Herd Behaviour: How Decisive is the Noise in the NSE and BSE Stock Markets?

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Abstract

Do investors in the stock markets act/react on true information or noise? Do they believe on their own information or simply herd? The study seeks to explore these typical research queries from the behavioural finance perspectives. In particular, it develops a new theory of herding behaviour and extends the models of Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992). The study also empirically tests the same on the Indian context with the high frequency intraday trading data for the real trade-time or timestamp, trade-volume, and trade-price of ten sample scripts listed for their trading in both markets - the Bombay Stock Exchange (BSE) and the National stock Exchange (NSE). The study contributes to the literature with original findings. It shows that investors in the two Indian stock markets show crowd of positive and negative herding as well significantly and there is huge noise along with information in the markets' equilibrium pricing mechanism.

Keywords: Equilibrium Pricing Mechanism, Behavioral Finance, Herding Behavior, Indian Stock Markets, Noise Trading, Intra-day Trading

Introduction

How do investors behave in the stock markets? Finance practitioners and academics have explored too many ideas on this basic query. A few are as follows. Do the investors prefer dividend to capital gains? Do they prefer long position to short positions? Do they hate realised losses at their actual trading and like "paper" gains at changes in the market prices? Do they have preference for "better" firms to "good" ones? Are they informed at times of their trading in the markets? Do the pricing mechanisms in the capital markets incorporate only information? Does the political stability of a country influence the other countries' stock prices? Which factors force the financial regulations in a country? Could the realised returns in the stock markets estimable? All these ideas include investors' behaviours and their interactions in the stock markets. The list of ideas involving investors' decision making, in practical, is too long!

These ideas are addressed both in the standard finance and behavioural finance literatures of the Financial Economics, which has led a few Nobel Prizes as well viz. Gunnar Myrdal and Friedrich Hayek in 1974, Franco Modigliani in 1985, Harry Markowitz, Merton Miller and William F. Sharpe in 1990, Ronald Coase in 1991, Gary Becker in 1992, Robert C. Merton and Myron Scholes in 1997, George Akerlof, Michael Spence, and Joseph E. Stiglitz in 2001, and Daniel Kahneman in 2002 (however, this is just an indicative list).

But the basic query is not fully resolved as yet. The bottleneck in the standard finance theories lies within the assumptions of investors' characteristic to be "rational" and "financial" men and the markets' characteristic to be "efficient". In the behavioural finance, investors are "normal" rather than "rational" and the markets are "inefficient". For the informed traders, there are limits to arbitrage benefits in the markets and it could only be possible if there are uninformed traders. Lee (2001; p. 238) has conjectured that "we cannot at once believe in the existence of lions, and reject the existence of the creatures that are essential to their survival." The uninformed traders supply liquidity in the stock markets as if the creatures supply the livelihood for the lions.

Further, normal investors (also read, people) form beliefs with their perceptions about the stock markets they use to live in and show preference for specific events over others. They try to perceive expected changes in the basic frameworks of the regulatory institutions, laws, political stability, and the crowd in the markets. The investors' decision set includes interdisciplinary aspects of the subjects of Finance, Commerce, Accounting, Economics, Psychology, Sociology, Political Science, and Business

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Law. In contrast to the standard finance, the researchers in behavioural finance thus study the relationships between financial knowledge and other social science branches.

In a market economy, both informed traders and uninformed traders should live together. Once there is cost for new information, the stock markets could not accumulate all information into prices. At the presence of both "noise" (pseudo information) and the noise traders, in the equilibrium pricing mechanism, how do the investors behave among the market participants in the markets? This paper seeks to address this grave problem in the broader area of Financial Economics.

Literature Review

Against the limited arguments in the standard finance studies on the effects of investors' perceptions in the pricing formation, their perceptions on value, management of risk and return and their trading practices have advanced a few path braking developments in the behavioural finance literature (DeBondt, 1998; Fama 1998). A brief review of the arguments of the both schools is followed.

