these other sources the same emotional weight, nor can they remember or use information from these other sources of information. The word of mouth transmission of ideas does not have to infect the entire nation to affect national prices in stock market. Moreover, word of mouth may function to amplify public reaction to news events or to media accounts of such events. Thus the likelihood of any event affecting market prices is enhanced if there is a good, vivid, tellable story about the event. The influence of conversation on trading may arise from individual's overconfidence about their ability to distinguish pertinent information from noise or propaganda. Process of belief formation has also been found to be leading towards "availability cascades" wherein an expressed perception is perceived to be more plausible as a consequence of its increased availability in public discourse. Moreover conversation pools information surprisingly poorly. Groups of people tend to talk much more about information signals that they already share than individual specific signals (Stasser, Taylor and Hanna 1989).As a result groups sometimes fail to detect patterns that are discernable by combining individual specific signals (Stasser and Titus 1985).Environmental pressures such as crowding and unusual circumstances cause group members to experience 'cognitive overload' and rigid thinking (Argote,Turner and Fichman 1988).When communicating information , people tend to sharpen and level i.e. emphasize what they construe to be the main point and deemphasize qualifying details that might confuse this point. This is necessary for clarity given cognitive constraints (Allport and Postman, 1947) , but tends to cause listener beliefs to move to extremes.

Direct interpersonal communication, coupled with media reporting with limited attention bias, anxiety and distress of being seeing as foolish before the others, reputational concern, perceived authority of others etc. (Asch 1956, Milgram1974 , Bond and Smith 1996) at individual level have found to be the critical determinant in contagion of public opinion. People tend to pay much more attention to ideas or facts that are reinforced by conversation, rituals or symbols (Shiller 1999). In consequence

culture becomes an important determinant of behaviour and expression of ideas can be self – reinforcing.

In sum, it is observed that the herd behaviour is the prominent one amongst the psychological attributes to explain the formation of beliefs and decisions .In fact, almost all the recent suggestions of the scholars researching in the field of behavioural finance grossly converges to explain the behaviour of the investors either in the framework of herd behaviour or structurally heterogeneous group of market players that observe almost the prescriptions of bounded rationality. In the next chapter, it is our humble attempt to describe and form model on the attributes that are prominently prescribed and attested by the scholars to explain the stock market upheavals.

References:

Allport, G.W. and Postman, L.J.(1947), "The psychology of rumor", New York, Holt.

Argote, L., Tuner, M.E. and Fichman, M.(1989), "To Centralise or not to centralize: The effects of uncertainty and threat on group structure and performance", *Organizational Behavior and Human Decision Processes,43, 58-74.*

Ackert.L. and Deaves, R, (2009),"Behavioural Finance, Decision Making and Markets",*Cengage Learning.*

Admati, Anat R. and Paul Pfleiderer, (1988), A theory of intraday patterns: Volume and price variability, Review of Financial Studies 1(1), 3-40.

Andries, M. (2012): "Consumption-Based Asset Pricing with Loss Aversion," *Working Paper*, Available at SSRN: http://ssrn.com/abstract=2140880 or http://dx.doi.org/10.2139/ssrn.2140880 (last accessed on 13.7.2014)

Akhtas, S.Faff William ,R.Oliver, B. and Subramanyam,A.(2012), "Stock Saliance and the asymmetric market effect of Consumer sentiment news",*Journal of Banking and Finance*, 36(12),3289-3301.

Asch, S.E.(1956), "Studies of independence and conformity:I A minority of one against a unanimous majority", *Psychological Monographs*, 70,1-70.

Avery, Christopher and Peter Zemsky, (1998), "Multi-dimensional uncertainty and herd behavior in financial markets", *American Economic Review*, 88(4), 724-748

Boussaidi,R.(2013),"Representativeness Heuristics,Investor Sentiment and Overeaction to Accounting Earnings:The case for Tunisian Stock Market", *Procedia-Social and Behavioural Sciences,* 81,9-21.

Brock,W., and Hommes, C., (1997), "A Rational Route to Randomness", Econometrica, 65, 1059-1095.

Brock, W., and Hommes, C.,(1998), "Heterogeneous beliefs and routes to chaos in a simple asset pricing model", Journal of Economic Dynamics and Control, 22, 1235-1274.

Banerjee. A, (1992), ' A Simple Model of Herd Behaviour', *The Quarterly Journal of Economics*;107 (3),797-817.

Bulow, Jeremy and Paul Klemperer, (1994), "Rational frenzies and crashes", *Journal of Political Economy* 102(1), 1-23.

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch,(1992), "A theory of fads, fashion, custom, and cultural change as informational cascades", *Journal of Political Economy* ,100(5), 992-1026.

Bikhchandani ,S. Sharma.(1996), "Optimal search with learnings", Journal of Economic Dynamics and Control, 20: 333-359.

Bikhchandani ,S. Sharma.(2001), " Herd Behaviour in Financial Markets", IMF Staff Papers, 47 (3).

Barberis, Nicholas, Ming Huang, and Tano Santos, (2001), "Prospect Theory and Asset Prices", *Quarterly Journal of Economics*, 116,1-53

Barberis, Nicholas, and Wei Xiong. (2012). "Realization Utility." *Journal of Financial Economics,* 104(2), 251-271

Barberis, Nicholas, and Wei Xiong. (2009). "What Drives the Disposition Effect? An Analysis of a Long-standing Preference-based Explanation." *Journal of Finance* 64(2):751-784.

Benartzi, Shlomo, and Richard H. Thaler, (1996), "Risk Aversion or Myopia: The Fallacy of Small Numbers and its implications for Retirement Savings,"Working Paper, University of California, Los Angeles.

Benartzi,S; Richard H. Thaler(1995) , "Myopic Loss Aversion and the Equity Premium Puzzle,"*The Quarterly Journal of Economics,* 110, No. 1, 73-92.

Battaglini, M. (2005) "Sequential voting with abstention.", *Games Econ. Behav.* 51, 445–463

Brennan, Michael J., (1993), "Agency and Asset Pricing", Working paper (UCLA, Los Angeles, CA).

Bond, R. and Smith, B (1996), "Culture and Conformity:A Meta- Analysis of Studies Using Asch's(1952b, 1956) Line Judgement Task", *Psychological Bulletin*,119(1),111-137.

Busse, R Meghan,Lecetera, N.Pope, G Davin,Risso, S.J.Sydnor, R.J.(2013), "Estimating the Effect of salience in wholesale and retail car market,NBER, Working Paper No.18820, available at : http://www.nber.org. Last accessed on 13.7.2014.

Chamley, Christophe and Gele Douglus , (1994), "Information Revelation and Strategic Delay in a model of Investment" , *Econometrica*, 62(5), 1065 - 1085

Caplin and John Leahy,(1993), "Business as Usual, Market Crashes, and Wisdom After the Fact" *The American Economic Review*, 84(3), 548-565.

Devenow A., Welch, I. (1996). "Rationalherding in financial economics". *European Economic Review* ,40, 603–615.

Dimmock, Stephen, and Roy Kouwenberg. (2010). "Loss-aversion and Household Portfolio Choice." *Journal of Empirical Finance* ,17(3): 441-459.

Durba, J.(2004), "Optimism and overconfidence in search", *Review of Economic Dynamics,*7,198-218.

Eisner, R. and Strotz, R.H. (1961). "Flight insurance and the theory of choice".*Journal of Political Economy* ,69(4), 355—68.

Erlich, D., P. Guttman, P. Schopenbach, and J. Mills (1957). "Postdecision Exposure to Relevant Information," *Journal of Abnormal and Social Psychology*, 54: 98–102.

Farmer, J. Doyne. (2001), "Toward Agent Based Models for Investment. In Benchmarks and Attribution Analysis. Association for Investment and Management Research.

Efferson, C. Lalive,R., Richerson , J.P., McElreath , R. and Lubell, M. (2008), " Conformists and mavericks: the empirics of frequency- dependent cultural transmission", *Evolution and Human Behaviour, 29,56-64*

Frazzini, Andrea. (2006). "The Disposition Effect and Underreaction to News." *Journal of Finance,* 61(4): 2017-2046.

Festinger, L. (1957). A Theory of Cognitive Dissonance., Stanford, CA: *Stanford University Press.*

Ferris, S. P., R. A. Haugen and A. K. Makhija (1988). "Predicting Contemporary Volume with Historic Volume at Differential Price Levels: Evidence Supporting the Disposition Effect," *Journal of Finance*, 43(3): 677–697.

Freud, Sigmund(1981) , "Group Psychology and the Analysis of the Ego". Standard Edition, vol. XVIII, pp. 67–143. The Hogarth Press, London.. ISBN 0-7012-0067-7

Gal, D. (2006) , "Psychological law of inertia and the illusion of loss aversion. Judgment and Decision Making", 1, 23-32. Available at http://journal.sjdm.org/06002/jdm06002.htm. (Last accessed on 14.7.2014)

Fischhoff, B., P. Slovic and S. Lichtenstein (1977). "Knowing With Uncertainty: The Appropriateness of Extreme Confidence," *Journal of Experimental Psychology: Human Perception and Performance*, 3: 552–564

Gaunersdorfer A., 2000. "Endogenous fluctuations in a simple asset pricing model with heterogeneous beliefs". *Journal of Economic Dynamics and Control* ,24,. 799–831.

Gaunersdorfer A. (2001). "Adaptive belief systems and the volatility of asset prices", *Central European Journal of Operations Research* , 9, .5–30.

Gaunersdorfer A., Hommes C.H., 2007. "A nonlinear structural model for volatility clustering. In:Teyssiere, G., Kirman, A. (Eds.), Long Memory in Economics". Springer: Berlin/Heidelberg, 265– `288.

Graham, John R., (1994), Herding among investment newsletters: Theory and evidence, Working paper (TheUniversity of Utah, Salt Lake City, UT).

Goetzmann, W. N. and N. Peles (1997). "Cognitive Dissonance and Mutual Fund Investors," *Journal of Financial Research,* 20(2), 145–158.

Genesova, David, and Christopher Mayer, (2001), "Loss Aversion and Seller's Behaviour, Evidence From the Housing Market", *Quaterly Journal of Economics,* 116:4, 1233-60.

Kahneman, Daniel and Amos Tversky, (1979), "Prospect Theory: An Analysis of Decision under Risk", *Econometrica* 47, 263-291.

Kahneman, D.Knetsch (1991), "The Endowment Effect, Loss Aversion and Status Quo Bias Anomalies", Journal of Economic Perspectives,5(1),193-206.

Kumar, M. (2007) , "A Journey into the Bleeding City: Following the Footprints of the Rubble of Riot and Violence of Earthquake in Gujarat, India". *Psychol. Dev. Soc.* 19, 1–36

Kirman, A. (1993) "Ants, rationality and recruitment", *Quarterly Journal of Economics* ,108 ,137-156.

Keynes, J.M. (1935), "The General Theory of Employment, Interest and Money",Mc Millan Cambridge University Press For Royal Economic Society in 1936.

LeRoy, S. F., and R. D. Porter (1981). "Stock Price Volatility: "A Test Based on Implied Variance Bounds, " *Econometrica,* 49: 97–113.

Le Bon, G. (1895, trans. 1947) The Crowd: A Study of the Popular Mind. London: Ernest Benn.

Luo,Ying , G.(2012), "The Representativeness Heuristic and Asset Price Reaction to New Information", *Journal Of Trading,*7(3), 40-51

Munier, B. (2010), "Bounded rational exuberance on commodity markets",*Risk and Decision Analysis,* 02 (01),. 33-50

Mehra, R., and C. Prescott, "The Equity premium puzzle", *Journal of Monetary Economics,* XV (19851, 145-61

Maug, Ernst and Narayan Naik, (1995), "Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation", *Working paper (London Business School, London).*

Milgram,S, (1974), "Obidience to Authority", *New York,:Harper and Row.*

Northcraft, G. B. and M. A. Neale (1987). "Experts, Amateurs, and Real Estate: An Anchoring-and- Adjustment Perspective on Property Pricing Decisions," *Organizational Behavior and Human Decision Processes*, 39: 84–97.

Olsen, Robert A.(1998), "Behavioral Finance and Its Implications for Stock-Price Volatility"; *Financial Analysts Journal*, 54(2),10-18.

Odean, Terrance. (1998). "Are Investors Reluctant to Realize Their Losses?" *The Journal of Finance* 53(5): 1775-1798.

Prendergast, C. and Stole, L. (1996), ''Impetuous Youngsters and Jaded Old-Timers: Acquiring a Reputation for Learning.'' *Journal of Political Economy*, 104 ,1105–113

Pagel, M.(2012), "Expectations – Based Reference – Dependent Life Cycle Consumption", Dept. of Economics,University of California at Berkeley, (Un published paper), Available at: www.stanford.edu (Last accessed on 13.7.2014)

Ross, L. (1987). "The problem of construal in social inference and social psychology." In N. E. Grunberg, R. E. Nisbett, J. Rodin, & J. E. Singer (Eds.), A distinctive approach to psychological research: The influence of Stanley Schachter, 118-150. *118–150). Hillsdale, NJ: Erlbaum*

Roll, Richard, (1992), "A mean/variance analysis of tracking error", *Journal of Portfolio Management*, 13-22.

Richerson, P.J. and Boyd, R. (2005) Gene-Culture Coevolution and the Evolution of Social Institutions. In Better than Conscious? Decision Making, the Human Mind, and Implications for Institutions (Engel, C. and Singer, W., eds), pp. 305–324, MIT Press

Simon, A. (1955), "A Behavioral Model of Rational Choice", *The Quarterly Journal of Economics,* 69(1) ,99-118

Siegel, Jeremy J. (1994); "Stocks for the long run:A guide to selecting Markets for Long Term Growth", *Burr Ridge , III; Irwin Professional Publishing .*

Siegel, Jeremy J. and Thaler, R.,(1997); "Anomalies: The Equity Premium Puzzle",*The Journal of Economic Perspectives*,11(01),191-200.

Shiller, R. J. (1979). "The Volatility of Long Term Interest Rates and Expectations Models of the Term Structure," Journal of Political Economy, 87: 1190–1219.

Shiller, R. J. (1981a). "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?" American Economic Review, 71(3): 421–436.

Shiller, R.J. (2002), "Bubbles, human judgment, and expert opinion". *Financial Analysts Journal.* 58, 18–26.

Shiller, R.J. (2005) , "Irrational exuberance", Princeton University Press.

Shiller, R.J. (2008), "The subprime solution: how today's global financial crisis happened and what to do about it," *Princeton University Press.*

Shiller, R.J.(2001), "Human Behaviour and Efficiency of Financial System",Cowles Foundation Paper No.1025,1305-1340.

Shiller, R.J.(2000), "Measuring Bubble Expectations and Investor Confidence", *Journal of Psychology and Financial Markets,* 1(1),49-60

Shiller, R.J. and J.Pound (1986), "Survey Evidence of Diffusion of Interest Among Institutional Investors", *Journal of Economic Behaviour and Organisation,*12 47-66

Shleifer, A. and L. Summers (1990). "The Noise Trader Approach to Finance," *Journal of Econometrics,* 4(2): 19–23.

Sornette, D. et al. (2009) , "The 2006–2008 oil bubble: Evidence of speculation, and prediction. Physica A - Stat. Mech. Applic.", 388, 1571–1576.

Scharfstein, David S. and Jeremy C. Stein, (1990), "Herd behavior and investment", *American Economic Review* ,80(3), 465-479.

Stasser,G., Taylor,L.A. and Hanna, C. (1989), "Information sampling in structured and unstructured discussions of three and six persons group", *Journal of Personality and Social Psychology,*57,67-78.

Stasser, G and Titus, W.(1985), "Pooling of unshared information in group decision making: Biased information sampling during discussion", *Journal of Personality and Social Psychology,*48,1467-1478.

Shefrin, Hersh, and Meir Statman. (1985). "The Disposition to Sell Winners Too Earlyand Ride Losers Too Long: Theory and Evidence." *Journal of Finance* 40(3): 777-790.

Szyszka, A. (2013), "Behavioural Finance and Capital Markets:How Psychology influences Investors" *Business and Economics, Palgrave Macmillan.*

Thaler, R., Tversky, A., Kahneman, D. and Schwartz, A. (1997): "The Effect of Myopia and Loss Aversion on Risk Taking: an Experimental Testing". *The Quarterly Journal of Economics,* 112, 647-661.

Thaler, R., Kahneman, D. & Knetsch, J. L. (1992). The endowment effect, loss aversion and status quo bias. In R. Thaler, The Winner's Curse. Princeton: Princeton University Press, 63-78

Thaler, H, Richard,(2008), "Mental Accounting and Consumer Choice",*Marketing Science,* 27(1),15-25..

Tversky, A. and Kahneman, D. (1992), "Advances in Prospect Theory:Cumulative Representation of Uncertainity", *Journal of Risk and Uncertainity*,5 , 297-323

Tversky, Amos and Daniel Kahneman (1991), "Loss Aversion in Riskless Choice: A Reference-Dependent Model," Quarterly Journal of Economics, 106 (4), 1039–1061

Trueman, Brett, (1994), "Analyst forecasts and herding behavior", *Review of Financial Studies,* 7(1), 97-124.

Trotter, Wilfred(1914), "Instincts of the Herd in Peace and War",T. FISHER UNWIN LTD., London:ADELPHI TERRACE.

Veblen, Thorstein (1953) [1899]. "The Theory of the Leisure Class: An Economic Study of Institutions", the *Mentor Edition. Introduction by C. Wright Mills. New York:The Macmillan Company*

Woodford, M.(2000), "An interview with William A. Broke" , *Macoeconomic Dynamics* , 4, 108-138

Zwicbel, Jeffrey, (1995), "Corporate conservatism and relative compensation", *Journal of Political Economy* 103(1), 1-25.

Chapter – III

Asset Market Behaviour:
A Theoretical Approach

3.1. Introduction

Theorizing expectation or belief formation is the central part in any economic approach trying to model for capital market upheavals. Since its introduction in the sixties by Muth (1961) and its popularization in macroeconomics by Lucas (1971), the Rational Expectation Hypothesis has become the dominating expectation formation paradigm in economic theories. Although many economists nowadays views the ongoing paradigm as something inadequate in explaining the market upheavals, but a generally accepted alternative paradigm is yet to be developed. Theories from other social sciences like sociology, anthropology, psychology etc. have motivated much empirical works in recent past in analyzing less than perfect behaviour in making investment decisions. But studies of human psychologies in analyzing decision making under risk and uncertainty is a multifaceted issue. Wide ranges of literature are available claiming the influence of an array of complex set of psychological antecedents in decision making. It is perhaps the most formidable task to quantify the relevance of one particular psychological issue playing its role in course of a decision. Basically the anomalies to the existing paradigm are observed in complex real world settings, where many possible factors may be at work, not in the experimental psychologist's laboratory. However, to overcome such difficulties, a rapidly increasing number of structural heterogeneous agent models have been introduced in the financial literature recently. These multi agent heterogeneous framework offers a more coherent approach particularly, towards analyzing psychological underpinnings of expectation or belief formation in capital market decisions. This approach draws heavily from a new school of thought widely emphasized in literature by the Santa Fe Institute of New Mexico (see Hommes and Gounresdorfer ,2007, Gounresdorfer 2000,2001, Simon 1955 , Johansen and Sornette 1999,2000,2010,Aurther et.al 1997,Le Baron et al 1999,Lux and Marchesi 1999 Broke and Hommes 1998 etc.).The major emphasis of the model is on explaining psychological implications of human interactions that generate epidemics in opinion and bubble grows. Basically, it allows employing the bottom up approach, focusing on micro level of the agents' interaction but aiming at studying the behavioural macro effects on asset price dynamics. Market is viewed as a "soup' of diverse agents who interact with each other making it resemble a constantly boiling mixture.Going by this

emerging direction, our humble approach, in this present chapter, is to study Indian equity market in multi agent framework.

Unlike the conventional framework, the heterogeneous market model does not make any stereotypical assumptions about investor's behavior. Rather it questions some fundamental epistemological issues that are not fully addressed in the rationality driven market theory (Fiedman, 1953 and Fama, 1970). In the conventional wisdom, distinctions are often made between rational and non rational agents and it has been found useful in mathematical modeling approach. Why is it that some agents are rational and others are not? Although the difference between rational and non rational behaviour is quite fundamental, are there are two fundamentally different types of human being in societies? And if these types exist, how are they selected? To avoid these basic debates, the present framework has been developed under the condition of bounded rationality with evolutionary belief (see Simon 1955, Kahneman, 2003, Johansen and Sornette (1999, 2000). In this present framework all market participants are similar victim of cognitive limitations in their decision making. All of them have similar information complexity and use the best possible strategies within the confines of their limited ability. Forecast about the future asset prices are made by applying simple but different trading rules. They are thought to check the relative fitness of the comparative trading rule , update their belief and switch over to more profitable ones to maximize own utility function(See Brock and Hommers 1997, 1998 Lux 1998, Gaunersdorfer and Hommes, 2007). Here the model introduces concepts borrowed from evolutionary economics school of thought under adaptive belief mechanism. This concept has also been influenced highly by the literatures of behavioral finance (see Tversky and Khneman 1981, Thaler 1994, Shleifer 2000, Barberis and Thaler 2003).

3.2. The model[5]:

We assume that , there are different type of agents in the market denoted by 'i' depending on their beliefs about the future asset price. Each agent can invest in two assets; a risk free asset with same pay off and risky asset. The agent's utility function according to Grauwe and Grimaldi (2004) can be defined as follows:

$$u(W_{t+1}) = E_t(W_{t+1}) - \frac{1}{2}\mu V(W_{t+1}) \text{----------Eq. No. (1)}$$

where w_{t+1} is the wealth of the agent of type 'i' at the time (t + 1), E_t is the expectation operator , μ is the coefficient of risk aversion and $V^i(W^i_{t+1})$ represents the conditional variance of wealth of agent 'i', while 'μ' does not include any specific shape considered in some of the earlier studies, The wealth is specified as follows:

$$W^i_{t+1} = (S_{t+1} + Y_{t+1})d^i_t + (1 + r)(W^i_t - S_t d^i_t) \text{--------- Eq. No. (2)}$$

S_{t+1} is the price per share at the time t+1, d^i_t represents the unit of risky assets holding at time 't',the term Y_{t+1} is the amount of dividend received,'r' being the risk free rate of interest known with certainty. The first term of the right hand side of the above equation represents the value of the risky asset at t+1 and the second term represents the value of risk less asset at t+1.

Substituting equation (2) in equation (1) and maximizing utility with respect to $d_{i,t}$ allows us to derive the standard optimal holding of risky assets by agents' type 'i':

$$d_{i,t} = \frac{E^i_t(s_{t+1} + y_{t+1}) - (1 + r)s_t}{\mu\sigma^2_{i,t}} \text{,.....Eq. No. (3)}$$

[5] The mathematical expressions used in the models have been grossly adopted from Grauwe.P and Grimaldi.M.(2004); "Bubbles and Crashes in a Behavioural Finance Model",(Center for Economic Studies & Ifo Institute for Economic Research ,CESifo ,Working Paper No. 1194) due to its simplicity and clarity.

