Herding Behaviour of Institutional Investors: Evidence from an Emerging Market

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Abstract

Using a unique and exhaustive database of transactions conducted by foreign institutional investors from 2003-2021, we investigate the impact of buy and sell herding on asset prices. Our analysis shows that sell herding is associated with significant return reversals and drives stock prices below their fundamental values. Further, we find that volume turnover, information asymmetry, and volatility are positively and significantly associated with the overall herding measure. Our results are robust at the Industry level and by using quarterly data. The implications of our research findings are particularly significant in understanding the behavior of foreign institutional investors in the Indian capital market, especially during periods of financial turbulence such as the sub-prime crisis and the aftermath of the COVID-19 pandemic.

Keywords: FII; Herding; Returns Dispersion; Mispricing; India ; Crisis ; Uncertainty

1 Introduction

In the field of economics and finance, the concept of herding has been widely discussed and explored. It refers to the phenomenon where economic agents, such as fund managers or investors, imitate the actions of others or make investment decisions based on the actions of their peers. Various definitions of herding behavior have been proposed in the existing literature. Avery and Zemsky (1998) define herding as the tendency of investors to disregard

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their own initial assessments and instead follow the trend established by previous trades. Nofsinger and Sias (1999), on the other hand, describe herding as the simultaneous trading in the same direction. In our study, we adopt the definition of herding provided by Sias (2004), which characterizes herding as a situation where a group of investors collectively follow each other by entering or exiting the same securities.

The Indian equity markets, constituting a diverse and expansive landscape encompassing a multitude of firms across sectors and of different sizes, is always a subject of profound academic inquiry. Offering a lens into the dynamics of a rapidly advancing emerging economy, they provide an invaluable platform to scrutinize the intricate interplay between economic growth, demographic factors, regulatory frameworks, and globalization influences. Moreover, the global inflow of foreign investments and the concomitant influence of international economic trends on domestic market dynamics warrant meticulous analysis. Beyond their practical implications, these markets offer a fertile ground for theoretical inquiries, encompassing studies on market efficiency, behavioral biases, and anomalies that punctuate the market landscape. Thus, the meticulous study of Indian equity markets bears paramount significance within the academic sphere, transcending as a linchpin for deciphering multifaceted economic intricacies, refining theoretical paradigms, and fostering a comprehensive understanding of financial ecosystems.

The ownership stake of foreign institutional investors (FIIs) in NIFTY 500 firms has experienced a notable surge, reaching nearly 13% over the past five years. The visual representation in Figure 1 portrays the discernible upward trajectory of FII shareholding in Indian corporations. This substantial elevation underscores the heightened influence that FIIs presently exert upon the performance of the Indian stock markets compared to the preceding decade. A pivotal juncture in this trajectory occurred in September 1992, coinciding with the implementation of the economic reforms of 1991, when the Indian stock market embraced the participation of Foreign Institutional Investors (FIIs). Subsequently, FIIs have emerged as consequential stakeholders within the contours of the Indian equity market. As of December

31st, 2022, it is notable that FII funds singularly account for an average of approximately 47% of the cumulative institutional shareholding, among other contributing entities.[1]

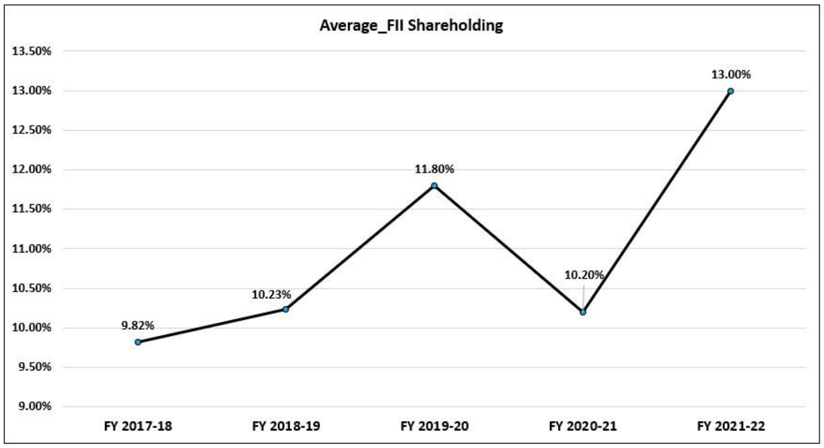

Figure 1: NIFTY 500 – FII Shareholding pattern

Figure 2 shows how closely the de-trended Foreign Institutional Investor (FII) net Equity fund flows track the de-trended NIFTY 500 index, thus underscoring the relationship between these two financial indicators. The co-movement and synchrony evident in their trajectories imply a discernible interdependence, suggesting the potential influence of underlying market dynamics on the FII net Equity fund flows. The calculated correlation coefficient is found to be 0.596, substantiating the linkage. However, it is imperative to acknowledge that while Foreign Institutional Investors (FIIs) play a pivotal role in market dynamics, their collective behavior has the potential to induce market instability through herding tendencies, wherein they emulate one another's investment patterns. Given these dynamics, it is of paramount importance to embark upon a comprehensive exploration of FII herding behavior and its implications for the Indian equity markets.

Figure 3 depicts consistent Foreign Institutional Investor (FII) net equity selling patterns during both the COVID-19 health crisis and the 2008 subprime crisis. This underscores the imperative for a thorough investigation into FII behavior in the Indian stock market, particularly

[1] Data Analysis by the authors have been provided in the Appendix - 1.1

in crisis periods. The study should encompass short and long-term effects on stock prices, the role

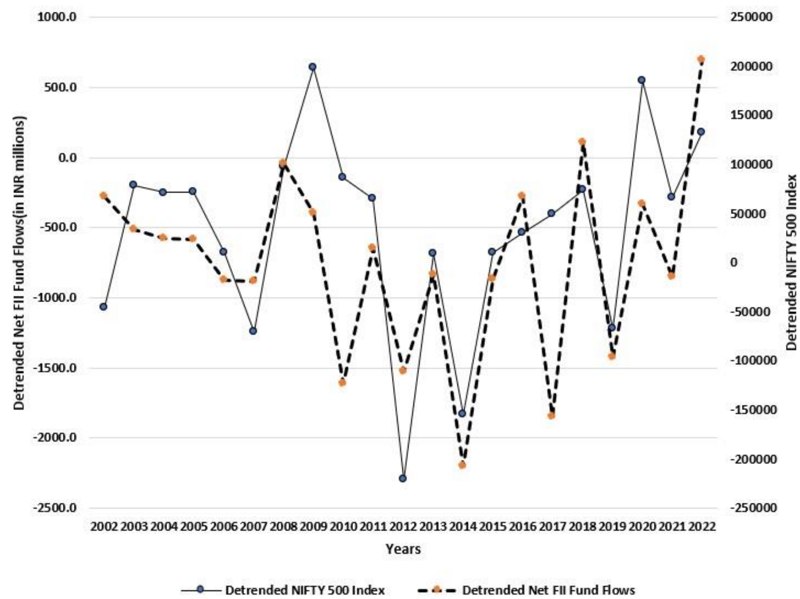

Figure 2: Correlation between Net FII Fund Flows and NIFTY 500 Index

of these events in either exacerbating or counteracting securities mispricing in the Indian context, and resulting implications for investors. Financial crises induce uncertainty and heightened risk aversion, prompting shifts in investor beliefs and preferences. Initially, FII fund flows may decrease as caution prevails. Nonetheless, financial crises can present opportunities for FIIs to identify undervalued assets, potentially prompting strategic portfolio reallocations or new investments to capitalize on eventual market rebounds. This may lead to increased FII inflows during the crisis aftermath. Notably, the impact of financial crises on FII fund flows hinges on factors like crisis severity, duration, and broader economic conditions. Comprehending these dynamics is pivotal for policymakers, regulators, and market participants to manage the ramifications of crises on capital markets and economies.

