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Market-Wide Herding and the Impact of Institutional Investors in the Indian Capital Market

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1. INTRODUCTION & BACKGROUND DETAILS:

1.1. Introduction:

The Indian economy embarked on a process of liberalisation in 1992 and since then the Indian capital markets have been on a process of integration with the global markets. Over the last decade, India has attracted investments from Foreign Institutional Investors (FIIs) from across the world, the initial trickle ballooning into a torrent. Fund mobilisation by domestic institutional investors like Mutual Funds (MFs) has been increasing in view of the increasing rate. Like any other developing economy, the Indian capital markets have welcomed institutional investors as they provide the much-needed liquidity for the markets; however, the increased role of the institutional investor, particularly the FII has also lead to a rise in negative perceptions about their impact on the markets. The issue of stability of the financial markets thus gained prominence.

The subject of Institutional Investors and their impact on capital markets has been a topic of considerable interest in the developed economies. Of late, interest on the subject has increased in emerging economies too on account of globalisation and the increased flow of funds across the globe. However, there has not been much analysis in emerging markets, especially in the Indian context on the impact of these Institutional investors on the capital market.

This Study seeks to assess whether there is market-wide Herding in Indian Capital market. The Study also aims to find whether the increasing flows of Institutional Investors into the Indian Capital Market have increased the Herding tendency in the Indian Capital market.

1.2. Institutional Investors in India:

Over the years, the Indian capital markets have been opened up to various institutional investors. Five types of Institutional investors are active in the Indian capital markets:

- Foreign Institutional Investors-FIIs,
- Mutual Funds (MFs): Public sector and Private sector
- Insurance Companies:
  - Life Insurance Companies – Public sector and Private sector
  - General Insurance Companies – Public sector and Private Sector
- Development Financial Institutions (DFIs) - IDBI, IFCI, Provident Funds (EPFO) and Pension Funds
- Commercial Banks

Post-liberalisation in 1992, a flood of Mutual Funds (MF) was launched in India, both in the Public sector and the Private sector. These funds mobilized substantial funds from the public and channelized them into the Indian capital market. Beginning in 1992, Securities Exchange Board of India (SEBI) has also progressively allowed the entry of Foreign Institutional Investors (FIIs) into the Indian Capital market. Exposure of Indian Banks to Capital markets is controlled by Reserve Bank of India (RBI) regulations in India. The role of Development Financial Institutions (DFIs) in the Indian capital market has diminished over time, either due to their conversion into banks or due to the decline in business prospects. However, the role of Provident Funds like Employee Provident Fund Organisation (EPFO) have been on the rise. Under the New Pension Scheme (NPS) launched in India, Pension Funds too are entering the Indian market. FIIs and MFs typically have a shorter time return horizon while the other Institutional Investors viz., Financial Institutions, Banks, Insurance Companies, Provident Funds (PFs) etc are essentially long-term players. Since **FII**s and **MF**s are the most active institutional investors in India we focus on them in this study.

Ever since FIIs were allowed into Indian capital markets in 1992, the number of FIIs registered with SEBI in India has steadily risen over the years and in March 2010 stood at over 1,700, with their cumulative investment in Indian equities being over US$ **72** billion (Source: SEBI web site).

Mutual Fund (MF) industry in India began with the setting up of the Unit Trust of India (UTI) in 1964 by the Government of India (GoI). While Public-sector Public Sector banks and Insurance companies were allowed into the Mutual Funds arena since 1987, the sector realy started growing after Private sector MFs was allowed in 1993. MF assets in India have grown at a compounded annualized growth rate of **48%** over a period of four decades, 1965 – 2005 (Source: Association of Mutual Funds in India (AMFI)). By May 2009, the Assets Under Management (AUM) of MF industry touched a peak of Rs 6.38 lac crores (INR 6.38 trllion), which is still only 16% of the aggregate bank deposits of Rs 39.5 lac crores (INR 39.50 trillion) (Personal FN.com).

The paper is organized as follows: Section 2 gives a background setting to the research problem and outlines the motivation for the study. Section 3 reviews extant literature on Herding. Section 4 discusses the methodology, data, and variables employed to conduct the research. Section 5 discusses the results and Section 6 highlights the conclusions from the study.

2. MOTIVATION FOR THE STUDY:

2.1. Importance of Institutional Investors (IIs):

The shareholdings and trading activity of institutional investors have increased dramatically over the past few decades, thereby raising important questions concerning the nature and impact of institutional trading on securities prices. Various studies have documented the power of Institutional Investors in developed markets like US. According to Lakonishok – Shleifer – Vishny (**LSV, 1**991), Institutional Investors held about 50% of equities and their trading accounted for approximately 70% of trading volume in the US. Cai, et. al. (2000) estimated that Institutional investors as a group own more than half of U.S. publicly traded equities and make more than 50% of all trades in the U.S. stock markets. A similar study by Gompers and Metrick (2001) found that Institutions account for more than 60% of all equity ownership and an even greater percentage of the average daily trading volume in U.S. markets. According to the Securities Industry Fact Book (2002), holdings of U.S. equities by Institutions increased from 16.2% in 1965 to 61.3% in 2001. Sias (2004) shows that Institutional investors accounted for 50% of the total US equity ownership in 1999 compared to 28% in 1970. Non – retail trading accounted for 96% of New York Stock Exchange (NYSE) trading volume in 2002 (Jones & Lipson, 2004).

Germany has also seen the emergence of Institutional Investors as dominat market participants. In 1950, institutional investors held 3.8% of all stocks, which slowly increased to 13.3% in 1970 and 22.4% in 1990. In 2002, institutional investors controlled 39.0% of all stocks in Germany (Walter and Weber, 2006). Globally, professional investors manage financial assets exceeding US$ 45 trillion (including over US$ 20 trillion in equities) according to the International Monetary Fund (IMF), 2005. Contrast this with the Global GDP of USD 60 trillion.

Institutional investors are major players not just in developed markets; their role is growing even in emerging market countries (Khorana et al, 2005). Local investors in emerging markets remain most important group – so influence of FIs likely to be result of 'herding' rather than size itself (**Ong**–Sy, 2004).

2.2. Concerns about Institutional Investors (IIs):

There are two extreme views of the impact of institutional investors on stock prices. While the negative view is more predominant, there is a positive side too.

The concern about institutional investors is that they destabilize stock prices, increasing long-term volatility. This view rests on the premise that swings in institutional demand have a larger effect on stock prices than swings in individual demand, as institutional trades are usually larger.

de Long et. al. (1990) and Cutler, Poterba and Summers (1989) have talked about the concern of Institutional Investors following short-term trading strategies based 'not on fundamentals', but on technical analysis. Sias and Whidbee (2006) on the other hand, find that institutional investors are more likely to drive prices from fundamental values than individual investors. Dornbusch and Park (1995) argue that foreign investors pursue strategies that make stock prices overreact to changes in fundamentals. They say that foreign investors indulge in Positive Feedback trading, ie., their trades are affected by past returns. Buying when prices have increased and selling when they have fallen would lead to herding. Conceptually, the term “herding” refers to the aspect of aligning of one’s behaviour to the behaviour of others, while “feedback trading” relates to trading on the basis of historical prices – this is highlighted by Kallinterakis and Ferreira (2005). Herding is a phenomenon commonly attributed to foreign investors – indicating that their trades are highly correlated. In other words, they buy and sell the same stocks at the same time. If foreign investors trade as a group i.e. indulges in Herding, they could destabilize the market by throwing the market into disarray.

Chiyachantana et. al. (2004) show that Institutional purchases have bigger price impact than sells in bullish markets, which is reversed in bearish markets. Theoretical models have found evidence that if large investors buy when prices increase and sell when prices decrease, it can destabilize the stock market – a fact illustrated by Gompers and Metrick (2001). Due to the preference of Institutional investors for liquidity and size, as shown by Falkenstein (1996) and Gompers and Metrick (2001), greater herding may be observed in large capitalization stocks. Ko – Kim - Cho (2005) find that foreign investors have a clearer preference for stocks with large capitalization and low book-to-market ratios than do domestic institutional investors in both Japanese and Korean stock markets. Dahlquist – Robertsson (2001) find that foreign investors in Sweden (typically MFs & Other Institutional Investors) prefer large firms, firms with high liquidity, firms with presence in international markets, firms paying low dividends and firms with large cash on their balance sheets and underweight firms with a dominant owner. Dennis and Strickland (2002) find that institutions react more strongly than individuals when the absolute value of the return on the market is large on any given day.