Thus optimal holding of risky asset depends on expected excess return (corrected for risk) of the equity. The market demand for risky asset at time t is the sum of individual demands,

$$\text{i.e.:} \quad \sum_{i=1}^{N} n_{i,t} d_{i,t} = D_t, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq. No. (4)}$$

where $n_{i,t}$ the number of agents of type 'i' at time 't'.

Market equilibrium implies that market demand is equal to the market supply Z_t which we assume to be exogenous. Thus,

$$Z_t = D_t, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq.No.(5)}$$

Grauwe and Grimaldi (2004) finally substituted the optimal holdings into the market demand and then into the market equilibrium equation and solving for S_t yields the market clearing price:

$$S_t = \left(\frac{1}{1+r}\right) \frac{1}{\sum_{i=1}^{N} \frac{w_{i,t}}{\sigma_{i,t}^2}} \left[\sum_{i=1}^{N} w_{i,t} \frac{E_t^i(s_{t+1})}{\sigma_{i,t}^2} - \Omega_t Z_t \right] \ldots\ldots\ldots \text{Eq.No. (6)}$$

where $w_{i,t} = \dfrac{n_{i,t}}{\sum_{i=1}^{N} n_{i,t}}$ is the weight (share) of agent i, and

$$\Omega_t = \frac{\mu}{\sum_{i=1}^{N} n_{i,t}}$$

Thus, share price is determined by expectations of diverse agents, E_t^i, about the future return. These forecasts are weighted by their respective variances $\sigma_{i,t}^2$. when agent's i forecast have a high variance the weight of this agent in the determination of market price is reduced.

We will now attempt to specify how the agents in the market formulate their expectations about future prices and how they evaluate portfolio risk. We start with an analysis of the rules that agents use in forecasting speculative prices.

(a) Expectation formation and selection of rules:

We assume that two types of forecasting rules are used, one is called a "fundamentalist strategy", and the other is "technical trading" rule. The idea of distinguishing between fundamentalists and technical traders rules was first introduced by Frankel and Froot (1986). Agents using the fundamentalists rule, base their forecast on a comparison between the market and the fundamental value. They forecast the market rate of return to the fundamental rate in future. In this sense they use a negative feedback rule that introduces a mean reverting dynamics into stock price movements. The speed with which the market price returns to the fundamental is assumed to be determined by the speed of adjustment in the goods market which is assumed to be in the information source of fundamentalists. Thus, the forecasting rule for the fundamentalist can be formulated as:

$$E_t^f(\Delta s_{t+1}) = -\psi(s_{t-1} - s_{t-1}^*) \quad \text{.....Eq.No.(7)}$$

where S_t^* is the fundamental share price at time t, which is assumed to follow a random walk and $0 < \psi < 1$.Moreover, fundamental value is exogenous and in forecasting future value, fundamentalists use information up to period t-1.This agents do not know the full model structure and as a result, they cannot compute the equilibrium price of time t which will be the result of their decisions made in period t.

The agents using the technical analysis, the "technical traders", forecast future price by extrapolating from past price movements. Their forecasting rule can be specified as:

$$E_t^c(\Delta s_{t+1}) = \beta \sum_{i=1}^{T} \alpha_i \Delta s_{t-i} \quad \text{,.....Eq.No (8)}$$

The technical traders compute a moving average of the past stock price changes and they extrapolate this into the future stock price changes. The degree of extrapolation is given by the parameter β.Technical traders take into account information concerning the fundamental value indirectly, i.e. through the stock price movements itself. In addition, technical rule can be interpreted as an attempt to detect "market sentiments" which is prone to generate price to price feedback (Shiller 2003. Hirshleifer et al. 2006). Chartists virtually observe sequence of price changes before they chase the trend and they do not respond instantaneously to price movements. "Price to price channel" shape the expectation of future price movements for technical analysts.

(b) Modeling of risk perception:

In the evolutionary economics with adaptive belief, risks are measured by the variance terms which are defined as the weighted average of the squared (one period ahead) forecasting errors made by technical traders and fundamentalists, respectively. Thus,

$$\sigma_{i,t} = \sum_{k=1}^{\infty} \theta_k \left[E^{i}_{t-k-1}(s_{t-k}) - s_{t-k} \right]^2 \quad \text{.....Eq.No (9)}$$

where $\theta_k = \theta(1-\theta)^{k-1}$ are geometrically declining weights ($0<\theta<1$) and i = f,c.This approach of assessing risk is highly influenced by the concept of "Loss Aversion" in the literature of reference dependent decision making in behavioural finance (Kahneman and Tversky, 1979).

(c) Potential solutions to the model:

Assumption of bounded rationality offers the scope for explaining behavioural biases in decision making that can lead the market towards its potential solutions. Adaptive belief in the market is formed either in favour of technical or fundamental rule subject to its evolutionary fitness. More the actual prices converges to the predictions made using a particular rule, lesser its perceived risk (see equation 09) and higher its evolutionary fitness. Thus, it is immaterial whether a decision rule is ridiculous or rational. Rather, the model requires the use of a particular decision

rule that is context specific based on its suitability in expectation formation weighted in terms of deviation from actual. Accordingly, when adaptive belief is formed in favour of fundamentalists, they dominate the market; technical rules consistently make large forecasting error, thereby decreases evolutionary fitness. Prices systematically approach to informational efficiency, and in its extreme all arbitrage profits are eliminated. Alternatively when technical traders dominate, evolutionary update in belief is formed in favour technical rules, market continues to undervalue quality of information, asset price becomes noisy, and tend to deviate from its fair value. Thus, adaptive belief formation either in favour of fundamentalists or chartists tips balance in the market. Following the traditional dictum, if deviations are due to idiosyncratic demand from ill informed, rational arbitragers instantly indulge themselves to take appropriate position, snap up profit opportunities created by misalignment of prices (Friedman 1953). Then they virtually substitute the behavior of trend chasers and produce an outcome consistent with rational model. In such a way better informed rational traders are rewarded with more wealth and financial market is shielded from ill informed and optimal allocation of resources are ensured. In contrast, if fundamentalists continue to make large forecasting errors, risk perception of using their own strategy increases and then evolutionary belief tends to form in favour of technical rules. Under such conditions, fundamentalists virtually complement the behavior of trend chasers, arbitrage operation gets limited and bubble grows(Andrei Shleifer; Robert W. Vishny1997). Thus the presence of strategic substitutability or complementarity *seems* to be the key condition in determining when a population, that is a priori heterogeneous with regard to their expectation or belief, make the market to reach either "fundamental or bubble solution" (Fehr and Tyran 2005).

Behavioural finance theories under the cover of "strategic complimentary and substitutability" (Fehr and Tyran 2005), nicely describes how and when agents revise their forecasting rules and how it affects aggregate market behavior. In the next section we will be interested specifically to study underlying socio – psychological and cultural underpinnings of investor's mind that put strategic complementarily into action and bubble grows.

(d) Social and Psycho-economic foundations of bubble solution:

At the outset, we must mention one pre requisite condition for bubble formation, widely recognized in the literature. Strong positive or negative shifts in economic fundamentals have been identified as a common denominator in all psychological manias in a wide range of literature around the globe. Bubbles have been found to generate in the backdrop of strong and burgeoning economic conditions (Kindelberger 1978, Groundersforder, 2000, 2001 etc.).Specifically, in growing economies positive shock in fundamentals occurs more frequently thus chances of getting positive bubbles are also higher. In this context, the heterogeneous market model predicts some common features of a typically endogenously generated bubbles and crashes. Once a bubble emerges, it sets into motion bandwagon effects. As the price moves steadily in one direction, evolutionary fitness of using technical trading rules increases initially. Technical traders, who tend to derive information about fundamental condition indirectly by looking at the price trend, psychologically tend to promote self confidence and generate excitement over their own ability. Their perceived riskiness in using their own rule thus diminishes by ongoing movements in price (see equation no.09) thereby, attract more and more technical traders in the market.But a sustained upward movements in prices cannot develop into full scale bubble if at some point market does not get sufficiently dominated by technical traders.Thus the basic essential condition for a bubble formation requires that, at some points most agents in the market are not willing to take contrarian fundamentalists view.However the theories of market efficiency demands, rational arbitragers being the guardians of market can take care of any possible misalignment in prices. Otherwise a sustained upward or downward movement in prices may get itself converted into a full scale bubble or crash. At this point, very naturally the question is raised : why arbitragers fails to take corrective actions and fundamentalists do not take opposite position thereby preventing bubble from growing. After all, larger the deviation of the price from fundamental, more the fundamentalists expect to make profits.But the empirical evidences of bubbles and crashes point towards that solution of the model where fundamentalists do not take the contrarian position , and massively leave the market place to the technical traders.Therefore a self-fulfilling force is to develop in the market in favour of profitability of technical traders and

losses for fundamentalists. Theories of behavioural finance offer explanations to this respect.

Once the speculative prices starts to deviate steadily in a direction,(may be due to an overreacting response to a strong shifts in underlying macroeconomic conditions)[6], evolutionary fitness of using technical trading rule increases dramatically. Technical traders tend to ascribe psychologically their "successes" in asset market as a result of "brilliant ability to recognize pattern", strong "wishful thinking" "superb caliber" to explain asset prices (Barberis and Thaler (2003), Daniel et al. (2002), De Bondt (2002, 2005, 2008a b), Shiller (2002). Ultimately chartists start to make better prediction and their dependency on this "naïve" but "rewarding" investment strategy increases. Evolutionary fitness of technical rule derives more utility to its users through its higher relative profitability and ultimately more and more traders are drawn into the market as technical traders which push prices further and make the technical trading more profitable (see equation no.01). On the other side of the story, fundamental traders having bounds on their cognitive resources to analyse the situation optimally, tend to perceive high relative riskiness[7] in using their own rule (see equation no.09). Moreover consecutive forecasting errors resulting out of adverse movements in prices to their prediction model, fundamentalists psychologically locate themselves in the losing quadrant of their value function. Reference dependency in decision making (exhibited through a kink in the value function) tends to play its role as a key determinant factor here in subsequent decisions. At this stage any potential threat of losing statuquo in terms of initial wealth (W) are valued psychologically more heavily and this often get strongly intensified with the presence of other related biases like myopic horizon, urge to avoid post decisional regret of not taking right decisions in time, pain of cognitive dissonance, career and reputational concerns etc. (see Andrea Devenow, Ivo Welch,1996, Welch 2000, Scharfstein and Stein 1990, Trueman 1994, Zweibel 1995, Prendergast and Stole 1996, Graham 1999, Brennan

[6] Overeaction has been widely studied in the literature in the context of Mean Reversion (see De Bondt and Thaler ,1985; Summers ,1986; Fama and French 1988; Poterba and Summers, 1988).

[7] Risk is being measured in terms of deviation from actuals, (equation no. o9)

1993, Roll 1992, Maug and Naik 1996, Brennan 1993, and Roll 1992). Thus aversion of losses but not the risk tends to be the prominent consideration here in subsequent decision by the fundamentalists (Kahneman and Tversky 1979). Added to this, fundamentalists on experiencing repeated failures, tend to be dragged socially in favour of technical traders gradually for clarification and affiliation. Information conveyed through competitive winning strategies of others seems to be here as an important source of reassurance and clarification for fundamentalists. Need for affiliation both within the organization and with the ongoing wisdom in the outside tend to become particularly stronger and this seem to override well established previous standards in determining optimum behavior towards risk and expectation. It ultimately tends to result in strengthening the commonality in thinking and increases group cohesiveness.In such a societal state of assuring and reassuring credentialties in favour of technical rules, it is likely to be more difficult for an individual to take an unpopular independent course of action than to be influenced heavily by whims of the moment.Both fundamental and technical traders, thereby tend to develop a representative mind whereby salient images of past price trend is programmed automatically to follow its trend in future. Thus sentiment and ideas of all the type of traders in the market gradually tend to take one and the same direction and their conscious personality tend to vanish. Whoever be the individuals that compose it, however like or unlike their mode of life, their occupations, their characters or intelligence the fact that they are all transformed into a crowd puts them in possession of a sort of collective mind which makes them think, feel and act in a manner different from one in isolation.

Thus to reach a bubble solution, it becomes essential that adaptive belief among majority of market traders has been formed in favour of technical traders and fundamentalists cannot exert any more influence to bring the mean reversion dynamics at work. The latter is necessary; otherwise fundamentalists are still expected to use their own rule and their forecast of a revision to the fundamental would move stock prices.

The above stated switching mechanism can be incorporated in the heterogeneous pricing model as (Broke and Hommes 1998):

$$w_{c,t} = \frac{\exp\left[\gamma\pi'_{c,t-1}\right]}{\exp\left[\gamma\pi'_{c,t-1}\right] + \exp\left[\gamma\pi'_{f,t-1}\right]} \text{ ..... Eq.No (10)}$$

$$w_{f,t} = \frac{\exp\left[\gamma\pi'_{f,t-1}\right]}{\exp\left[\gamma\pi'_{c,t-1}\right] + \exp\left[\gamma\pi'_{f,t-1}\right]} \text{ ..... Eq.No (11)}$$

Weights of forecasting rule are function of relative profitability. $\pi'_{c,t-1}$ and $\pi'_{f,t-1}$ are the risk adjusted net profits made by technical traders' and fundamentalists' forecasting the price in the period t-1, i.e. $\pi'_{c,t-1} = \pi_{c,t-1} - \mu\sigma^2_{c,t-1}$ and $\pi'_{f,t-1} = \pi_{f,t-1} - \mu\sigma^2_{f,t-1}$. This depicts exactly the switching rules where participants follow an adaptive behaviour. When the risk adjusted profit by trend chasers exceed the risk adjusted net profit of fundamentalists rules, then the share of the total agents who switches to technical rule in period t increases and vice versa. The parameter 'γ' is the measure of inertia that reflects the intensity with which trend chasers and fundamentalists revise their forecasting rules. With an increasing 'γ' agents react strongly to the relative profitability of the rules. In the limit when γ tends nearer to infinity all agents choose the forecasting rule which appear more profitable and changes camp from chartist's(c) to fundamentalist's (f) or vice versa .Trading will be impossible if either 'c' or 'f' becomes exactly equal to zero. This parameter is of great importance in generating bubbles. Degree of extrapolation is denoted by the parameter β (see equation No.08) whereas fundamentalists have some rational valuation of the 'risky asset', the technical analysts use a simple extrapolation rule to forecast asset prices. Technically speaking, during a bubble phase, larger the deviation of prices from fundamentals, higher the relative profitability of using technical trading rule and greater the influence of associated socio economic and psychological constraints in optimum decision making. Bounded rational traders having not very perfect information about the optimum course of action, tend to be a very natural candidate of wild eyed speculations. Gradually, they become prone to follow emerging price movements to derive private information of others on the mistaken

belief that, most of the others cannot be wrong (that is the case of information cascade.). Prices so emerge, subsequently, fails to convey private information of predecessors but tend to generate an informationally inefficient adaptive belief favouring the ongoing market movements. Rise in prices thereby; tend to become a single obsessive topic of conversation, usually embellished with each telling, of the fortunes made who got into early. Those who are still on the sidelines seem to be wasting the golden opportunities and more and more people are drawn into the boiling market as technical traders. Caution is thrown into the winds, voices of reasons and moderations are shouted down, arbitragers operating against the asset price misalignment tend to drop out. Thus, movements in prices gradually results into generating evolutionary confidences in favour of price to price feedback which justify further expectation for increases. Ultimately a self fulfilling prophecy emerges whereby larger movements in prices results in more profit for technical traders accumulate more wealth which in turn justifies further demands. The great bubble of hope, unreason confidence and greed floats upward.

Thus, large price increases at the beginning of a bubble converts agents from fundamentalists group as well as from those who are standing on the sidelines into optimistic chartists group. For a more or less extended time span, the attraction of additional traders entering on the demand side heats up the bubble. Once the bubble has infected a certain number of traders, the exhaustion of the pool of additional participants causes to slow down the ongoing price trend. On the other hand, with a relatively large deviation from fundamentals, there is a high potential gain from the fundamentalist's strategy. Both tendencies gradually change the profit differential in favour of fundamentalists' strategy fostering transition of chartists to the fundamentalists group. In this situation under consideration, agents switch from the demand side to the supply side of the market. As a result, the price will eventually cease to rise further reaches its turning points shortly after the turning point of chartist's share. The ensuing price drop, then leads to an erosion of confidence among the remaining chartists which, in turn, will reinforce the downward price trend. The general pattern of downward waves is very similar with the upwards. Emerging pessimism causes a downward price trend which in turn confirms the speculator's

belief and reinforces contagion of fear. As a consequence , more and more fundamentalists join the pessimistic group in order not to incur huge losses.Again exhaustion of pool of additional sellers eventually leads to a slowdown of the negative trend.As the threat of capital losses diminishes, lasting undervaluation induces a change of the profit differential in favour of the fundamental strategy. Accordingly, when the ratio of fundamentalists increases in the population , again, a reversal of the price trend is brought about because of an increasing demand.At last, the resulting recovery induces a change of prevailing mood of the market.

Thus acquiring solely from numerical consideration, a sentiment of invincible power allows individual to yield to instincts, where the capacity of any group to rule over the other becomes a function of numbers (n) and wealth (w). With this assumption we virtually negate the hypothesis of rational expectation theorists that people with better information will rule over the market. Arbitrage operation thus appears to be useless if wealth not information decides destiny of the market.

In this backdrop, now we will attempt to analyze intricate relationship between wealth and numbers of fundamentalists (W_{nf}) and chartists (W_{nc}), its impact on asset prices and resource allocation ignoring the early dogma of "rationality", "independence of decision making" and "informational efficiency". We have viewed asset market to be typically populated by heterogeneous agents who differ in belief function, continuously update their belief and switch over to more profitable investment and trading strategy to benefit from it. The model is pointing towards certain solutions in asset price dynamics that may irritate the advocacies of "perfectionists", but capable enough to capture more accurately the underlying behaviour of market participants:

1) Investors in asset market continuously update their belief and expectation based on current experiences, i.e. the decisions of investors are context specific , they learn from experiences.
2) Investors favour one strategy ignoring the others.They switch over from one camp to another and it creates impact on both numbers (n) and wealth (W). The following situations may result:

(a) If $W_C = W_f$ (where W_C is the wealth of chartists and W_f is wealth of fundamentalists and where $W_C + W_f = 1$, when strength of both the camps are equal (see equation 10 and 11) their interaction will result into "tired looking anemic market".

(b) If $W_f \rangle W_C$ and W_f > 0.5 occurs, fundamentalists trading rule is generating more risk adjusted profit consistently than technical analysts. Fundamentalists become wealthier at the cost of noise traders and dominate the market. Because of their adaptive nature technical traders will gradually switch over from their " naïve" strategy to fundamental rule. Price will be moved based only on information and converges towards fundamental value. Thanks to bounded rationality , even when $W_f > 0.5$, price may deviate from fundamental but this will be short lived and much discussed phenomenon of mean reversion dynamics will take care of it (De Bondt and Thaler ,1985; Summers ,1986; Fama and French 1988; Poterba and Summers, 1988).

(c) When $W_f \langle W_C$ and W_C > 0.5, in this variety chartists dominate the market. Trend chasers consistently earn a risk adjusted return that is higher than fundamentalists.

As chartists become wealthier than fundamentalists, their wealth increases (initial wealth plus accumulated profit) and capacity to influence price movement also increases. The situation will attract new investors who so long avoided the market as gambling den, now to minimize regret of losing the option of earning quick bucks will enter into the market. New wealth under the command of trend chasers will be equal to $W_c + W_{c1}$ (new entrants and its wealth). Finally this will result into $W_{C'} + W_f \rangle 1$ (where $W_{C'} = W_c + W_{c1}$). Here prices and opinion index move broadly in a line with each other. Shifts in opinion index in favour of chartists may be taken as a characterization of displaying waves of optimism and pessimism which are

accompanied by deviation of asset's price from its fundamental value. The ratio of the chartists in determination of price increases during both optimistic and pessimistic waves and declines when revision towards the fundamental value sets in. Further, socio psychological hindrances restrict independence of decision by the fundamentalists. They fail to pursue any strategy that punishes but not reward investors. This result into a condition where W_f tends to w_c but $w_c \neq 1$and $w_f \neq 1$, which would cause a trading deadlock.

Of course, the timing and extent of future bursts of optimism and pessimism as well as the timing of its reversals remains unforcastable, but the qualitative picture remains as described. If investors can predict that market would collapse on time 't'undeniably it will occur before "t" say at "t-1".

In sum, to reach the market upheavals, the heterogeneous model under the condition of bounded rationality, requires the decisions to be context specific. Adaptive belief is to be formed among the majority traders in favour of evolutionary fitness of using technical trading rules. More and more traders including the prior fundamentalists are turned into technical traders with sufficient numbers and wealth. This ultimately results in making the arbitrage operation powerless and subsequent changes in prices become a model endogenous phenomenon generating out of the trading process itself. If this happens then any small changes in prices due to random news are reinforced and can become more and larger due to trend following trading rules. But the trend cannot persist forever. Once sufficiently large numbers of traders have been converted to follow the technical traders, the self reinforcing forces in prices tend to slow down. Now an exogenous development in fundamental condition tends to reverse the direction of market movements and bring it back to its normal level of tranquility. Thus heterogeneous market model with bounded rationality and evolutionary learning predicts the market to switch irregularly between phases of low volatilities and high volatilities. Large changes in price movements tend to be followed by large changes – of either sign-and small changes tend to be followed by small changes, irregularly interchanging with each other. In this backdrop, our major emphasis in the empirical part of the present thesis would be on examining the patterns of price movements in Indian context. Pattern in prices in turn can be taken

as an explanatory device for explaining the influences of social psychological underpinning of human decision making under uncertainties towards market upheavals.

3.3. Hypothesis:

The present study hypothesize that to maximize expected utility participants in the market behave rationally ,they use all available information independently, form unbiased estimation about the future and maintains an optimum relation between risk and return.

3.4. Research Questions:

To test the above stated hypothesis the following research questions are raised in the background of heterogeneous market model with evolutionary adaptive belief system under the condition of bounded rationality.

1) Whether their decisions in the market become context specific?
2) Do investors continuously follow a trading rule that satisfy rational expectation model?
3) Do investors constantly evaluate the profitability of other strategies and never hesitate to switch over to relative profitable tools, no matter whether it is ridiculous or rational?
4) Do the prices moves randomly?

3.5. Methodology:

In the context of evolutionary adaptive belief with bounded rationality, prices ultimately become an outcome of strategic complimentarity or substitutability in favour of a trading rule. If strategic complimentarity occurs in favour the technical rules , prices tend to deviate from fundamentals.Evolutionery learning from sustained deviation of price from fundamentals gradually tend fundamentalists to ignore their own decision rules. Fundamentalists switch over to technical rules significantly reduces their importance in price determination. Increased dominance of trend chasers ultimately results in generating a self fulfilling dynamics whereby large deviations from fundamentals justify further deviation. Moreover once sufficiently large number of traders has been converted to follow the technical traders the self reinforcing forces in prices tend to slow down. Now an exogenous development in fundamental condition tends to reverse the direction of market movements and bring it back to its normal level of tranquility. Thus movements in prices in this evolutionary learning set up may be characterized by irregular switches between phases of low volatilities, where price changes are small, and phases of high volatility where small price changes become large due to trend following trading rules. In this context we will apply Generalised Autoressive Conditional Heteroskedastic model (GARCH) and Extreme Value Theory to identify empirically the evidences of prolonged rise and fall in asset prices and its clustering over stretches of time in Indian capital market. The presence of extreme movements in price changes and its clustering over time, may be taken as macro effects on prices of socio- psycho economic dynamic forces in forming adaptive belief at the micro level of agent's interactions, proposed under the heterogeneous market model with bounded rationality.