This study addresses a gap in herding behavior research, specifically focusing on Foreign Institutional Investors (FIIs). While institutional herding has been extensively studied in developed economies, this study aims to fill the gap in understanding herding behavior among

FIIs in diverse economies like India. The existing Indian herding behavior research is limited by outdated data (up to 2017). *The study's unique contribution lies in analyzing the differential impact of buyand-sell herding on asset prices*. It utilizes comprehensive transaction-level daily and quarterly

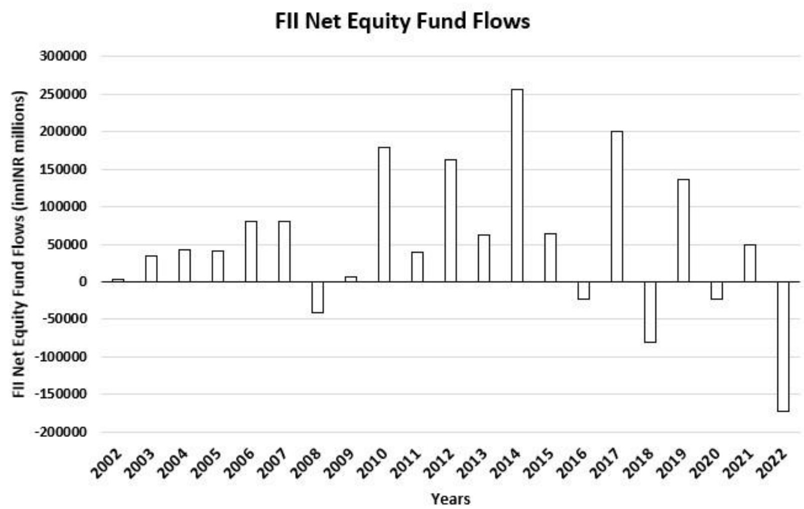

Figure 3: FII Net Equity Fund Flows - Over the years

data from FIIs spanning 18 years from January 2003 to April 2021. The herding behavior among FIIs is calculated using the Lakonishok, Shleifer, and Vishny (LSV) measure. The study extends beyond individual security analysis and contributes to multiple literature strands. It aligns with existing herding determinant research, identifies differential effects on buy and sell herding, empirically examines industry-level herding, and provides empirical evidence linking herding levels to financial upheavals.

The findings of the study indicate that buy and sell herding behaviors have varying effects on cumulative returns. Specifically, the Buy Herding Measure (BHM_{it}) significantly increases cumulative returns over time, suggesting that institutional buy herds do not destabilize stock prices and institutional traders' correlated buy activities are driven by new information. Conversely, Sell Herding Measure (SHM_{it}) leads to significant return reversals, with cumulative returns decreasing in the short term and coefficients losing significance after five days, eventually changing sign. This reversal of returns indicates that sell herds push prices below their fundamental values. Additionally, our study establishes result robustness across diverse scenarios. This is evident as our findings remain consistent when we use excess cumulative returns, shift from daily to quarterly stock observations, and even at an industry-daily level. Our results remain valid during times of financial crisis, reinforcing their reliability and stability.

The rest of this paper is structured as follows: Section 2 provides an overview of pertinent literature and the development of hypotheses. Section 3 outlines the research questions and hypotheses under examination. Section 4 elaborates on the data and methodology employed, while Section 5 presents the Results and Discussions. To ensure the soundness of our conclusions, Section 6 offers robustness tests. The implications of our study are deliberated in Section 7, and the paper culminates in Section 8 with a conclusive summary.

2 Literature Review and Hypotheses Development

In contemporary research, there is a great deal of focus on investigating various aspects of investor behavior, encompassing their beliefs, biases, and preferences. One particularly significant facet that has garnered substantial attention is the phenomenon of herding behavior. Herding behavior pertains to the tendency of investors to make decisions based on the actions and choices of others rather than solely relying on their individual analysis and assessment of available information. As a result, herding behavior can exert a considerable influence on financial markets, potentially affecting asset prices in ways that are not always in line with fundamental values.

In particular, institutional herding may occur when investors sharing similar educational and professional backgrounds rely on common factors and information to form similar conclusions about individual stocks (Hirshleifer et al. (1994)). This tendency may also arise from institutions being attracted to stocks with specific characteristics, such as higher liquidity (Falkenstein (1996)). Additionally, sentiment can drive herding behavior, as investors imitate others in the market, leading to simultaneous buying or selling of the same stocks, irrespective of their prior beliefs or information sets.

Researches such as Kahneman and Tversky (1979) and (1985) highlight the substantial role of emotional factors in shaping individual decision-making, a crucial consideration for comprehending financial market pricing dynamics. Contrary to mainstream economic models, behavioral asset pricing models acknowledge the weight of the social context within which market participants function—an influence on decisions, behaviors, and preferences. Market dynamics are an intricate interplay where individuals respond to their surroundings, which, in turn, respond to their actions, constituting a feedback loop (Schelling (2006)). Within this economic framework, social dynamics impel individuals to align their economic choices with those of friends, peers, family, or influential media-provided models, particularly amid complex environments or limited personal experience. It becomes evident that market conduct transcends mere independent and rational micro-level decisions, instead mirroring behavior influenced by others' choices (Salganik et al. (2006); Fenzl and Brudermann (2009)).

Theoretical frameworks offer many insights into herding behavior. Rational traders may imitate the investment patterns of peers under the assumption that others possess relevant information (Bikhchandani et al. (1992), Avery and Zemsky (1998), Park and Sabourian (2011)). The preservation of one's reputation, safeguarding forecasting prowess, and fortifying perceived credibility constitutes another plausible explanation for engaging in herding behavior (Scharfstein and Stein (1990), Cote and Sanders (1997), Swank and Visser (2008)). Additionally, fund managers might gravitate towards stocks, portfolios, or sectors that have garnered popularity or become trends (Barberis and Shleifer (2003), Choi and Sias (2009)). The compulsion for confidence, conformity, and reduced uncertainty also contributes to the phenomenon of herding (Rook (2006), Goldbaum (2008), Vaughan and Hogg (2013)). Empirical evidence provided by Barberis et al. (2005) reveals coordinated behavior among trading participants in financial markets. This phenomenon stems from noise traders chasing market trends, generating a self-reinforcing cycle as more participants join in, bolstering confidence and reducing selectivity. Prechter Jr and Parker (2007) postulates that herding arises from unconscious impulses sensed by market participants during uncertainty, fortified by intense emotional reactions. This instigates collective psychological dynamics that induce non-mean-reverting dynamism in financial markets. Individuals tend to emulate others in uncertain scenarios, employing observed behavior as a benchmark for correctness or prudence. Further research by Shiller (1990) posits that traders, including professionals, respond to each other under heightened emotional arousal, attempting to anticipate actions. Professionals may also herd to evade underperformance relative to rivals. Emulation emerges as a potent, enduring, and vigilant economic motive within the financial market landscape to prevent falling short of competitors' benchmarks.

Previous research has shed light on various aspects of herding behavior. Studies like Barber et al. (2009) analyzed trading records and household-level investor data and found that individual trading is highly correlated and persistent, indicating the role of psychological biases in the correlated trading of individuals. These biases lead investors to buy stocks with recent strong performance, hold on to stocks held for a loss, and purchase stocks with unusually high trading volume.Choi and Sias (2009) identified strong evidence of institutional industry herding, where the cross-sectional correlation between the fraction of institutional traders buying in an industry this quarter and the fraction buying last quarter is approximately 40%. Hsieh (2013) used highfrequency intraday data in the Taiwan stock market to detect herding behavior among institutional and individual investors, with a stronger tendency among institutional investors. Choi and Skiba (2015) investigated the herding behavior of institutional investors in international markets and reported the existence of widespread herding in 41 countries. They also examined the relationship between contemporaneous institutional demand and future returns and found that institutional herding stabilizes prices. Furthermore, they found evidence that institutional investors herd more frequently in markets with low levels of information asymmetry.

Foreign Institutional Investors (FIIs) contribute significantly to a nation's economic vitality by bolstering financial resources and enhancing market liquidity (Chattopadhyay et al. (2018)).

Research by Kumar et al. (2013) accentuates the pronounced short-term impact of FIIs, intensifying over time. The literature encompasses diverse studies examining the multifaceted outcomes of FII investments in host markets. For instance, Froot et al. (2001) delve into the lasting effects of unexpected institutional investments on host countries' stock markets, revealing enduring stock price deviations. Additionally, Bekaert et al. (2002) demonstrate how foreign capital flows trigger transient price hikes, generating momentum effects across 20 emerging markets. Collectively, these studies illuminate the intricate impact of FII investments on host country markets, unraveling their underlying dynamics and enduring implications. The realm of Indian capital markets has also been a subject of extensive inquiry regarding the influence of Foreign Institutional Investor (FII) investments, yielding valuable insights. Gordon and Gupta (2003) unearth a negative correlation between FII flows and lagged returns, while Mukherjee and Mishra (2002) posit FIIs as return chasers with limited market impact. Griffin, Nardari, and Stulz (2004) observe FII investment predicting stock returns, reflecting anticipatory behavior. Trivedi and Nair (2003) identify bidirectional causality between returns and FII investment. The cumulative literature underscores the discernible impact of FIIs on Indian stock returns, sparking debates concerning the duration and permanence of these effects. Choi (2015) underscores potential herding-induced price discrepancies. Given their substantial influence, understanding FII herding tendencies assumes heightened significance.

In prior research, diverse metrics quantify herding levels using transaction data. Key measures are the LSV Measure (Lakonishok et al. (1991)), the Christie and Huang (1995) measure, and the Chang et al. (2000) measure. The LSV measure calculates herding based on the net buyers' ratio to total traders, adjusting for activity volume. Christie and Huang (1995) measure gauges herding toward market consensus, aiming to reduce the cross-sectional standard deviation of returns during market movements.Chang et al. (2000) using Cross-Sectional Absolute Deviation of Returns (CSAD) assesses dispersion, acknowledging non-linear relationships during market fluctuations. Figure 4. presents an overview of the metrics employed in prior research studies.