In studies on emerging markets, it has been found that portfolio flows are usually positively associated with earlier stock market returns; see Brennan and Cao (1997) and Bekaert and Harvey (1999). The reason for the co-movement of returns and flows is that flows contain information about future value, ie., current inflows predict future inflows and future inflows drive up prices. However, there is a divergence between industrialised and emerging economies as foreign investors are less informed about emerging markets. Frenkel and Menkoff (2004) indicate that activities of FIIs following the opening-up of the capital account in emerging economies are not just positive for these countries but can also exert adverse effects. This is due to asymmetric distributions of information between local and foreign investors and between fund holders and managers. FIIs are assumed to have relatively little information on specific developments in emerging markets.

Studies have also been made on changes in institutional ownership and returns. Nofsinger and Sias (1999), working on New York Stock Exchange (NYSE) data find that there is a strong positive relation between annual changes in institutional ownership and returns over the herding interval. It is hypothesized that this is due to price pressure caused by institutional trades, which seems quite intuitive – if institutions as a group are adding to their holdings of a certain stock, we can expect their buying activity to push up the price of the stock or due to inventory/ liquidity reasons, or because market participants infer information from institutional trades. Sias – Starks - Titman (2001) find that the price impact of institutional trading is primarily responsible for positive covariance between quarterly changes in institutional ownership and quarterly returns. They also suggest that the price pressure results from information revealed through institutional trading.

Further, as Barber and Odean (2006) show, Individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume and stocks with extreme one-day returns. Individual investors have to search thousands of stocks they can potentially buy, while they don’t face such a problem when they sell, since it is a small subset of stocks they already own .

2.3. Indian market conditions:

Douma et al. (2006) provide empirical evidence that FIIs in India, invest in large, liquid companies, which enable them to exit their positions quickly at relatively lower cost. Ananthanarayanan et al. (2004) find that as of August 2003, net FII investment was 9% of BSE market capitalization, which is small, compared to the size of the market. The value of FII holdings in S & P CNX 500 stocks stood at Rs 12 lac crores (INR 12 trillion) as at the end of December 2007 (Business Line 19/02/08). **Pal** (2004) indicates that the FII holding of Sensex companies was over 20% as at June 2004, i.e., FIIs as an investor group are the biggest non-promoter shareholders of the Sensex companies.

However, the important factor is not market capitalization but the level of free float, i.e., shares that are actually publicly available for trading. As floating stock in India is about 25% on the aggregate, it implies that FII have garnered about 20% of the market free float. Further, only about 3,000 of the 8,000 stocks listed on Bombay Stock Exchange (BSE) are frequently traded. FIIs followed a 'bottom-up'approach in India, investing in high quality, high growth, and large cap stocks. Thus, FIIs probably own 50% of the free float in most of the big stocks (**Banaji**, **2000**).

2.4. Motivation for the Study:

There has been only one study on herding in India by Batra (2003) and that too using the LSV(1991) model. There has been no Indian study so far on market – level herding using Hwang – Salmon (2004) method. The study aims to fill this gap in literature.

2.5. Scope of the Study:

Thus, this study would focus on market - wide herding and the impact of

Institutional Investors. The impact of FIIs and MFs on herding is studied. To study herding daily data of an index and its constituents is used. In this study, the stocks used are the Nifty50 stocks, the index used is the National Stock Exchange (NSE) Nifty 50 index. Changes in Nifty 50 over time have been accounted for by obtaining the historical Nifty constituent lists from the website of NSE. The data period is 12 years; from 1996 (when NSE was launched) – 2008; such a long study period covers many crucial phases in the history of the Indian stock market. The impact of Market Return and volatility on Herding is also assessed.

2.6. Research Objectives:

The basic objective of this research is to evaluate whether there is market-wide herding on the Indian capital market. Also, whether Institutional Investors impact Herding tendencies in Indian Capital markets is assessed. Finally, the impact of market return and volatility on herding in Indian capital market is assessed.

3. HERDING BY INSTITUTIONAL INVESTORS:

3.1. Institutional Trading & Impact on Security Prices:

Sias-Starks-Titman (2001) postulate that there are *three* reasons to believe that institutional trading may impact security prices. First, trades initiated by institutions may require price concessions because they push individuals and other liquidity providers away from their preferred inventory or portfolio positions (liquidity hypothesis). Second, information revealed through trading is primarily responsible for price changes and due to economies of scale, institutional investors are better informed than other traders ("informed trading hypothesis"). Third, positive relation between changes in institutional ownership and returns arises from intra-period institutional "positive feedback trading". If investors 'chase' returns in the immediate past (like the previous day or week) then aggregating their fund flows over the month can lead to a positive relationship in the contemporaneous monthly data.

Many studies find little evidence to support the hypothesis that institutional herding destabilizes asset prices. Wermers (1999) and Sias (2004) provide evidence that asset prices continue in the direction of the herd during subsequent periods. These results support the contention that herding helps drive asset prices to fundamental values more quickly than would otherwise be the case.

3.2. Herd Behaviour of Institutional Investors:

One of the most oft-repeated criticisms against Institutional Investors is 'herd behaviour'. Herding arises when investors decide to imitate observed decisions of others or movements in the market rather than follow their own beliefs and information. Herd behaviour refers to correlated trading i.e. buying (selling) the same stocks as other managers buy (sell) at the same time. Institutional investors buy (sell) the same stocks as other managers buy (sell) at the same time, which could destabilize market. When foreign investors move in or out as a herd, their entry could lead to overheating and their exit could trigger a fall. Numerous definitions of herding have been proposed. Nofsinger and Sias (1999) define herding as 'a group of investors trading in the same direction over a period of time' while Banerjee (1992) suggests that herding involves 'everybody doing what everyone else is doing even when their private information suggests doing something else'.

There are two polar views of herding behaviour of institutional investors, the non-rational and rational views.

- ☐ Irrational view: focuses on investor psychology where an investor behaves like a lemmings, forego rational analysis and follow others blindly
- ☐ Rational view: Imperfect information, concerns for reputation and compensation structures also foster rational herd behavior, see Devenow and Welch (1996) for details. Herding can be rational (utility maximising), for example when it is thought that other market participants are better-informed or where there is uncertainty - market participants hold mistaken but rational beliefs that most traders possess accurate information

Various theories have been proposed to explain the reason behind herding by Institutional Investors:

1. According to Scharfstein and Stein (1990), managers disregard private information and trade with the crowd. As managers are evaluated against each other, there is a high penalty for falling behind others . In such environments, managers of institutions may find it optimal to mimic the trading patterns of other institutions.

2. Managers trade together as they receive correlated private information, ie., they analyse the same indicators, a view subscribed to by Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994)

3. Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992) believe that managers infer private information from prior trades of better-informed managers and trade in the same direction.

4. According to Falkenstein (1996), Institutional Investors are averse to stocks with lower liquidity or having high transaction costs .

3.3. Empirical testing of Herding:

Lakonishok – Schleifer - Vishny (LSV,1991) can be regarded as the pioneers of empirical tests of herding behaviour. LSV (1991) define herding as the average tendency of a group of fund managers to buy and sell particular stocks simultaneously relative to what would be expected if the managers traded independently.

In terms of the LSV measure, herding refers to a statistical correlation of trading among a particular group of market participants. As a market consists of a supply and a demand side, not all market participants can flock together in a herd. Thus, herding is only likely to occur when a homogeneous subgroup of traders is investigated. In particular, the LSV measure gauges the average tendency of say, Mutual Fund managers to accumulate on the same side of the market in a particular stock and in a given time period, relative to what could be expected if managers traded independently.

The LSV (1991) model measures herding by studying a subset of market participants over time – they look at end – of – quarter portfolio holdings for a set of money managers over time and treat each quarterly change as an observation. Further, LSV measure does not account for quantity of stock investors buy or sell. The herding measure for stock i in period t (stock-period i,t) is defined as follows:

$$HM_{i.t} = |p_{i,t} - p_t| - AF_{i,t}$$

$$with\, p_{i,t} = \frac{B_{i,t}}{B_{i,t}+S_{i,t}};\; p(t) = \frac{\sum_{i=1}^{i=N} a\, B(i,t)}{[\sum_{i=1}^{i=N} a\, S(i,t) + \sum_{i=1}^{i=N} a\, B(i,t)]};$$

Where,

$HM_{i,t}$ is a measure of herding for stock *i* at time *t*.