3.6. Data and time period:

In the present study we have considered a period ranging from July 1997 to September 2013.Historical daily price data on BSE SENSEX 30, the widely recognized price index in Indian context comprising nearly forty percentage of market capitalization have been collected. The entire data base consists of BSE SENSEX 30

daily closing values which is adjusted for dividends have been obtained from web portal of Bombay Stock Exchange, India.

References:

Arthur, W.B.,Holland, J.H., LeBaron, B.,Palmer,R and Taylor, P.(1997), "Asset pricing under endogenous expectations in an artificial stock market, *in:Arthur, W.B.,Durlauf, S.N., and Lane, D.A.(Eds), The Economy as an Evolving Complex System II.Redwood City, Addison- Wesley, 15-44.*

Broke, W.A. and Hommes, C.H.(1997), "A rational route to randomness", *Econometrica,*65,1059-1095

Broke, W.A. and Hommes, C.H.(1998), "Heterogeneous beliefs and routes to chaos in a simple asset pricing model", *Journal of Economic Dynamics and Control,* 22,1235-74.

Brennan, Michael, (1993), *"Agency and Asset Prices,"* Finance Working Paper No. 6-93, UCLA.

Barberis,N. Thaler,R ,(2003); A survey of behavioral finance ;In:George M CONSTANTINIDES , *Milton Harris, and Rene M. STULZ, eds. Handbook of the Economics of Finance, Volume 1B, Financial Market and Asset Pricing. Elsevier,North Holland, Chapter 18,1053-1128*

Brennan, Michael, (1993), *"Agency and Asset Prices,"* Finance Working Paper No. 6-93, UCLA.

Daniel, K., Hershleifer, D., Teoh, H.S.(2002), "Investors psychology in capital markets: evidence and policy implications," *Journal of Monetary Economics*, 49, 139-209

De Bondt, F.M.Werner, Shefrin, H.,Muradoglu , Y. G.,Staikouras, K.S.(2008), "Behavioural Finance: Quo Vadis?", Journal of Applied Finance, 19,7-21

De Bondt, W.F.M., (2002), \Bubble Psychology,] in W. Hunterand G. Kaufman (eds.), Asset Price Bubbles: Implicationsfor Monetary, Regulatory, and International Policies, MITPress.

De Bondt, W.F.M., 2005, The Psychology of World EquityMarkets, Edward Elgar.

De Bondt, W.F.M., 2008a, \Stock Prices: Insights fromBehavioral Finance,] in Alan Lewis (ed.), The Cambridge Handbook of Psychology and Economic Behavior,Cambridge University Press.

De Bondt, W.F.M., 2008b, \Investor Psychology andInternational Equity Markets,] Revue Economique etSociale 66 (No. 4), 107-121.

De Bondt and Thaler, R.(1985), "Does the Stock Market Overreact? *The Journal Of Finance*,40(3),793-805.

Devenow A., Welch, I. (1996). "Rationalherding in financial economics". *European Economic Review* ,40, 603–615.

Frankel, J. and Froot, K, (1986), "The dollor as a speculative bubble:A Tale of fundamentalists and Chartists", NBER Working paper , no.1963

Fama, E. F. (1970), *"Efficient capital markets: A review of theory and empirical work"*, The Journal of Finance ,25(2), 383–417.

Friedman, M. (1953), The Case for Flexible Exchange Rates, in M. Friedman (ed.), Essays in positive economics, University of Chicago Press, Chicago, pp.157–203.

Farmer, J. Doyne. (2001). Toward Agent Based Models for Investment. In Benchmarks and Attribution Analysis. Association for Investment and Management Research.

Fehr, E. and Tyran Robert , J. (2005); " *Individual Irrationality and Aggregate Outcomes*"; Jounal of Economic Perspectives, Vol. 19 , No. 4 , 43-66

Fama, Eugene F.,French, R.K.(1988), "Dividend Yield and Expected Stock Returns", Journal of Financial Economics, 22, 3-25.

Gaunersdorfer A., 2001. "Adaptive belief systems and the volatility of asset prices", Central European Journal of Operations Research 9, 5–30.

Gaunersdorfer A., Hommes C.H., 2007. "A nonlinear structural model for volatility clustering. In:Teyssiere, G., Kirman, A. (Eds.), Long Memory in Economics". Springer: Berlin/Heidelberg, 265– `288.

Gaunersdorfer A., 2000. "Endogenous fluctuations in a simple asset pricing model with heterogeneous beliefs". *Journal of Economic Dynamics and Control* 24, 799–831.

Graham, John R., (1999), "Herding among Investment Newsletters: Theory and Evidence," *The Journal of Finance*, 54, pp. 237–68.

Grimaldi.M.(2004); "Bubbles and Crashes in a Behavioural Finance Model",(Center for Economic Studies & Ifo Institute for Economic Research ,CESifo ,Working Paper No. 1194

Hirshleifer, D., Subrahmanyam, A. and Titman, S., (2006,) 'Feedback and the success of irrational traders',Journal of Financial Economics, Vol. 81, pp. 311–388.

Johansen, A and Sornette,D, (2010); "Shocks, Crashes and Bubbles in Financial Markets, " *Brussels Economic Review, , vol. 53, issue 2, pages 201-253*

Johansen and Sornette, (1999) , "Critical Crashes", *RISK* ,12 (1), 91-94.

Johansen and Sornette, (2000), "The Nasdaq crash of April 2000: Yet another example of log-periodicity in a speculative bubble ending in a crash", *Eur. Phys. J. B* 17 pp. 319-328.

Kindleberger,C.(1978), "Manias, Panics and Crashes, A History of Financial Crises", John Wiley & Sons, New York,263 pages.

Kahneman, D., and A. Tversky (1979), "Prospect theory: an analysis of decision under risk", Econometrica 47:263–291.

Kahneman,D, (2003), "Maps of Bounded Rationality: Psychology for Behavioral Economics" *The American Economic Review*, Vol. 93, No. 5 pp. 1449-1475.

Lux, T., and Marchesi, M. (1999): Scaling and criticality in a stochastic multi-agent model of a financial market, *Nature,* 397, 498–500.

Lux T., 1998, "The socio-economic dynamics of speculative markets: interacting agents, chaos, and fat tails of return distributions", Journal of Economic Behaviour and Organisation, vol.33.

Lucas, R.E. (1971), "Econometric Testing of natural rate hypothesis. In. O. Eckstein, Editor, *The Econometrics of Price Determination Conference, Board of Governors of the Federal Reserve System and Social Science Research Council, 1971.*

LeBaron,B," W. Brian Arthur"(1999), Richard Palmer Journal of Economic Dynamics & Control 23 1487}1516 Time series properties of an artificial stock market

Muth, J.F. (1961)', "Rational Expectations and Theory of Price Movements",*Econometrica* 29,315-335

Maug, Ernst and Narayan Naik, (1995), "Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation", *Working paper (London Business School, London).*

Prendergast, C. and Stole, L. (1996), ''Impetuous Youngsters and Jaded Old-Timers: Acquiring a Reputation for Learning.'' *Journal of Political Economy,* 104 ,1105–113

Poterba,James M. and Summers Lawrence, H. (1988), "Mean Reversion in Stock Prices, Evidence and Implications", *Journal of Financial Economics*,,22, 27-59.

Roll, Richard, (1992), "A mean/variance analysis of tracking error", *Journal of Portfolio Management*, 13-22.

Summers, H.L.(1986), "Does the Stock Market Rationally Reflect Fundamental Values?"*The Journal of Finance*, XLI (3).

Scharfstein, David S. and Jeremy C. Stein, (1990), "Herd behavior and investment", *American Economic Review* ,80(3), 465-479.

Shiller Robert J. (2003),;From Efficient Markets Theory to Behavioral Finance The Journal of Economic PerspectivesVol. 17, No. 1 pp. 83-104

Shleifer,A; Robert W. Vishny, (1997); The Limits of Arbitrage, The Journal of Finance, Vol. 52, No. 1., pp. 35-55.

Shleifer, A.(2000), Introduction to Behavioural Finance, Clarendon Press.

Shiller, R.J. (2002), "From Efficient Market Theory to Behavioural Finance", Cowels Foundation Discussion Paper No.1385.

Simon, Herbert A,(1955). "A Behavioral Model of Ra- tional Choice." *Quarterly Journal of Economics*, F, 69(1), pp. 99-118.

Trueman, Brett, (1994), "Analyst forecasts and herding behavior", *Review of Financial Studies,* 7(1), 97-124.

Thaler , R.,(1994), "Quasi Rational Economics, Russell Sage Foundation, New York

Tversky, A., and Kahneman,D., (1981), "The framing of decisions and the psychology of choice, *Science*,211,453-458

ZWIEBEL, J. (1995). Corporate Conservatism and Relative Compensation. *Journal of Political Economy*, 103, 1-25.

Chapter: IV

Feedback Behaviour, Market Upheavals and Extreme Value Theory

4.1. Introduction:

In heterogeneous structural model the essence of a speculative bubble is a sort of feedback mechanism, whereby rise in prices generate increased investor's enthusiasm and demand, shaping expectation for further rise. The high demand for the asset is a result of public memory of high past returns, and the optimism that those high returns would also generate in the future. This sort of feedback can amplify positive forces affecting the market, making the market to reach higher levels not explainable with fundamentals. Moreover, a bubble is not indefinitely sustainable. Prices cannot go up forever, and when price increases end, then increased demand for shares resulting from price increases also ends. Now, a downward feedback can replace the upward feedback. This kind of bubble theory requires that only past price changes produce an inconstancy to investor's judgments, not that they foolishly believe past increases must continue. The theory does not require that investors forecasting future price changes by some mechanical extrapolation rule, or those they are placing rulers to chart paper to forecast. It only requires that investor's observations of the past price changes alter the way they resolve the confusing array of conflicting information that they must all sift through in judging the market More the prices consistently converges to the prediction of a type of forecasting rule, more it appears as intuitively fit in formulating further opinion and lesser the perception for risk in using it (see equation nos. 09, 10 and 11 of chapter III). Better the prediction of a particular rule, more its evolutionary force in generating adaptive belief in its favour and higher its weight in determination of price. In this way, if fundamentalists dominate then, market converges to rational solution. On the contrary, if technical traders dominate then more and more traders with their more wealth becomes inclined toward using technical trading rules and its weightage in determination of further price increases. In this situation evolutionary forces in the market set in favour of price to price feedback and ultimately results into bubble formation either positive or negative. These phenomenons tend to be reflected in the presence of extreme increases and decreases in market prices constituting return distribution having fat tail which ultimately produces leptokurtic shape of the distribution. In this backdrop, we

will attempt to use Extreme Value Theory to identify and measure the presence of extreme movements in Indian stock market for the period under review. According to the prediction of heterogeneous market model under rationality, if we ignore the fundamental solution of the asset price, the other may be the bubble solution. Bubbles are in effect collection of infinite number of bounded rationality models which may help to explain non random movement of asset price and its impact on correlated errors on long memory properties of the market (Sims 1980;Lillo and Farmer, 2004;Alfarano and Lux,2005;Farmer et.al.2006, Farmer and Geanakoplos,2008).

Though extreme value theory is widely used in climatology and hydrology [de Hann1990,] currently financial economists interested in banking, insurance [Mcneil 1997, Embrechts and Klupperbag, Mikosch, 1997], stock and exchange markets that are exposed to catastrophic loss are using extensively this tool to estimate and manage tail related risk. Earlier studies of Mandelbrot [1963] and Fama [1965] based on commodity and stock markets revealed that the logarithmic returns are far from normal and suggested that they might be drawn from Levy distribution[8]. Later Engle [1982] proposed an alternative autoregressive model, dubbed ARCH , that could both exhibit the predictability in volatility while retaining the zero mean for the returns reflecting the absence of arbitrage opportunities. The studies by Lillo et.al.[2005], Lillo and Farmer [2004], Farmer et.al.[2004] also attest the hypothesis that probability of extreme movements is more frequent relative to if the distributions were normal. Hence, fat tails and temporal dependence of second moment leading to "clustering of volatility" particularly to be analyzed in detail by those who are not exclusively interested on minimizing a quadratic loss around the mean to the neglect of possibility and consequences of extreme events occurring. Some commendable research showing relevance of EVT in risk management based on experiences of different markets around the world are:the studies of Gencay et.al.(2003),Danielson and Morimoto(2003),LeBaron and Samanta (2004), Tolikas and Barron (2005), Gettingby et.al.(2006) etc. Available information suggests that, till date, very few

[8] In probability theory and statistics, the Levy distribution, named after Paul Lévy, is a continuous probability distribution for a non-negative random variable. Paul Pierre Lévy (15 September 1886 – 15 December 1971) was a French mathematician who was active especially in probability theory, introducing martingale and Lévy flight.

studies using Extreme Value Theory are available on Indian experiences. Most of the remarkable studies carried on Indian context were targeted towards estimation and management of extreme losses based on EVT (Karmakar,2013; Bhattacharyya and Ritolia, 2008 ;Sarma ,2002). But no such studies have been carried so far to offer behavioural interpretations of extreme losses and gains in Indian context. Hence, findings of the present thesis may add to our knowledge about the behavior of this emerging market that enjoys tremendous focus of foreign portfolio investors.

4.2. Data and its properties:

The study is based on daily return data of Indian stock market for a period ranging from 1.7.1997 to 31.08.2013 We considered BSE SENSEX that consists of 30 most popular shares and account for nearly forty percent of market capitalization. Inadequate data may pose some problem as only few points may qualify for extreme observations thus any meaningful study on long memory may not be possible. Altogether our data series consists of 3995 observations and covers a period more than 12 years that may be considered suitable to study the behavior of the Indian market.We analyze the continuously compounded rates of return:

$r_t = \ln\left(S_t / S_{t-1}\right)$, where S_t denotes the stock index in day t.

4.3. Exploratory Statistical Analysis:

The Table 4.1 summarizes the results on distributional pattern of return in Indian context for the total period under study.Espesially we will emphasise on the form of the distribution of price changes since it provides descriptive information concerning the nature of the process generating price changes

Table :4.1
Summary Statistics of Indian Capital market(daily log return1.7.1997 to 30.8.2013)

Statistics	values
Mean	0.00036
Median	0.00099
Minimum	-0.11
Maximum	0.15
Standard deviation	0.016
C.V.	45.18
Skewness	-0.09
Ex. kurtosis	5.53
Standard Error of skewness	0.039
Standard error of kurtosis	0.077
Jarque bera test	test statistic: 5107.4901 p-Value: 0.0000

The single strongest feature that emerges out of this preliminary analysis is the non normality of return distribution. The series is clearly leptokurtic indicating presence of fat tail in empirical distribution. The above results tend to indicate towards the presence of a distribution which is more peaked in the centre with longer tails than normal distribution. If the tails of the empirical frequency distribution is longer than those of the normal distribution, the slopes of extreme tail areas of normal probability graphs should be lower than those in the central parts of the graphs. The graph in general take the shape of an elongated 'S' with the curvature at the top and the bottom varying directly with excess relative frequency in the tails of empirical

distribution. This tendency for the extreme tails to show lower slopes than the main portion of the distribution will be accentuated by the fact that the central bell of empirical frequency distribution are higher than those of normal distribution. In this situation central portion of the normal probability graph should be steeper than the one which would be in the case if underlying distribution was strictly normtal.The finding are thus in contrary to the proposition of ongoing paradigm where normality of return distribution is widely accepted underlying phenomenon of market behaviour and which in turn confirms the notion of random movement in speculative asset prices. In an efficient market setting, however, leptokurtosis of returns could result only from similar leptokurtosis in the news arrival process and is therefore, explained by the statistical distribution of the news. According to the existing paradigm in market equilibrium; volatility should be caused by new information while it is difficult to measure new information. As the arrival of new information cannot be predicted successive price changes ought to be random. Information arrives in the market infrequently and thus large movements in prices will be rare. Ordinarily, price will move within a narrow band due to investor's liquidity needs or portfolio rebalancing consideration. However many recent studies based on both long and short time intervals suggest that the correlation between volatility and news is weak [Cutler 1989, R.Engle and J.Rangel 2005, R.F.Engle et.al 2006].

Admittedly above analysis is a weak measure of departures from Gaussian statistics and we will look for a somewhat sharper characterization of empirical distribution that has emerged from recent applied literature.

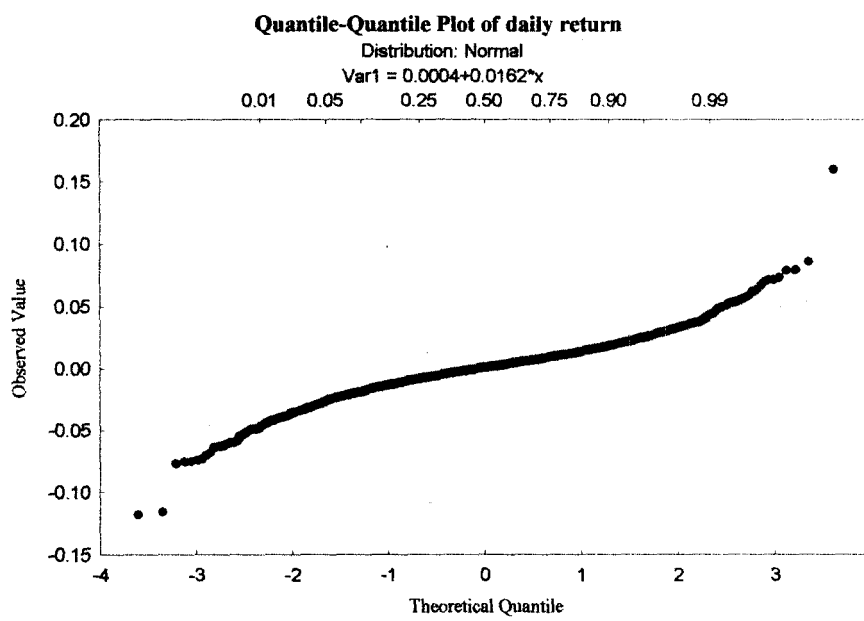
A more sensitive tool for examining deviations from normality is Q-Q graph. The QQ-plot against the Normal distribution is a widely used technique to measure heavy – tailed ness of a series. It examines visually the hypothesis that the returns come from Normal distributions, i.e. from a distribution with medium sized tail. The quantiles of the empirical distribution function on the X axis are plotted against the quantiles of distribution function on the Y-axis. The plot is

$$\left\{ X_{k,n,}\, F^{-1}\left(\frac{n-k+1}{n+1}\right) \quad k = 1 \ldots n \right\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq. No(01)}$$

where, $X_1, X_2 \ldots\ldots X_n$ be a succession of random variables that are independent and identically distributed(iid), and $Xn,n < \ldots\ldots < X1$,n the order statistics,Fn being the empirical distribution. Note that $Fn\ (Xk\ ,n) = (n-k+1)/n$ and F is the estimated parametric distribution of the data.

If the parametric model fits the data well, this graph must have a linear form. Thus, the graph helps to compare various estimated models and choose the best. The more linear the Q-Q plots, the more appropriate the model in terms of goodness of fit. Also, if the original distribution of the data is more or less known, the Q-Q plots can help to detect outliers; (Embrechts, Kluppelberg, and Mikosch ,1997). Finally, this tool makes it possible to assess how well the selected model fits the tail of the empirical distribution. For example, if the series is approximated by a normal distribution and if the empirical data are fat-tailed, the graph will show a curve on the top at the right end or to the bottom at the left end.

Figure: 4.1



A concave departure from the ideal shape as in the case of India [See Figure-4.1] indicates a heavier tailed distribution. Central part of the distribution (Fig-4.1) aligns well with our expectations of normal distribution; however outside this area the curve in the tail indicates departure from normality i.e. a stronger concentration around mean, more probability mass in the tails of the distribution and

thinner shoulders. Specifically, we will try to identify and measure these extreme observations in Indian market which ultimately vitiates the return distribution from normality , that is,departs from the traditional "Mean - Variance" framework in expectation formation.

4.4. Extreme Value Theory [EVT][9].

Extreme Value Theory considers extreme events, provides a classification of continuous distributions according to the behavior of the tail region or their extreme realizations. The theory distinguishes three limiting stable distributions for the maximum values of a random variable, called Generalized Extreme Value Distributions [GEV], and the three associated Generalized Pareto Distributions [GPD] which are the limiting distributions for the tail region. The central limit theorem suggests that the limiting distribution of the sample mean is normally distributed. Whereas EVT proposes that the limiting distribution of sample maximum is an extreme value distribution and for a wide class of severity distribution which exceeds high enough threshold the GPD holds true [Balkema & de Haan theorem 1974,Pickands 1975].

4.4.1. GEV: Limiting Distributions for Extrema:

Let us consider a stationary sequence of i.i.d. variables[10] $\{x_i\}_{i=1}^{N}$ with a common distribution function F(x). By dividing the entire data-set into L non-overlapping sub-samples, and taking the maximum M_j from every sub-sample, we will end up with a subset of maxima $\{M_j\}_{j=1}^{L}$ (the so-called block maxima). It turns out that the distribution of maxima converges to one of the three distributions known as the extreme value distributions as suggested by Fischer and

[9] See Alfarano, S. and Lux,T. (2010) Extreme Value Theory as a Theoretical Background for Power Law Behavior. Kiel Institute for the World Economy, Working Paper No. 1648, September 2010.

[10] The same limiting distribution is obtained if the i.i.d. hypothesis is relaxed.Bermen (1963) shows the same result stand if the variables are correlated and if the series of squared correlation coefficients is finite.Assumption of independence is less important for extreme values than it would seem at first sight (Longin 2005, Mc.Neil and Frey 1999)

Triplett[1928].Acording to their suggestion, let X_n be a sequence of independent and identically distributed random variables and let $M_n = \max(X_1, X_2, X_3, \ldots\ldots\ldots X_n)$ be the maximum of the first n terms. If there exists constants an > 0 and bn and some non-degenerate distribution function H such that

$$\frac{M(L) - b_L}{a_L} \xrightarrow{d} H$$

where the subscript'd' indicates convergence in distribution, then H belongs to one of the following extreme value distributions:

Frechet : $G_{1,\alpha}(x) = \begin{cases} 0 & x < 0 \\ \exp\left[-x^{-\alpha}\right] & x \geq 0 \end{cases}$ .....Type –I.....Eq.No.(02)

Weibull: $G_{2,\alpha(x)} = \begin{cases} \exp\left[-x^{-\alpha}\right] & x \leq 0 \\ 1 & , x > 0 \end{cases}$ .....Type – II.....Eq.No.(03)

Gumbell: $G_3(x) = \exp\left[-e^{-x}\right]$, $x \in \Re$ ....Type – III.....Eq.No.(04)

where α is the shape parameter.