Researcher	Period	Findings
LSV (1991)	1985-89, US	No Herding by Fund Managers except in smaller stocks, but no destabilizing influence on stock prices.
Christie and Huang's (1995)	The daily data for NYSE and Amex fims from July 1962 to December 1988, and the monthly data for NYSE firms extend from December 1925 to December 1988.	Estimated the standard cross-sectional deviation of single stock returns with respect to portfolio returns (CSSD). If the dispersion of equity re-turns is low, it may be a sign of herding. The CSSD of returns was regressed with respect to the extreme and normal market phases.
Grinblatt,Titman and Wermers(1995)	1974-84, US	Mutual Funds Herd, but the 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.
Choe etal. (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.
Chang, Cheng, and Khorana (2000)	US, Hong Kong, Japan, South Korea, and Taiwan (January 1963 - December 1997)	Analyzed the hypothesis that the relationship of dispersion to market returns is non-linear. In the absence of herding, the relationship is linear and increasing: the dispersion increases concurrently with the increasing returns of the market. In the presence of herding, the relationship can be increasing, but at a decreasing rate. The authors hypothesize that the relationship between CSAD and market returns is also asymmetric
Hwang and Salmon (2001 & 2004)	US and South Korea (1993 -2002)	Estimate the beta of single stocks and the market. They standardize the coefficient of systematic risk by dividing the single estimate by its standard error. Finally, they calculate H, the variance of the standardized beta values.
Bonser-Nealetal. (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.
Lobao and Serra (2002)	1998-2002, Portugal	Strong evidence of herding by MFs, but more pronounced in mid-cap funds
Borensztein and Gelos (2003)	1996-2000, Emerging Markets	The degree of herding among funds is statistically significant but moderate and is more prevalent during crises. Herding by Funds is more intense in larger markets.
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.

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Sias (2004)	1975-94, 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.
Voronkova and 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.
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.
Kim and Nofsinger (2005)	1975-2001, Japan	Herding lower than in US but with larger impact on price movements.
Alemanni and Ornelas (2006)	2000-2005, 9 Emerging Markets	Herding by foreign investors decreased from 1995-2000 to 2000-05
Walter and Weber(2006)	1998-2002, 60 MFs, Germany	Herding and Positive Feedback Trading in MFs slightly higher in Germany than in US and UK, but Herding does not destabilize stock prices.
Agarwal et al. (2007)	1995-2003, Indonesia	Both domestic and foreign investors exhibit significant herding behavior but such behavior is much stronger for foreign investors.
Puckett & Yan (2007)	1999-2004, US	Institutional herding is more among large, young, volatile, growth, S&P 500 stocks and stocks with poor prior performance.
Tanet al. (2008)	1994-2003, China	Herding is 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 the Shanghai market is more pronounced under conditions of rising markets, high trading volume, and high volatility, while no asymmetry is apparent in the B-share market.
Agudo et al. (2008)	1994-2002, Spain, Equity Funds	Significant herding in value stocks, and growth stocks. Higher than that found in previous studies.
Paulo Lao & Harminder Singh (2011)	1999 to 2009, BSE 30 stocks, India	Documents the existence of herding and report it to be significantly prevalent during extreme market conditions
Lakshman M.V. , Sankarshan Basu , R. Vaidyanathan (2013)	1996 to 2008 , NIFTY 50 Stocks, India	FII flows or normalized FII flows do not significantly impact the herding behavior; overall market-level herding is not impacted whether the FII flows increase or decrease
Garg and Jindal (2014)	2000 - 2012 , NIFTY 50 Stocks, India	Provides evidence against the presence of herding in the Indian stock market for the years 2000-2012
Kapil Choudhary , Parminder Singh , Amit Soni (2021)	1999 to 2017, NIFTY 50 Stocks, India	Herding levels are considerably higher than those observed in other international markets, and herding is prevalent in small stocks

Figure 4: Synopsis of Herding Studies using LSV/CH/ Chang Measure Our research delves into the prevalence of herding behavior exhibited by Foreign Institutional Investors (FIIs) within the Indian market, with a specific focus on discerning the impact of buy and sell herding on asset price destabilization, drawing insights from the research of (Kremer and Nautz (2013)). Herding behavior can be categorized into intentional and unintentional herding. Intentional herding occurs when traders ignore their private information, opting instead to follow the crowd under the assumption that others possess superior knowledge. Factors such as information cascades, reputation concerns (Holmes et al. (2013)), and compensation incentives often drive this type of herding. In contrast, unintentional herding manifests when investors react similarly to public information due to shared characteristics, such as similar educational and investment backgrounds, or due to the constraints of a common regulatory framework (Teh et al. (1997) and Voronkova and Bohl (2005)). The manner in which future stock returns are influenced by institutional herding depends on whether such behavior is driven by a thorough analysis of public information and stock fundamentals or if it results from peer pressure, reputation considerations, or characteristic preferences. In the former case, institutional herding might contribute to aligning stock prices with their intrinsic values. In contrast, the latter case could lead to a divergence of prices from intrinsic value. Empirical research on the impact of institutional herding on future stock returns has yielded mixed findings. While studies by Wermers (1999) and Sias (2004) suggest a positive link between institutional trade imbalances and nearterm stock returns, implying a potential role of herding in reducing stock mispricing and aiding price discovery, Dasgupta et al. (2011) and others have documented instances of long-term stock return reversals following the identification of herding, indicating extended periods of price distortions. Such divergence in findings underscores the complexity of institutional herding's impact on stock prices.

In the context of India, unintentional herding behavior is highly unlikely due to the pronounced diversity in educational and investment backgrounds among investors and fund managers. Instead, intentional herding is expected to be more prevalent among institutional investors, particularly Foreign Institutional Investors (FIIs), given the intense competitiveness of Indian capital markets. In this environment, concerns about reputational damage or career prospects arising from unfavorable outcomes likely encourage intentional herding. Moreover, the less stringent disclosure norms in India compared to more developed markets like Japan, the USA, and the UK may compel fund managers to rely on peers' actions for decision-making, driven by incomplete and less accurate asset value information. Moreover, our study hypothesizes that the phenomenon of sell herding among Foreign Institutional Investors (FIIs) will exert a more pronounced influence on distorting prices within the Indian markets compared to the observed buy herding behavior. The rationale behind this expectation lies in the shared reliance on standard risk assessment tools among FIIs, which prompts them to respond collectively when faced with heightened market uncertainty. In the event of increased volatility or destabilization, FIIs tend to react by aligning their actions to accentuate sell-offs, thereby exerting downward pressure on asset prices. This synchronized sell-off behavior amplifies the price-distorting effect, potentially pushing prices below their fundamental valuations. Conversely, the impact of buy herding is expected to be comparatively less influential on price distortions. This is due to the likelihood that FIIs' coordinated buying activities, driven by the incorporation of new information, may not result in the same level of distortion as observed during sell-herding episodes.

Empirical investigations into herding behavior's impact on asset prices within the Indian context have yielded varied results. For instance, Lakshman and Jain (2013) identify the presence of herding behavior in the Indian market, albeit without significant severity. In contrast, Garg and Arora (2014) analyze herding in the Indian stock market during 2000-2012 based on daily and monthly data, negating the existence of herding, especially during periods of extreme price fluctuations. Investigating the relationship between foreign portfolio investors (FPIs) and domestic mutual funds (MFs) in the Indian stock market, Kumar (2021) identifies elevated herding levels in India compared to other international markets, particularly in small stocks. Additional research by Lao et al. (2011) also finds a strong presence of herding behavior in India using BSE 30 and BSE-500 stocks.

Existing research predominantly examines the combined influence of various institutional investors—Mutual Funds, Pension Funds, VC Funds, and Foreign Institutional Investors (FIIs)—and their trading activities. However, a gap persists in investigating herding behavior, particularly among FIIs. This study fills this gap by investigating FIIs' engagement in herding behavior and its impact on forthcoming market returns. While extensive research on institutional herding exists for developed economies, a research gap exists in the context of diverse economies like India. Leveraging unique transaction-level data spanning 18 years, this paper scrutinizes FIIs' herding behavior within the Indian capital markets. The existing literature on Indian herding behavior is limited by outdated data (up to 2017) and fails to consider the ramifications of the COVID-19 pandemic. Given the pandemic's influence on volatile FII fund flows in India and the resultant shifts in investment trends (see Figure 3), this study comprehensively examines the consequences of financial crises on FII fund outflows and ensuing herding behavior in the Indian stock market. A comprehensive grasp of the determinants and effects of institutional herding on asset mispricing in the Indian market is still lacking. Additionally, this study seeks to differentiate between buy herding and sell herding concerning their respective impacts on asset prices deviating from their intrinsic values. The study's findings indicate that buy herding minimally distorts stock prices in the short term, whereas the Sell Herding Measure contributes to substantial return reversals, leading to short-term cumulative return reduction.