The standard finance rests on the modern portfolio theory of Markowitz (1952, 1959), the capital asset pricing model of Linter (1965), Sharpe (1964), and Black (1972), the arbitrage pricing theory of Miller and Modigliani (1961) and Ross (1976), the option pricing theory of Black and Scholes (1973), and the efficient market hypothesis (EMH) of Fama (1965, 1970). Investors' characteristic is assumed to be "rational" and the market to be "efficient" at certain levels. There are critics of the EMH (Elton, 1999; Kothari, 2001; Malkiel, 2003). There are also anomalies those are not explained by the said market microstructure theories (Frankfurter & McGoun, 2001; DeBondt, 1998; Fama 1998).

In the Behavioural Finance, however, the interpretations of psychology, sociology, and finance about investors' behaviours have provided foundations stones. The investors in the stock markets (hereinafter, stock- traders) are broadly classified as "informed" and "uninformed" traders (Grossman, 1976; Grossman & Stiglitz, 1976). They acknowledge realised losses and show reluctance to "paper" losses (Shefrin & Statman, 1985). They frame their investments with cognitive biases and emotions (Shefrin & Statman, 1985), by the behavioural portfolio theory (Statman, 2000), the behavioural asset pricing model (Shefrin & Statman, 1994; Statman, 1999), and by the presence of "noises" along with information in the stock markets (Grossman & Stiglitz, 1980; Black, 1986; Shiller, 2003; Berkman & Koch, 2007; Lee, 2001). They are "normal" traders rather than "rational" ones and the markets are "inefficient" ones (Statman, 2008).

Thus, according to the behavioural finance, all the investors in the stock markets are not informed ones. They all are not rational as well. An investor's behaviours in the stock markets are inconsistent with the classical economic theories of rational behaviour (Odean, 1999). Noise traders and rational traders live in the markets at presence of costs for new and relevant information (Dow, 2002; Chinco & Mayer, 2011).

The unsettled quests in both the schools as yet are (i) how do the investors vis-à-vis the stock prices behave in the market places, and (ii) how do the stock markets remain liquid at presence of information costs. Both the queries lead us to explore the dynamics of the liquidity traders in the stock markets. On the queries, the theoretical studies are vast but they are inconclusive empirically. DeLong, Shleifer, Summers, and Waldmann (1990) and Shleifer & Vishny (1997) explore short run miss-pricing in the US stock markets. Implementation costs or transaction costs play a major role in limiting the arbitrage benefits in the IPO issue of the 3Com bubbles in the USA (Lamont & Thaler, 2003). There are evidences on investors' overconfidence (Alpert & Raiffa, 1982; Fischhoff, Slovic, & Lichtenstein, 1977), experiences in the market (Barber, Odean, Lee, & Liu, 2007), optimism and wishful thinking (Weinstein, 1980; Buehler, Griffin, & Ross, 1994), representativeness (Kahneman & Tversky, 1974), belief perseverance (Lord, Ross, & Lepper, 1979) conservatism (Edwards, 1968), and the law of small numbers (Rabin, 2002), and anchoring and ability biases (Kahneman & Tversky, 1974).

On the said issues, there is little research in the developing countries' (specifically in Indian) contexts. On the association between per capita income and level of happiness (risk), Statman (2008) shows that the Indian investors rank above (or below) the general tendency curve even if they belong to moderate associations. Iyer and Bhaskar (2002) have explored the role of psychology in the investors stock trading behaviours in India. Prosad, Kapoor, and Sengupta (2012) find evidences in favour of the implication of the standard finance and reject herding behaviours in the context of Indian stock markets. Sahni (2012) has explored the loss aver-ness behaviours and the effects of anchoring on the Indian stock traders. Subash (2012) has showed that the younger investors in the Indian stock markets show regret aversion, gamblers' fallacy and hindsight bias while the experienced investors could be separated with lesser degree to their erroneous decisions. Chandra (2009) has showed evidences in favour of the individual investors' self-perceived competences and own-judgments. Kathuria and Singhania (2012) have explored implications of gender in stock trading in India. Campbell, Ramadorai, and Ranish (2013) have showed that the experienced investors tilt their portfolios profitably towards the value stocks and those stocks with low turnover while they tend to have lower turnover and disposition bias.