$B_{i,t}$ denotes the number of managers that increase their holdings in a particular stock i in a given period t.

$S_{i,t}$ denotes the number of managers that decrease their holdings in a particular stock i in a given period t.

p_t is the 'average trade imbalance measure' for all stocks at time *t*. p_t controls for aggregate shifts into or out of stocks during a particular time period. Trading decisions may be influenced by net fund flows. In times of large net inflows, for instance, fund managers tend to be on the buy-side rather than on the sell-side of the market. The subtraction of p_t corrects for such 'market-wide herding'. As per LSV, p_t equals the number of fund managers *buying*, relative to the number active, aggregated across all stocks that the fund managers traded in that period.

$AF_{i,t}$ is the Adjustment factor given by $E|p_{i,t} - p_t|$. $AF_{i,t}$ accounts for the fact that the first term in the equation, which is an absolute value, is greater than zero even under the null hypothesis of no herding.

Therefore, a value for $p_{i,t}$ of 0.66 can be interpreted as 66% of all managers being net purchasers of stock i in period t.

The measure $HM_{i,t}$ is expected to be calibrated to zero, if no herding actually exists. Since the first expression of the LSV measure $HM_{i,t}$ is defined in absolute value ($|p_{i,t} - p_t|$), without inclusion of the adjustment factor $AF_{i,t}$, the measure is likely to take positive values, even where no herding exists. $AF_{i,t}$ is the expected value of $|p_{i,t} - p_t|$ calculated under the assumption that trades follow a binomial distribution with $B_{i,t}$ (success) and $S_{i,t}$ (failure) as possible outcomes. Under the null hypothesis of no herding, the probability of $B_{i,t}$ is p_t. Thus, under the Null hypothesis of no herding, we expect the metric $HM_{i,t}$ to be insignificantly different from zero.

Values of the LSV measure $HM_{i,t}$, can be interpreted as the tendency of a particular group of market participants to trade a given stock in a given period together above random distribution of trade decisions. Positive values of the LSV measure that significantly differ from zero provide evidence of herding behaviour.

Shortcomings of LSV (1991) Model:

Bikhchandani & **Sharma** (2000) stress the fact that the LSV measure follows a purely statistical approach, assessing the correlation in trading patterns for a particular group of market participants. It documents synchronical trading irrespective of the reasons underlying such behaviour. For this reason, the measure is not able to differentiate between intentional and unintentional herding. While this objection certainly is true, it is not a specific drawback of the LSV measure, but applies to every statistical device for measuring herding. Bikhchandani & Sharma also point out that while the measure is able to document whether herding in a particular stock persists over time, it is unable to indicate whether it is the same managers who continue to herd. However, if we are interested in herding as a phenomenon itself, and not in the organic composition of herds, this drawback does not affect the study.

Wylie (2005) demonstrates that the LSV measure rests on two crucial assumptions, thereby indicating non-zero levels of herding, even where no herding exists: first, legal restrictions prohibit mutual fund managers from undertaking short sales in general. As a consequence, only those managers having a holding in a stock at the beginning of the period are able to sell it. Thus, the number of stock sales is restricted. While calculation of the LSV measure assumes a binomial distribution for $B_{i,t}$, the distribution is actually left truncated. Second, the assumption of a binomial distribution for $B_{i,t}$ causes another problem, as the propensity pt of fund managers to buy a stock is invariant for all stocks. Under real conditions, however, the propensity to buy may be conditioned by both the size of the fund managers initial holding and net fund flows.

Wylie carries out accuracy tests to gauge the effect of the crucial assumptions on the accuracy of the measure. Two estimates of the sampling distribution of the LSV measure, with and without the assumptions being valid, are compared. Wylie finds that except when only a very small number of managers trade, the LSV measure is not biased in measuring herding.

A summary of Herding studies using LSV method and its variants is given below:

Table 3-1 Summary of Herding Studies using LSV/ Christie-Hwang method

Researcher	Period	Findings
LSV (1991)	1985-89, US	No Herding by Fund Managers except in smaller stocks, but no destabilising influence on stock prices.
Grinblatt-Titman-Wermers, (1995)	1974-1984, US	MFs Herd, but average level of Herding and momentum investing is statistically significant but not large
Wermers, (1999)	1975-94, US	Level of Herding by MFs in average stock is low but herding is higher in trades of smaller stocks and in trading by growth-oriented Funds.
Sias (2004)	1975-1994, US	Institutions herd more in smaller stocks, supporting the view that herding is informationally biased.
Sharma (2004)	1998-2001, US NASDAQ	Institutional Investors herded in Technology stocks , but very little herding by all investors in an average stock.

Puckett & Yan (2007)	1999-2004, US	Institutional herding is more among large, young, volatile, growth, S&P 500 stocks & stocks with poor prior performance.
Wylie (2005)	1986-93, UK, 268 MFs	Modest level of MF manager herding in largest and smallest stocks but little in other stocks. Herding does not have a material effect on stock prices.
Walter-Weber (2006)	1998-2002, 60 MFs, Germany	Find Herding and Positive Feedback Trading in MFs slightly higher in Germany than in US and UK, but Herding does not destabilise stock prices. Buy-side herding is high during boom periods and sell-side herding during crash periods. Small stocks are not more vulnerable to herding behavior (contrary to earlier findings).
Kim-Nofsinger(2005)	1975-2001, Japan	Herding lower than in US but with larger impact on price movements.
Agudo et al (2008)	1994-2002, Spain, Equity Funds	Significant Herding in value stocks, growth stocks. Higher than that found in previous studies.
Lobao-Serra (2002)	1998-2002, Portugal	Strong evidence of Herding by MFs, but more pronounced in mid-cap funds, 4-5 times higher than the herding found in mature markets.
Voronkova & Bohl (2005)	1999-2001, Poland	'Herding' and Positive Feedback Trading (PFT) present more often than in mature markets. But trading by Pension Funds does not impact future stock prices.
Borensztein & Gelos (2003)	1996 to 2000, Emerging markets	On average, Funds withdrew money one month prior to the crises. The degree of herding among Funds is statistically significant, but moderate and is more prevalent during crises than during tranquil times. Herding by Funds is more intense in larger markets, with higher liquidity as portfolios can be adjusted often.
Alemanni and Ornelas (2006)	2000-2005, 9 Emerging markets	Herding by foreign investors decreased from 1995-2000 to 2000-2005. Results differ from Borensztein & Gelos (2003).
Choe et .al. (1999)	1996-1997, Korea	Find strong evidence of herding by foreign investors before the Asian crisis of 1997, but the evidence is much weaker during the crisis period.
Kim-Wei (2002)	1996-1998, Korea	Individual investors always herd more than institutions and the Herding measure for the individuals is generally twice or more than that for institutional investors. Herding is induced by informational asymmetry.

Bonser-Neal et. al. (2002)	1995-2000, Indonesia	Both foreign and domestic investors herd but foreign investors herd more. Herding by foreign investors increased over time from the Pre-Asian Crisis to the Crisis period. No evidence that foreign trading behavior destabilized market prices during the Crisis.
Bowe and Domuta (2004)	1997-1999, Indonesia	Both foreign and domestic investors herd, but foreigners herd more. Foreign herding increases following the onset of the 1997 Asian crisis, while domestic herding does not increase during the crisis and even diminishes subsequently.
Agarwal et. al. (2007)	1995-2003, Indonesia	Both domestic and foreign investors exhibit significant herding behaviour but such behaviour is much stronger for foreign investors.
Chen et. al. (2003)	1996-2002, China	During periods of extreme price movements, Herding present in both Shanghai-B and Shenzhen-B. For both Shanghai-A and Shenzhen-A, results are mixed (weak support for herding). Foreign participants tend to herd due to lack of fundamental and private information on firms.
Tan et. al. (2008)	1994-2003, China	Herding present in both Shanghai and Shenzhen A-share markets and within both B-share markets. Herding occurs in both rising and falling market conditions. Herding by A-share investors in Shanghai market is more pronounced under conditions of rising markets, high trading volume and high volatility, while no asymmetry is apparent in B-share market.