Hence, distributions are categorized into three groups: (i) heavy-tailed distributions, whose extremes follow the first type of law:Extreme positive or negative returns resulting out of strong increase or decrease of prices on account of price to price channel or feedback loop may be characterized under this category[11].. (ii) short-tailed distributions with finite end-point, whose extremes follow the Weibull's type; and (iii) medium tailed distributions, whose extremes are governed by the distributions of the type III above. In case (i) and (ii) we have a one-parameter family of distributions, parameterized by the shape coefficient α. Representative members of the three groups are respectively: the Student-t, the uniform and the Normal . distribution The Von Mises [1936] representation of the GEV provides a unified formula for the previous three limiting distributions (I), (II) and (III):

[11] Thus it captures class to mass theory, representativeness heuristics etc.

$$G_\gamma = \exp[-(1+\gamma x)^{-\frac{1}{\gamma}}] \quad \text{.....Eq. No.(5)}$$

where, positive γ represents the Frechet distribution (Frechet 1927), negative γ corresponds to the Weibull type (Weibull 1939), and the limit case γ→ 0 suggests Gumbel distribution (Gumbel 1958). The shape parameters of the two representations are related to each other by the formula $\alpha = \frac{1}{\gamma}$ for the distribution Type-I, and α = -$\frac{1}{\gamma}$ for the type (II).Von Mises[1936] approach turns out to be very useful in the sense it nests all these types of limiting behavior in a unified framework through estimation of γ ,and allow to infer about the characteristics of limit laws.

4.4.2.GPD: Limiting Distributions for the Tail:

Investors, policy makers most presumably are concerned about any loss or gain that exceeds a predetermined threshold level often referred as attachment point. Let us suppose that $X_1, X_2 ....., X_n$ represent the ground-up losses or gains over a given period. Again let u be the predetermined threshold and Y = [X − u|X ≥ u] be the excess of X over u given that the ground-up loss exceeds the threshold. The risk managers will be interested in the distribution of the exceedances; that is, in the conditional distribution of Y = X − u given that X exceeds the threshold (u).

Let F denote the distribution of the random variable X,

$$F(x) = \text{Prob}\ (X < x),$$

and let Fu denote the conditional distribution of the exceedance Y = X − u given that X exceeds the threshold

$$F_u(y) = \frac{F(y+u) - F(u)}{1 - F(u)} \quad \text{.....Eq.No.(06)}$$

The exceedances for a high enough threshold always converge in generalized Pareto distribution [Pickands 1975 and Balkema & de Haan 1974].

Hence, result of the GPD focuses on the tails of the distributions instead of maxima; the selected events , in this case, are those events that exceed a given threshold u. Using the so-called α parameterization the Generalized Pareto Distributions can be represented as:

$$W_{1,\alpha} = 1 - x^{-\alpha}, \qquad x \geq 1, \quad \text{.....Eq. No.(07)}$$

$$W_{2,\alpha} = 1 - (-x)^{\alpha}, \qquad -1 \leq x \leq 0, \quad \text{.....Eq. No.(08)}$$

$$W_3 = 1 - \exp(-x), \qquad x \geq 0, \quad \text{..... Eq. No.(09)}$$

All the three distributions assume the value zero outside the pertinent intervals. For the GPD a similar one-parameter representation exists as with the extreme value distributions, symbolically:

$$W_{\gamma} = 1 - (1 + \gamma x)^{-\frac{1}{\gamma}} \quad \text{.....Eq. No. (10)}$$

where for $\gamma > 0, \gamma < 0$ and $\gamma \rightarrow 0$ we recover the first, second and third group, respectively where γ is the shape parameter. The relations between α and γ are again $\alpha = 1/\gamma$ for the first type, and $\alpha = -1/\gamma$ for the second type. The GPD formalization is very flexible in describing the tail behavior, although it depends on one parameter only, index α, after accounting for location and scale parameter.

While in applying the above theorem the most difficult task is selection of an appropriate threshold. To point a threshold, we have to trade off between bias and variance. If we choose a low threshold the number of observations increase and that includes some events from the centre of the distribution and the estimation becomes biased. Similarly choosing too high a threshold will result in an inadequate fit. Therefore, a careful combination of several techniques such as QQ Plot, Mean Excess Function (MEF), and Hill Estimation in general, are considered in determination of the threshold.

4.4.3. Mean Excess Function:

Mean Excess Function may be defined as:

$$e(u) = E(X - u / X > u) \quad 0 \le u \le x_F \text{ .....Eq.No(11)}$$

where $X_{1:n}$ and $X_{n:n}$ are the 1st and n-th order statistics and $e_n(u)$ is the sample mean excess function defined by McNeil [1997] as:

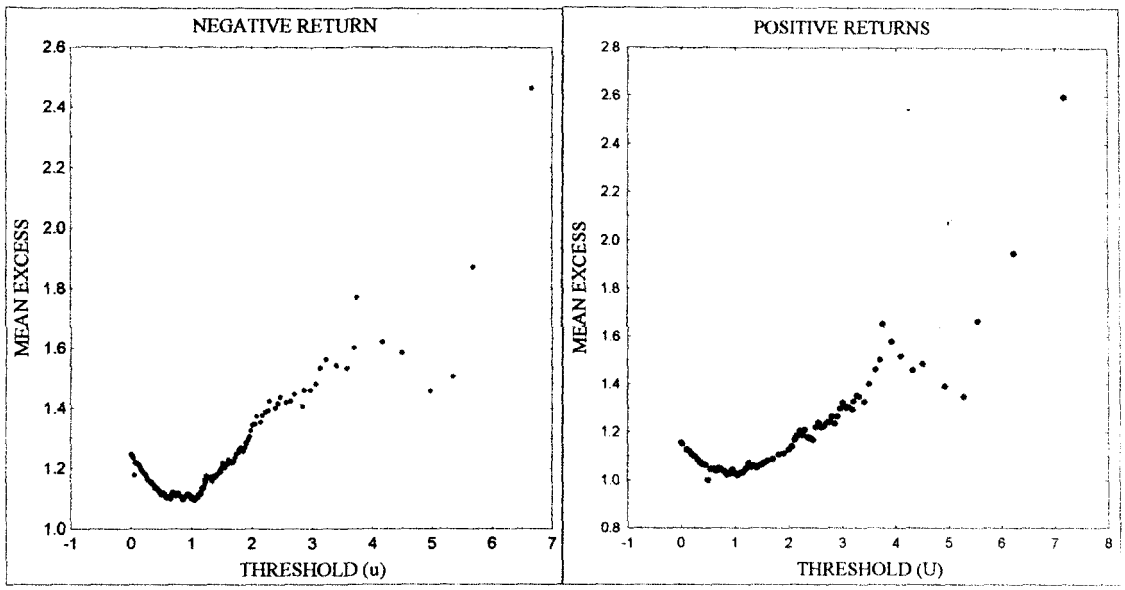
Thus Mean Excess Function is the sum of the excesses over the threshold u divided by the number of data points which exceed the threshold u.

$$e_n(u) = \frac{\sum_{i=1}^{n}(X_i - u)}{\sum_{i=1}^{n} 1_{\{X_i > u\}}} \text{ .....Eq.No.(12)}$$

The detailed interpretation of the mean excess plot is available in the studies of Embrechts et al. [1997],Beirlant et al, [2004]. If the points show an upward trend, then this is a sign of heavy tailed behavior [See Fig.3.2].Exponentially distributed data would result in an approximately horizontal line and data from a short tailed distribution would show a downward trend. In particular, if the empirical plot seems to follow a reasonably straight line with positive gradient above a certain value of u, then this is an indication that data follow a generalized Pareto distribution with positive shape parameter in the tail area above u. "S" shape of the curve suggests that tails of the density function have higher probabilities than with the normal distribution thus the distribution under the study has fat tails.

Since the mean excess function for the generalized Pareto distribution is a straight line with positive slope, we are looking for the threshold points from which the mean excess plot follows a straight line.

Figure – 4.2
(Mean Excess Return of Indian capital market)
(Period from 1.7.1997 to 31.08.2013)



Above mean excess plots (Fig.4.2) help us to get an insight regarding tail behavior of the series, nonetheless they fail to define objectively the threshold values, quantify density function and suggest distribution to which it belongs. The "sketchy" estimation offers an impression that threshold in Indian asset market lies at nearly 1.10 and 1 percentage for right and left tail, respectively, beyond which any observation may be treated as extreme that deserve attention of investors and policy makers. However we go beyond this "sketchy" estimation and apply some stringent test to the series under our study so that we can be sure that it belongs to long memory with high degree of confidence.

4.4.4. Hill Estimation:

Estimation of the index α is the central issue of our empirical research dealing with extreme events and we relied on nonparametric Hill Index (Hill 1975) to estimate tail behavior of market return. Hill index is the conditional maximum likelihood estimator for heavy-tailed distributions. If we assume that the data points

exceeding a given threshold u follow a Pareto distribution with index α, the distribution of realizations exceeding u reads (Alfarano and Lux 2010):

$$F(x \geq u) = 1 - \left(\frac{u}{x}\right)^{\alpha}; u \geq 0 \text{.....Eq.No.(13)}$$

Virtually there are two approaches for estimating "excess distribution", first, semi-parametric model based on the Hill estimator and another, fully parametric model based on the Generalized Pareto Distribution (GPD). We relied on Hill estimator for two reasons: (i) its simplicity over maximum likelihood method and (ii) ability of the model to define precisely the threshold point beyond which any observation may be treated as extreme.

For our estimation, at the first step, we obtain the order statistics $X_{(t)}$, $X_{(t-1)}$, ----------$X_{(1)}$ from our sample, where $X_t > X_{t-1} >$, ...$> X_1$.Then ,the following Hill index is estimated by :

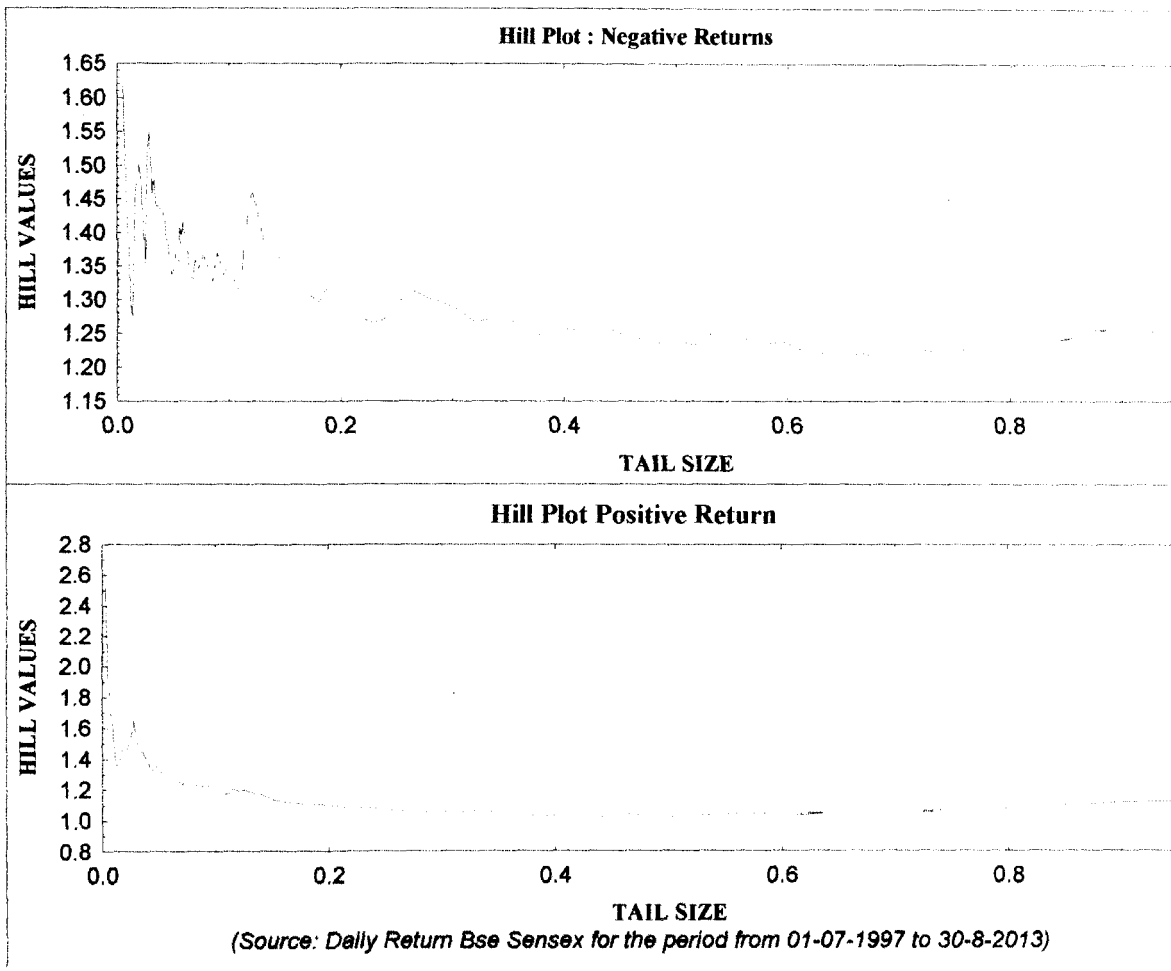
$$\hat{\gamma}_{k,n} = \left(\hat{\alpha}_{k,n}\right)^{-1} = \frac{1}{k}\sum_{i=1}^{k}[\ln x_{(n-i+1)} - \ln x_{(n-k)}] \text{.....Eq.No.(14)}$$

with x_i the order statistics of the series x, $x_{(N)} > x_{(N-1)} > .... > x_{(1)}$, i.e. $x_{(N)}$ is the maximum of x, $x_{(N-1)}$)is the second largest value etc. As it is assumed that above equation only applies to a fraction k/N of the largest values, we only consider the x_i above the threshold u, $x_{(N-k)} = u > x_{(N-k-1)}$, where k is the number of selected large realizations, from the entire sample of N observations. It has been shown that under some mild additional restrictions on the behavior of the underlying distribution function, $\hat{\gamma}_{k,N}$ is asymptotically Gaussian with mean γ (i.e. the inverse of the true index) and variance $\left(\gamma^2 k\right)^{-1}$.Where k is the number of upper order statistics included, N is the sample size , and $\alpha = 1/\gamma$ is the tail index. While the concept of Hill estimator is straight forward, the choice of k is not. The problem may be defined as

threshold selection problem. One has to decide which events from the complete set of data points, belong to the subset relevant for the estimation of α.

Taking the daily return values of 3995 observations starting from July 1997 to August 2013, Hill estimation of the shape parameter alpha (α) has been obtained using the above mentioned methodology and the Hill values are plotted as below: (Fig. 4.3)

Figure- 4.3
Hill Plot of return of Indian Capital Market Return
(Time period : 01.07.1997 to 31.08.2014)



(Source: Daily Return Bse Sensex for the period from 01-07-1997 to 30-8-2013)

It is evident that Hill Values of the Shape Parameter (α) is inversely related with the corresponding tail size based on different values of threshold (u). For this reason, it is not immediately obvious what the appropriate tail fraction would suggest the best estimator for the 'true' parameter. A possible practical approach for identification of threshold point could be an 'eyeball method', searching for a region in the Hill plot where the estimated values are approximately constant (Alfarano and Lux, 2010). However, the Hill's estimator is most effective when the underlying distribution is Pareto type or approximate to Pareto (Chin Wen Cheong et al.2008).Undeniably, this approach has all the drawbacks of a subjective graphical

data analysis. This estimation along with others can effectively help to trade off between bias and variance while estimating threshold value. Our findings suggest some intrinsic features of Indian capital market. We mention some unique feature of Indian market that may help investors to decide upon strategy to maximize gains and to minimize loss when market is essentially turbulent. One interesting feature is threshold level varies in our market. It is one percentage for left tail and nearly (1.10%) for positive return. Furthermore, forty two percentages of negative returns and nearly forty percent of positive return are found as extreme. Findings about threshold, the focal point of discussion of this section are in consonance with the results of so called sketchy estimation of Mean Excess Function. Altogether approximately forty two percent of total observation falls in the extreme region either positive or negative. Thus our finding in this chapter sharply contradicts the basic propositions of Gaussian distribution underlying the efficient market hypothesis.

Table: 4A. Frequency Distribution of Extreme Gains:

(Observations 1-849,Number of bins = 29, Mean = 2.14907, S.D. = 1.22695)

Interval	Mid point	Frequency	Relative frequency	Cumulative Frequency
< 1.3916	1.1016	214	25.21%	25.21%
1.3916 - 1.9715	1.6816	276	32.51%	57.71%
1.9715 - 2.5514	2.2615	155	18.26%	75.97%
2.5514 - 3.1313	2.8414	89	10.48%	86.45%
3.1313 - 3.7113	3.4213	52	6.12%	92.58%
3.7113 - 4.2912	4.0012	21	2.47%	95.05%
4.2912 - 4.8711	4.5811	9	1.06%	96.11%
4.8711 - 5.4510	5.1611	11	1.30%	97.41%
5.4510 - 6.0309	5.7410	9	1.06%	98.47%

6.0309 - 6.6109	6.3209	3	0.35%	98.82%
6.6109 - 7.1908	6.9008	2	0.24%	99.06%
7.1908 - 7.7707	7.4807	4	0.47%	99.53%
7.7707 - 8.3506	8.0606	2	0.24%	99.76%
8.3506 - 8.9305	8.6406	0	0.00%	99.76%
8.9305 - 9.5104	9.2205	1	0.12%	99.88%
9.5104 - 10.090	9.8004	0	0.00%	99.88%
10.090 - 10.670	10.380	0	0.00%	99.88%
10.670 - 11.250	10.960	0	0.00%	99.88%
11.250 - 11.830	11.540	0	0.00%	99.88%
11.830 - 12.410	12.120	0	0.00%	99.88%
12.410 - 12.990	12.700	0	0.00%	99.88%
12.990 - 13.570	13.280	0	0.00%	99.88%
13.570 - 14.150	13.860	0	0.00%	99.88%
14.150 - 14.730	14.440	0	0.00%	99.88%
14.730 - 15.310	15.020	0	0.00%	99.88%
15.310 - 15.890	15.600	0	0.00%	99.88%
15.890 - 16.469	16.179	0	0.00%	99.88%
16.469 - 17.049	16.759	0	0.00%	99.88%
>= 17.049	17.339	1	0.12%	100.00%

Table: 4B. Frequency distribution of Extreme Losses:

(Observations 1-849 Number of bins = 19, Mean = -2.18807, S.D. = 1.27396)

Interval	Midpoint	Frequency	Relative Frequency	Cumulative Frequency
< -9.6359	-9.8898	2	0.59%	0.59%
-9.6359 - -9.1283	-9.3821	0	0.00%	0.59%
-9.1283 - -8.6206	-8.8744	0	0.00%	0.59%
-8.6206 - -8.1129	-8.3667	0	0.00%	0.59%
-8.1129 - -7.6052	-7.8590	0	0.00%	0.59%
-7.6052 - -7.0975	-7.3514	0	0.00%	0.59%
-7.0975 - -6.5898	-6.8437	0	0.00%	0.59%
-6.5898 - -6.0822	-6.3360	4	1.18%	1.78%
-6.0822 - -5.5745	-5.8283	3	0.89%	2.66%
-5.5745 - -5.0668	-5.3206	3	0.89%	3.55%
-5.0668 - -4.5591	-4.8129	9	2.66%	6.21%
-4.5591 - -4.0514	-4.3053	5	1.48%	7.69%
-4.0514 - -3.5437	-3.7976	13	3.85%	11.54%
-3.5437 - -3.0361	-3.2899	20	5.92%	17.46%
-3.0361 - -2.5284	-2.7822	33	9.76%	27.22%
-2.5284 - -2.0207	-2.2745	54	15.98%	43.20%
-2.0207 - -1.5130	-1.7668	55	16.27%	59.47%
-1.5130 - -1.0053	-1.2592	136	40.24%	99.70%
>= -1.0053	-0.75147	1	0.30%	100.00%

Frequency distribution of extreme gains and losses are shown in Table 4A and 4B. Information available from the tables would help portfolio managers to assess the pattern of asset returns of Indian market at its extreme. For example nearly cent percent (99.76% app.) of positive extreme return fall below 8.3%. Beyond this, any large movement is virtually nonexistent. Majority of extreme returns (95% approx.) cluster up to four percentages approximately. While in the negative domain most of the extreme return clusters around 1.5% to 4.5%, approximately.

4.5. Conclusion:

Our analysis based on BSE SENSEX 30 as a proxy for the equity market indicates some serious departure from those obtained using the assumption of normal return distribution. The normal distribution gives us a fair idea of return distributions for every day events; alternatively EVT gives an impression about best or worst case of returns and the frequency thereof. Fat tail is not an exclusive syndrome of India instead it pervasively dominates worldwide financial markets. These extreme movements in share prices with leptokurtic distribution of return cannot be captured under the dictum of rational expectations. Rather it is a potential threat to the theory of equilibrium and a formidable challenge for investors interested in risk reduction. These findings however confirm the social and psychological dynamic forces predicted under heterogeneous market model with bounded rationality. The model predicts the price changes to be driven by a combination of exogenous random news and an evolutionary force generate endogenously in favour of either fundamental or technical trading rule. The presence of prolonged rise and fall in prices in Indian market confirms the influence of persisting evolutionary forces operating in the market in favour of using technical trading rules and it is increasing over time. These sort of evolutionary forces are explained in the heterogeneous model as an influence of various social and psychological attributes in decision making. A self fulfilling prophecy has therefore developed with this psychological bias in human decision in favour of evolutionary fitness in using technical rules ignoring the early dogma of rationality. Perceived profitability in using technical trading rules coupled with considerable undermining of risks conditional on subsequent movement in prices thus

makes the decision making context specific. Influences of socio psychological forces in decision making are thereby confirmed to be the factor behind in generating convergence in opinion, undermining of risk, limiting the arbitrage operation and bubble formations.

eferences:

farano, S. and Lux, T.: (2005). "A Noise Trader Model as a Generator of Apparent nancial Power Laws and Long Memory", *Macroeconomic Dynamics*. 11(S1),80-1

farano, S. and Lux,T. (2010) "Extreme Value Theory as a Theoretical Background r Power Law Behavior". *Kiel Institute for the World Economy*, Working Paper No. 48, September 2010.

attacharyya, M and Ritolia, G.(2008), "Conditional VAR using EVT - Towards a anned Margin Scheme." , *International Review of Financial Analysis,* 17, 382-395

lkema, A. A., and L. de Haan, (1974), "Residual lifetime at great age," *Annals of obability*, 2, 792–804

irlant, J., J. Teugels, Yu. Goegebeur, and J. Segers, (2004): "*Statistics of extremes: eory and applications,*" *Wiley*

rman, S.M., (1963). "Limiting theorems for the maximum term in stationary quences". *Annals of Mathematical Statistics*, 35, 502–516.

in Wen Cheong, Abu Hassan Shaari Mohd Nor and Zaidi Isa, (2008); "Modelling treme Financial Return of Malaysian Stock Exchange", *World Applied Sciences urnal* ,3 (2): 254-258,

tler, D. M., Poterba, J. M., and Summers, L. H. (1989) ,"What moves stock ices?" *The Journal of Portfolio Management* 15, (3), 4-12.

nielsson, J. and Y. Morimoto: (2003): "Forecasting extreme financial risk: a critical alysis of practical methods for the Japanese market," *Monetary and Economic udies*, 18,(2), 25-48

Haan, L. (1990), "Fighting the ARCH-enemy with mathematics",*Statistica erlandica*, 44, 45–68,

Embrechts, P., Klüppelberg, C. & Mikosch, T. (1997), "Modeling Extremal Events for Insurance and Finance", *New York: Springer.*

Engle R.F., (1982); "Auto Regressive Conditional Heteroskedasticity with estimates of variance of United Kingdom Inflation" *Economerica*, 50 (4), 987- 1007.