The said studies offer contradictory evidences while they have utilised either the opening or the closing price data of stocks' trading. They have missed the role of "noise" i.e., liquidity traders in the stocks' price formation process. In exploring the behaviours of stock-traders at presence of "noise" (pseudo information) and noise traders (uninformed traders), the task of theory building is also neglected.

Objectives of the Study

The behavioural finance is new in explaining the investors' characteristics and the market microstructures. Investors are expected to show behavioural dynamics. The paper explores this dynamics in the equilibrium pricing mechanism of the stocks. In particular, it firstly develops a new theory of herd behaviour and thereby extends the models of Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992). It then empirically tests the same on the Indian context with the stocks' intraday high frequency trading data. The study contributes to the literature with original findings. In the next section, the paper sets forth the theoretical model and formulates a few propositions.

Dynamic Model of Herding Behaviour

In Banerjee (1992), an investor has options either to invest in an asset or not while he receives a signal with some probability and it has some probability to be true. With some tie-breaking assumption, he has showed that one person at random if starts a decision-tree then his followers always neglect their own information and follow the predecessors in the herd. The basic flaws here are that (i) a trade requires both buyer and seller simultaneously while in the model there is an investor who starts trading but against none, (ii) a trade never starts with uninformed traders, and (iii) cascades are irreversible. Upward or downward pricing cascade may also start even if informed trader takes positions in contrast to his information content. In Bikhchandani, Hirshleifer, and Welch (1992), informational cascades explain conformity of investors' choices along with rapid and short-lived fluctuations such as fads, fashions, booms, and crashes. They suggest that if the decision makers ignore their private information at some stage and act on information provided by their previous trader, then an information cascade starts. Like the model of Banerjee (1992), here also a joint decision making between buyer and seller is neglected. In the following, the present work puts forward a dynamic model where the buyers and sellers both involve in decision making and thereby, in trading of an asset out of two or more assets equally available for trade.

Let us assume that there are n (>1) number of financial assets (say, stocks) in the market with N (>2) number of investors. There is uncertainty on receipt of a quality signal about changes in the jth ($j = 1, 2, 3....n$) stock's prices P_{jt}s at time t on a particular day. Also assume that α_i ($0 \leq \alpha_i \leq 1$) is the probability that ith ($i = 1, 2, 3...N$) investor receives a signal X_{ij}, β_i ($0 \leq \beta_i \leq 1$) is the probability that the signal is correct, and γ_j ($0 \leq \gamma_j \leq 1$) is probability that the signal is related to jth stock. At buying or selling, ith investor's decision is related to α_i, β_i, and γ_j. In the transmission channel, assume that distortion of information happens. The *ex-ante* information about the *ex-post* events, that is instantaneous random signal and its quality at recipient's hands, is not fully independent of its recipient at time t. That is, the extent of α_i is independent of β_i is $\alpha_i \beta_i$ and $0 \leq \alpha_i \beta_i \leq 1$. The *spread* of information and its direction in a form of signal, however, may or may not be specific to jth stock. His right decision, therefore, has the probability defined as $p_{ijt} = \alpha_i \beta_i \gamma_j$ and it being wrong is $p'_{ijt} = (1 - \alpha_i \beta_i \gamma_j)$.

Now, let us advance for possible herd behaviour. For jth stock, assume that there are four investors in sequential order two at each of the "Buy" and "Sell" windows of the pricing mechanism with no past memory, call it the "Black Box". All of them are with endogenous probability of $p_{ijt}(X_{ij})$ for the right price and of $p'_{ijt}(X_{ij})$ for the wrong price. The trade decision at a price P_{jt} over the windows

Table 1: Specification of Probabilities P (X_{ij}) for an Exogenous Buyer or Seller for *j* Stock