Another method used to measure Herding is the Hwang – Salmon (2004) method. The details of the Hwang – Salmon method and its difference from LSV method are detailed in the next Section, viz., 4.1.

Table 3-2 Summary of Herding Studies using Hwang-Salmon method

Researcher (s)	Period	Findings
Hwang-Salmon (2004)	1993-2002, US, Korea	Find significant but not extreme herding towards market portfolio in both bull and bear markets
Kallinterakis-Ferriera (2005)	1993-2005, Portugal	Significant Herding and Feedback Trading

Kallinterakis (2007)	2002-2007, Vietnam	Both Positive and Adverse Herding observed, but no distinctive pattern over time.
Andronikidi-Kallinterakis (2007)	1997-2006, Israel	Find significant but not extreme herding towards market portfolio
Kallinterakis-Kratunova (2007)	2000-2006, Bulgaria	Herding significant but not extreme
Gavriilidis, Kallinterakis*, Micciullo (2007)	2000-2006, Argentina	Herding significant but not extreme

4. METHODOLOGY & DATA:

4.1. Methodology to test Herding:

Two streams of empirical literature have developed to investigate the existence of herding:

i. The first approach analyzes the tendency of individuals or certain groups of investors, such as mutual fund managers and financial analysts to follow each other and trade an asset at the same time. This requires detailed records of investors' trading activities. The LSV (1991) method indicated in section 3.3. uses this approach.

ii. The second approach focuses on market-wide herding, ie., collective behavior of all participants towards the market views and therefore buying or selling a particular asset at same time.

In this study, we focus on market-wide Herding and to test for it, we employ the empirical framework developed by **Hwang** and **Salmon** (2004). This method is similar to the Christie – Hwang (1995) model which uses cross – sectional standard deviation of returns (CSSD) to detect herd behaviour; low values of dispersion of returns implies herd behaviour. Both Hwang and Salmon (2004) and Christie – Hwang (1995) methods exploit information held in cross-sectional movements of market. Unlike Christie – Hwang (1995), the Hwang and Salmon (2004) approach focusses on cross-sectional variability in factor sensitivities (betas) rather than factor returns. As the Hwang and Salmon model captures 'market-wide herding' it differs from LSV. However, herding of both forms leads to mispricing of individual assets as equilibrium beliefs are suppressed.

Further, the Hwang and Salmon (2004) measure is based on observed returns and data is easier to obtain. On the other hand, the LSV (1991) method needs detailed records of individual trading activities which is quite difficult to obtain. Hwang and Salmon (2004) implicitly assume that herding should be viewed in a relative sense rather than as an absolute and that no market will ever be completely free of herding. Most Herding measures like LSV (1991) and Christie – Hwang (1995) try to identify herding in absolute terms.

Hwang and Salmon (2004) aim at extracting herding from the factor-sensitivity of assets at the cross-sectional level. The Hwang and Salmon model presupposes that when investors are driven by behavioural biases, their perceptions of the risk-return relationship of assets may be distorted. If they herd towards the market consensus, then it is possible that as individual asset returns follow the direction of the market, their CAPM-betas will deviate from their equilibrium values. Consequently, the beta of a stock is not expected to remain constant but change with the fluctuations of investors' sentiment. In the event of herding prevailing in the market, the cross-sectional dispersion of the stocks' betas would be expected to be smaller, i.e., asset betas would tend towards the value of the market beta, viz., unity. The Herding measure developed by Hwang and Salmon is based on this premise.

Conventional CAPM assumes that β_{imt} does not change over time. However empirical evidence shows that the betas are not constant; the empirical evidence of time-varying betas arises from behavioural anomalies like herding, rather than fundamental changes in beta$_t$.

Hwang-Salmon assume the equilibrium beta (β_{imt}) and its behaviourally biased equivalent (β^{b}_{imt}), whose relationship is assumed as follows:

$$\{ Eb_t (r_{it}) / E_t (r_{mt})\} = \beta^{b}_{imt} = \beta_{imt} - h_{mt} (\beta_{imt} - 1). \qquad \textit{Equation 4-1}$$

$Eb_t (r_{it})$: behaviourally-biased conditional expectation of excess returns of asset *i* at time *t*.

$E_t (r_{mt})$: conditional expectation of excess returns of market at time *t*.

$h_{mt} \leq 1$: a time-variant herding parameter. .

To measure h_{mt} (herding on a market-wide basis), Hwang-Salmon calculate the cross-sectional dispersion of β^{b}_{imt} as:

$$Std_c (\beta^{b}_{imt}) = Std_c \beta_{imt} (1 - h_{mt}) \qquad \textit{Equation 4-2}$$

Hwang and Salmon assume that the herding parameter follows an AR(1) process and resolve their model as:

$$\log [Std_c (\beta^{\mathbf{b}}_{imt})] = \mu_m + H_{mt} + \upsilon_{mt} \qquad \text{Equation 4-3}$$

$$\mathbf{H}_{mt} = \phi_m \mathbf{H}_{m,t-1} + \eta_{mt} \qquad \textit{Equation 4-4}$$

where $\eta_{mt} \sim iid\ (0, \sigma^2_{m,n})$.

β_{imt} is the beta for asset *i* for market at time *t* and Std is the Standard Deviation.

H_{mt} is the Herding parameter.

$\mu_m = E[\log [Std_c (\beta^{\mathbf{b}}_{imt})]]$ and $\upsilon_{mt} \sim iid\ (0, \sigma^2_{mv})$.

The above system of equations accommodates herding as an unobserved component and in order to extract it, Hwang and Salmon employ the Kalman filter. Thus, $\log [Std_c(\beta^{b}_{imt})]$ is expected to vary with herding levels, and its change is reflected through H_{mt} . If $\sigma^2_{m,n} = 0$, then $H_{mt} = 0$, in such a case, $\beta^{\mathbf{b}}_{imt} = \beta_{imt}$ so there is no herding and the equilibrium CAPM applies. A significant value of $\sigma^2_{m,\eta}$, would imply the existence of herding and this would further be reinforced by a significant ϕ_m. The absolute value of the latter is taken to be smaller than or equal to unity, as herding is not expected to be an explosive process. When $H_{mt} = 1$, $\beta^{\mathbf{b}}_{imt} = 1$, which is the Beta on the market portfolio. This indicates perfect Herding towards market portfolio, ie., all individual assets move in the same direction with the same magnitude as the market portfolio. In other words, whenever $0 < H_{mt} < 1$, we can say that some degree of herding exists in the market.

To estimate the above system of equations, the OLS-estimates of the betas are first made using daily excess return data within monthly windows in the standard market model:

$$r_{itd} = \alpha^{b}_{it} + \beta^{b}_{imt}\, r_{mtd} + \varepsilon_{itd} \qquad \textit{Equation 4-5}$$

where subscript "*td*" indicates daily data for month *t* & r_{mtd} indicates excess market returns.

To calculate excess returns, first derive the percentage log-differenced returns from the closing prices of the index and its constituents and then adjusts them by using the appropriate risk-free rate. Having estimated these monthly betas for the stocks in month *t*, cross-sectional standard deviation for that month is then estimated, thus constructing a monthly time-series.

4.2. Variables and Data:

Exchange/ Market: The study is conducted with the data obtained from the National Stock Exchange of India (NSE).

Data requirement: The key input for testing market-wide herding are the index values and the prices of stocks constituting the index. For the pupose of the sudy, the S & P CNX Nifty Index (or **Nifty50**) is used as India does not have an all-shares Index. Nifty 50 has the properties required of an index suitable for measuring herding using H – S method, as historical details of its constituents are available from NSE website. The H – S method (2004) requires estimation of cross-sectional standard deviation of the betas of the stocks comprising the Nifty 50 portfolio for each month during the study period. The NSE website (www.nseindia.com) details the index construction methodology. Nifty 50 is a well-diversified 50-stock index accounting for 22 sectors of the Indian economy.

Study Period: Though Nifty50 was launched in April 1996, NSE provides changes to Nifty50 from 18th September 1996. Thus, the study period is taken between 1st September 1996 and 31st October 2008, a period of over 12 years (146 months). In particular, the data comprises of daily prices for both the Nifty50 as well as its constituent stocks. The historical constituent lists for Nifty50 were obtained from the website of NSE (given at

Table 4- 1). Thereafter, a month-wise list of NIFTY 50 stocks from 01 – 09 – 1996 to 31 – 10 – 2008 was constructed. The adjusted closing prices of each of the NIFTY 50 stocks for the period when they were in the index NIFTY 50 were downloaded from CMIE Prowess database.