Engle, R. and Rangel,:(2005) "The spline garch model for unconditioanl volatlity and its global macroeconomic causes". *Technical report, NYU and UCSD,*

Engle, R.F.Gysels, and B. Sohn.: (2006) "On the economic sources of stock market volatility. Technical report", *New York University and University of North Carolina at Chapel Hill.*

Fama, E.: (1965), "The behavior of stock-market prices." *The Journal of Business*, 38(1):34-105,

Fisher, R. A. and L. H. C. Tippett, (1928), "Limiting forms of the frequency distribution of the largest or smallest member of a sample," *Proceedings of Cambridge Philosophical Society*, 24,180–190

F. Lillo and J. D. Farmer (2004)"The long memory of the efficient market." *Studies in Nonlinear Dynamics & Econometrics,* 8(3), 1-33.

Farmer,J.D.Gerig,A., Lillo, F. and Mike, S. (2006),: "Market efficiency and the long-memory of supply and demand: Is price impact variable and permanent or Fixed and temporary?" *Quantitative Finance*, 6(2), 107-112

Farmer, J. D., and Geanakoplos, J. (2008), Power laws in economics and elsewhere. Tech. rep., Santa Fe Institute,New Maxico. source: *http://tuvalu.santafe.edu/~jdf/papers/powerlaw3.pdf* (last accessed on 8th April,2014)

Frechet, M. (1927): Sur la loi de probabilit de l'ecart maximum, *Ann. Soc. Polon. Math.* (Cracovie), 6, 93-116.

Gettinby, G., C. D. Sinclair, D. M. Power, and R. A. Brown, (2006), "An analysis of the distribution of extremes in indices of share returns in the US, UK and Japan from 1963 to 2000," *International Journal of Finance & Economics*, 11:2, 97-113

Gençay, R., F. Selçuk, and A. Ulugülyagci, (2003), "High volatility, thick tails and extreme value theory in value-at-risk estimation," *Insurance Mathematics and Economics*, 33,337-356

Gumbel, E.J. (1958), "Statistics of Extremes", *Columbia University Press*, New York.

Hill, B.M., 1975. "A simple general approach to inference about the tail of a distribution", *Annals of Statistics*. 3: 1163-1173.

Karmakar. M (2013), "Estimation of tail – related risk measures in the Indian stock market: An extreme value approach" , *Review of Financial Economics*,22, 79-85.

Lillio, Fabrizio, Mike S , Farmer D.J.; (2005) , " Theory of Long Memory in Supply and Demand", *Physical Review E,Statistical*, Non Linear and Soft Matter Physics, American Physical Society. 71(6), 122-11

Lillo, F., and Farmer, J. D. (2004). "The long memory of the efficient market." *Studies in Nonlinear Dynamics & Econometrics* , 8(3) ,1-33

LeBaron, B., and R. Samanta, (2004), "Extreme value theory and fat tails in equity markets," *working papers, Brandeis University ,source::people.brandeis.edu/~blebaron/wps/tails.pdf.(last accessed on 8th April,2014)*

Longin , F.(2005) ; "The choice of the distribution of asset returns: How extreme value theory can help?". *Journal of Banking & Finance*, Elsevier, 29, 1017-1035.

Mandelbrot, B (1963); "The variation of certain speculative prices". *The Journal of Business of the University of Chicago*, 36, 394-419.

McNeil, A. J. (1997) "Estimating the tails of loss severity distributions using extreme value theory, *ASTIN Bulletin*, 27, 1117–137.

Mc Neil and Frey (1999), "Estimation of Tail- Related Risk Measures of Heteroscedastic Financial Time Series : An Extreme Value Approach", *Manuscript, Federal Institute of Technology.*

Pickands, J., (1975); "Statistical inference using extreme order statistics," *Annals of Statistics,* 3, 119–131

Sharma .M: "Extreme Value Theory and Financial Risk Management"; Indira Gandhi Institute of Development Research, Goregaon, Mumbai, March 2002, (http://ravi.lums.edu.pk/aesm/papers/extreme%20value%20theory%20and%20Financial%20risk%20management.pdf).

Sims, C. A.: (1980), "Macroeconomics and reality." *Econometrica* 48, 1, 1-48.

Tolikas, K., and R. A. Brown, (2005), "The distribution of the extreme daily returns in the Athens Stock Exchange," *working paper, University of Dundee*.SSRN (Last visited on 8th April,2014).

Von Mises, R. (1936). "La distribution de la plus grande de n valeurs". Reprinted in Selected Papers, Volume II, *American Mathematical Society*, Providence, R.I., 1954, 271-294.

Weibull, W., (1939), "A statistical theory of the strength of material". *Ingeniors Vetenskaps Akademiens,* Stockholm 151.

Chapter V:
Volatility Clustering:

Market Upheavals and Switching Behaviour: A GARCH Approach

5.1. Introduction:

In our study to offer behavioural explanations to Indian capital market upheavals, we have applied heterogeneous structural model. Traders are divided in the market in two heterogeneous groups on the basis of their respective expectation formulation models viz. Fundamental and technical traders. This approach departs from rationality driven behaviour in expectation formation, model decision makers as bounded rational. Prices in this model are driven by exogenous random news about fundamentals and evolutionary forces underlying the trading process itself. An evolutionary force is generated out of their interactions and generates adaptive belief favouring fitness of either of these two heterogeneous forecasting techniques. This evolutionary force switches itself between the groups conditioning upon actual price changes from fundamentals. (See equations nos.06, 07, 08, 09, 10, and 11 of chapter III).When adaptive belief is formed in favour of fundamentals, then the model expect rational solution. Otherwise when evolutionary belief is formed in favour of technical traders, then a self fulfilling prophecy is set into motion, arbitrage operation gets restricted and bubble grows. At this juncture, the model introduces socio psychological underpinnings of human behaviour as a source of generating evolutionary forces which tips balances between either fundamental or bubble solution. In such a way the model predicts changes in prices to switch itself irregularly between phases of low volatilities where price changes are small, and phases of high volatilities, where small price changes due to random news are reinforced and may become large due to trend following trading rules. Thereby, volatility clustering becomes a model endogenous phenomenon. Taking cue from this, we will be interested to study the presence of volatility clustering in Indian market. The evidence of which will reflect more structurally the influences of socio psychological underpinning of human interactions generating evolutionary forces resorting either to fundamental or bubble solution.

The phenomenon of clustering of volatility was observed and reported first by Mandelbrot in 1963 in commodity prices . Since the pioneering paper by Engle(1982) and Bollerslev (1986) on autoregressive conditional heteroskedastik (ARCH) models and their generalization to GARCH models , volatility clustering has

been shown to be present in a wide variety of financial markets including stocks , exchange rates and interest rate securities markets (see Pagan A 1996, Broke 1997).Recently, a large number of heterogeneous agent models generating volatility clustering have been introduced in a wide range of literature and the trend is increasing (see Le Baron, Arthur and Palmer 1999,Lux and Marchesi 1999,2000,Kirman and Teyssiere 2002,De Grauwe and Grimaldi 2004,Gounersdorfer and Hommes 2007, Le Baron 2004, Amilon 2008,Corsi 2009).An interesting feature of these models is that , due to heterogeneity in expectations and switching between strategies , the deterministic skeleton that is the model with exogenous shocks shut off to zero, is a nonlinear dynamical system that exhibits periodic and even chaotic fluctuations in asset prices and returns. Thus, depending upon the initial state, different types of long run dynamical behaviour can occur. Particularly this group of models, furthermore, exhibit, coexistence of stable steady state and a stable limit cycle. Hence market prices , depending on initial condition, will either settle down to the locally stable fundamental steady state price, or converge to a stable cycle fluctuating in a regular pattern around the fundamental steady state. In the presence of dynamic noise, the market will then switch irregularly between close to 'fundamental steady state fluctuations' with small price changes, and 'periodic fluctuations' triggered by technical trading with large price changes. An important critique from 'rational expectation finance' upon heterogeneous agent models using simple habitual rule of thumb in forecasting is that 'irrational' traders will not survive in the market. This point has been extensively discussed by several scholars (Broke and Hommes 1997 and 1998).These papers emphasized more on the fact that, in an evolutionary framework, technical analysts are not irrational, but they are in fact bounded rational. In periods when prices deviate from rationality driven fundamental solution, chartists make better forecasts and earn higher profits. Basically these models are based on simple formalization of general ideas from behavioural finance, where markets are populated by different agents using trading strategies based on psychological heuristics. Moreover, the traditional benchmark rational expectation model is nested as a special case within this heterogeneous framework and provides a link between the traditional framework and the new behavioural approach in finance.

5.2. Volatility clustering: The Model[12]:

Let, R_t be the rate of return from a particular index from period t-1 to t.Also let ψ_{t-1} be the information set containing the realized values of all relevant variables up to the time t-1.Since investors know the information in ψ_{t-1} when they make their investment decision at time t-1, the relevant expected return and volatility to the investors are the conditional expected value of R_t, given ψ_{t-1} and conditional variance of R_t given ψ_{t-1} .These are denoted by m_t and h_t respectively. That is, $m_t = E(R_t / \psi_{t-1})$ and $h_t = \text{var}\, E(R_t / \psi_{t-1})$ .Given these definitions, the return series R_t can be defined as:

$$R_t = E(R_t / \psi_{t-1}) + \varepsilon_t = m_t + \varepsilon_t \text{.....Eq. No (01)}$$

where, the unexpected return at time t is $\varepsilon_t = R_t - m_t$, ε_t is treated as a collective measure of news at time t. A positive ε_t (an unexpected increase in price) suggests the arrival of good news while a negative ε_t (an unexpected decrease in price) suggests the arrival of bad news. Further, a large value of $|\varepsilon_t|$ implies that the news is 'significant' or big in the sense that it produces a large unexpected change in price.

Now the conditional variance h_t can be modeled as a function of the lagged $\varepsilon's$ (Engle ,1982)where, the predictive volatility is assumed to be dependent on past news(Engel 1982). The most generalized model the author, developed is the qth order *ARCH* model, below:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \text{.....} + \alpha_q \varepsilon_{t-q}^2 \text{.....Eq. No. (02)}$$

where , $\varpi > 0$, $\alpha_1, \alpha_2 \ldots\ldots\ldots \alpha_q \geq 0$ and $\varepsilon_t / \psi_{t-1} \sim N(0, h_t)$. The effect of a return shock i periods ago $(i \leq q)$ on current volatility is governed by the

[12] See Karmakar. M (2005), "Modeling Conditional Volatility of Indian Stock Markets", *VIKALPA* • Vol. 30 • No. 3 • July– September.

parameter α_i. Normally, we would expect that $\alpha_i < \alpha_j$ for $i > j$. That is , the older the news , the less effect it has on current volatility. In a $ARCH(q)$ model, old news which arrived at the market more than q periods ago has no effect at all on current volatility. Alternatively, if a major market movement occurred yesterday, the day before or up to q days ago; the effect will be to increase today's conditional variance.

The $ARCH(q)$ model can be generalized the to the $GARCH(p,q)$ model as (see Bollerslev ,1986) :

$$h_t = \omega + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots\ldots + \alpha_q\varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \ldots + \beta_p h_{t-p}, \ldots\ldots \text{Eq.No.(03)}$$

where $\omega > o, \alpha_1, \alpha_2 \ldots\ldots\ldots\ldots \alpha_q \geq 0, \beta_1, \beta_2, \ldots\ldots\ldots\ldots \beta_q \geq 0$.

This $GARCH(p,q)$ process is stationary when

$$(\alpha_1 + \alpha_2 + \ldots\ldots + \alpha_q) + (\beta_1 + \beta_2 + \ldots\ldots\ldots\ldots + \beta_q) < 1.$$

Over the times, there have been numerous refinements of the approach in modeling conditional volatility to better capture the volatility clustering applying a variety of time periods and data around the globe. Of these models, GARCH (1,1) is considered by most studies to be an excellent model for estimating conditional volatilities for a wide range of financial data Gujrati and Bollerslev et. al 1992). This simplest but often very useful $GARCH(1,1)$ process is given by:

$$h_t = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \ldots\ldots\ldots\ldots \text{Eq.No.(04)}$$

where $\omega > 0, \alpha_1 \geq 0, \beta_1 \geq 0$. The stationary condition of $GARCH$ (1,1) is $\alpha_1 + \beta_1 < 1$.

In the $GARCH$ (1,1) model,the effect of a return shock on current volatility declines geometrically over time. As referred earlier , the $GARCH$ (1,1) model is found to be an excellent model for a wide range of financial data (Bollerslev et. al. 1992).

The sizes of the parameters α_1 and β_1 are the crucial determinant factors of short run dynamics of the resulting volatility time series. Large $GARCH$ lag coefficient β_1 indicate that shocks to conditional variance takes a long time to die out,

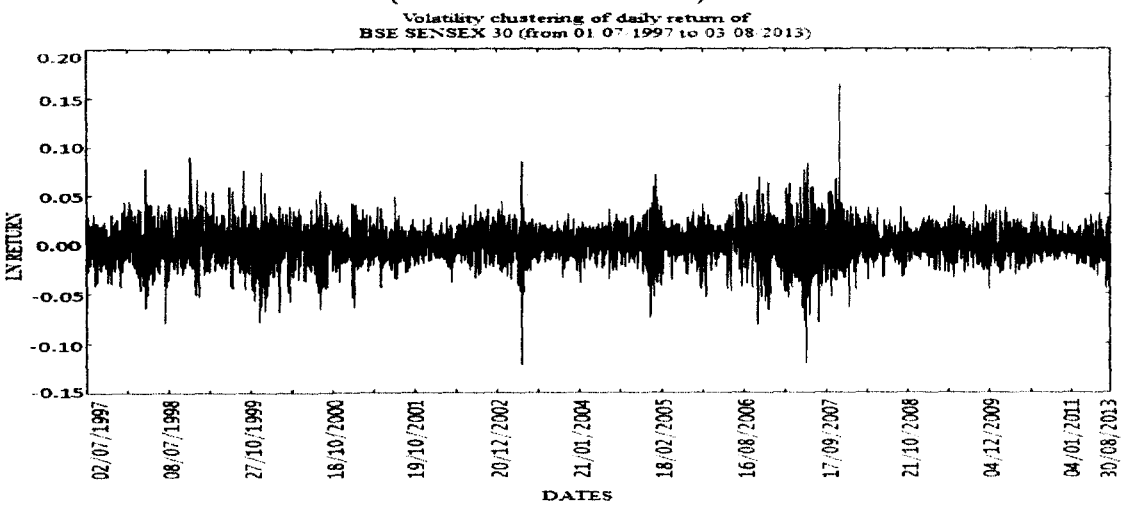
so volatility is 'persistent'.Large $GARCH$ error coefficient α_1 means that volatility react quite intensely to market movements and so if α_1 is relatively high and β_1 is relatively low , then volatilities tend to be more 'spiky'.In financial markets , it is common to estimate lag (or, persistence')coefficients based on daily observations in excess of 0.8 and error (or reaction) coefficient not more than 0.2.If $\alpha_1 + \beta_1$ is close to unity , then a 'shock 'at time t will persists for many future periods. A high value of $\alpha_1 + \beta_1$ therefore implies a 'long memory'. For $\alpha_1 + \beta_1 = 1$, we have what is known as an integrated $GARCH$ process,. For integrated $GARCH$, the conditional variance is non stationary and the unconditional variance is unbounded.

5.3. Identification of conditional Volatility:

In this section we will try to fit appropriate GARCH model to find the presence, if any, of the time varying volatilities in Indian equity for the period ranging from 1.7.1997 to 30.8.2013

Figure 5.1 below is the graphical representation of daily return series of BSE SENSEX 30.

Figure: 5.1
(Serial correlation test)



From the above figures (figure 5.1) we can identify visually that, there are stretches of periods where the volatility is relatively low and in other periods the volatility is relatively high. This suggests an apparent volatility clustering in daily

return series of BSE Sensex 30 in some periods. Statistically we would find a strong autocorrelation in squared returns (see table 5.1).

Initially here we are interested to compute the first order auto correlation coefficient in daily data on squared returns. To test joint hypothesis that all the serial correlations of the returns for lag one through k are simultaneously equal to zero, we will apply the modified Box Pierce statistics (Q), (Ljung and Box 1978).Mathematically the statistic is given as $Q = n(n+2)\sum r^2/(n-k)$, where n is the sample size and k the lag length (Ljung and Box 1978).In the large sample, the Q statistic is approximately distributed as the chi- square distribution with k degrees of freedom .In an application , if the computed Q/Q^2 exceeds the critical Q/Q^2 value from the chi-square table at the chosen level of significance, one can reject the null hypothesis that all r_k are zero; at least some of them must be non zero.

Table: 5.1
(Unit Root Test)

Statistic	Value
$Q(24)$	88.088 (P=0.0000)
$Q^2(24)$	817.735 (P=0.0000)

The values of $Q/Q^2(24)$ test statistic (Table 5.1) reject the joint hypothesis that all the serial correlations of squared returns for lags 1 through k are simultaneously equal to zero and thereby suggest the presence of serial autocorrelation in the return series under this study.

Table: 5.2

(Unit Root Test)

Series	Augmented Dickey-Fuller (t-Statistic)		Phillips-Perron (Adj. t-Statistic)		Dickey-Fuller (ERS) (t-Statistic)	
	Constant	Constant with linear trend	Constant	Constant with linear trend	Constant	Constant with linear trend
LN (At log Level)	-58.87618^	-58.87146^	-58.80847^	-58.80283^	-58.86011^	-58.58013^

(Note: critical values at 1% level are -3.431802 (constant) and -3.960336 (constant and linear trend) for Augmented Dickey-Fuller (t-Statistic) and Phillips-Perron (Adj. t-Statistic); critical values at 1% level are -2.565541 (constant) and -3.480000 (constant and linear trend) for Dickey-Fuller (ERS) (t-Statistic); ^ indicates rejection of null hypothesis at 1% level .)

Table:5.3

(Unit Root Test)

Exogenous: Constant
Lag length: 0 (Spectral GLS-detrended AR based on SIC, MAXLAG=30)
Sample: 7/01/1997 8/30/2013
Included observations: 3996

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-1987.45	-31.5214	0.01586	0.01322
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001)

Table: 5.4

(Unit Root Test)

Exogenous: Constant, Linear Trend
Lag length: 0 (Spectral GLS-detrended AR based on SIC, MAXLAG=30)
Sample: 7/01/1997 8/30/2013
Included observations: 3996

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-1986.05	-31.5112	0.01587	0.04695
Asymptotic critical values*:	1%	-23.8000	-3.42000	0.14300	4.03000
	5%	-17.3000	-2.91000	0.16800	5.48000
	10%	-14.2000	-2.62000	0.18500	6.67000

*Ng-Perron (2001)

We have employed ADF test (Said and Dicky ,1984) ,DF –GLS, Phillip – Peron Test(Phillips and Perron, 1988) and Ng Paren Test (Ng, and Perron, 2001) to estimate the order of integration of the return series under the study. The optimal lag order is searched and used in the Unit Root Test on the basis of either by AIC (Akaike, 1974), and SIC(Schwarz ,1978),.The results obtained confirmed that the series is I(0) at log level and hence can be used to measure volatility through GARCH in VAR framework.

5.4. Measuring the GARCH (1, 1) coefficients:

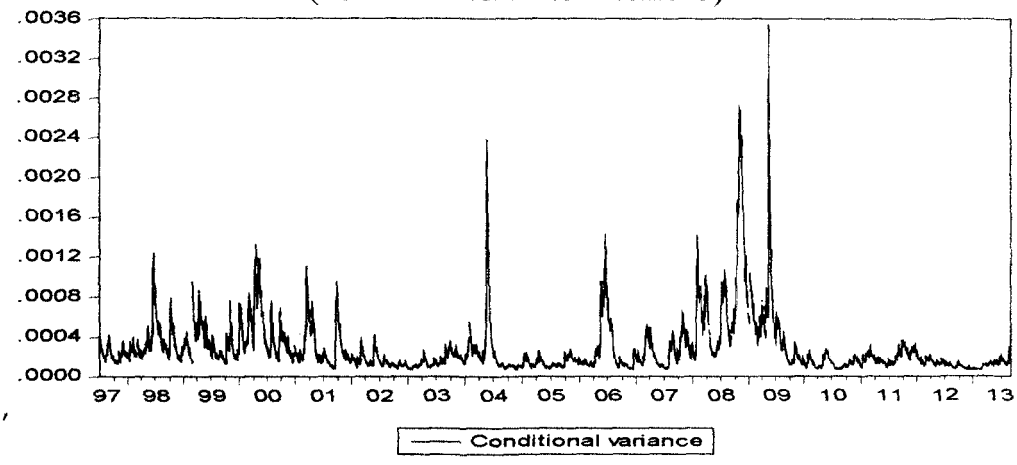
Once the presence of volatility clustering is evident in the series under the study, now, our focus is on determining the fitted GARCH model applicable to the return series. We, at the first step, run the $GARCH(1,1)$ on the daily data of return series of the period under review.The results so obtained are summarized in Table 5.5. We have estimated the parameters, viz. $\omega, \alpha_1 and \beta_1$, for the GARCH (1, 1) model and computed the series $\hat{h}_t$ for the BSE Sensex and plotted the series in figure 5.2.We have used the software, Microfit 5.0.

Table:5.5
Results on GARCH (1,1)

Dependent Variable: RETURN				
Method: ML - ARCH (Marquardt) - Normal distribution				
Sample (adjusted): 01/07/1997 30/08/2013				
Included observations: 3995				
Convergence achieved after 13 iterations				
Bollerslev-Wooldridge robust standard errors & covariance				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.001044	0.000215	4650.485	0.0000
AR(1)	0.023738	0.004903	4.841504	0.0000
	Variance Equation			
C	3.98E-06	1.00E-06	3.974784	0.0001
RESID(-1)^2	0.102345	0.014678	6.972796	0.0000
GARCH(-1)	0.886761	0.014787	59.96714	0.0000
R-squared	0.000901	Mean dependent var		1.000504
Adjusted R-squared	0.000651	S.D. dependent var		0.016577
S.E. of regression	0.016571	Akaike info criterion		-5.630946
Sum squared resid	1.096486	Schwarz criterion		-5.623071
Log likelihood	11252.82	Hannan-Quinn criter.		-5.628154
Durbin-Watson stat	1.904605			
Inverted AR Roots	.02			

From the results we found the presence of large GARCH lag coefficient (Table 5.5).The results also point to the fact that shocks to the conditional variance take a long time to die out, thus volatility is persistent in Indian equity market. Large value of GARCH lag coefficient along with a low value of GARCH error coefficient indicates larger conditional variances to cluster together. The study found similar inferences for the low values also.