Quality of Signal (probability) *Receiving Signal (probability)*	*Signal is Correct* (β_i)		*Signal is Incorrect* ($1-\beta_i$)	
	j chosen	*j not chosen*	*j chosen*	*j not chosen*
Signal is received (α_i)	$\alpha_i\,\beta_i\,\gamma_j, = P_1$	$\alpha_i\,\beta_i\,(1-\gamma_j) = P_2$	$\alpha_i\,(1-\beta_i)\,\gamma_j = P_3$	$\alpha_i\,(1-\beta_i)\,(1-\gamma_j) = P_4$
Signal is not received ($1-\alpha_i$)	$(1-\alpha_i)\,\beta_i\,\gamma_j = P_5$	$(1-\alpha_i)\,\beta_i\,(1-\gamma_j) = P_6$	$(1-\alpha_i)\,(1-\beta_i)\,\gamma_j = P_7$	$(1-\alpha_i)\,(1-\beta_i)\,(1-\gamma_j) = P_8$

Table 2: Matrix for Joint Probabilities with Single Buyer and Single Seller at the First Trade

Buyer's P_k *Seller's* P_k	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
P_1	$P_1\,P_1$	$P_1\,P_2$	$P_1\,P_3$	$P_1\,P_4$	$P_1\,P_5$	$P_1\,P_6$	$P_1\,P_7$	$P_1\,P_8$
P_2	$P_2\,P_1$	$P_2\,P_2$	$P_2\,P_3$	$P_2\,P_4$	$P_2\,P_5$	$P_2\,P_6$	$P_2\,P_7$	$P_2\,P_8$
P_3	$P_3\,P_1$	$P_3\,P_2$	$P_3\,P_3$	$P_3\,P_4$	$P_3\,P_5$	$P_3\,P_6$	$P_3\,P_7$	$P_3\,P_8$
P_4	$P_4\,P_1$	$P_4\,P_2$	$P_4\,P_3$	$P_4\,P_4$	$P_4\,P_5$	$P_4\,P_6$	$P_4\,P_7$	$P_4\,P_8$
P_5	$P_5\,P_1$	$P_5\,P_2$	$P_5\,P_3$	$P_5\,P_4$	$P_5\,P_5$	$P_5\,P_6$	$P_5\,P_7$	$P_5\,P_8$
P_6	$P_6\,P_1$	$P_6\,P_2$	$P_6\,P_3$	$P_6\,P_4$	$P_6\,P_5$	$P_6\,P_6$	$P_6\,P_7$	$P_6\,P_8$
P_7	$P_7\,P_1$	$P_7\,P_2$	$P_7\,P_3$	$P_7\,P_4$	$P_7\,P_5$	$P_7\,P_6$	$P_7\,P_7$	$P_7\,P_8$
P_8	$P_8\,P_1$	$P_8\,P_2$	$P_8\,P_3$	$P_8\,P_4$	$P_8\,P_5$	$P_8\,P_6$	$P_8\,P_7$	$P_8\,P_8$

with the first investor at each window is determined jointly. It is observable to their successors for next trade at the windows. The "Black Box" can not reveal magnitudes of $p(X_{ij})$ and $p^{/}(X_{ij})$ to successor investors. It discloses P_{jt} only. A joint decision, in the next trade, demonstrates effects on P_{jt} going up or coming down. Table 1 shows the probabilities (p_k, k=1, 2,…8). An information that is either received or not, either correct or not, and either related to *j*th stock or not provides eight endogenous states[1]. Since an investor may be a buyer or a seller, Table 2 shows the matrix for joint probabilities $p_m p_n$ on trades (*m* and *n* are any values of *k*).

From Table 2 of joint probability distribution of $p_m p_n$ with the seller and buyer for any *k* and *m*, *n* = 1, 2, ….8, it is evident that at $m, n = 1$ in $p_m p_n$, trade reveals information even if it is not of the same quality to next buyer and seller while the rest 63 possibilities reveal noises. These possibilities include transaction where it carries signal but it loses its merits for "correct" "signal" or it is not related to *j*th stock. That is, at the first trade the possibility of inclusion of noise, $p_1^* = (1 - 1/2^6)$, is pervasive.