This paper contributes to the literature by analyzing herding behavior in the dynamic Indian financial market over time. It extends beyond individual security analysis, contributing to four literature strands. Firstly, it sheds light on how institutional herding affects future returns and the price effects of buy and sell herding. Secondly, it aligns with existing herding determinant research, identifying differential effects on buy and sell herding. Thirdly, it empirically examines industry-level herding, contributing to "style investing" literature (Barberis and Shleifer (2003)).

Lastly, it provides empirical evidence linking herding levels to financial upheavals, revealing insights into herding behavior's role in market volatility and instability.

3 Research Questions and Hypothesis Testing

Our research questions are designed to investigate the following aspects:

- ”Whether foreign institutional investors (FIIs) exhibit herding behavior in the Indian Stock market and the impact of (buy and sell) herding on the asset prices?”
- ”What are the key determinants of institutional herding behavior in Indian equity markets?” We are trying to test the following hypothesis :

1. FIIs in Indian stock markets exhibit herding behavior, with FIIs following each other in and out of the same securities.
2. BUY Herding behavior leads to stock prices deviating from their fundamental values, resulting in significant return reversals.
3. SELL Herding Behaviour drives stock prices away from fundamental values; one would expect to observe significant return reversals

By formulating these hypotheses, we aim to provide a framework for empirical analysis and testing, contributing to a deeper understanding of the complex dynamics between FII investments and their varied impact on asset pricing.

4 Data and Methodology

The data sample consists of daily equity transaction data of Foreign Institutional investors from January 2003 to April 2021, collected from the National Securities Depository Limited (NSDL) website. The data set used in this paper contains the daily level transactions of the

NIFTY 50 stocks (listed on the National Stock Exchange (NSE)) carried out by Foreign Institutional investors. Our data covers market upturns as well as the recent market downturn. For each institution, we compute the daily trade imbalance.

In our investigation, we adopt the herding measure introduced by Lakonishok, Shleifer, and Vishny Lakonishok et al. (1991) (referred to as the LSV measure) as the basis for our analysis. The LSV measure characterizes herding as the inclination of traders to cluster their activities on one side of the market for a specific stock while also considering this behavior in relation to what would be anticipated if these traders were acting independently. As outlined by the LSV framework, this metric operates on the premise that when the null hypothesis assumes the absence of herding, the decision to buy or sell manifests as a Bernoulli-distributed random variable. This variable holds an equal probability of success for all stocks at any given point in time.

Let us consider a set of transactions (N_{it}) executed by institutional traders in stock 'i' at a specific time 't'. Within this set of transactions, the quantity of purchases is represented as b_{it}. To establish the pivotal component of the LSV measure, the buyer ratio (br_{it}) is calculated by dividing b_{it} by N_{it}. Another crucial variable is $\bar{br}_t$, signifying the average buyer ratio across all stocks at the time 't'. This average buyer ratio is a vital indicator of the prevailing market trend during that period. The LSV herding statistic is given by :

$$HM_{it} = |br_{it} - \overline{\mathrm{br}}_{\mathrm{t}}| - E_t[|Dbr_{it} - \overline{\mathrm{Dbr}_{\mathrm{t}}|}] \quad (1)$$

The first component of the LSV measure, denoted as $|br_{it} - \overline{\mathrm{brt}}|$, quantifies the degree of divergence exhibited by the buyer ratio of stock 'i' at time 't' from the overall buy probability prevailing during that period. This measurement of divergence captures an excess dispersion beyond the anticipated norm, facilitating the identification of akin trading patterns that transcend market trends. Importantly, this computation effectively neutralizes the impact of market-wide herding, enhancing the measure's capacity to highlight analogous trading behaviors independent of overarching market influences. The subsequent component, termed

the Adjustment Factor, $E_t[|Dbr_{it} - \overline{\mathrm{Dbr}_t}|]$, encapsulates the anticipated disparity between the binomial buyer ratio and the average buyer ratio for the specific period. Considering the nature of the decision to buy or sell as a Bernoulli-distributed random variable, characterized by an equal likelihood of success for all stocks at a given time, we compute the buyers for each stock within each period employing the inverse binomial distribution. This entails determining the number of trials based on the count of active traders for the stock during the period while adopting a probability of success set at 0.5. Furthermore, we adopt an alpha level of 95% to underpin the statistical framework.

After obtaining the distribution of buyers for each stock and each period, the distribution buyer ratio (Dbr_{it}) is calculated by dividing the distribution buyers by the number of active traders. The average distribution buyer ratio over a time period, represented by $\overline{\mathrm{Dbr}_t}$, is then determined. The deviation of the distribution buyer ratio for each stock and time period from the distribution average buyer ratio for that period, denoted as $|Dbr_{it} - \overline{\mathrm{Dbr}_t}|$, is then calculated. The expected value of this deviation is obtained for each time period as $E_t[|Dbr_{it} - \overline{\mathrm{Dbr}_t}|]$. This adjustment factor ensures that the herding measure HM_{it} is zero when trades are independent. The mean herding measure HM for the overall market, represented by $\overline{\mathrm{HM}}$, is calculated using the mean across all stocks and periods. A positive and significant value of $\overline{\mathrm{HM}}$ indicates a tendency of the investigated group to accumulate in their trading decisions. A higher $\overline{\mathrm{HM}}$ suggests stronger herding. This methodology is used to test hypothesis 1.

The herding measure HM_{it} quantifies the extent of herding in trading decisions, regardless of whether the trades are buys or sells. This study extends prior research by distinguishing between "buy herding" BHM_{it} and "sell herding" SHM_{it}, to determine whether institutions tend to buy or sell stock 'i' in herds. Specifically, BHM_{it} is equivalent to HM_{it} when $br_{it} > \overline{br_t}$, and SHM_{it} is equivalent to HM_{it} when $br_{it} < \overline{br_t}$. By differentiating between buy and sell herding, we can capture potential asymmetries in institutional behavior. Next, we examine the implications of buy and sell herding on stock prices. In such cases, positive (negative) correlations between buy (sell) herding and subsequent returns should persist over time. On the other hand, if herding leads to stock prices deviating from their fundamental values, we would expect to observe significant return reversals.

4.1 Price impact of Buy and Sell herding measures

To test our hypotheses 2 and 3, we use the following regression model(2).

Let $r_{i,t,t+k}$ denote the cumulative return of stock i from t to t + k days. To investigate the impact of herding on subsequent returns, we estimate the following fixed effects panel regression models for each k:

$$\begin{aligned} r_{i,t,t+k} = {} & A_k + B_k * BHM_{it} + C_k * SHM_{it} + D_k * Size_{it} + E_k * B2M_{it} \\ & + F_k * r_{i,t,t-250} + G_k * Std_{it} + H_k * r_{i,t,t-5} + I_k * MRP_{it} + \alpha_{ki} + \gamma_{kt} + \epsilon_{it} \end{aligned} \tag{2}$$

This regression model contains six control variables following Puckett and Yan (2008) and Barber et al.(2009) where:

- $Size_{it}$ is the logarithm of closing market capitalization of stock i
- $B2M_{it}$ is the book-to-market ratio of stock i
- $r_{i,t,t-250}$ is the past cumulative return to control for momentum in returns

- Std_{it} is the standard deviation of the past 250 daily stock returns
- $r_{i,t,t-5}$ is the past cumulative 5 day return of stock i
- MRP_{it} is the excess market return
- α_{ki} is the stock specific effects
- γ_{kt} is the time-specific effects

With the help of this regression model(2), we intend to investigate the correlation between future cumulative returns over different time horizons (e.g., +1 days, +2 days, +3 days, +5 days, +10 days, +20 days) and two measures of herding behavior, namely Buy Herding Measure (BHM) and Sell Herding Measure (SHM). To demonstrate the destabilizing impact of herding on stock prices, the study seeks to identify significant return reversals, which would manifest as an initial positive (or negative) relationship between herding measures and future returns, followed by a subsequent negative (or positive) relationship.

4.2 Determinants of Herding

In accordance with Venezia et al. (2011), we examine the relationship between institutional herding and its determinants using the following fixed effects panel regression model (3).

$$\begin{aligned}\mathrm{HM}_{it} = {} & A_k + B_k * SIZE_{it-1} + C_k * VOL_{it} + D_k * |ret_{it-1}| + E_k * Std_{it} \\ & + F_k * INFOASSYMETRY_{it-1} + \alpha_{ki} + \gamma_{kt} + \epsilon_{it} \qquad (3)\end{aligned}$$

where:

- HM_{it} is the daily LSV herding measure of the stock 'i' at time period 't'
- $SIZE_{it-1}$ is the logarithm of the previous day's closing MCAP of stock 'i'
- VOL_{it} is the logarithm of the trading volume of stock i during trading day t

- $|ret_{it-1}|$ is the absolute value of the return of stock i
- Std_{it} is the standard deviation of the past 250 daily stock returns
- $INFOASSYMETRY_{it-1}$ captures the previous day's micro-structure information asymmetry measure (bid-ask spread) of a stock 'i'
- α_{ki} is the stock specific effects
- γ_{kt} is the time-specific effects

This specification enables us to identify the factors that influence herding behavior. These factors have been widely established in the literature to have a significant impact on future stock returns, as documented in previous studies such as Ang et al. (2006), Bae et al. (2007), Ang et al. (2009) and Huang (2009).