Figure :5.2
Conditional variance of BSE daily return data
(Period : 1.7.1997 to 30.8.2013)



From the above figure 5.2 it is noticed that, estimated volatility is high for some periods and low for other periods. This attests the fact that large values of conditional volatilities are clustered together and so are the small values and shocks to the conditional volatility takes a long time to die out , hence, volatility is persistent in Indian asset market.

5.5. Diagnostics for GARCH (1,1) Model:

If the GARCH (1, 1) model perfectly describes the data, then standardized residuals should have zero mean and unit variance and be independently and identically distributed. Some diagnostic information on the estimation is presented in Table 5.6.

Table :5.6
Descriptive Statistics of standardized Residuals

Descriptive statistics	Value
Mean	-0.036717
Median	-0.008489
Maximum	7.326411
Minimum	-4.926539
Std. Deviation	0.999231
Skewness	0.008680
Kurtosis	5.332110

Figure : 5.3
Figurative Presentation of Standerised residuals from 1.7.1997 to 30.8.2013

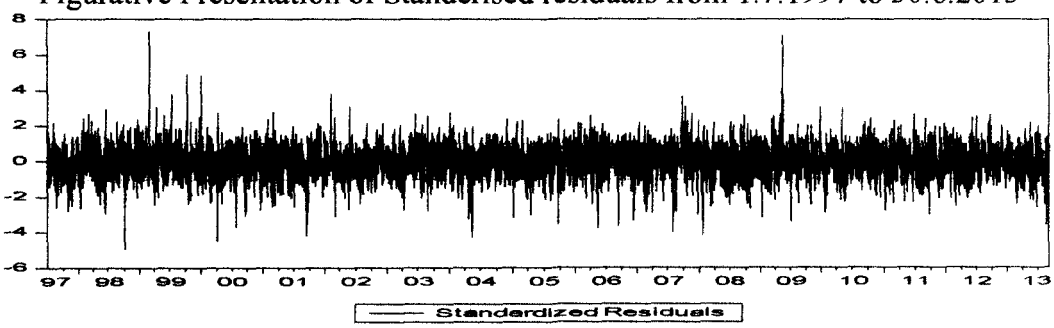


Figure: 5.4

ACF and PCF Plots of Standardized Residuals

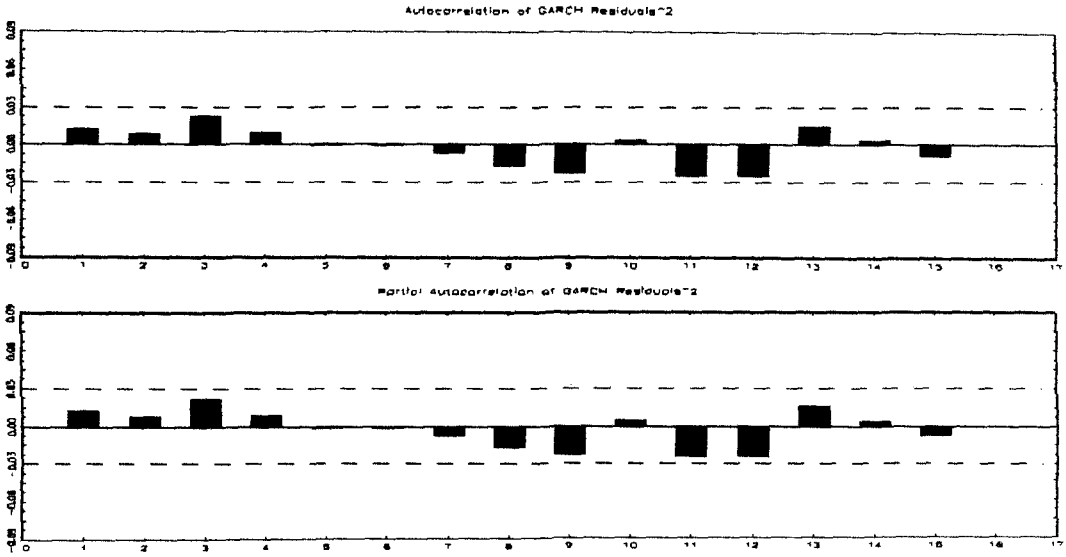


Table :5.7
ACF, PCF and Residuals

Included observations: 3996

Sample: 7/01/1997 8/30/2013

Lag	AC	PAC	Q-Stat	Prob
1	0.011	0.011	0.5144	0.473
2	0.008	0.008	0.7705	0.680
3	0.023	0.023	2.9229	0.404
4	0.009	0.008	3.2458	0.518
5	-0.001	-0.002	3.2506	0.661
6	-0.002	-0.002	3.2629	0.775
7	-0.007	-0.007	3.4351	0.842
8	-0.018	-0.018	4.7994	0.779
9	-0.025	-0.024	7.2295	0.613

10	0.003	0.005	7.2778	0.699
11	-0.026	-0.025	9.9943	0.531
12	-0.026	-0.025	12.797	0.384
13	0.015	0.016	13.735	0.393
14	0.003	0.004	13.765	0.467
15	-0.008	-0.007	14.040	0.523
16	0.001	0.001	14.048	0.595
17	0.001	-0.001	14.050	0.664
18	-0.016	-0.016	15.025	0.660
19	-0.012	-0.012	15.563	0.686
20	0.002	0.001	15.583	0.742
21	-0.001	-0.000	15.586	0.792
22	0.010	0.011	16.014	0.815
23	-0.020	-0.021	17.551	0.781
24	0.004	0.004	17.619	0.821
25	-0.036	-0.036	22.821	0.588
26	-0.007	-0.006	22.997	0.633
27	-0.013	-0.014	23.657	0.649
28	0.005	0.007	23.770	0.694
29	0.017	0.017	24.916	0.683
30	-0.008	-0.009	25.156	0.717
31	-0.009	-0.010	25.513	0.744
32	-0.003	-0.005	25.556	0.783
33	-0.023	-0.023	27.633	0.731
34	0.011	0.010	28.143	0.750
35	0.016	0.015	29.211	0.743
36	-0.003	-0.004	29.245	0.780

The mean and variance shown in the Table 5.6 are found to be -0.036717 and 0.999231 .The coefficients, Q-Statistics and the corelleogram of ACF and PCF (See table .5.7 and Fig.5.4)confirms the presence of no auto correlation in the residuals. In other words the residuals are random. This suggests that the GARCH (1, 1) model is an adequate description of the volatility process in Indian context.

5.6. Conclusions:

In the Indian equity market return series, we found that , the series is integrated at order zero which allows us to use GARCH process in the VAR framework to measure the clustering of volatility. The GARCH residuals are found to be random which validates the GARCH model applied on the series under our study. The GARCH coefficients like β_1 and α_1 are statistically significant and the values are 0.88(app.) and 0.10 (appx.) which clearly indicates the presence of 'long memory' and volatility would persist in future also. Low α_1 value describes the slow but converging reaction of the traders to the shocks or news. The results attests the results of Karmakar(2005,2013, Bhattacharyya and Ritolia, 2008). The existences of volatility clustering in Indian market fairly validate the major propositions of underlying behavioural dynamics of non linear heterogeneous model under the assumptions of bounded rationality. This pattern of price changes in Indian market also points towards "coexistence of attractors" in belief formation. Our findings also suggest that decisions of Indian investors are context specific. They are divided into heterogeneous groups in terms of their expectation formation rule and under the condition each groups are facing similar cognitive limitations. They are changing the sides definitely as we found the values of β_1 is very high which is indicative for the clustering of return volatility. Hence, the hypothesis of this study is grossly rejected.

References:

Amilion, H.,(2008), "Estimation of the Adaptive stock market model with heterogeneous agents",*Journal of Empirical Finance*,15,342-362.

Akaike, H. (1974), "A New Look at the Statistical Model Identification". *IEEE Transactions on Automatic Control*, 19,716-723. http://dx.doi.org/10.1109/TAC.1974.1100705.

Bhattacharyya, M and Ritolia, G.(2008), "Conditional VAR using EVT - Towards a Planned Margin Scheme." , *International Review of Financial Analysis,* Vol.17, 382-395

Broke, W.A.(1997)."Asset price behavior in complex environment," *in:*Arthur,W.B.,Durlauf, S.N., and Lane, D.A.(Eds.), *The Economy as an Evolving Complex System II.Addison- Wesley, Reading,* MA, 385-423.

Broke, W.A. and Hommes, C.H.(1997), "A rational route to randomness", *Econometrica,*65,1059-1095

Broke, W.A. and Hommes, C.H.(1998), "Heterogeneous beliefs and routes to chaos in a simple asset pricing model", *Journal of Economic Dynamics and Control*, 22,1235-74.

Bollerslev, T. (1986). "Generalized Autoregressive conditional heteroscedasticity". *Journal of Econometrics* 31(3),307-327.

Bollerslev, T.,Chou, Ray Y and Kroner, Kenneth F, (1992), "ARCH Modelling in finance", *Journal of Econometrics,*52 (1/2), 5-59

Campbell, J.Y., A.W. Lo, and A.C. MacKinlay.(1997). "The econometrics of financial markets". *Princeton University Press.*

Corsi, F.(2009), "A simple long memory model for realized volatility",*Journal of Financial Econometrics,* 7(2),174-196.

De Long , E.,W.F.C.Vershoor, and R.C.J.Zwinkles,(2009), "Behavioural Heterogeneity and Shift – contagion: Evidence from the Asian Crisis, *Journal of Economic Dynamics and Control*,33, 1929-1944

Engle, R.F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation". *Econometrica* ,50 (4):987-1007.

Engle, R.F. and T. Bollerslev. (1986). "Modelling the persistence of conditional variances". *Econometric Reviews*, 5, 1-50.

Elliott, G., Rothenberg, T. J. and Stock, J.H. (1996) , "Efficient Test for an Autoregressive Unit Root". *Econometrica*, 64, 813-836. http://dx.doi.org/10.2307/2171846

Grauwe.P and Grimaldi.M.(2004); "Bubbles and Crashes in a Behavioural Finance Model",(Center for Economic Studies & Ifo Institute for Economic Research ,CESifo ,Working Paper No. 1194.

Gaunersdorfer A., Hommes C.H., 2007. "A nonlinear structural model for volatility clustering. In:Teyssiere, G., Kirman, A. (Eds.), Long Memory in Economics". Springer: Berlin/Heidelberg, 265– `288.

Karmakar. M (2005), "Modeling Conditional Volatility of Indian Stock Markets", *VIKALPA* • Vol. 30 • No. 3 • July– September.

Karmakar. M (2013), "Estimation of tail – related risk measures in the Indian stock market: An extreme value approach" , *Review of Financial Economics,*22, 79-85.

Kirman, A. and Teyssiere, G. (2002). "Microeconomic models for long memory in the volatility of financial time series", *Studies in Nonlinear Dynamics and Econometrics*, 5,281-302.

Le Baron, B.,Arthur, W.B. and Palmer, R.(1999), *"The time series properties of an artificial stock market"*, Journal of Economic Dynamics and Control, *23,1487-1516.*

Ljung, G.M. and Box, GPE (1978), "On a Measure of Lack for fit in Time Series Models", *Biometrika*, 66, 66-72.

Lux, T. and Marchesi, M.(1999)." Scaling and criticality in a stochastic multi agent model of a financial market. *Nature,* 397,498-500.

Lux, T. and Marchesi, M.(2000). "Volatility Clustering in Financial Markets:A Microsimulation of Interacting Agents",*International Journal of Theoritical and Applied Finance,* 3,675-702.

Mandelbrot, B (1963); "The variation of certain speculative prices". *The Journal of Business of the University of Chicago,* 36, 394-419.

Ng, S. and Perron, P. (2001), " Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power". *Econometrica,* 69, 1519-1554. http://dx.doi.org/10.1111/1468-0262.00256

Phillips, P.C.B, and Perron, P.(1988), "Testing for a unit root in time series regression",*Biometrika,* 75(2), 335-346

Pagan,A.(1996)."The Ecomometrics of Financial Markets, Journal of Empirical Finance,3,15-102.

Said, S. and Dicky, D.A. (1984), "Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order". *Biometrika,* 71, 599-607. http://dx.doi.org/10.1093/biomet/71.3.599

Schwarz, G. (1978), "Estimating the Dimension of a Model". *Annals of Statistics,* 6, 461-464.http://dx.doi.org/10.1214/aos/1176344136

Chapter – VI

SUMMARY AND CONCLUSIONS

6.1. Overview:

This thesis attempted to analyse the implications of behavioural biases in explaining Indian capital market upheavals. To achieve our target market has been studied in the backdrop of heterogeneity in expectation and evolutionary learning. The present approach departs from the existing paradigm of market economics where some agents are rational and others are not. Individual agents are overwhelmed by the complexity of the informational environment; they are all categorized as bounded rational, and therefore use simple rules of forecasting return and risk assessment. Two typical types of trader in the market have been distinguished on the basis of their expectation formation. Traders of the first type are the fundamentalists or the 'smart money traders'. They believe that prices of speculative assets return back to its fundamental value and it follows random movements. However, there may be a deviation of actual prices from fundamental value, but mean reversion dynamics of the market is posited to bring the prices in line. The traders in the second category are the chartists or technical analysts. These traders believe that, asset prices can be predicted by simple technical trading rules based on patterns, trends or cycles. Risk is assessed by both type of traders in terms of variance of actual price from expectations .In this respect the behaviour of investors in the market is modeled in terms of 'loss aversion'. That is, their decisions in the market are assumed to be 'reference dependent'. In this heterogeneous set up prices are determined by an adaptive belief which is generating out of evolutionary force resulting from trading between these groups. The importance of one group of traders over others is context specific and conditional upon deviation of actual price from fundamental. Socio psychological underpinnings of human decision under uncertainty suitably explain conditions making the decisions context specific. The model predicts for two potential solutions in the asset price dynamics. If fundamentalists can set aside cognitive bounds and other associated socio psychological biases in information processing, dominate in the market in terms of both numbers and wealth and thereby normative solution in price is restored. On the contrary if socio psychological constraints take over rationality, fundamentalists constantly loss their evolutionary fitness, technical traders start to dominate and ultimately a bubble (either positive or negative) grows. The dominance

of a particular trader type driven by their socio psychological impact in decision making thus can be identified with patterns of price movements. Prices are expected to be driven by "coexistence of attractors"; switch irregularly between phases of low volatilities and high volatilities. More categorically small change in prices due to random news are reinforced and become larger and larger due to trend following trading rules, irregularly change its direction and switch to phases of small price changes. To reach the objective of the study we have tried to capture these patterns in price movements in Indian equity market which can be taken as an explanatory device to model investor's behaviour towards upheavals.

Specifically we have applied two sophisticated tools on the daily return data of price changes over the period from 1.7.1997 to 30.8.2013.Extreme Value theory has been applied to daily data on price changes to identify and measure the existence of extreme movements in Indian equity market. The presence of extreme movements points towards the role of behavioural biases in uncertainty whereby price itself feeds it back for further changes. Apart from this, Generalised Auto Regressive Conditional Heteroskedastic i.e. GARCH(1,1) model has been applied to capture more specifically "coexistence of attractors" in speculative behaviour of Indian investors whereby, phases of extreme changes in prices cluster together and irregularly switches towards phases of small changes.

6.2. Summary of findings:

Preliminary investigations using some common statistical tools exhibited leptokurtic patterns in daily return distribution with the presence of fat tail in Indian market. Q-Q graph of the daily return data has been plotted against the Normal Distribution. Empirical concave departure from normal distribution more prominently indicates the presence of heavier tailed distribution. However central part of the distribution aligns well with the normal distribution. But outside this area the curve in the tail indicates departure from normality i.e. a stronger concentration around mean, more probability mass in the tails of the distribution and thinner shoulders. These indicate towards the presence of extreme movements in Indian market that constitute fat tail with a leptokurtic distributional pattern. These findings

are however in consonance with observed phenomenon of asset markets around the world, which cannot be captured under the dictum of rational expectations. Presence of more probability mass in the tails of the distribution may be taken as a confirmation of price to price channel in bubble formation and its subsequent crashes. More sophisticated techniques of Extreme Value Theory have been applied to capture more objectively the pattern of daily return distribution. The finding suggests that forty two percentages of negative returns and forty percentage of positive return may be treated as extreme in the Indian market. Altogether approximately forty two percentage of total observation falls in the extreme region either positive or negative.Presence of extreme movements in prices points towards the existence of price to price feedback whereby movements in prices tend to justify further movements.

Generalised Auto Regressive Conditional Heteroskedastic (GARCH (1,1)) model has been applied to the time series of daily return data on BSE Sensex. Presence of large GARCH lag coefficient indicates shocks to the conditional variance take a long time to die out, thus volatility is persistent. Large value of GARCH lag coefficient with low values of GARCH error coefficient indicates larger conditional variances to cluster together.This result points to similar inferences for the low values also. This findings, however, points towards presence of coexistence of attractors speculative belief formation whereby market prices either settle down to the locally stable fundamental steady state or fluctuate in a regular pattern around the fundamental steady state price.

6.3. Concluding remarks:

Our findings in the Indian equity market sharply confirm the patterns of price changes predicted under heterogeneous market model. These empirical findings point towards the similar behavioural patterns of Indian investors' as hypothesized in the heterogeneous framework. Our findings suggest Indian investors as bounded rational, face cognitive limitations in processing all available information and are prone to use heuristic simplifications in forming expectations and risk assessment. Their decision

in the market seems to be context specific. Adaptive belief over the suitability of using a particular trading rule is weighted by its evolutionary fitness in the context of price movements. Prices but not the information takes over as a predominant consideration in decision making. It induces investors to develop an evolutionary psychological subtle urge in deriving information by looking at the action of others. Regret avoidance, cognitive dissonance, myopic loss aversion, reputational externalities, wishful thinking, social comparison, leaning to the wind effect etc. may be associated here as potential traits of market behaviour causing arbitragers and fundamentalists often to lose evolutionary confidences in taking corrective actions. Changes in prices being the predominant consideration in decision making ,generates commonality in thinking ,which ultimately vitiates the rationality assumptions of 'independence of opinion', 'perfect relation between risk and returns', 'full reflection of information' through prices and its 'random movements'. Thereby, the findings suggest, investors in Indian market are dominated highly by the psychological whims of the moment. Evolutionary fitness in using the technical trading rules are geared up intuitively, a self fulfilling prophecy is evolved in their mind in favour of price to price channel, and makes arbitrage operation increasingly vulnerable and bubble grows. Moreover, the presence of volatility clustering also points towards a '*coexistence of attractors*' in Indian investors' behaviour. In some occasions they develop evolutionary belief in favour of fundamental steady state which is irregularly interchanged with phases of large price changes exhibiting price to price feedback in generating market upheavals. Speculative dynamic in Indian market thus can be model to swing their sentiments irregularly either in favour of fundamentalists or technicalists.

Our findings in Indian market throw considerable challenges to the proponents of rationality driven theories of market efficiency. It questions the basic underpinnings of independence of opinion, perfect relation between risk and return, full disclosures of information through prices ensuring optimal allocation of resources .This ultimately questions the central theme of modern financial economics whereby market is posited to be taken as the most powerful device to take care of all ills and the thing that a good governance can do is not to interfere in the market. Some economists often suggest not to indulge non- equilibrium theory – it is a temporal

phenomenon and market will take care of it, hence the theory may be ignored. Undeniably theory of Power law appeases non equilibrium theory. But, if we cast aside the entire literatures on behavioural finance and its recent advancements, we would be failing to analyze some frequently observed phenomenon of the market where there is no equilibrium based solution.

Bibliography

Abreu, D. and Brunnermeier, M., (2003), "Bubbles and Crashes", *Econometrica*,71(1), 173-204.

Allport, G.W. and Postman, L.J.(1947), "The psychology of rumor", New York, Holt.

Argote, L., Tuner, M.E. and Fichman, M.(1989), "To Centralise or not to centralize: The effects of uncertainty and threat on group structure and performance", *Organizational Behavior and Human Decision Processes,43, 58-74.*

Ackert,L. and Deaves, R, (2009),"Behavioural Finance, Decision Making and Markets",*Cengage Learning.*

Admati, Anat R. and Paul Pfleiderer, (1988), A theory of intraday patterns: Volume and price variability, Review of Financial Studies 1(1), 3-40.

Andries, M. (2012): "Consumption-Based Asset Pricing with Loss Aversion," *Working Paper*, Available at SSRN: http://ssrn.com/abstract=2140880 or http://dx.doi.org/10.2139/ssrn.2140880 (last accessed on 13.7.2014)

Akhtas, S.Faff William ,R.Oliver, B. and Subramanyam,A.(2012), "Stock Saliance and the asymmetric market effect of Consumer sentiment news",*Journal of Banking and Finance*, 36(12),3289-3301.

Asch, S.E.(1956), "Studies of independence and conformity:I A minority of one against a unanimous majority", *Psychological Monographs*, 70,1-70.

Avery, Christopher and Peter Zemsky, (1998), "Multi-dimensional uncertainty and herd behavior in financial markets", *American Economic Review*, 88(4), 724-748

Arthur, W.B.,Holland, J.H., LeBaron, B.,Palmer,R and Taylor, P.(1997), "Asset pricing under endogenous expectations in an artificial stock market, *in:Arthur,*

W.B.,Durlauf, S.N., and Lane, D.A.(Eds), The Economy as an Evolving Complex System II.Redwood City, Addison- Wesley, 15-44.

Alfarano, S. and Lux, T.: (2005). "A Noise Trader Model as a Generator of Apparent Financial Power Laws and Long Memory", *Macroeconomic Dynamics*. 11(S1),80-101

Alfarano, S. and Lux,T. (2010) "Extreme Value Theory as a Theoretical Background for Power Law Behavior". *Kiel Institute for the World Economy*, Working Paper No. 1648, September 2010.

Amilion, H.,(2008), "Estimation of the Adaptive stock market model with heterogeneous agents",*Journal of Empirical Finance*,15,342-362.

Akaike, H. (1974), "A New Look at the Statistical Model Identification". *IEEE Transactions on Automatic Control*, 19,716-723. http://dx.doi.org/10.1109/TAC.1974.1100705.

Boussaidi,R.(2013),"Representativeness Heuristics,Investor Sentiment and Overeaction to Accounting Earnings:The case for Tunisian Stock Market", *Procedia-Social and Behavioural Sciences,* 81,9-21.

Brock,W., and Hommes, C., (1997), "A Rational Route to Randomness", Econometrica, 65, 1059-1095.

Brock, W., and Hommes, C.,(1998), "Heterogeneous beliefs and routes to chaos in a simple asset pricing model", Journal of Economic Dynamics and Control, 22, 1235-1274.

Broke, W.A.(1997). "Asset price behavior in complex environment," *in:*Arthur,W.B.,Durlauf, S.N., and Lane, D.A.(Eds.), *The Economy as an Evolving Complex System II.Addison- Wesley, Reading,* MA, 385-423.

Banerjee. A, (1992), ' A Simple Model of Herd Behaviour', *The Quarterly Journal of Economics*;107 (3),797-817.