4.3. Statistical Tests for Herding:

Using prices of NIFTY 50 constituent stocks over time, the following tests are conducted:

i) Test for herding using Hwang - Salmon (2004) model.
ii) Check results by adding **FII Flows** to the herding model.
iii) Check results by adding **MFs Flows** to the herding model.
iv) Check results by adding Monthly Nifty **Return** to the herding model
v) Check results by adding Monthly Nifty **Volatility** to the herding model

5. HERDING – RESULTS & DISCUSSION:

5.1. Herding - Base Case:

To estimate the Herding measure, we first estimate the OLS estimates of the ***betas*** using daily excess return data within monthly windows in line with Hwang – Salmon (2004) model .

$$r_{itd} = \alpha^{\mathbf{b}}_{it} + \beta^{\mathbf{b}}_{imt}\, r_{mtd} + \varepsilon_{itd} \qquad \text{Equation 5-1}$$

where r_{itd} refers to excess returns; r_{mtd} refers to excess market returns. The subscript "*td*" indicates daily data for month *t*.

To calculate r_{itd}, we first derive the percentage log – differenced returns from the closing prices of the Nifty50 index and its constituent stocks and then adjust them by using the Risk-free rate (91-day Treasury Bill Rate). Having estimated these monthly *betas* for the stocks in month *t*, we then estimate their cross-sectional standard deviation for that month, and construct a monthly time-series. Following the argument of Hwang and Salmon (2004) that the choice of monthly windows is driven by both estimation considerations (to reduce the estimation error of the betas) as well as practical ones (to maintain a number of observations sufficient to detect herding), the cross-sectional standard deviation derived is then used (in its logarithmic form) as the input for the estimation of the herding measure.

$$\log [Std_c (\beta^b_{imt})] = \mu_m + H_{mt} + \upsilon_{mt} \text{ where } \upsilon_{mt} \sim \text{iid } (0, \sigma^2_{m,v}) \qquad \textit{Equation 5-2}$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt} \textit{ where } \eta_{mt} \sim \text{iid } (0, \sigma^2_{m,n}). \qquad \textit{Equation 5-3}$$

We follow the above-given Hwang – Salmon model equations.

Hwang – Salomon (2004) tested for the robustness of their results by re-estimating their original model by adding several variables of both fundamental (dividend-price ratio, relative treasury bill rate, term spread, default spread) as well as non-fundamental (market volatility, market direction, "size", "book-to-market" ratio) nature in the model. The idea was to gauge whether herding (H_{mt}) would remain robust in the presence of variables corresponding to different states of the market.

In a study on the Israeli market using Hwang – Salmon (2004) method, due to the relative unavailability of data on fundamentals' variables, Andronikidi - Kallinterakis (2007) test for robustness of the results using market direction (reflected through index returns) and market volatility separately in the construction of equation. We re-estimate the Hwang and Salmon (2004) model using two versions:

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + c_1\, r_{INDEX,t} + \upsilon_{mt} \qquad \textit{Equation 5-4}$$

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + c_2 \log\sigma_{INDEX,t} + \upsilon_{mt} \qquad \textit{Equation 5-5}$$

where $r_{INDEX,t}$ is the market's return at time t and $\log\sigma_{INDEX,t}$ is the market logarithmic volatility calculated on the premises of the Index. The index returns ($r_{INDEX,t}$) are defined as the percentage log-differenced returns of the Index, while the market volatility ($\sigma_{INDEX,t}$) of equation is calculated with squared daily returns using the **Schwert** (1989) methodology. The idea is that if changes in the $\log[Std_c(\beta^b_{imt})]$ were to be attributed to such variables and not herding, then their inclusion in the model would render the latter insignificant.

On similar lines, we use Institutional Flows as the external variables to test whether Herding is caused by Institutional Flows.

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + C_1\, FII_t + \upsilon_{mt} \qquad \textit{Equation 5-6}$$

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + C_2\, MF_t + \upsilon_{mt} \qquad \textit{Equation 5-7}$$

where FII and MF are Flows of Foreign Institutional Investors (FIIs) and Mutual Funds (MFs) respectively.

The Sample Statistics for the estimated cross-sectional Standard Deviation of Betas of Nifty50 constituents, as well as Logarithmic cross-sectional Standard Deviation of Betas of Nifty50 constituents are shown in **Table 5-1** in Annexure.

The results indicate that the cross-sectional standard deviation of the Betas is significantly different from zero. The distribution exhibits a significant positive skewness and kurtosis, while the Jarque-Bera statistic indicates departures from normality (non-Gaussian). We therefore apply logarithims to the values of Beta and present the statistics. From these statistics it can be observed that the Jarque-Bera statistics improve significantly. We therefore estimate the state-space model of Hwang and Salmon (2004) using the Kalman filter.

We begin with testing the basic model of Herding as given below.

$\log [\mathrm{Std}_c (\beta^{\mathbf{b}}_{imt})] = \mu_m + H_{mt} + \upsilon_{mt}$ *where* $\upsilon_{mt} \sim iid\ (0, \sigma^2_{m,v})$

$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt};$ where $\eta_{mt} \sim iid\ (0, \sigma^2_{m,n})$.

β_{imt} is the beta for asset i for market at time t and Std is the Standard Deviation.

H_{mt} is the Herding parameter.

It may be noted that E.Views 6.0 software is used to estimate the parameters.

We find (**Table 5- 2** in Annexure) that estimates for both the important parameters of the state-equation, viz., ϕ_m and $\sigma_{m\eta}$, are significant, indicating the presence of herding. The persistence parameter (ϕ_m) is statistically significant (1% level), while the standard deviation ($\sigma_{m\eta}$) of the state-equation error (η_{mt}) is significant at the 1% level. These results thus indicate that there existed significant herding towards the Nifty50 index during the period 1996-2008. The value of μ_m reflects the mean level of the logarithmic cross-sectional standard deviation of the index-portfolio betas as adjusted through herding-expressed here through H_{mt}. We find that μ_m is statistically significant at the 1% level. Similarly, the estimate of the logarithmic cross-sectional standard deviation of the Nifty50-constituent Betas, $\sigma_{m\upsilon}$ is significant at 1% level. The signal-proportion value indicates what proportion of the variability of the logarithmic cross-sectional standard deviation of the betas is explained by Herding (Hwang and Salmon, 2004). The bigger the value of the signal-to-noise ratio, the less smoothly over time herding evolves. The signal-proportion value of approximately 16% indicates a smooth evolution of herding over the sample-period.

Figure 5- 1 in Annexure provides the course of Herding vis-a-vis Nifty. It indicates that herding was never too high, i.e., its values fluctuated between 0.20 and -0.60. Herding touched a peak during the middle of 1997, coinciding with the

Asian crisis. Herding exhibited a fall thereafter till May 98, but increased again to a high of 0.20 in May 99. It fell from then on and moved into the negative territory in Sep 2000. It remained negative till Sep 2004, for about 4 years. An interesting feature is that the Indian market shows significant adverse herd behaviour since September 2000 reaching its lowest value in Sep 2001. This suggests that when the market went down, stocks with large betas (larger than 1) went down further than their long run average levels would suggest, while stocks with small betas (smaller than 1) went down less than their long-run average levels suggest. Herding increased steadily from Sep 2004, rising to a peak value of 0.20 in Sep 2006. After Sep 2006, herding declined and has not reached its earlier peaks.

5.2. Herding – with FII Flows:

We now go on to test the alternative models. We next repeat the test, this time adding the **FII Flows**. The Herding equations are modified as shown below:

$$\log [\mathrm{Std}_c (\beta^{\mathbf{b}}_{imt})] = \mu_m + H_{mt} + C_5 \ \mathrm{FII}_t + \upsilon_{mt} \ \ \textit{where} \ \ \upsilon_{mt} \sim iid\ (0, \sigma^2_{m,v})$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}; \text{ where } \eta_{mt} \sim iid\ (0, \sigma^2_{m,n}).$$

As we find (**Table 5- 3** in Annexure) that the coefficient of FII Flows is insignificant, it implies that herding is not impacted whether the FII Flows increase or decrease.