4.3 Differential impacts of the determinants of herding on Buy and Sell measures?

In line with previous studies, it is plausible that the variables outlined in regression equation

(3) can have varying impacts on buy and sell herding measures. Thus, we independently estimate equations (4) and (5) for buy and sell herding, utilizing the same explanatory variables. Notably, the absolute return variable $|r|$ is replaced with the signed return variable r, as the direction of recent price movements can influence the direction in which momentum investors herd, either on the buy or sell side.

$$\begin{aligned}\mathrm{BHM}_{it} = A_k + B_k * SIZE_{it-1} + C_k * VOL_{it} + D_k * ret_{it-1} + E_k * Std_{it} \\ + F_k * INFOASSYMETRY_{it-1} + G_k * Dummy_{bit-1} + \alpha_{ki} + \gamma_{kt} + \epsilon_{it}\end{aligned} \tag{4}$$

$$\mathrm{SHM}_{it} = A_k + B_k * SIZE_{it-1} + C_k * VOL_{it} + D_k * ret_{it-1} + E_k * Std_{it}$$

$$+ F_k * INFOASSYMETRY_{it-1} + G_k * Dummy_{sit-1} + \alpha_{ki} + \gamma_{kt} + \epsilon_{it} \quad (5)$$

where:
The specifications (4) and (5) include a dummy variable $Dummy^b{}_{it}$ and $Dummy^s{}_{it}$, which equals one if buy herding (sell herding) also occurred on the previous day t -1 and is zero otherwise. The regression specification includes additional variables previously defined in this study.

5 Results and Discussion

Table 1 provides the results for the LSV Herding Measure, Buy Herding Measure, and Sell Herding Measure for the overall time period as well as for four sub-sample periods, i.e., Period 1: Jan'2003 - Dec' 2008, Period 2: Jan' 2009 - Dec' 2013, Period 3: Jan'2014 Dec'2019, Period 4: Jan'2020 - April'2021. To ensure consistency, we have partitioned our comprehensive analysis from January 2003 to April 2021 into three distinct sub-periods of six years each. The remaining one-year period constitutes the fourth sub-period. The primary aim of this division is to examine potential fluctuations in HM (Herding Measure), BHM (Buying Herding Measure), and SHM (Sell Herding Measure) across the aforementioned duration.

5.1 Period-wise Analysis

INSERT TABLE 1. HERE

The mean daily LSV herding measure across all stocks was found to be 2.48% for the overall period of study. We can further find that the LSV Herding Measure is significant across all the sub-periods, indicative of that strong herding in Indian Markets. This LSV Herding Measure is found to be highly significant for the post-2020 vis-a-vis other sub-` periods.

5.2 Results of Regression Analysis: Price impact of Buy and Sell herding measures

In order to examine hypotheses 2 and 3, we estimate the regression model (2) as previously defined. We present the panel regression results below, with each unit of observation at the stock-day level.

INSERT TABLE 2. HERE

The findings of this panel regression analysis demonstrate that buy and sell herding have differential effects on cumulative returns. Specifically, our results indicate that BHM_{it} positively and significantly impacts cumulative returns over the entire time period examined. This suggests that institutional buy herding does not lead to return reversal, nor does it destabilize stock prices in the aftermath of such herd behavior. Instead, the continued increase in returns following buy herding suggests that correlated buy activities of institutional traders are driven primarily by new information about underlying fundamentals. In contrast, our analysis shows that sell herds (SHM_{it}) are associated with significant return reversals. While cumulative returns decline significantly in the short run, the coefficients lose their statistical significance after 5 days and eventually even change their sign. These results suggest that sell herds drive stock prices below their fundamental values.

5.3 Determinants of Herding and varied impact on Buy and Sell Herding Measures

Our analysis employs a fixed effects panel regression model as outlined in equations (3), (4), and (5) to examine the relationship between institutional herding and its determinants. We seek to investigate whether the determinants of herding behavior have differing effects on Buy Herding and Sell Herding Measures.

INSERT TABLE 3. HERE

Our panel regression analysis reveals that Volume Turnover, Information Asymmetry, and Standard deviation are positively and significantly associated with the overall herding measure. Interestingly, Signed Return and Standard Deviation have a significant negative association with the Buy Herding Measure, whereas they have a significant positive association with the Sell Herding Measure.

6 Robustness Tests

6.1 Alternative measures of future returns

For the purpose of hypothesis testing, we employ regression equation (6) by substituting cumulative returns with *excess cumulative returns* as an alternative measure of future returns. The cumulative excess return of stock i from t to t+k is denoted by $r_{i,t,t+k}$. To examine the influence of herding on future returns, we conduct a fixed effects panel regression analysis for each k by estimating the following model:

$$r_{i,t,t+k} = A_k + B_k \cdot BHM_{i,t} + C_k \cdot SHM_{i,t} + D_k \cdot Size_{i,t} + E_k \cdot B2M_{i,t} + F_k \cdot r_{i,t,t-250} + G_k \cdot Std_{i,t}$$

$$+ H_k \cdot r_{i,t,t-5} + I_k \cdot MRP_{i,t} + J_k \cdot ILLQ_{i,t} + \alpha_{ki} + \gamma_{kt} + \epsilon_{i,t} \qquad (6)$$

where: $ILLQ_{it}$ is the Amihud(2002) Illiquidity Measure. The regression specification includes additional variables previously defined in the study. The regression equation (6) includes additional variables previously defined in this study.

Through this regression specification, we intend to investigate the association between *future cumulative excess returns* (for various k-values, such as +1 day, +2 days, +3 days, +5 days, +10 days, and +20 days) and the Buy Herding Measure (BHM) and Sell Herding Measure (SHM). To demonstrate the destabilizing impact of herding on stock prices, it is essential to observe significant return reversals: an initial positive (negative) relationship followed by a subsequent negative (positive) relationship.

6.1.1 Results of Regression : Alternative Measures of Future Returns

INSERT TABLE 4. HERE

Even when employing *cumulative excess returns* as the dependent variable, our analysis reveals distinct effects of buy and sell herding. Specifically, our findings indicate that the Buy Herding Measure (BHM) has a positive and statistically significant impact on *cumulative excess returns* throughout the entire examined time period. This suggests that institutional buy herding does not result in return reversal or destabilize stock prices in the aftermath of such herding behavior. Instead, the persistent increase in returns following buy herding implies that the correlated buying activities of institutional traders primarily stem from new information about underlying fundamentals. On the other hand, our study demonstrates that sell herds (SHM) are associated with significant return reversals. Hence, our findings demonstrate robustness even when *cumulative excess returns* are used as the dependent variable instead of cumulative returns.

6.2 Analysis of FII transactions at quarterly level

To check the robustness of our empirical analysis, we aggregate the data available at *the quarterly level* instead of the daily level and use the regression specification (7). Let $r_{i,t,t+k}$ denote the cumulative return of stock i from t to t + k. To investigate the impact of herding on subsequent returns, we estimate the following fixed effects panel regression models for each k:

$$r_{i,t,t+k} = A_k + B_k * BHM_{it} + C_k * SHM_{it} + D_k * Size_{it} + E_k * B2M_{it}$$
$$+F_k*r_{i,t,t-250}+G_k*Std_{it}+H_k*r_{i,t,t-5}+I_k*MRP_{it}+J_k*ILLQ_{it}+\alpha_{ki}+\gamma_{kt}+\epsilon_{it} \quad (7)$$

where:

γ_{kt} is the time(quarter) specific effects. The model includes additional variables previously defined in the study.

We conduct analysis at the *stock-quarter* level. Our aim is to investigate the relationship between *future cumulative excess returns* (for various k-values: +1 day, +2 days, +3 days, +5 days, +10 days, +20 days) and the Buy Herding Measure (BHM) and Sell Herding Measure (SHM) when the unit of observation is changed to quarterly level from daily level.

6.2.1 Results of Regression: Analysis at quarterly level

INSERT TABLE 5. HERE

Our regression analysis underscores the robustness of our conclusions, as they withstand variations in the unit of observation, transitioning from daily to quarterly assessments. The outcomes is suggestive of distinct impacts of buy and sell herding behaviors on *cumulative excess returns*. Specifically, our results point towards the Buy Herding Measure (BHM) exerting a positive and statistically significant influence on cumulative excess returns across the entire span of the study. This implies that institutional buy herding does not engender return reversals nor destabilize stock prices subsequent to such herding conduct. Instead, the consistent upsurge in returns following buy herding underscores that the coordinated buying patterns of institutional traders predominantly arise from new insights into fundamental market factors. In contrast, our analysis reveals that sell herds (SHM) correlate with significant return reversals. This divergence in results emphasizes the distinct impact of buy and sell herding behaviors on cumulative excess returns.