Bulow, Jeremy and Paul Klemperer, (1994), "Rational frenzies and crashes", *Journal of Political Economy* 102(1), 1-23.

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch,(1992), "A theory of fads, fashion, custom, and cultural change as informational cascades", *Journal of Political Economy* ,100(5), 992-1026.

Bikhchandani ,S. Sharma.(1996), "Optimal search with learnings", Journal of Economic Dynamics and Control, 20: 333-359.

Bikhchandani ,S. Sharma.(2001), " Herd Behaviour in Financial Markets", IMF Staff Papers, 47 (3).

Barberis, Nicholas, Ming Huang, and Tano Santos, (2001), "Prospect Theory and Asset Prices", *Quarterly Journal of Economics*, 116,1-53

Barberis, Nicholas, and Wei Xiong. (2012). "Realization Utility." *Journal of Financial Economics,* 104(2), 251-271

Barberis, Nicholas, and Wei Xiong. (2009). "What Drives the Disposition Effect? An Analysis of a Long-standing Preference-based Explanation." *Journal of Finance* 64(2):751-784.

Benartzi, Shlomo, and Richard H. Thaler, (1996), "Risk Aversion or Myopia: The Fallacy of Small Numbers and its implications for Retirement Savings,"Working Paper, University of California, Los Angeles.

Benartzi,S; Richard H. Thaler(1995) , "Myopic Loss Aversion and the Equity Premium Puzzle,"*The Quarterly Journal of Economics,* 110, No. 1, 73-92.

Battaglini, M. (2005) "Sequential voting with abstention.", *Games Econ. Behav.* 51, 445–463

Bond, R. and Smith, B (1996), "Culture and Conformity:A Meta- Analysis of Studies Using Asch's(1952b, 1956) Line Judgement Task", *Psychological Bulletin*,119(1),111-137.

Busse, R Meghan,Lecetera, N.Pope, G Davin,Risso, S.J.Sydnor, R.J.(2013), "Estimating the Effect of salience in wholesale and retail car market,NBER, Working Paper No.18820, available at : http://www.nber.org. Last accessed on 13.7.2014.

Blanchard, O.J., and Watson, M.W, (1982), "Bubbles, rational expectations and speculative markets", in Wachtel, P., eds., Crisis in economic and financial structure: bubbles, bursts, and shocks. Lexington books: Lexington.

Blanchard ,O.J., (1979), "Speculative bubbles, crashes and rational expectations", *Economics Letters*, 3, 387-389..

Brennan, Michael, (1993), *"Agency and Asset Prices,"* Finance Working Paper No. 6-93, UCLA.

Barberis,N. Thaler,R ,(2003); A survey of behavioral finance ;In:George M CONSTANTINIDES , *Milton Harris, and Rene M. STULZ, eds. Handbook of the Economics of Finance, Volume 1B, Financial Market and Asset Pricing. Elsevier,North Holland, Chapter 18,1053-1128*

Bhattacharyya, M and Ritolia, G.(2008), "Conditional VAR using EVT - Towards a Planned Margin Scheme." , *International Review of Financial Analysis,* 17, 382-395

Balkema, A. A., and L. de Haan, (1974), "Residual lifetime at great age," *Annals of Probability*, 2, 792–804

Beirlant, J., J. Teugels, Yu. Goegebeur, and J. Segers, (2004): "*Statistics of extremes: theory and applications," Wiley*

Berman, S.M., (1963). "Limiting theorems for the maximum term in stationary sequences". *Annals of Mathematical Statistics*, 35, 502–516.

Bollerslev, T. (1986). "Generalized Autoregressive conditional heteroscedasticity". *Journal of Econometrics* 31(3),307-327.

Bollerslev, T.,Chou, Ray Y and Kroner, Kenneth F, (1992), "ARCH Modelling in finance", *Journal of Econometrics,*52 (1/2), 5-59

Campbell, J.Y., A.W. Lo, and A.C. MacKinlay.(1997). "The econometrics of financial markets". *Princeton University Press.*

Corsi, F.(2009), "A simple long memory model for realized volatility",*Journal of Financial Econometrics,* 7(2),174-196.

Chamley, Christophe and Gele Douglus , (1994), "Information Revelation and Strategic Delay in a model of Investment" , *Econometrica*, 62(5), 1065 - 1085

Caplin and John Leahy,(1993), "Business as Usual, Market Crashes, and Wisdom After the Fact" *The American Economic Review*, 84(3), 548-565.

Chin Wen Cheong, Abu Hassan Shaari Mohd Nor and Zaidi Isa, (2008); "Modelling Extreme Financial Return of Malaysian Stock Exchange", *World Applied Sciences Journal* ,3 (2): 254-258,

Cutler, D. M., Poterba, J. M., and Summers, L. H. (1989) ,"What moves stock prices?" *The Journal of Portfolio Management* 15, (3), 4-12.

Devenow A., Welch, I. (1996). "Rationalherding in financial economics". *European Economic Review* ,40, 603–615.

Dimmock, Stephen, and Roy Kouwenberg. (2010). "Loss-aversion and Household Portfolio Choice." *Journal of Empirical Finance* ,17(3): 441-459.

Durba, J.(2004), "Optimism and overconfidence in search", *Review of Economic Dynamics,*7,198-218.

De Long , E.,W.F.C.Vershoor, and R.C.J.Zwinkles,(2009), "Behavioural Heterogeneity and Shift – contagion: Evidence from the Asian Crisis, *Journal of Economic Dynamics and Control*,33, 1929-1944

De Long, J., Bradford, B., Schleiffer and Summers, L.,(1990), "Noise Trader Risk in Financial Markets", *Journal of Political Economy.*

Daniel, K., Hershleifer, D., Teoh, H.S.(2002), "Investors psychology in capital markets: evidence and policy implications," *Journal of Monetary Economics*, 49, 139-209

De Bondt, F.M.Werner, Shefrin, H.,Muradoglu , Y. G.,Staikouras, K.S.(2008), "Behavioural Finance: Quo Vadis?", *Journal of Applied Finance, 19,7-21*

De Bondt, W.F.M., (2002), "Bubble Psychology, in W. Hunterand G. Kaufman (eds.), Asset Price Bubbles: Implicationsfor Monetary, Regulatory, and International Policies", *MITPress.*

De Bondt, W.F.M.,(2005), "The Psychology of World EquityMarkets", *Edward Elgar.*

De Bondt, W.F.M., (2008a), "Stock Prices: Insights fromBehavioral Finance,] in Alan Lewis (ed.), *The Cambridge Handbook of Psychology and Economic Behavior,Cambridge University Press.*

De Bondt, W.F.M., (2008b), "Investor Psychology andInternational Equity Markets*",Revue Economique et.Sociale 66 (No. 4), 107-121.*

De Bondt and Thaler, R.(1985), "Does the Stock Market Overreact? *The Journal Of Finance*,40(3),793-805.

Devenow A., Welch, I. (1996). "Rationalherding in financial economics". *European Economic Review* ,40, 603–615.

Danielsson, J. and Y. Morimoto: (2003): "Forecasting extreme financial risk: a critical

analysis of practical methods for the Japanese market," *Monetary and Economic Studies*, 18,(2), 25-48

De Haan, L. (1990), "Fighting the ARCH-enemy with mathematics",*Statistica Neerlandica*, 44, 45–68,

Engle, R.F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation". *Econometrica* ,50 (4):987-1007.

Engle, R.F. and T. Bollerslev. (1986). "Modelling the persistence of conditional variances". *Econometric Reviews*, 5, 1-50.

Elliott, G., Rothenberg, T. J. and Stock, J.H. (1996) , "Efficient Test for an Autoregressive Unit Root". *Econometrica*, 64, 813-836. http://dx.doi.org/10.2307/2171846

Eisner, R. and Strotz, R.H. (1961). "Flight insurance and the theory of choice".*Journal of Political Economy* ,69(4), 355—68.

Erlich, D., P. Guttman, P. Schopenbach, and J. Mills (1957). "Postdecision Exposure to Relevant Information," *Journal of Abnormal and Social Psychology*, 54: 98–102.

Efferson, C. Lalive,R., Richerson , J.P., McElreath , R. and Lubell, M. (2008), " Conformists and mavericks: the empirics of frequency- dependent cultural transmission", *Evolution and Human Behaviour, 29,56-64*

Embrechts, P., Klüppelberg, C. & Mikosch, T. (1997), "Modeling Extremal Events for Insurance and Finance", *New York: Springer.*

Engle, R. and Rangel,:(2005) "The spline garch model for unconditioanl volatlity and its global macroeconomic causes". *Technical report, NYU and UCSD,*

Engle, R.F.Gysels, and B. Sohn.: (2006) "On the economic sources of stock market volatility. Technical report", *New York University and University of North Carolina at Chapel Hill.*

Frankel, J. and Froot, K, (1986), "The dollor as a speculative bubble:A Tale of fundamentalists and Chartists", NBER Working paper , no.1963

Fama, E. F. (1970), "*Efficient capital markets: A review of theory and empirical work*", The Journal of Finance ,25(2), 383–417.

Friedman, M. (1953), The Case for Flexible Exchange Rates, in M. Friedman (ed.), Essays in positive economics, University of Chicago Press, Chicago, pp.157–203.

Farmer, J. Doyne. (2001). Toward Agent Based Models for Investment. In Benchmarks and Attribution Analysis. Association for Investment and Management Research.

Fehr, E. and Tyran Robert , J. (2005); " *Individual Irrationality and Aggregate Outcomes*"; Jounal of Economic Perspectives, Vol. 19 , No. 4 , 43-66

Fama, Eugene F.,French, R.K.(1988), "Dividend Yield and Expected Stock Returns", Journal of Financial Economics, 22, 3-25.

Fama, Eugene F.(1991), "Efficient Capital Markets II." *Journal of Finance* ,46, no. 5 ,*PP.*1575–1617.

Fama, Eugene F. (1965), "The Behavior of Stock Market Prices." *Journal of Business* ,38, *PP.* 34–105.

Fama, Eugene F, (1998), "Market efficiency, long-term returns, and behavioral finance", *Journal of Financial Economics* ,49, *pp.*283-306.

Farmer, J. Doyne. (2001), "Toward Agent Based Models for Investment. In Benchmarks and Attribution Analysis. Association for Investment and Management Research.

Frazzini, Andrea. (2006). "The Disposition Effect and Underreaction to News." *Journal of Finance,* 61(4): 2017-2046.

Festinger, L. (1957). A Theory of Cognitive Dissonance., Stanford, CA: *Stanford University Press.*

Ferris, S. P., R. A. Haugen and A. K. Makhija (1988). "Predicting Contemporary Volume with Historic Volume at Differential Price Levels: Evidence Supporting the Disposition Effect," *Journal of Finance*, 43(3): 677–697.

Freud, Sigmund(1981) , "Group Psychology and the Analysis of the Ego". Standard Edition, vol. XVIII, pp. 67–143. The Hogarth Press, London.. ISBN 0-7012-0067-7

Fisher, R. A. and L. H. C. Tippett, (1928), "Limiting forms of the frequency distribution of the largest or smallest member of a sample," *Proceedings of Cambridge Philosophical Society*, 24,180–190

F. Lillo and J. D. Farmer (2004)"The long memory of the efficient market." *Studies in Nonlinear Dynamics & Econometrics,* 8(3), 1-33.

Farmer,J.D.Gerig,A., Lillo, F. and Mike, S. (2006),: "Market efficiency and the long-memory of supply and demand: Is price impact variable and permanent or Fixed and temporary?" *Quantitative Finance*, 6(2), 107-112

Farmer, J. D., and Geanakoplos, J. (2008), Power laws in economics and elsewhere. Tech. rep., Santa Fe Institute,New Maxico. source: *http://tuvalu.santafe.edu/~jdf/papers/powerlaw3.pdf* (last accessed on 8th April,2014)

Frechet, M. (1927): Sur la loi de probabilit de l'ecart maximum, *Ann. Soc. Polon. Math.* (Cracovie), 6, 93-116.

Fischhoff, B., P. Slovic and S. Lichtenstein (1977). "Knowing With Uncertainty: The Appropriateness of Extreme Confidence," *Journal of Experimental Psychology: Human Perception and Performance*, 3: 552–564

Grauwe.P and Grimaldi.M.(2004); "Bubbles and Crashes in a Behavioural Finance Model",(Center for Economic Studies & Ifo Institute for Economic Research ,CESifo ,Working Paper No. 1194.

Gaunersdorfer A., Hommes C.H., 2007. "A nonlinear structural model for volatility clustering. In:Teyssiere, G., Kirman, A. (Eds.), Long Memory in Economics". Springer: Berlin/Heidelberg, 265– `288.

Gaunersdorfer A., 2000. "Endogenous fluctuations in a simple asset pricing model with heterogeneous beliefs". *Journal of Economic Dynamics and Control* ,24,. 799–831.

Gaunersdorfer A. (2001). "Adaptive belief systems and the volatility of asset prices", *Central European Journal of Operations Research* , 9, .5–30.

Graham, John R., (1994), Herding among investment newsletters: Theory and evidence, Working paper (TheUniversity of Utah, Salt Lake City, UT).

Goetzmann, W. N. and N. Peles (1997). "Cognitive Dissonance and Mutual Fund Investors," *Journal of Financial Research,* 20(2), 145–158.

Genesova, David, and Christopher Mayer, (2001), "Loss Aversion and Seller's Behaviour, Evidence From the Housing Market", *Quaterly Journal of Economics*, 116:4, 1233-60.

Grossman, Sanford J., and Joseph E. Stiglitz, (1980). "On the Impossibility of Informationally Efficient Markets." *American Economic Review*, 7, *pp.*393–408.

Gal, D. (2006) , "Psychological law of inertia and the illusion of loss aversion. Judgment and Decision Making", 1, 23-32. Available at http://journal.sjdm.org/06002/jdm06002.htm. (Last accessed on 14.7.2014)

Gaunersdorfer A., 2000. "Endogenous fluctuations in a simple asset pricing model with heterogeneous beliefs". *Journal of Economic Dynamics and Control* 24, 799–831.

Graham, John R., (1999), "Herding among Investment Newsletters: Theory and Evidence," *The Journal of Finance*, 54, pp. 237–68.

Grimaldi.M.(2004); "Bubbles and Crashes in a Behavioural Finance Model",(Center for Economic Studies & Ifo Institute for Economic Research ,CESifo ,Working Paper No. 1194

Gettinby, G., C. D. Sinclair, D. M. Power, and R. A. Brown, (2006), "An analysis of the distribution of extremes in indices of share returns in the US, UK and Japan from 1963 to 2000," *International Journal of Finance & Economics*, 11:2, 97-113

Gençay, R., F. Selçuk, and A. Ulugülyagci, (2003), "High volatility, thick tails and extreme value theory in value-at-risk estimation," *Insurance Mathematics and Economics*, 33,337-356

Gumbel, E.J. (1958), "Statistics of Extremes", *Columbia University Press*, New York.

Hirshleifer, D., Subrahmanyam, A. and Titman, S., (2006,) 'Feedback and the success of irrational traders',Journal of Financial Economics, Vol. 81, pp. 311–388.

Hill, B.M., 1975. "A simple general approach to inference about the tail of a distribution", *Annals of Statistics*. 3: 1163-1173.

Hommes, C. H. (2007), "Bounded Rationality and Learning in Complex Markets", CeNDEF School of Economics, University of Amsterdam.. (http://dare.uva.nl/document/110509, Last accessed on 15.06.2014)

Johansen, A and Sornette,D, (2010); "Shocks, Crashes and Bubbles in Financial Markets," *Brussels Economic Review,* vol. 53, issue 2, pages 201-253

Jensen M. (1978) ,"Some anomalous evidence regarding market efficiency," *Journal of Financial Economics*, Elsevier, vol. 6(2-3), pp. 95-101.

Johansen, A and Sornette,D, (2010); "Shocks, Crashes and Bubbles in Financial Markets, " *Brussels Economic Review, , vol. 53, issue 2, pages 201-253*

Johansen and Sornette, (1999) , "Critical Crashes", *RISK* ,12 (1), 91-94.

Johansen and Sornette, (2000), "The Nasdaq crash of April 2000: Yet another example of log-periodicity in a speculative bubble ending in a crash", *Eur. Phys J. B* 17 pp. 319-328.

Kindleberger,C.(1978), "Manias, Panics and Crashes, A History of Financial Crises", John Wiley & Sons, New York,263 pages.

Kahneman, D., and A. Tversky (1979), "Prospect theory: an analysis of decision under risk", Econometrica 47:263–291.

Kahneman,D, (2003), "Maps of Bounded Rationality: Psychology for Behavioral Economics" *The American Economic Review*, Vol. 93, No. 5 pp. 1449-1475.

Kahneman, D.Knetsch (1991), "The Endowment Effect, Loss Aversion and Status Quo Bias Anomalies", Journal of Economic Perspectives,5(1),193-206.

Kumar, M. (2007) , "A Journey into the Bleeding City: Following the Footprints of the Rubble of Riot and Violence of Earthquake in Gujarat, India". *Psychol. Dev. Soc.* 19, 1–36

Kirman, A. (1993) "Ants, rationality and recruitment", *Quarterly Journal of Economics* ,108 ,137-156.

Keynes, J.M. (1935), "The General Theory of Employment, Interest and Money",Mc Millan Cambridge University Press For Royal Economic Society in 1936.

Karmakar. M (2013), "Estimation of tail – related risk measures in the Indian stock market: An extreme value approach" , *Review of Financial Economics,*22, 79-85.

Karmakar. M (2005), "Modeling Conditional Volatility of Indian Stock Markets", *VIKALPA* • Vol. 30 • No. 3 • July– September.

Kirman, A. and Teyssiere, G. (2002). "Microeconomic models for long memory in the volatility of financial time series", *Studies in Nonlinear Dynamics and Econometrics*, 5,281-302.

Lillio, Fabrizio, Mike S , Farmer D.J.; (2005) , " Theory of Long Memory in Supply and Demand", *Physical Review E,Statistical*, Non Linear and Soft Matter Physics, American Physical Society. 71(6), 122-11

Lillo, F., and Farmer, J. D. (2004). "The long memory of the efficient market." *Studies in Nonlinear Dynamics & Econometrics* , 8(3) ,1-33

LeBaron, B., and R. Samanta, (2004), "Extreme value theory and fat tails in equity markets," *working papers, Brandeis University ,source::people.brandeis.edu/~blebaron/wps/tails.pdf.(last accessed on 8th April,2014)*

Longin , F.(2005) ; "The choice of the distribution of asset returns: How extreme value theory can help?". *Journal of Banking & Finance*, Elsevier, 29, 1017-1035.

Lux T. (1998), "The socio-economic dynamics of speculative markets: interacting agents, chaos, and fat tails of return distributions", *Journal of Economic Behaviour and Organisation*, vol.33,*143-165.*

Lux T., Marchesi M., (2000), "Volatility clustering in financial markets: a microsimulation of interacting agents", *International Journal of Theoretical and Applied Finance.*

Lux, T. and Marchesi, M.(1999)." Scaling and criticality in a stochastic multi agent model of a financial market. *Nature,* 397,498-500.

Lux, T. and Marchesi, M.(2000). "Volatility Clustering in Financial Markets:A Microsimulation of Interacting Agents",*International Journal of Theoritical and Applied Finance,* 3,675-702.

LeRoy, S. F., and R. D. Porter (1981). "Stock Price Volatility: "A Test Based on Implied Variance Bounds, " *Econometrica*, 49: 97–113.

Le Bon, G. (1895, trans. 1947) The Crowd: A Study of the Popular Mind. London: Ernest Benn.

Luo,Ying , G.(2012), "The Representativeness Heuristic and Asset Price Reaction to New Information", *Journal Of Trading*,7(3), 40-51

Lucas, R.E. (1971), "Econometric Testing of natural rate hypothesis. In. O. Eckstein, Editor, *The Econometrics of Price Determination Conference, Board of Governors of the Federal Reserve System and Social Science Research Council, 1971.*

LeBaron,B," W. Brian Arthur"(1999), Richard Palmer Journal of Economic Dynamics & Control 23 1487}1516 Time series properties of an artificial stock market

Le Baron, B.,Arthur, W.B. and Palmer, R.(1999), *"The time series properties of an artificial stock market"*, Journal of Economic Dynamics and Control, *23,1487-1516.*

Ljung, G.M. and Box, GPE (1978), "On a Measure of Lack for fit in Time Series Models", *Biometrika*, 66, 66-72.

Mandelbrot, B (1963); "The variation of certain speculative prices". *The Journal of Business of the University of Chicago,* 36, 394-419.

Muth, J.F. (1961)', "Rational Expectations and Theory of Price Movements",*Econometrica* 29,315-335

Maug, Ernst and Narayan Naik, (1995), "Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation", *Working paper (London Business School, London).*

Mandelbrot, B (1963); "The variation of certain speculative prices". *The Journal of*

Business of the University of Chicago, 36, 394-419.

McNeil, A. J. (1997) "Estimating the tails of loss severity distributions using extreme value theory, *ASTIN Bulletin*, 27, 1117–137.

Mc Neil and Frey (1999), "Estimation of Tail- Related Risk Measures of Heteroscedastic Financial Time Series : An Extreme Value Approach", *Manuscript, Federal Institute of Technology.*

Munier, B. (2010), "Bounded rational exuberance on commodity markets",*Risk and Decision Analysis*, 02 (01),. 33-50

Mehra, R., and C. Prescott,(1985), "The Equity premium puzzle", *Journal of Monetary Economics*, XV 1, 145-61

Maug, Ernst and Narayan Naik, (1995), "Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation", *Working paper (London Business School, London).*

Milgram,S, (1974), "Obidience to Authority", *New York,:Harper and Row.*

Ng, S. and Perron, P. (2001), " Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power". *Econometrica*, 69, 1519-1554. http://dx.doi.org/10.1111/1468-0262.00256

Northcraft, G. B. and M. A. Neale (1987). "Experts, Amateurs, and Real Estate: An Anchoring-and- Adjustment Perspective on Property Pricing Decisions," *Organizational Behavior and Human Decision Processes*, 39: 84–97.

Olsen, Robert A.(1998), "Behavioral Finance and Its Implications for Stock-Price Volatility"; *Financial Analysts Journal*, 54(2),10-18.

Odean, Terrance. (1998). "Are Investors Reluctant to Realize Their Losses?" *The Journal of Finance* 53(5): 1775-1798.

Phillips, P.C.B, and Perron, P.(1988), "Testing for a unit root in time series regression",*Biometrika*, 75(2), 335-346

Prendergast, C. and Stole, L. (1996), ''Impetuous Youngsters and Jaded Old-Timers: Acquiring a Reputation for Learning.'' *Journal of Political Economy*, 104 ,1105–113

Pagel, M.(2012), "Expectations – Based Reference – Dependent Life Cycle Consumption", Dept. of Economics,University of California at Berkeley, (Un published paper), Available at: www.stanford.edu (Last accessed on 13.7.2014)

Pagan,A.(1996)."The Ecomometrics of Financial Markets, Journal of Empirical Finance,3,15-102.

Poterba,James M. and Summers Lawrence, H. (1988), "Mean Reversion in Stock Prices, Evidence and Implications", *Journal of Financial Economics*,,22, 27-59.