The 2nd pair of buyer and seller out of the N-2 investors in the "awaiting-crowd" knows that the first trade involves any one out of the said 64 stochastic situations. They only observe $\mathbf{P}_{1jt}$, at which the first two traders jointly traded the stock *j*. A signal about *j* ($j = j^*$) becomes visible to these (N – 2) awaiting-investors, even if the true γ_j is unknown. To them in sequential, information about α_i, β_i and γ_j are identically distributed. Since the second investors do not have confirm prior information about *j* ($\gamma_j \neq 1$), and they may (i) follow signal j^* or (ii) reject it and follow j ($= j^{/}$), where $j^{/}$ is any *j* but not j^*. If they follow j^* as is their prior γ_j-s were at j^*, a positive cascade (i.e., the latter follows the predecessors) starts while at $j^{/}$ a negative one (the latter deviates from the predecessors) starts. Given that $\gamma_j \neq 1$, the positive cascade always starts herding behaviour immediately and the negative one always delays likely herding at the second trade. Apart from these cascades at the choice history with a *j*th stock, cascades would appear with the second investors' choices at unknown α_i and β_i. The conditional probability for inclusion of noise at the 2nd traders would be $[p_2^* = (p_1^*)^2 = (p_k p_l).(p_r p_s)]$ for any *k, l, r, s* =1, 2,…8.

With probability $(p_1 p_1)^2$, the second trade incorporates information where it is true and passes the same to the awaiting-crowd while the other possible trades passes

1 It is assumed earlier that in the transmission channel, distortion of information may happen. That is, an end user trader (i.e., buyer and seller as well) may receive no signal at al and by way of observing the prices in the market or the behaviours of his predecessors he may become bound to speculate about it. The case of "signal is not received", hence, does not restrict traders from trading. It would be shown latter that a "no-signal" situation allows a trader to make his decision choice randomly.

noise. The followings are the tie-breaking assumptions on sequential trades:

Assumption 1: If the first buyer or seller has signal (no signal) of *j*, he chooses *j*th, $j = j^*$ stock (any stock arbitrarily) from the set of stocks viz., $j = 1, 2, 3 \ldots n$ on expectation of arbitrage opportunity at a few minutes' lag in the markets. This initiates the first trade and avoids a "no-trade" situation, but may pass noise to successor traders.

Assumption 2: If an informed buyer or seller is indifferent between following his own signal or some others' choice about *j*, he always follows his own signal. This assumption reduces possible herding and focuses on the best possible informative equilibrium.

Assumption 2.a: An uninformed noise trader being indifferent would put more weights on the market price than own signals.

Assumption 3: If the buyer or seller is indifferent between two or more of the choices made by the previous traders, he follows the one who has the highest value of *j*.

Equilibrium Decision Rules

From Assumption 1 it is clear that the choices of the first trade (i.e., set of buyer and seller) depend on whether they have signals or not. If they both have signals about *j*th stock, it results into informative equilibrium even if the signal may not be correct. If either one of them has chosen j^* on own signal and the other has chosen $j = j^*$ arbitrarily, it becomes less informative. If the both have chosen $j = j^*$ randomly, it becomes least informative.

The 2nd set of buyer and seller does not know the informational quality of the first set. They observe price P_{jt}, speculate its information content from price P_{jt}, consider their own signals, and decide on trading. If they do not have a signal about *j*, they speculate the information content about P_{jt}, superimpose their own belief and expectation, and trade on *j*th stock accordingly. If they have signals about *j*, they may assume that the same are as likely as their own and may imitate starting a positive cascade. But, if they have signals other than *j* and they are indifferent between own signals and the first trade, Assumption 2 insists that they will follow their own signals.

The third pair of decision makers face five possible histories: (i) either or both of the predecessors have chosen *j* stock, (ii) either or both have chosen j^* but not *j* stock, (iii) and neither of them has chosen *j* and j^* stock but some other stocks. If the third pair of buyer and seller does not have signal, they become indifferent between the above histories and according to Assumption 3, they will follow that trade who has the highest value of *j*. If they have signal *j* and face the above history (i), they follow their own signal and advances positive cascade. At signal *j*, if they face history (ii) and become indifferent in choosing *j* over j^* and vice-versa, then Assumption 3 tells that they follows the one with the highest value of *j* (where *j* includes j^*). However at signal *j* if they face history (iii) and become indifferent, Assumption 2 suggests that they follow their own signal.