However, instead of using FII Flows, we normalise them by dividing by Market Capitalisation (MC) and re-do the testing. We find (**Table 5- 4** in Annexure) that even though we *normalize* FII Flows, the results remain unaltered. The coefficient of FII Flows is found to be insignificant, thus implying that herding is not impacted whether the FII Flows increase or decrease. We therefore conclude that FII Flows do not significantly impact Herding.

5.3. Herding – with MF Flows:

We repeat the exercise for **Mutual Funds**. However, in the case of Mutual Funds, we have monthly data only from January 2000.

The Herding equations are modified as shown below:

$$\log[Std_c(\beta^{b}_{imt})] = \mu_m + H_{mt} + C_5\ MF_t + \upsilon_{mt} \quad where\ \upsilon_{mt} \sim iid(0, \sigma^2_{m,v})$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt};\ \text{where}\ \eta_{mt} \sim iid(0, \sigma^2_{m,n}).$$

We find that the coefficient of MF Flows is insignificant, thus implying that herding is not impacted whether the MF Flows increase or decrease.

However, instead of using MF Flows we normalise them by dividing by Market Capitalisation (MC) and re-do the testing using this adjusted data. From **Table 5- 5** in Annexure we find that MF Flows are significant at the 5% level. The coefficient for MF Flows is found to be significantly negative (@ 5% level). This implies that the *log [Std$_c$ $(\beta)^{b}_{imt}$] in*creases/ decreases when MF Flows falls/ rises. When the MF Flows decline, Herding decreases. In other words, Mutual Funds increase the Herding tendency. The persistence factor ϕ_m is still highly significant.

5.4. Herding – with Index Return & Volatility:

We next use the Kallinterakis model to estimate the impact of Nifty Return and Volatility on Herding using the following Equations.

$$\log[Std_c(\beta^{b}_{imt})] = \mu_m + H_{mt} + c_5\ r_{INDEX,t} + \upsilon_{mt} \quad where\ \upsilon_{mt} \sim iid(0, \sigma^2_{m,v})$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt};\ \text{where}\ \eta_{mt} \sim iid(0, \sigma^2_{m,n}).$$

From **Table 5- 6** in Annexure, we find that the impact of Nifty Returns on Herding is significant. The coefficient of Monthly Nifty Returns is found to be significant @ 5% level, thus implying that herding is impacted by Nifty Returns. **Figure 5- 2** in Annexure gives the evolution of Herding vis-à-vis Nifty 50 in the presence of Monthly Return variable.

We run the Kalman filter again this time with the Monthly Volatility of Returns.

$\log[\mathrm{Std_c}\,(\beta^{b}_{imt})] = \mu_m + H_{mt} + c_5 \log\sigma_{INDEX,t} + \upsilon_{mt}$ *where* $\upsilon_{mt} \sim iid\,(0, \sigma^2_{m,v})$

$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}$; where $\eta_{mt} \sim iid\,(0, \sigma^2_{m,n})$.

From **Table 5- 7** in Annexure, we find that the impact of Nifty Volatility on Herding is significant. The coefficient of Monthly Nifty Volatility is found to be significant, thus implying that herding is impacted by Nifty Volatility. Interestingly, the mean value μ falls from around -0.70 to 0.05 and becomes insignificant. **Figure 5-3** in Annexure gives the evolution of Herding vis-à-vis Nifty 50 in the presence of Monthly Volatility variable.

Next, we run the Kalman filter with both the Monthly Return and Volatility of Nifty included.

$\log[\mathrm{Std_c}\,(\beta^{b}_{imt})] = \mu_m + H_{mt} + c_5\, r_{INDEX,t} + c_6 \log\sigma_{INDEX,t} + \upsilon_{mt}$

where $\upsilon_{mt} \sim iid\,(0, \sigma^2_{m,v})$

$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}$; where $\eta_{mt} \sim iid\,(0, \sigma^2_{m,n})$.

Table 5- 8 in the Annexure shows that the impact of Nifty Volatility on Herding is significant, while that of Nifty Return is not. The coefficient of Monthly Nifty Returns is found to be insignificant, while coefficient of Monthly Nifty Volatility is significant. This implies that herding is not impacted by Nifty Return, but impacted by Nifty Monthly Volatility. In the presence of Volatility, the Return variable becomes insignificant. Interestingly, the mean value μ of logSDβ moves from negative to positive territory, ie., from around -0.70 to 0.10 and becomes insignificant. **Figure 5-4** in Annexure gives the evolution of Herding vis-a-vis Nifty 50 in the presence of Monthly Return and Volatility variables. Volatility proves to be a strong variable in influencing Herding. When the market becomes riskier, Herding increases, and when the market becomes less risky, Herding also declines.

6. Conclusions and Remarks:

This work attempts to ascertain the presence of herding and whether Institutional Investors impact herding. It is observed that herding exists on the Indian market, but is not very severe. Policy makers need not be unduly worried about Herding in Indian market. The presence of adverse herding in the Indian market is interesting. Adverse herding must exist if herding exists as there must be some systematic adjustment back towards the equilibrium CAPM (mean reversion towards long-term equilibrium β_{imt}) from mispricing both above and below equilibrium.

FII Flows or normalized FII Flows does not significantly impact the herding behaviour; i.e., overall market-level herding is not impacted whether the FII Flows increase or decrease. As the study period includes 2007, the year of peak FII Inflows and 2008 the year of peak FII Outflows, this finding should give comfort to Regulators about FII Flows. While countries like Brazil have imposed tax on FII Flows to curb them, our policy suggestion is that we need not be hasty in the matter. Herding declines before the 2008 crisis; this suggests that periods of market crisis/ stress can help markets return to equilibrium. Many studies have demonstrated that Institutional Investors do not destabilize the capital markets by excessive Herding. This finding has been corroborated in India too, in the case of FIIs. The findings to some extent dispel the popular notion that FII's destabilize the Indian capital market.

An interesting finding is that the mutual funds increase the herding tendency. As Fund managers are evaluated more frequently than other types of managers, their focus is more short-term. Consequently, Fund managers of MFs tend to exhibit a larger tendency to 'run with the herd' than other types of institutional managers. Our finding that Mutual Fund (MF) Flows increase Herding tendency corroborates this hypothesis. However, the activity of MFs may be watched closely by Regulators and the reasons for Herding explored further.

While studying the impact of Nifty return and volatility on herding, it is found that the impact of Nifty return on Herding is insignificant. However, the impact of Volatility is significant, it increases the Herding tendency. Therefore, regulators need to watch for Herding tendency (eg., Bulk trades) when Volatility shoots up.

Plotting the Herding tendency against Nifty Index, we can see mildly fluctuating Herding towards the market portfolio between 1996 and 2000 when the market (Nifty) hovered between 800 and 1500. From 2000 to mid-2003, when the market (Nifty) declined from around 1500 level to the 1000 level, we see Herding away from the market, in fact we see Adverse Herding. From 2003 to 2008, when the market witnessed a period of secular growth trend, we find the presence of Herding. From 2003 to 2005, while the market was in a rising trend, even though there was Adverse Herding, Herding too was on the rise. Herding crossed into the positive territory and was on the uptrend up to mid-2006. It is observed that Herding has been declining since then, even as the market was still rising. It is interesting to note that Herding started declining much before the market peaked in early 2008. This interesting phenomenon suggests that periods of market crisis or stress can help return markets to equilibrium, implying that efficient pricing may be helped by market stress. Contrary to common belief that herding is significant when the market is in stress, we find that herding can be more apparent before a crisis. Once a crisis appears, herding toward the market returns becomes much weaker.

An extension to this work could be, to estimate the value-weighted cross-sectional dispersion, adjusted for free float. For value-weighted beta dispersions, one can use market capitalization. Further, one can also estimate the volume-weighted cross-sectional dispersion using trading volumes. As regards the validity of CAPM, the different approaches presented by the APT, Consumption-based CAPM, Fama-French, Carhart and higher co-moment CAPMs (with skewness, kurtosis, semi-skewness, semi-kurtosis, semi-variance et al) can also be tried.