Pickands, J., (1975); "Statistical inference using extreme order statistics," *Annals of Statistics,* 3, 119–131

Ross, L. (1987). "The problem of construal in social inference and social psychology." In N. E. Grunberg, R. E. Nisbett, J. Rodin, & J. E. Singer (Eds.), A distinctive approach to psychological research: The influence of Stanley Schachter, 118-150. *118–150). Hillsdale, NJ: Erlbaum*

Roll, Richard, (1992), "A mean/variance analysis of tracking error", *Journal of Portfolio Management*, 13-22.

Richerson, P.J. and Boyd, R. (2005) Gene-Culture Coevolution and the Evolution of Social Institutions. In Better than Conscious? Decision Making, the Human Mind, and Implications for Institutions (Engel, C. and Singer, W., eds), pp. 305–324, MIT Press

Sharma .M: "Extreme Value Theory and Financial Risk Management"; Indira Gandhi Institute of Development Research, Goregaon, Mumbai, March 2002, (http://ravi.lums.edu.pk/aesm/papers/extreme%20value%20theory%20and%20Financial%20risk%20management.pdf).

Sims, C. A.: (1980), "Macroeconomics and reality." *Econometrica* 48, 1, 1-48.

Savage, L.J. (1954). "The Foundations of Statistics". New York: John Wiley.

Simon, A. (1955), "A Behavioral Model of Rational Choice", *The Quarterly Journal of Economics,* 69(1) ,99-118

Siegel, Jeremy J. (1994); "Stocks for the long run:A guide to selecting Markets for Long Term Growth", *Burr Ridge , III; Irwin Professional Publishing* .

Siegel, Jeremy J. and Thaler, R.,(1997); "Anomalies: The Equity Premium Puzzle",*The Journal of Economic Perspectives*,11(01),191-200.

Shiller, R.J. (2002) ,"Bubbles, human judgment, and expert opinion". *Financial Analysts Journal*. 58, 18–26

Shiller, R. J. (1979). "The Volatility of Long Term Interest Rates and Expectations Models of the Term Structure," Journal of Political Economy, 87: 1190–1219.

Shiller, R. J. (1981a). "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?" American Economic Review, 71(3): 421–436.

Shiller, R.J. (2005) , "Irrational exuberance", Princeton University Press.

Shiller, R.J. (2008), "The subprime solution: how today's global financial crisis happened and what to do about it," *Princeton University Press.*

Shiller, R.J.(2001), "Human Behaviour and Efficiency of Financial System",Cowles Foundation Paper No.1025,1305-1340.

Shiller, R.J.(2000), "Measuring Bubble Expectations and Investor Confidence", *Journal of Psychology and Financial Markets*, 1(1),49-60

Shiller, R.J. and J.Pound (1986), "Survey Evidence of Diffusion of Interest Among Institutional Investors", *Journal of Economic Behaviour and Organisation*,12 47-66.

Shiller, R.J. (2002), "From Efficient Market Theory to Behavioural Finance", Cowels Foundation Discussion Paper No.1385.

Shiller Robert J. (2003),;From Efficient Markets Theory to Behavioral Finance The Journal of Economic PerspectivesVol. 17, No. 1 pp. 83-104

Shleifer, A. and L. Summers (1990). "The Noise Trader Approach to Finance," *Journal of Econometrics*, 4(2): 19–23.

Shleifer,A; Robert W. Vishny, (1997), "The Limits of Arbitrage", *The Journal of Finance*, Vol. 52, No. 1., pp. 35-55.

Sornette, D. et al. (2009) , "The 2006–2008 oil bubble: Evidence of speculation, and prediction. Physica A - Stat. Mech. Applic.", 388, 1571–1576.

Scharfstein, David S. and Jeremy C. Stein, (1990), "Herd behavior and investment", *American Economic Review* ,80(3), 465-479.

Stasser,G., Taylor,L.A. and Hanna, C. (1989), "Information sampling in structured and unstructured discussions of three and six persons group", *Journal of Personality and Social Psychology,*57,67-78.

Stasser, G and Titus, W.(1985), "Pooling of unshared information in group decision making: Biased information sampling during discussion", *Journal of Personality and Social Psychology,*48,1467-1478.

Summers, H.L.(1986), "Does the Stock Market Rationally Reflect Fundamental Values?"*The Journal of Finance*, XLI (3).

Shleifer,A; Robert W. Vishny, (1997); The Limits of Arbitrage, The Journal of Finance, Vol. 52, No. 1., pp. 35-55.

Shleifer, A.(2000), Introduction to Behavioural Finance, Clarendon Press.

Simon, Herbert A,(1955). "A Behavioral Model of Ra- tional Choice." *Quarterly Journal of Economics*, F, 69(1), pp. 99-118.

Said, S. and Dicky, D.A. (1984), "Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order". *Biometrika*, 71, 599-607. http://dx.doi.org/10.1093/biomet/71.3.599

Schwarz, G. (1978), "Estimating the Dimension of a Model". *Annals of Statistics*, 6, 461-464.http://dx.doi.org/10.1214/aos/1176344136

Shefrin, Hersh, and Meir Statman. (1985). "The Disposition to Sell Winners Too Earlyand Ride Losers Too Long: Theory and Evidence." *Journal of Finance* 40(3): 777-790.

Szyszka, A. (2013), "Behavioural Finance and Capital Markets:How Psychology influences Investors" *Business and Economics, Palgrave Macmillan.*

Thaler, R., Tversky, A., Kahneman, D. and Schwartz, A. (1997): "The Effect of Myopia and Loss Aversion on Risk Taking: an Experimental Testing". *The Quarterly Journal of Economics*, 112, 647-661.

Thaler, R., Kahneman, D. & Knetsch, J. L. (1992). The endowment effect, loss aversion and status quo bias. In R. Thaler, The Winner's Curse. Princeton: Princeton University Press, 63-78

Thaler, H, Richard,(2008), "Mental Accounting and Consumer Choice",*Marketing Science,* 27(1),15-25..

Tversky, A. and Kahneman, D. (1992), "Advances in Prospect Theory:Cumulative Representation of Uncertainity", *Journal of Risk and Uncertainity*,5 , 297-323

Tversky, Amos and Daniel Kahneman (1991), "Loss Aversion in Riskless Choice: A Reference-Dependent Model," Quarterly Journal of Economics, 106 (4), 1039–1061

Trueman, Brett, (1994), "Analyst forecasts and herding behavior", *Review of Financial Studies,* 7(1), 97-124.

Trotter, Wilfred(1914), "Instincts of the Herd in Peace and War",T. FISHER UNWIN LTD., London:ADELPHI TERRACE.

Trueman, Brett, (1994), "Analyst forecasts and herding behavior", *Review of Financial Studies,* 7(1), 97-124.

Thaler , R.,(1994), "Quasi Rational Economics, Russell Sage Foundation, New York

Tversky, A., and Kahneman,D., (1981), "The framing of decisions and the psychology of choice, *Science*,211,453-458

Tolikas, K., and R. A. Brown, (2005), "The distribution of the extreme daily returns in the Athens Stock Exchange," *working paper, University of Dundee*.SSRN (Last visited on 8th April,2014).

Veblen, Thorstein (1953) [1899]. "The Theory of the Leisure Class: An Economic Study of Institutions", the *Mentor Edition. Introduction by C. Wright Mills. New York:The Macmillan Company*

Von Mises, R. (1936). "La distribution de la plus grande de n valeurs". Reprinted in Selected Papers, Volume II, *American Mathematical Society*, Providence, R.I., 1954, 271-294.

Weibull, W., (1939), "A statistical theory of the strength of material". *Ingeniors Vetenskaps Akademiens,* Stockholm 151.

Woodford, M.(2000), "An interview with William A. Broke" , *Macoeconomic Dynamics* , 4, 108-138

Zwicbel, Jeffrey, (1995), "Corporate conservatism and relative compensation", *Journal of Political Economy* 103(1), 1-25.

Appendix-1A
(History of Market Upheavals)

Name	Brief descriptions
Tulip mania Bubble of 1637:	A bubble (1633–37) in Netherlands during which contracts for bulbs of tulips reached extraordinarily high prices, and suddenly collapsed. At the peak of tulip mania, in March 1637, some single tulip bulbs sold for more than 10 times the annual income of a skilled craftsman. It is generally considered the first recorded speculative bubble (or economic bubble),although some researchers have noted that the Kipper- und Wipperzeit episode in 1619–22, a Europe-wide chain of debasement of the metal content of coins to fund warfare, featured mania-like similarities to a bubble.The term "tulip mania" is now often used metaphorically to refer to any large economic bubble (when asset prices deviate from intrinsic values).The 1637 event was popularized in 1841 by the book " Extraordinary Popular Delusions and the Madness of Crowds", written by British journalist Charles Mackay. According to Mackay, at one point 12 acres (5 ha) of land were offered for a Semper Augustus bulb. Mackay claims that many such investors were ruined by the fall in prices, and Dutch commerce suffered a severe shock.
South Sea Bubble of 1720 :	The South Sea Company (officially The Governor and Company of the merchants of Great Britain, trading to the South Seas and other parts of America, and for the encouragement of fishing) was a British joint-stock company founded in 1711, created as a public–private partnership to consolidate and reduce the cost of national debt. The company was also granted a monopoly to trade with South America, hence its name. At the time it was created, Britain was involved in the War of the Spanish Succession and Spain controlled South America. There was no realistic prospect that trade would take place and the company never realised any significant profit from its monopoly. Company stock rose greatly in value as it expanded its operations dealing in government debt, peaking in 1720 before collapsing to little above its original flotation price; this became known as the South Sea Bubble.The Bubble Act 1720 , which forbade the creation of joint-stock companies without royal charter, was promoted by the South Sea company itself before its collapse. This was an effort to prevent the increasing competition for investors, which it saw from companies springing up around it.A considerable number of people was ruined by the share collapse, and the national economy greatly reduced as a result. The founders of the scheme engaged in insider trading, using their advance knowledge of when national debt was to be consolidated

	to make large profits from purchasing debt in advance. Huge bribes were given to politicians to support the Acts of Parliament necessary for the scheme. Company money was used to deal in its own shares, and selected individuals purchasing shares were given loans backed by those same shares to spend on purchasing more shares. The expectation of vast wealth from trade with South America was used to encourage the public to purchase shares, despite the limited likelihood this would ever happen. The only significant trade that did take place was in slaves, but the company failed to manage this profitably. A parliamentary enquiry was held after the crash to discover its causes. A number of politicians were disgraced, and people found to have profited unlawfully from the company had assets confiscated proportionately to their gains (most had already been rich men and remained comfortably rich). The company was restructured and continued to operate for more than a century after the Bubble. The headquarters were in Threadneedle Street at the centre of the financial district in London, in which street today can be found the Bank of England. At the time of these events this also was a private company dealing in national debt, and the crash of its rival consolidated its position as banker to the British government.
Crisis of 1772 :	The peacetime Credit Crisis of 1772 originated in London and then spread to other parts of Europe, such as Scotland and Netherlands. On June 8, 1772, Alexander Fordyce, a partner in the banking house Neal, James, Fordyce and Down in London, fled to France to avoid debt repayment, and the resulting collapse of the firm stirred up panic in London. Economic growth at that period was highly dependent on the use of credit, which was largely based upon people's confidence in the banks. As confidence started ebbing, paralysis of the credit system followed: crowds of people gathered at the banks and requested debt repayment in cash or attempted to withdraw their deposits. As a result, twenty important banking houses went bankrupt or stopped payment by the end of June, and many other firms endured hardships during the crisis. At that time, the Gentleman's Magazine commented, "No event for 50 years past has been remembered to have given so fatal a blow both to trade and public credit".
Financial Panic of 1792:	The Panic of 1792 was a financial credit crisis that occurred during the months of March and April of 1792, precipitated by the expansion of credit by the newly formed Bank of the United States as well as by rampant speculation on the part of William Duer, Alexander Macomb and other prominent bankers. Duer, Macomb and

	their colleagues attempted to drive up prices of US debt securities and bank stocks, but when they defaulted on loans, prices fell causing a bank run. Simultaneous tightening of credit by the Bank of the United States served to heighten the initial panic. Secretary of the Treasury Alexander Hamilton was able to deftly manage the crisis by providing banks across the Northeast with hundreds of thousands of dollars to make open-market purchases of securities, which allowed the market to stabilize by May of 1792.
Panic of 1796–1797:	The Panic of 1796–1797 was a series of downturns in Atlantic credit markets that led to broader commercial downturns in both Britain and the United States. In the U.S., problems first emerged when a land speculation bubble burst in 1796. The crisis deepened when the Bank of England suspended specie payments on February 25, 1797 under the Bank Restriction Act of 1797. The Bank's directors feared insolvency when English account holders, who were nervous about a possible French invasion, began withdrawing their deposits. In combination with the unfolding collapse of the U.S. real estate market, the Bank of England's action had disflationary repercussions in the financial and commercial markets of the coastal United States and the Caribbean at the start of the 19th century.By 1800, the crisis had resulted in the collapse of many prominent merchant firms in Boston, New York, Philadelphia, and Baltimore, and the imprisonment of many American debtors. The latter included the famed financier of the revolution Robert Morris and his partner James Greenleaf who had invested in backcountry land. Former Associate Justice of the Supreme Court James Wilson was forced to spend the rest of his life fleeing from creditors until he died at a friend's home in Edenton, North Carolina.George Meade, the grandfather of the American Civil War Union General George Gordon Meade was ruined by investments in Western land deals and died in bankruptcy due to the panic. The fortune of Henry Lee III, father of Confederate General Robert E. Lee, was reduced by speculation with Robert Morris. The scandals associated with these and other incidents prompted the U.S. Congress to pass the Bankruptcy Act of 1800, which was not renewed after its three-year duration expired in 1803.
Panic of 1825:	The Panic of 1825 was a stock market crash that started in the Bank of England, arising in part out of speculative investments in Latin America, including the imaginary country of Poyais. The crisis was felt most acutely in England where it precipitated the closing of six London banks and sixty country banks in England, but

	was also manifest in the markets of Europe, Latin America, and the United States. An infusion of gold reserves from the Banque de France saved the Bank of England from complete collapse.The panic has been referred to as the first modern economic crisis not attributable to an external event, such as a war, and thus the start of modern economic cycles. The period of the Napoleonic Wars had been exceptionally profitable for all sectors of the British financial system, and the expansionist monetary actions taken during transition from wartime to peacetime economy initiated a surge of prosperity and speculative ventures. The stock market boom became a bubble and banks caught up in the euphoria made risky loans.
Panic of 1837:	The Panic of 1837 was a financial crisis in the United States that touched off a major recession that lasted until the mid-1840s. Profits, prices and wages went down while unemployment went up. Pessimism abounded during the time. The panic had both domestic and foreign origins. Speculative lending practices in western states, a sharp decline in cotton prices, a collapsing land bubble, international specie flows, and restrictive lending policies in Great Britain were all to blame. On May 10, 1837, banks in New York City suspended specie payments, meaning that they would no longer redeem commercial paper in specie at full face value. Despite a brief recovery in 1838, the recession persisted for approximately seven years. Banks collapsed, businesses failed, prices declined, and thousands of workers lost their jobs. Unemployment may have been as high as 25% in some locales. The years 1837 to 1844 were, generally speaking, years of deflation in wages and prices.
Panic of 1847:	The Panic of 1847 was started as a collapse of British financial markets associated with the end of the 1840s railway industry boom. As a means of stabilizing the British economy the ministry of Robert Peel passed the Bank Charter Act of 1844. This Act fixed maximum quantity bank notes that could be in circulation at any one time and guaranteed that definite reserve funds of gold and silver would be held in reserve to back up the money in circulation. Furthermore, the Act required that the supply of money in circulation could only be increased when gold or silver reserves were proportionately increased. However, in 1847, the Peel Banking Act was circumvented when the Bank of England requested a suspension of the Bank Charter Act. This caused excessive monetary inflation due to the Bank of England and fractional reserve banking. It was this circumvention of the Peel Banking Act that caused the Panic of 1847.

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Appendix-1A
(History of Market Upheavals)

Wall Street Crash of 1929:	The Wall Street Crash of 1929, also known as Black Tuesday or the Stock Market Crash of 1929, began in late October 1929 and was the most devastating stock market crash in the history of the United States, when taking into consideration the full extent and duration of its fallout. The crash signaled the beginning of the 10-year Great Depression that affected all Western industrialized countries..
1973–1974 stock market crash:	Lasting 23 months, dramatic rise in oil prices, the miners' strike and the downfall of the Heath government. The 1973–1974 bear market was a bear market that lasted between January 1973 and December 1974. Affecting all the major stock markets in the world, particularly the United Kingdom, it was one of the worst stock market downturns in modern history. The crash came after the collapse of the Bretton Woods system over the previous two years, with the associated 'Nixon Shock' and United States dollar devaluation under the Smithsonian Agreement. It was compounded by the outbreak of the 1973 oil crisis in October of that year. It was a major event in the 1970s recession. In the 699 days between 11 January 1973 and 6 December 1974, the New York Stock Exchange's Dow Jones Industrial Average benchmark lost over 45% of its value, making it the seventh-worst bear market in the history of the index. 1972 had been a good year for the DJIA, with gains of 15% in the twelve months. 1973 had been expected to be even better, with Time magazine reporting, just 3 days before the crash began, that it was 'shaping up as a gilt-edged year'. In the two years from 1972 to 1974, the American economy slowed from 7.2% real GDP growth to −2.1% contraction, while inflation (by CPI) jumped from 3.4% in 1972 to 12.3% in 1974
Silver Thursday of 1980s:	Silver price crash: Silver Thursday was an event that occurred in the United States in the silver commodity markets on Thursday, March 27, 1980. A steep fall in silver prices led to panic on commodity and futures exchanges.

Appendix-1A
(History of Market Upheavals)

Black Monday of 19 Oct 1987:	In finance, Black Monday refers to Monday, October 19, 1987, when stock markets around the world crashed, shedding a huge value in a very short time. The crash began in Hong Kong and spread west to Europe, hitting the United States after other markets had already declined by a significant margin. The Dow Jones Industrial Average (DJIA) dropped by 508 points to 1738.74 (22.61%).In Australia and New Zealand the 1987 crash is also referred to as Black Tuesday because of the timezone difference. The terms Black Monday and Black Tuesday are also applied to October 28 and 29, 1929, which occurred after Black Thursday on October 24, which started the Stock Market Crash of 1929.
1997 Asian financial crisis:	Investors deserted emerging Asian shares, including an overheated Hong Kong stock market. Crashes occur in Thailand, Indonesia, South Korea, Philippines, and elsewhere, reaching a climax in the October 27, 1997 crash.
Dot-com bubble of 2000:	Collapse of a technology bubble, world economic effects arising from the September 11 attacks and the stock market downturn of 2002.
Stock market downturn of 2002	Downturn in stock prices during 2002 in stock exchanges across the United States, Canada, Asia, andEurope. After recovering from lows reached following the September 11 attacks, indices slid steadily starting in March 2002, with dramatic declines in July and September leading to lows last reached in 1997 and 1998.
United States bear market of 2007–2009	Till June 2009, the Dow Jones Industrial Average, Nasdaq Composite and S&P 500 all experienced declines of greater than 20% from their peaks in late 2007.
Late-2008's	On September 16, 2008, failures of large financial institutions in the United States, due primarily to exposure of

financial crisis	securities of packaged subprime loans and credit default swaps issued to insure these loans and their issuers, rapidly devolved into a global crisis resulting in a number of bank failures in Europe and sharp reductions in the value of equities (stock) and commodities worldwide. The failure of banks in Icelandresulted in a devaluation of the Icelandic króna and threatened the government with bankruptcy. Iceland was able to secure an emergency loan from the IMF in November. Later on, U.S. President George W. Bushsigns the Emergency Economic Stabilization Act into law, creating a Troubled Asset Relief Program (TARP) to purchase failing bank assets.
2010 Flash Crash	The Dow Jones Industrial Average suffers its worst intra-day point loss, dropping nearly 1,000 points before partially recovering.

Appendix-1B

Cases for Indian Market (10 biggest falls in the Indian stock market history):

Jan 21, 2008: The Sensex saw its highest ever loss of 1,408 points at the end of the session on Monday. The Sensex recovered to close at 17,605.40 after it tumbled to the day's low of 16,963.96, on high volatility as investors panicked following weak global cues amid fears of the US recession.

Jan 22, 2008: The Sensex saw its biggest intra-day fall on Tuesday when it hit a low of 15,332, down 2,273 points. However, it recovered losses and closed at a loss of 875 points at 16,730. The Nifty closed at 4,899 at a loss of 310 points. Trading was suspended for one hour at the Bombay Stock Exchange after the benchmark Sensex crashed to a low of 15,576.30 within minutes of opening, crossing the circuit limit of 10 per cent.

May 18, 2006: The Sensex registered a fall of 826 points (6.76 per cent) to close at 11,391, following heavy selling by FIIs, retail investors and a weakness in global markets. The Nifty crashed by 496.50 points (8.70%) points to closeat5,208.80points.

December17, 2007: A heavy bout of selling in the late noon deals saw the index plunge to a low of 19,177 - down 856 points from the day's open. The Sensex finally ended with a huge loss of 769 points (3.8%) at 19,261. The NSE Nifty ended at 5,777, down 271 points.

October 18, 2007: Profit-taking in noon trades saw the index pare gains and slip into negative zone. The intensity of selling increased towards the closing bell, and the index tumbled all the way to a low of 17,771 - down 1,428 points from the day's high. The Sensex finally ended with a hefty loss of **717** points (3.8%) at 17,998. The Nifty lost 208 points to close at 5,351.

January 18, 2008: Unabated selling in the last one hour of trade saw the index tumble to a low of 18,930 - down 786 points from the day's high. The Sensex finally ended with a hefty loss of 687 points (3.5%) at 19,014. The index thus shed 8.7% (1,813 points) during the week. The NSE Nifty plunged 3.5% (208 points) to 5,705.

November,21, 2007: Mirroring weakness in other Asian markets, the Sensex saw relentless selling. The index tumbled to a low of 18,515 - down 766 points from the

previous close. The Sensex finally ended with a loss of 678 points at 18,603. The Nifty lost 220 points to close at 5,561.

August 16, 2007: The Sensex, after languishing over 500 points lower for most of the trading sesion, slipped again towards the close to a low of 14,345. The index finally ended with a hefty loss of 643 points at 14,358.

April 02, 2007: The Sensex opened with a huge negative gap of 260 points at 12,812 following the Reserve Bank of India decision to hike the cash reserve ratio and repo rate. Unabated selling, mainly in auto and banking stocks, saw the index drift to lower levels as the day progressed. The index tumbled to a low of 12,426 before finally settling with a hefty loss of 617 points (4.7%) at 12,455.

August 01, 2007: The Sensex opened with a negative gap of 207 points at 15,344 amid weak trends in the global market and slipped deeper into the red. Unabated selling across-the-board saw the index tumble to a low of 14,911. The Sensex finally ended with a hefty loss of 615points at 14,936. The NSE Nifty ended at 4,346, down 183 points. This is the third biggest loss in absolute terms for the index.