Therefore, the decision rules are as follows:

A. **The first two traders are informed traders:** Trade happens for *j*th stock even if their magnitudes of α_i, β_i, and γ_j, may not differ and a positive cascade starts and continues till some other two traders i.e., buyer and seller assume that information already impounded into prices is incorrect.

B. **The first two traders are noise traders:** Trade happens for *j*th stock if they have randomly chosen *j*th stock and if their magnitudes of α_i, β_i, and γ_j may not differ. Here positive cascade starts and continues till some successors traders assume that the information impounded into prices is incorrect.

C. **One informed and other noise trader:** Trade happens for *j*th stock if informed trader trades for *j*th stock and the other randomly chooses *j*th stock even if their magnitudes of α_i, β_i, and γ_j, may not differ. A positive cascade here continues till some successors assume information impounded into prices is incorrect.

The said decision rules suggest that both the incorrect and the correct cascades are reversible once successor traders assumes that information already impounded into prices is incorrect. To complete the dynamic model of herd behaviour, the following proposition is proposed related to decisions rules A, B, and C.

Proposition: If at nth trade both buyer and seller identify a queue of length of (n - r) trades in cascade and if their information quality is in contrast to (n - r) pairs of predecessors, then following the cascade is not at their best interest.

The proposition is based on the following two lemmas.

***Lemma 1*:** At the nth trade, traders may initiate a correct trade even if their n-r pairs of predecessors in queue were incorrect but the first r-1 pairs were correct.

Let us assume that at event Ψ_n the *n*th pair of informed buyer and seller get signal about *j*th stock and observe an incorrect queue of length of *n- r* (*r = 1, 2, …n-1*). Then its probability Pr (Ψ_n) is defined as follows in identity (i). The first term is the probability that *n*th pairs of informed buyer and seller get signals, these being correct, and related to *j*th stock. The second term is the probability that the last (*n-r*) predecessor traders (both buyers and sellers) have made incorrect decisions. The last one is the probability that the first (*r-1*) pairs of traders have made correct decisions.

$$\Pr(\Psi_n) = (\alpha\,\beta\,\gamma)^{2} * (1-\alpha\,\beta\,\gamma)^{2\,(n-r)} * (\alpha\,\beta\,\gamma)^{2\,(r-1)} \quad \text{(i)}$$

***Lemma 2*:** At the nth trade, players may initiate an incorrect trade even if their n-r pairs of predecessors were correct while the first r-1 pairs were incorrect.

Assume that at event Φ_n the *n*th pair of informed buyer and seller get signal about *j*th stock that is incorrect and observe correct queue of length of *n- r* (for any value of *r*). Then its probability Pr (Φ_n) is defined in the identity (ii) as follows. Here, the first term is the probability that the *n*th pair of informed buyer and seller get signal, it being incorrect and related to *j*th stock, the second term is the probability that last (n-r) predecessor traders (both buyers and sellers) have made correct decisions, and the last is the probability that the first (r-1) pairs of traders have made incorrect decisions.

$$\Pr(\Phi_n) = (1-\alpha\,\beta\,\gamma)^{2} * (\alpha\,\beta\,\gamma)^{2\,(n-r)} * (1-\alpha\,\beta\,\gamma)^{2\,(r-1)} \quad \text{(ii)}$$

Empirical Methodology

The dynamic model has emphasized that noise is pervasive even if it may not be visible directly in the price data. In order to observe the noise effects in prices on possible herding behaviours, we need to identify noise effect and presence of herding as well. The procedure of the empirical methodology is as follows:

Identification of Noise

At market efficiency, stock's prices incorporate relevant information instantaneously. None may gain abnormal profits from their intraday trading in the markets. If traders have excess access to relevant information, insider information, or some short of technology in knowing miss-priced stocks, they would transact in large volume instantaneously or urgently since such access involves costs, this access is short lived, it may reverse in the near foreseeable future time, and there is noise traders' risk as well. Therefore, a presence of stocks' transactions in large (or small) volume in subsequent trades may proxy for the presence of informed (or noise) traders.