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Annexures

Table 4- 1 **CHANGES TO S&P CNX NIFTY**

Date of Inclusion	Securities Included	Securities Excluded	Date of Inclusion	Securities Included	Securities Excluded
12-Jan-09	RELCAPITAL	SATYAMCOMP	1-Sep-00	DIGITALEQP	BANKINDIA
10-Sep-08	RPOWER	DRREDDY	24-May-00	HCL-INSYS	EIHOTEL
14-Mar-08	DLF	GLAXO	24-May-00	ZEETELE	IDBI
14-Mar-08	POWERGRID	BAJAJAUTO	10-May-00	DABUR	TVSSUZUKI
12-Dec-07	IDEA	MTNL	8-Sep-99	BRITANNIA	IFCI
12-Dec-07	CAIRN	HINDPETRO	8-Sep-99	SATYAMCOMP	INDRAYON
5-Oct-07	UNITECH	IPCL	26-May-99	DRREDDY	ARVINDMILL
24-Sep-07	NTPC	DABUR	26-May-99	NOVARTIS	GESHIPPING
4-Apr-07	RPL	JETAIRWAYS	26-May-99	RECKCOLMAN	RELCAPITAL
4-Apr-07	STER	ORIENTBANK	7-Oct-98	BANKINDIA	THERMAX
1-Sep-06	RCOM	TATATEA	7-Oct-98	CIPLA	ANDRAVALLY
27-Jun-06	SUZLON	SCI	7-Oct-98	HEROHONDA	ASHOKLEY
27-Jun-06	SIEMENS	TATACHEM	7-Oct-98	INFOSYSTCH	BPCL
26-Sep-05	JETAIRWAYS	COLGATE	7-Oct-98	NIIT	INDOGULF
25-Feb-05	TCS	INDHOTEL	7-Oct-98	P&G	MRPL
10-Dec-04	LT	BRITANNIA	7-Oct-98	SMITKLBECH	PONDS
24-May-04	PNB	L&T	24-Dec-97	BPCL	ESSARGUJ
12-Apr-04	ONGC	DIGITALEQP	14-May-97	BHEL	SCICI
1-Mar-04	BHARTI	GSKCONS	14-May-97	HINDPETRO	DRREDDY
1-Mar-04	MARUTI	NIIT	7-May-97	MTNL	BROOKBOND
4-Aug-03	SAIL	NESTLE	18-Sep-96	ABB	CHAMBLFERT
2-May-03	GAIL	NOVARTIND	18-Sep-96	ASIANPAINT	HEROHONDA
2-May-03	NATIONALUM	CASTROL	18-Sep-96	EIHOTEL	APOLLOTYRE
28-Oct-02	BPCL	P&G	18-Sep-96	GLAXO	INDAL
28-Oct-02	HCLTECH	ASIANPAINT	18-Sep-96	M&M	MADRASREFN
10-Oct-02	SCI	RELPETRO	18-Sep-96	NESTLE	NAGARFERT
31-May-02	VSNL	ICICI			
25-Jan-02	ICICIBANK	RECKCOLMAN			

17-Jan-02	SUNPHARMA	HCL-INSYS			
17-Jan-02	WIPRO	COCHINREFN			

Table 5- 1 Descriptive Statistics of Std Deviation & Log Std Deviation of Betas of Nifty 50

Stat	Beta_sd	ln-Beta_sd
Mean	0.5311	-0.6820
Median	0.5032	-0.6868
Maximum	1.2267	0.20431
Minimum	0.1860	-1.6818
Std. Dev.	0.1714	0.3159
Skewness	1.0826	-0.1324
Kurtosis	5.0005	3.7753
Jarque-Bera	52.8675	4.0826
Probability	0.0000	0.1299
Sum	77.5380	-99.573
Sum Sq. Dev.	4.2614	14.4744
Observations	146	146

Table 5- 2 Kalman Filter results for basic Herding model

Kalman Filter-State Space Model						
Method: Maximum likelihood (Marquardt)						
Included observations: 146						
	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1)	-0.716452	0.121886	-5.878049	0.000000	μ_m	-0.716452
C(2)	0.966081	0.033721	28.649230	0.000000	ϕ_m	0.966081
C(3)	-5.863904	0.739781	-7.926544	0.000000	σ_{mn}	0.053293
C(4)	-2.937303	0.118121	-24.866940	0.000000	σ_{mv}	0.230236
					$\sigma_{m\eta}$ / log Std β	0.161196

Table 5- 3 Kalman Filter results for Herding model with FII Flows

Sspace: MODEL with FII Flows				
Method: Maximum likelihood (Marquardt)				
Included observations: 146				
	Coefficient	Std. Error	z-Statistic	Prob.

C(1)	-0.719519	0.122394	-5.878713	< 0.0001
C(2)	0.965305	0.033433	28.872850	< 0.0001
C(3)	-5.831215	0.741669	-7.862289	< 0.0001
C(4)	-2.970433	0.119332	-24.892080	< 0.0001
C(5)	0.000009	0.000007	1.284720	0.1989

Table 5- 4 Kalman Filter results for Herding model with FII/ MC Flows

Sspace: BETA_FII_MC						
Method: Maximum likelihood (Marquardt)						
Included observations: 146						
	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1)	-0.729297	0.120559	-6.049318	0.00000	μ_m	-0.729297
C(2)	0.963746	0.03488	27.63035	0.00000	ϕ_m	0.963746
C(3)	-5.821092	0.785284	-7.41272	0.00000	σ_{mn}	0.054446
C(4)	-2.961608	0.120669	-24.54319	0.00000	σ_{mv}	0.227455
C(5)	0.189649	0.152136	1.246575	0.21260	$\sigma_{m\eta}$ / log Std β	0.172326

Table 5- 5 Kalman Filter results for Herding model with 'MF/ MC' Flows

Sspace: Model with MF Flows by MCap						
Method: Maximum likelihood (Marquardt)						
Included observations: 106						
	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1)	-0.669610	0.100954	-6.632857	0.000000	μ_m	-0.669610
C(2)	0.954640	0.038109	25.050510	0.000000	ϕ_m	0.954640
C(3)	-5.566465	0.679734	-8.189188	0.000000	σ_{mn}	0.061838
C(4)	-3.291081	0.150881	-21.81241	0.000000	σ_{mv}	0.192908
C(5)	-0.704841	0.308394	-2.285522	0.022300	C5	-0.704841
					$\sigma_{m\eta}$ / log Std β	0.201425

Table 5- 6 Kalman Filter results for Herding model with 'Nifty Return

Sspace: **Model with Monthly Nifty Returns**						
Method: Maximum likelihood (Marquardt)					Included observations: 146	
	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1)	-0.7066	0.1153	-6.1268	0.0000	μ_m	-0.7066
C(2)	0.9618	0.0339	28.3752	0.0000	ϕ_m	0.9618
C(3)	-5.7061	0.6945	-8.2159	0.0000	σ_{mn}	0.0577
C(4)	-3.0123	0.1384	-21.7655	0.0000	σ_{mv}	0.2218
C(5)	0.0071	0.0030	2.3748	0.0176	C(5)	0.0071
					$\sigma_{m\eta}$ / log Std β	0.1825

Table 5- 7 Kalman Filter results for Herding model with 'Nifty Volatility'

Sspace: **Model with Monthly Volatility**						
Method: Maximum likelihood (Marquardt)						
Included observations: 146						
	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1)	0.0562	0.1606	0.3498	0.7265	μ_m	0.0562
C(2)	0.9646	0.0308	31.3534	0.0000	ϕ_m	0.9646
C(3)	-5.9655	0.6861	-8.6954	0.0000	σ_{mn}	0.0507
C(4)	-3.4380	0.1569	-21.9094	0.0000	σ_{mv}	0.1792
C(5)	-0.4027	0.0385	-10.4720	0.0000	C5	-0.4027
					$\sigma_{m\eta}$ / log Std β	0.1603

Table 5- 8 Kalman Filter results for Herding with Nifty Returns & Nifty Volatility

Sspace: **Model with Return & Volatility**						
Method: Maximum likelihood (Marquardt)						
Included observations: 146						
	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1)	0.1007	0.1736	0.5800	0.5619	μ_m	0.1007
C(2)	0.9649	0.0307	31.3871	0.0000	ϕ_m	0.9649
C(3)	-6.0060	0.6832	-8.7908	0.0000	σ_{mn}	0.0496
C(4)	-3.4406	0.1527	-22.5359	0.0000	σ_{mv}	0.1790
C(5)	-0.0025	0.0022	-1.1533	0.2488	C(5)	-0.0025
C(6)	-0.4276	0.0468	-9.1383	0.0000	C(6)	-0.4276
					$\sigma_{m\eta}$ / log Std β	0.1571

Figure 5- 1 Herding vis-à-vis Nifty from Sep '96 to Oct '08.