6.3 Analysis of FII transactions at industry level

Our analysis focuses on data aggregated at the *industry level* rather than the stock level. We include 3-digit National Industrial Classification (NIC) codes and employ regression equation (8) to estimate the mean cumulative return of stocks within industry i from t to t + k, denoted as $r_{i,t,t+k}$. We then use fixed effects panel regression models to examine the impact of herding on subsequent returns for each k.

$$r_{i,t,t+k} = A_k + B_k * BHM_{it} + C_k * SHM_{it} + D_k * Size_{it} + E_k * B2M_{it} + F_k * r_{i,t,t-250} + G_k * Std_{it} + H_k * r_{i,t,t-5} + I_k * MRP_{it} + J_k * ILLQ_{it} + \alpha_{ki} + \gamma_{kt} + \epsilon_{it} \quad (8)$$

where:

- $Size_{it}$ is the logarithm of the mean closing MCAP of stocks in an industry i
- $B2M_{it}$ is the mean book-to-market ratio of stocks in an industry i
- $r_{i,t,t-250}$ is the past mean cumulative return of stocks in an industry i
- Std_{it} is the mean std. deviation of the past 250 daily stock returns in an industry i
- $r_{i,t,t-5}$ is the past mean cumulative 5-day return of stocks in an industry i
- MRP_{it} is the excess market return of the stocks in an industry i
- $ILLQ_{it}$ is the mean Amihud Illiquidity measure of the stocks of an industry i
- α_{ki} is the industry-specific effects
- γ_{kt} is the time-specific effects

Using specification (8), we set to examine the relationship between future cumulative returns (for different k: say + 1 day, + 2 days, +3 days, + 5 days, +10 days, +20 days) and BHM (Buy Herding Measure) and SHM (Sell Herding Measure). We have adopted this specification to ensure the robustness of our findings across different industries.

6.3.1 Results of Regression: Analysis at Industry Level

INSERT TABLE 6. HERE

Furthermore, our analysis at the industry level, which is aggregated using a three-digit NIC code and industry-daily level unit of observation, yields consistent findings, albeit with less notable impacts.

6.4 Relationship between Herding measure and periods of crises

This section aims to analyze the strength of herding effects in periods characterized by *crises*. The occurrence of the global crisis in 2007–2008 and the Covid-19 pandemic in 2020 provide a suitable context for testing our hypothesis. *We propose that during times of crisis, herding behavior is likely to intensify*. Given the tendency of institutions to conform and follow each other, particularly in moments of crisis, we anticipate a positive 'G' coefficient when evaluating the crisis period. To investigate this, following Economou et al. (2011) and Lan and Lai (2011), we enhance our benchmark model (represented by equation 3) by introducing a dummy variable, D_{crisis}, which assumes a value of 1 on crisis days and 0 otherwise.

$$HM_{i,t} = A_k + B_k \cdot SIZE_{i,t-1} + C_k \cdot VOL_{i,t} + D_k \cdot |ret_{i,t-1}| + E_k \cdot Std_{i,t}$$

$$+ \mathrm{F}_k \cdot INFOASSYMETRY_{i,t-1} + G_k \cdot D_{crisis} + \alpha_{ki} + \gamma_k t + \epsilon_{it} \tag{9}$$

where: Variables that have been previously defined in this study.

The estimated coefficients for the model are presented in Table 9. In order to examine our hypothesis, we consider two distinct periods that represent financial crises. The first period corresponds to the global crisis of 2007–2008, which serves as an appropriate testing ground for our hypothesis (Event period: 1/Aug/2007 – 1/Dec/2008). The second period encompasses the period of the COVID-19 pandemic. Specifically, on 23 March 2020, Sensex experienced a decline of 3,934.72 points (13.15%), and Nifty plunged 1,135 points (12.98%) to 7610.25, as concerns over a global recession were triggered by lock-downs imposed worldwide (Event period: 01/Mar/2023 to 31/May/2023). The findings provide evidence supporting our hypothesis, indicating an overall increase in the herding measure during crisis periods, particularly in the context of sell herding.

INSERT TABLE 7. HERE

INSERT TABLE 8. HERE

Based on the findings depicted in Table 9, it is evident that the coefficient 'G' associated with the financial crisis period dummy variable, denoted as D_{crisis}, exhibits a positive and statistically significant relationship solely during instances of financial crises induced by the global sub-prime crisis and the Covid-19 pandemic. These results suggest that institutional traders, particularly during periods characterized by heightened financial strain, display a stronger inclination to emulate the trading behaviors of their peers compared to normal market conditions.

6.5 Synopsis of the findings of the study

The outcomes of our study indicate that buy and sell herding have differential impacts on cumulative returns. Specifically, BHM positively associates with cumulative returns over the entire time horizon, indicating that *institutional buy herding does not lead to return* *reversal or destabilization of stock prices*. The continued increase in returns after buy herding suggests that correlated buy activities of institutional traders are mainly driven by new information about underlying fundamentals. Conversely, *sell herds (SHM) result in significant return reversals, pushing prices below their fundamental values*. Moreover, our investigation demonstrates the robustness of our findings when employing excess cumulative returns as the dependent variable and shifting the unit of observation from a daily to a quarterly level for stocks. Additionally, our analysis conducted at an industry-daily level unit of observation yields consistent outcomes compared to our previous results, albeit with less pronounced effects. Our panel regression analysis also reveals that *volume turnover, information asymmetry, and standard deviation of returns are positively and significantly associated with the overall herding measure*. Furthermore, our results indicate a *significant negative relationship between the Buy Herding Measure and the signed return, as well as the standard deviation, while a significant positive association is observed between the Sell Herding Measure and these two variables*.

7 Implications of the Study

This study adds to the existing empirical literature on herding by utilizing daily investorspecific transaction data to investigate the herding behavior of FIIs in a broad cross-section of stocks listed on India's National Stock Exchange from January 2003 to July 2021. Our findings suggest that herding behavior by FIIs (mainly sell herding) can adversely affect stock prices and be a cause for concern for government bodies such as the capital market regulator (SEBI) and the central bank (RBI), who may need to formulate and implement appropriate policy responses to protect the interests of small retail investors.

8 Conclusion

Our research investigates the herding behavior of FIIs in India. Institutional investors, including mutual funds, pension funds, insurance companies, and foreign portfolio investors, have substantially impacted the Indian stock markets in recent years. These influential players have the ability to affect market liquidity and sentiment, and their large buy or sell orders can significantly impact stock prices. This research also aims to examine the impact of significant crises like the Covid-19 pandemic and the 2008 sub-prime crisis on the investing behavior of institutional investors because emerging markets, such as India, are highly reliant on FII flows which is evident from the strong correlation between stock market returns and FII fund flows.

The study calculates herding measures from daily equity transactions of FIIs from January 2003 to April 2021 by employing the LSV framework. The study's findings indicate that buy and sell herding behaviors have varying effects on cumulative returns. The Buy herding measure (BHM_{it}) significantly increases cumulative returns over time, suggesting that institutional buy herds do not destabilize stock prices. Conversely, the Sell herding measure (SHM_{it}) leads to significant return reversals, with cumulative returns decreasing in the short term and coefficients losing significance after five days, eventually changing sign. Furthermore, our study provides evidence of the robustness of our findings under different conditions. Our results remain consistent when we utilize excess cumulative returns as the dependent variable and shift the unit of observation from a daily to a quarterly level for stocks and even at an industry-daily level unit of observation. Furthermore, the findings provide evidence of an overall increase in the herding measure during crisis periods, mainly sell herding.

The study's implications are that herding behavior by FIIs can adversely affect stock prices and cause concern for government bodies such as SEBI and RBI. Formulating and implementing appropriate policy responses may be necessary to protect retail investors' interests.

9 TABLES

	HM	BHM	SHM
Observations (Overall)	3,08,347	1,67,399	1,40,948
Jan’2003 to April’2021	2.48**	2.67**	2.30**
	(0.03)	(0.04)	(0.04)
Observations (Period -1)	70,655	36,827	33,828
Jan’2003 - Dec’ 2008	1.99***	2.11***	1.86**
	(0.00)	(0.00)	(0.04)
Observations (Period -2)	83519	46872	36647
Jan’ 2009 - Dec’ 2013	2.36**	2.38**	2.32
	(0.01)	(0.01)	(0.07)
Observations (Period -3)	114352	63611	50741
Jan’2014 - Dec’2019	2.15**	2.24**	2.02**
	(0.01)	(0.01)	(0.04)
Observations (Period -4)	39821	20088	19733
Jan’2020 - April’2021	2.69***	2.81***	2.54**
	(0.00)	(0.00)	(0.03)

Table 1: NIFTY 500 Stocks: LSV Herding Measure

Note: This table provides mean values for LSV Herding Measure, Buy Herding Measure, and Sell Herding Measure for the overall time period as well as for four sub-sample periods, i.e., Period 1: Jan’2003 - Dec’ 2008, Period 2: Jan’ 2009 - Dec’ 2013, Period 3: Jan’2014 - Dec’2019, Period 4: Jan’2020 - April’2021.