Identification of price change in trades

The process of price formation may be described in the dynamic Gaussian random framework. The market price at the end of the t^{th} time interval is denoted by *P(t)* and updated via the following identity (iii).

$$P(t+1) = P(t) \exp\left[\sqrt{h}\,\Delta W(t) + \kappa\Delta\sigma(t)\right] \quad \text{(iii)}$$

where, $\Delta W(t)$ is the standard Gaussian random variable that represents creation of new, uncorrelated and generally available information over t^{th} time interval. The time step *h* is measured in units, where *h = 1* corresponds to interval of one second, over which the random variable $\Delta W(t)$ has unit variance. Since new uncorrelated and generally available information is not observable, the values of *h* represent quality of news. If the variable $\Delta\sigma(t) = \sigma(t) - \sigma(t-1)$ is the most recent change in the market sentiment related to the stock and the constant $\kappa > 0$ determines effects that an investor /stock trader has on its market price. The larger is the κ, the more tis its market price being influenced by internal market dynamics as opposed to the generation by new market information. Identity (iv) captures pricing dynamics incorporated in returns. $PR_{t+1,t} = P(t+1)/P(t)$) can be explained by the variables of time interval of consecutive trades ($\boldsymbol{h_t} = \sum h$) at trade time and recent change in market sentiments i.e., trade volume of the stock in particular, Δf_t.

$$P(t+1) / P(t) = \exp\left[\sqrt{h}\,\Delta W(t) + \kappa\Delta\sigma(t)\right] \quad \text{(iv)}$$

Identification of Herding

Herding behaviour essentially is replicating behaviour. This may be judged by mathematical simulation of price change for herd characteristics viz., the density of crowd (D_c). D_c may be identified from the order book data for trading. The crowd of herding (*CH*), viz., a positive herding (CH^+) or a negative herding (CH^-) derived from the consecutive return data may serve as proxy for D_c. The magnitudes of CH^+ and CH^- can be explained by presence of noise vis-à-vis information as envisaged in the volume data (Δf_t) in identity (v).

$$CH^+ = D(\Delta f_t) \quad \text{(v)}$$

$$CH^- = D(\Delta f_t) \quad \text{(vi)}$$

Data & Empirical Model

Given the theoretical development and stated empirical formulations stated earlier, empirical testing of noise vis-à-vis information and possible herding are accomplished with use of intraday one minute (that is., 1D Data) trading data for ten stocks' trade-price, trade-volume, and trade-time for the date of 14.07.2014. These scripts are ACC. LTD, ACL.LTD, ASSIANPAINTS.LTD, AXISBANK.LTD, BAZAZHIND.LTD, BHEL.LTD, BOB.LTD, BPCL.LTD, CARIN.LTD, and BHARATIARTL.LTD. These scripts are listed both in the BSE-SENSEX and the NSE-NIFTY. The trading data of the scripts are collected manually from the source of www.finance.yahoo.com and the data spreads over the trading hours in the BSE and the NSE markets for one minute intervals. Since the data generation procedure takes huge manual efforts, the study limits its scope within one trading day within the two markets over ten scripts. The data are processed through the following regression models (1), (2), (3), and (4) for each of the two markets.

Over the consecutive trade data, in the empirical regression model (1), the return data $PR_{t+1,t}$ is regressed with the explanatory trade-time interval ($\boldsymbol{h_t}$). The coefficient 'a' represents effects of new, uncorrelated and generally available information over interval $\boldsymbol{h_t}$. Since such information is generally available it makes a universal contribution at the equilibrium pricing system. If the information is pervasive in the pricing system, then it would lead to significant value for 'a_1', 'a_2' and 'a_3'in the cubic regression model (1). However, the error term in the model, $\boldsymbol{w_t}$ is the white noise term.

$$PR_{t+1,t} = c_0 + a_1\, ht + a_2\, ht^2 + a_3\, ht^3 + u_t \quad (1)$$

In model (2) given below, over consecutive real trade data, proportional return $PR_{t+1,t}$ is explained by the proxy for recent change in market sentiment ($\Delta \boldsymbol{f_t}$). If change in market sentiment and/ news for the script is high, its trade would involve transaction in large volume with significant impact on price change. Hence, we expect coefficients 'b_1', 'b_2', and 'b_3' would be significant for the trade data. $\boldsymbol{v_t}$ is a white noise term.