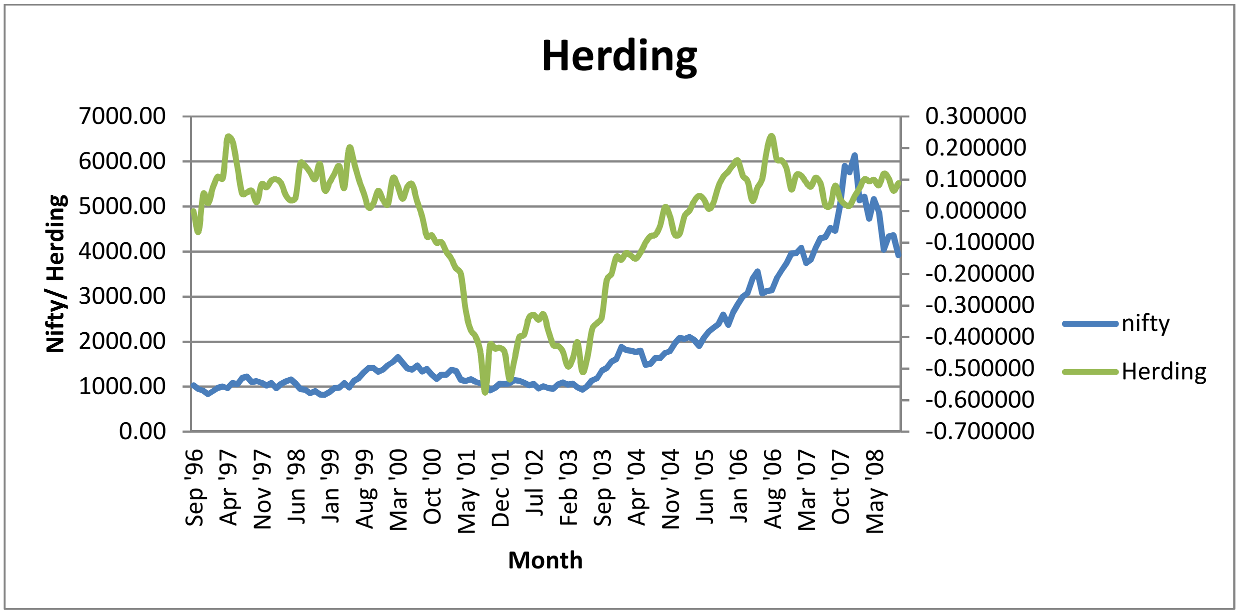

Figure 5- 2 Evolution of Herding with Nifty Monthly Return variable vis-à-vis Nifty

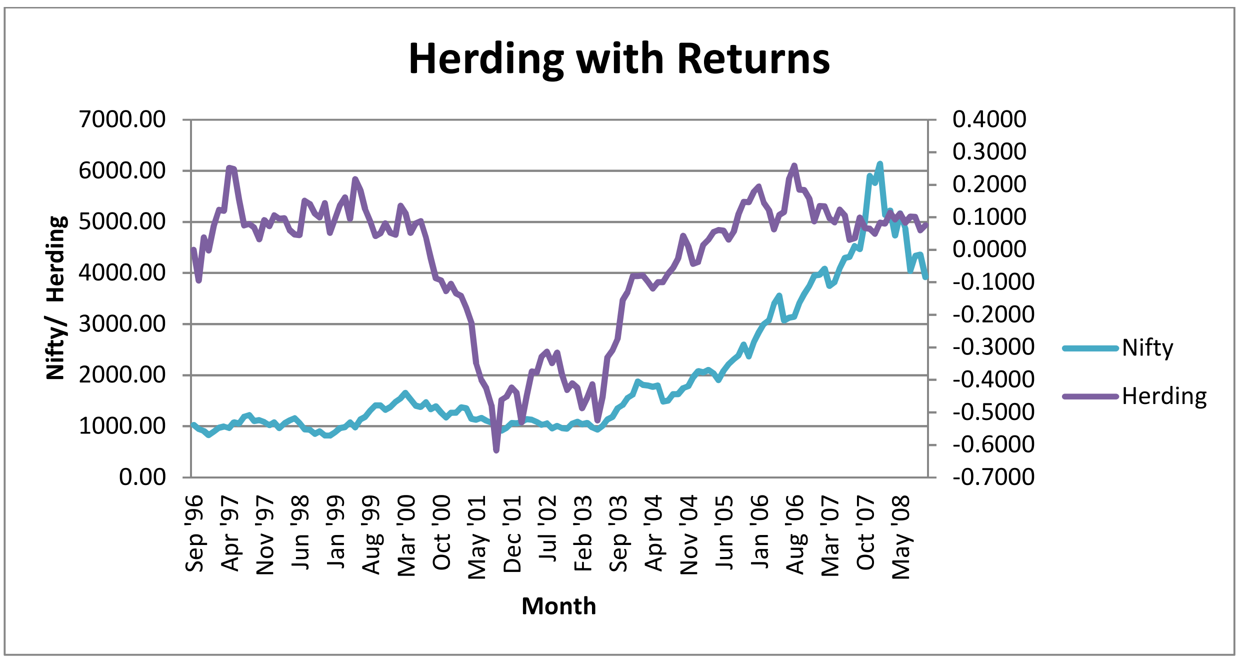

Figure 5- 3 Evolution of Herding with Nifty Volatility variable vis-à-vis Nifty

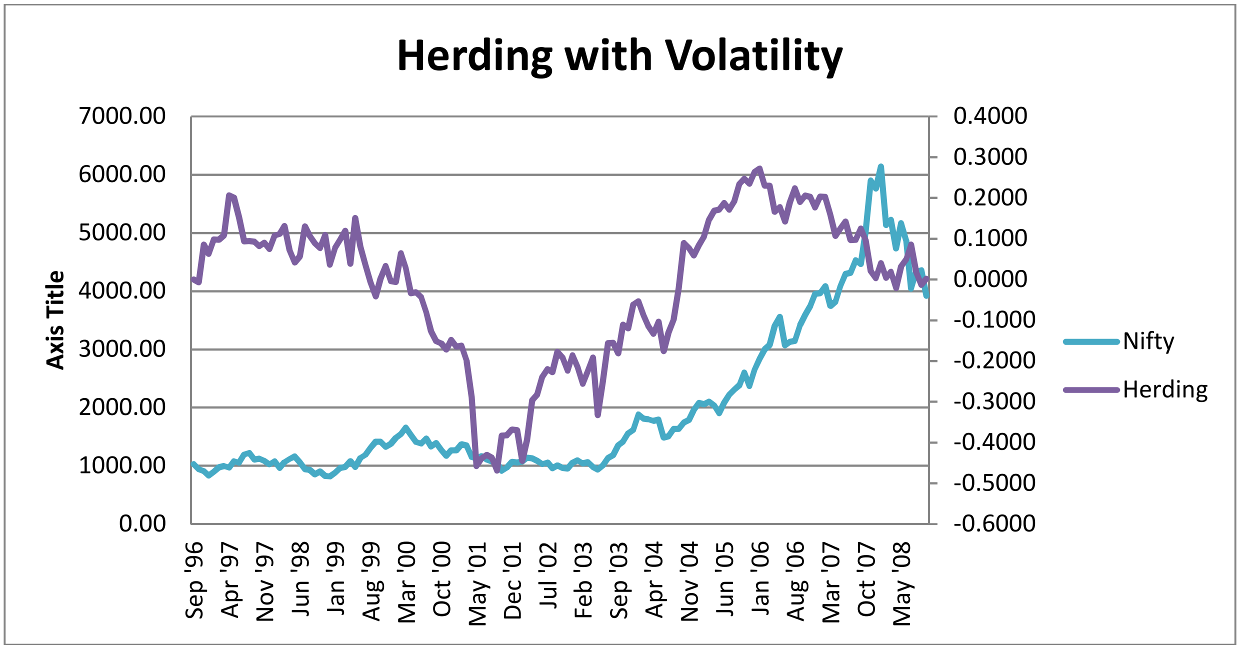

Figure 5- 4 Evolution of Herding vis-à-vis Nifty with Return & Volatility variables