Standard errors are double-clustered at the stock and daily level. p -values have been provided in the parenthesis.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%.

HM: Herding Measure, BHM: Buying Herding Measure, SHM: Sell Herding Measure

Dependent Variable : Cumulative Returns						
	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM	0.198	0.653***	0.897***	0.987***	1.398***	1.981***
	(0.161)	(0.238)	(0.322)	(0.377)	(0.512)	(0.698)
SHM	-0.503*	-0.915**	-0.697**	-0.986**	0.62**	0.696**
	(0.176)	(0.256)	(0.303)	(0.493)	(0.201)	(0.311)
Size	-1.134**	-1.362**	-1.845**	-2.017	-2.003**	-1.493***
	(0.359)	(0.433)	(0.561)	(0.328)	(0.512)	(0.466)
B2M	0.082**	0.250***	0.438*	1.010**	1.477***	2.025***
	(0.033)	(0.076)	(0.053)	(0.079)	(0.109)	(0.161)
$r_{i,t,t-250}$	0.003	0.013	0.027*	0.039**	0.098**	0.165***
	(0.007)	(0.109)	(0.014)	(0.017)	(0.024)	(0.032)
Std. dev returns	0.0915	0.310*	0.553	0.971***	1.962***	4.166**
	(0.021)	(0.031)	(0.038)	(0.049)	(0.066)	(0.096)
$r_{i,t,t-5}$	0.017	0.045	0.066	0.083**	0.026	0.016
	(0.003)	(0.05)	(0.006)	(0.008)	(0.01)	(0.014)
MRP	0.050***	0.012	0.013	0.144***	0.162**	0.081*
	(0.007)	(0.011)	(0.013)	(0.014)	(0.023)	(0.033)
Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	3,08,347	3,08,347	3,08,347	3,08,347	3,08,347	3,08,347

R_2	0.278	0.289	0.224	0.312	0.291	0.237
Adj. R^2	0.1668	0.19363	0.17248	0.1872	0.23571	0.19908
F-Statistics	15.63	21.39	33.85	29.63	38.09	47.27
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 2: Impact of Herding on asset prices

Note: To investigate the impact of herding on subsequent returns, we estimate the following fixed effects panel regression models for each k:

$$r_{i,t,t+k} = A_k + B_k \cdot BHM_{i,t} + C_k \cdot SHM_{i,t} + D_k \cdot Size_{i,t} + E_k \cdot B2M_{i,t} + F_k \cdot r_{i,t,t-250}$$

$$+ G_k \cdot Std_{i,t} + H_k \cdot r_{i,t,t-5} + I_k \cdot MRP_{i,t} + \alpha_{k,i} + \gamma_{k,t} + \epsilon_{i,t}$$

Standard errors are double-clustered at the stock and daily level.Std. errors are given in parentheses.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%.

	HM	BHM	SHM
Size	0.002	0.0029	0.0016
	(0.0027)	(0.002)	-0.0019
Vol.	0.0069***	0.0023***	0.0032**
	(0.0012)	(0.0007)	-0.0008
l r l	-0.0001		
	(0.0003)		
r (signed)		-0.0015***	0.0003**
		(0.0002)	-0.0002
Std	0.0031**	-0.0096***	0.0020**
	(0.0012)	(0.0009)	-0.0012

Info Assymetry	0.065**	0.023**	0.081***
	(0.027)	(0.011)	(0.017)
Dummy^b		0.0156***	
		(0.0011)	
Dummy^s			0.0111**
			(0.0002)
Observations	2,07,256	1,13,990	93,266

Table 3: Determinants of Herding

Note: We examine the relationship between institutional herding and its determinants using the following fixed effects panel regression model:

$$HM_{i,t} = A_k + B_k \cdot SIZE_{i,t-1} + C_k \cdot VOL_{i,t} + D_k \cdot |ret_{i,t-1}| + E_k \cdot Std_{i,t}$$

$$+ \mathrm{F}_k \cdot INFOASSYMETRY_{i,t-1} + \alpha_{ki} + \gamma_{kt} + \epsilon_{i,t}$$

Standard errors are double-clustered at the stock and daily level. Std. errors are given in parentheses.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%.

HM: Herding Measure, BHM: Buying Herding Measure, SHM: Sell Herding Measure

Dependent Variable : *Cumulative Excess Returns*						
	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM	0.175	0.756***	0.966***	0.967***	1.796***	1.961***
	(0.161)	(0.276)	(0.722)	(0.777)	(0.512)	(0.696)
SHM	-0.507***	-0.915**	-0.697**	-0.966**	0.62**	0.696**
	(0.176)	(0.256)	(0.706)	(0.597)	(0.204)	(0.71)
Size	-1.175**	-1.762**	-1.655**	-2.01***	-2.007**	-1.597***
	(0.759)	(0.577)	(0.561)	(0.726)	(0.512)	(0.566)

B2M	0.062**	0.250***	0.576***	1.010**	1.577***	2.025***
	(0.077)	(0.076)	(0.057)	(0.079)	(0.109)	(0.161)
$r_{i,t,t-250}$	0.007	0.017	0.027**	0.079**	0.096***	0.165***
	(0.007)	(0.109)	(0.015)	(0.017)	(0.025)	(0.072)
Std returns	0.0915***	0.710***	0.557***	0.971***	1.962***	5.166**
	(0.021)	(0.071)	(0.076)	(0.059)	(0.066)	(0.096)
$r_{i,t,t-5}$	0.017***	0.055***	0.066***	0.067***	0.026***	0.016
	(0.007)	(0.05)	(0.006)	(0.006)	(0.01)	(0.015)
MRP	0.050***	0.012	0.017	0.155***	0.162***	0.061**
	(0.007)	(0.011)	(0.017)	(0.015)	(0.027)	(0.077)
ILLQ	0.62**	0.750***	0.976***	2.010***	2.332***	1.025***
	(0.077)	(0.076)	(0.057)	(0.079)	(0.109)	(0.161)
Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	308347	308347	308347	308347	308347	308347
R_2	0.276	0.269	0.225	0.712	0.291	0.277
Adj R^2	0.1666	0.19767	0.17256	0.1672	0.27571	0.19906
F-Statistics	15.67	21.79	77.65	29.67	76.09	57.27
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 4: Alternative Measures of Future Returns: Using Cumulative Excess Returns

Note: To assess the robustness of our findings, we introduce cumulative excess returns as an alternative measure of future returns, replacing the use of cumulative returns. We conduct a fixed effects panel regression analysis for each k by estimating the following model:

$$r_{i,t,t+k} = A_k+B_k\cdot BHM_{i,t}+C_k\cdot SHM_{i,t}+D_k\cdot Size_{i,t}+E_k\cdot B2M_{i,t}+F_k\cdot r_{i,t,t-250}+G_k\cdot Std_{i,t}$$

$$+ H_k \cdot r_{i,t,t-5} + I_k \cdot MRP_{i,t} + J_k \cdot ILLQ_{i,t} + \alpha_{ki} + \gamma_{kt} + \epsilon_{i,t}$$

Standard errors are double-clustered at the stock and daily level. Std. errors are given in parentheses.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%

Dependent Variable : Cumulative Returns						
	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM	0.194	0.942***	0.922***	0.929***	1.992***	1.921***
	(0.121)	(0.292)	(0.922)	(0.999)	(0.412)	(0.292)
SHM	-0.409***	-0.914**	-0.299**	-0.922**	0.22**	0.292**
	(0.192)	(0.242)	(0.902)	(0.499)	(0.204)	(0.91)
Size	-1.194**	-1.922**	-1.244**	-2.01***	-2.009**	-1.499***
	(0.949)	(0.499)	(0.421)	(0.922)	(0.412)	(0.422)
B2M	0.022**	0.240***	0.492***	1.010**	1.499***	2.024***
	(0.099)	(0.092)	(0.049)	(0.099)	(0.109)	(0.121)
$r_{i,t,t-250}$	0.009	0.019	0.029**	0.099**	0.092***	0.124***
	(0.009)	(0.109)	(0.014)	(0.019)	(0.024)	(0.092)
Std returns	0.0914***	0.910***	0.449***	0.991***	1.922***	4.122**
	(0.021)	(0.091)	(0.092)	(0.049)	(0.022)	(0.092)
$r_{i,t,t-5}$	0.016***	0.044***	0.022***	0.026***	0.022***	0.012
	(0.006)	(0.04)	(0.002)	(0.002)	(0.01)	(0.014)
MRP	0.040***	0.012	0.016	0.144***	0.122***	0.021**
	(0.006)	(0.011)	(0.016)	(0.014)	(0.026)	(0.066)
ILLQ	0.62**	0.750***	0.976***	2.010***	2.332***	1.025***
	(0.077)	(0.076)	(0.057)	(0.079)	(0.109)	(0.161)
Fixed Effects	YES	YES	YES	YES	YES	YES

Observations	8760	8760	8760	8760	8760	8760
R_2	0.262	0.229	0.224	0.612	0.291	0.266
Adj R^2	0.1222	0.19626	0.16242	0.1262	0.26461	0.19902
F-Statistics	14.26	21.69	66.24	29.26	62.09	46.26
p-value	0.005	0.000	0.003	0.003	0.000	0.000

Table 5: Analysis at quarterly level

Note: We conduct the analysis at the *stock-quarter* level. we estimate the following fixed effects panel regression models for each k:

$$r_{i,t,t+k} = A_k+B_k \cdot BHM_{i,t}+C_k \cdot SHM_{i,t}+D_k \cdot Size_{i,t}+E_k \cdot B2M_{i,t}+F_k \cdot r_{i,t,t-250}+G_k \cdot Std_{i,t}$$

$$+ H_k \cdot r_{i,t,t-5} +I_k \cdot MRP_{i,t} +J_k \cdot ILLQ_{i,t} +\alpha_k \cdot i+\gamma_k \cdot t+\epsilon_{i,t}$$

Standard errors are double-clustered at the stock and daily level. Std. errors are given in parentheses.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%

Dependent Variable : Cumulative Excess Returns						
	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM	0.267	0.672***	0.622***	0.626***	2.662***	2.622***
	-0.222	-0.262	-0.622	-0.666	-0.722	-0.262
SHM	-0.706***	-0.627**	-0.266**	-0.622**	0.22**	0.262**
	-0.262	-0.272	-0.602	-0.766	-0.207	-0.62
Size	-2.267**	-2.622**	-2.277**	-2.02***	-2.006**	-2.766***
	-0.676	-0.766	-0.722	-0.622	-0.722	-0.722
B2M	0.022**	0.270***	0.762***	2.020**	2.766***	2.027***
	-0.066	-0.062	-0.076	-0.066	-0.206	-0.222
$r_{i,t,t-250}$	0.006	0.026	0.026**	0.066**	0.062***	0.227***

	-0.006	-0.206	-0.027	-0.026	-0.027	-0.062
Std returns	0.0627***	0.620***	0.776***	0.662***	2.622***	7.222**
	-0.022	-0.062	-0.062	-0.076	(0.022)	-0.062
$r_{i,t,t-5}$	0.026***	0.077***	0.022***	0.026***	0.022***	0.022
	(0.006)	-0.07	(0.002)	(0.002)	-0.02	-0.027
MRP	0.070***	0.022	0.026	0.277***	0.222***	0.022**
	(0.006)	-0.022	-0.026	-0.027	(0.026)	(0.066)
ILLQ	0.62**	0.750***	0.676***	2.020***	2.332***	2.025***
	(0.077)	(0.076)	(0.057)	(0.076)	(0.206)	(0.262)
Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	58880	58880	58880	58880	58880	58880
R_2	0.262	0.226	0.227	0.622	0.262	0.266
Adj R^2	0.2222	0.26626	0.26272	0.2262	0.26762	0.26602
F-Statistics	27.26	22.66	20.27	29.26	18.06	16.26
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 6: Analysis at Industry Level

Note: Our analysis focuses on data aggregated at the *industry level* rather than the stock level. We then use fixed effects panel regression models to examine the impact of herding on subsequent returns for each k.

$$r_{i,t,t+k} = A_k + B_k \cdot BHM_{i,t} + C_k \cdot SHM_{i,t} + D_k \cdot Size_{i,t} + E_k \cdot B2M_{i,t} + F_k \cdot r_{i,t,t-250} + G_k \cdot Std_{i,t}$$

$$+ H_k \cdot r_{i,t,t-5} + I_k \cdot MRP_{i,t} + J_k \cdot ILLQ_{i,t} + \alpha_{ki} + \gamma_k t + \epsilon_{it}$$

Standard errors are double-clustered at the stock and daily level. Std. errors are given in parentheses.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%

	HM	BHM	SHM

Observations (Period -1)	20,303	12,182	8,121
”Before the Global Financial crisis	1.72*	1.89**	1.68*
1st Jan’2003 to 31st Jul’2007”			
	(0.051)	(0.04)	(0.061)
Observations (Period - 2)	21,293	9,582	11,711
”Global Financial crisis of 2007–2008	2.18**	2.07**	2.77***
1st Aug’2007 to 31st Dec’2008”			
	(0.04)	(0.03)	(0.008)
Observations (Period -3)	2,25,583	1,35,350	90,233
”Post Global Financial Crisis	1.86***	2.01***	1.63**
1st Jan’2009 to 29th February,2020”			
	(0.006)	(0.005)	(0.045)
Observations (Period -4)	4,719	2,030	2,689
”Covid-19 Pandemic Period	2.36**	1.89**	2.65***
1st Mar’2020 to 31st May’2020”			
	(0.01)	(0.01)	(0.007)
Observations (Period -5)	17,022	10,554	6,468
”Post Covid-19 Pandemic period	2.12**	2.25**	1.96**
1st Jun’2020 to 30th Apr’2021”			
	(0.02)	(0.04)	(0.01)

Table 7: Sub-Periods analysis of Herding Measure

Note: This table provides the results for the LSV Herding Measure, Buy Herding Measure, and Sell Herding Measure for the five sub-sample periods, i.e., Before the Global Financial crisis: 1st

Jan’2003 to 31st Jul’2007, Global Financial crisis: 1st Aug’2007 to 31st Dec’2008, Post Global Financial Crisis: 1st Jan’2009 to 29th February 2020, Covid-19 Pandemic Period: J1st Mar’2020 to 31st May’2020 and Post Covid-19 Pandemic period: 1st Jun’2020 to 30th Apr’2021.

Standard errors are double-clustered at the stock and daily level. p-values are given in parentheses.

Sig. at 10% ** Sig. at 5%.***Sig. at 1%.

HM: Herding Measure, BHM: Buying Herding Measure, SHM: Selling Herding Measure.

Dependent Variable : Herding Measure(HM)					
	Before the GFC 1st Jan’2003 to 31st Jul’2007	GFC 1st Aug’2007 to 31st Dec’2008	Post GFC 1st Jan’2009 to 29th February,2020”	Covid-19 1st Mar’2020 to 31st May’2020	Post Covid-19 1st Jun’2020 to 30th Apr’2021
Size	0.002	0.04	0.007**	0.09**	0.012
	(0.0036)	(0.07)	(0.002)	(0.03)	(0.07)
Vol.	0.006***	0.008*	0.009***	0.007***	0.0069***
	(0.0012)	(0.007)	(0.003)	(0.002)	(0.0017)
l r l	-0.0001	-0.002***	-0.004***	-0.001***	-0.0003
	(0.0007)	(0.0003)	(0.0004)	(0.0003)	(0.0005)
Std	0.0013	0.0051**	0.0038**	0.0017	0.002*
	(0.0012)	(0.0021)	(0.0011)	(0.002)	(0.001)
Info Assymetry	0.043*	0.056**	0.088**	0.065**	0.043**
	(0.021)	(0.017)	(0.024)	(0.027)	(0.016)
D_{crisis}	0.37	0.65***	0.49*	0.86***	0.74*
	(0.45)	(0.08)	(0.31)	(0.09)	(0.32)
Observations	20,303	21,293	2,25,583	4,719	17,022
F-statistics	14	32	27	144	311

p-values	0.0573	0.032	0.021	0.007	0.009

Table 8: Analysis of herding behavior during periods of crisis

Note: We analyze the strength of herding effects in periods characterized by financial crises. we enhance our benchmark model (represented by equation 3) by introducing a dummy variable, D_{crisis}, which assumes a value of 1 on crisis days and 0 otherwise.

$$HM_{i,t} = A_k + B_k \cdot SIZE_{i,t-1} + C_k \cdot VOL_{i,t} + D_k \cdot |ret_{i,t-1}| + E_k \cdot Std_{i,t}$$

$$+ F_k \cdot INFOASSYMETRY_{i,t-1} + G_k \cdot D_{crisis} + \alpha_{ki} + \gamma_{kt} + \epsilon_{it}$$

Standard errors are double-clustered at the stock and daily level. Std. errors are given in parentheses.* Sig. at 10%.** Sig. at 5%.***Sig. at 1%

10 APPENDIX

10.1 Appendix - 1.1

Institutions	Avg. % of the institutional shareholding
Foreign Institutional Investors	47.61%
Mutual Funds / UTI	32.00%
Insurance Companies	15.18%
Other Institutional Non-promoters	4.71%
Venture Capital Funds	0.50%

Table 9: Average Percentage of the institutional shareholding as of Dec 31st, 2022

Source: CMIE PROWESS

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