$$PR_{t+1,t} = d_0 + b_1\, \Delta f_t + b_2\, \Delta f_t^{\,2} + b_3\, \Delta f_t^{\,3} + v_t \quad (2)$$

A crowd of herding may be related to series of positive or negative information cascades. A cascade refers to pattern of price movement towards some unique direction at either good or bad news. Thus a positive (or negative) cascade arises at gaining momentum (or rally) at recent changes in the market sentiments. At positive (or negative) cascade, price moves upward (or downward). At positive (or negative) cascade, crowd of herding moves forward (or backward) in discovering the true price of the stocks. If a crowd of herding with positive (or negative) cascade, CH^+ (or CH^-), increases with increase in $\Delta \boldsymbol{f_t}$, an upward rising crowd would show that the current prices are swelled in (or doomed off) during short-term the market rally (or bear trend). This upward rising crowd of herding portrays expectation (or frustration) of informed traders at positive (or negative) cascades. In contrast, if a crowd of herding with positive (or negative) cascades increases with decrease in $\Delta \boldsymbol{f_t}$, the downward falling crowd curve may show that the current prices are doomed off (or swelled in) during the short-term market rally (or bear trend). This downward falling crowd of herding thus will portray expectation (or frustration) of the noise traders at positive (or negative) cascades. CH^+ (or CH^-) nonetheless would produce different observations.

The values of CH^+ and CH^- are derived from the return data $PR_{t+1,t}$ and these are explained by proxy variable $\Delta \boldsymbol{f_t}$ in models (3) and (4) respectively. If change in market sentiment related to a stock, $\Delta \boldsymbol{f_t}$ is high, it may set forth significant price change and may results in large crowd of positive or negative herding. Large (or small) crowd of positive herding concentrated at thick (or thin) market sentiments refers to a rally with momentum (or vanishing) effects and thereby, it hints for delay (or speed) in impounding news leading to presence of noise (or information). Hence, at greater concentration of noise (or information) it is expected that the coefficient 'g_1', 'g_2', and 'g_3' in the model (3) would be significantly positive (or negative) for the variable $\Delta \boldsymbol{f_t}$. However, $\boldsymbol{w_t}$ is the white noise term.

$$CH^+ = h^+_0 + g_1\, \Delta f_t + g_2\, \Delta f_t^{\,2} + g_3\, \Delta f_t^{\,3} + w_t \quad (3)$$

In contrast at negative herding, price moves downward. Large (or small) crowd of negative herding at thick (or thin) market sentiments refers to a bear trend with momentum (or diminishing) effects in prices and, it hints speedy (or delayed) pattern in incorporating new information. It suggests for presence of information (or noise) in the pricing mechanism. In the model (4), at greater noise (or information) it is expected that coefficients 'k_1', 'k_2', and 'k_3' would be negatively (or positively) significant for the variable $\Delta \boldsymbol{f_t}$.

$$CH^- = h^-_0 + k_1 \Delta f_t + k_2 \Delta f_t^{\,2} + k_3 \Delta f_t^{\,3} + x_t \qquad (4)$$

Testable Hypotheses

On empirical testing of the regression models (1), (2), (3), and (4) (for each of the two markets separately) with intraday trading data of timestamp, price, and volume, we have four null four hypotheses respectively in the following.

H_{10}: The pricing mechanism in the BSE incorporates new, uncorrelated, and generally available information instantaneously and the market is informational efficient and two or more consecutive trade interval has no effect on price change.

H_{20}: In the pricing mechanism in the BSE, the recent change in market sentiments along with information is not relevant; and noise is not pervasive in nature and has no effect on the pricing system.

H_{30}: In the pricing mechanism in the BSE, the noise (if any) has no effect on the pricing cascades and positive or negative cascades do not lead to crowd of positive herding.

H_{40}: In the pricing mechanism in the BSE, the noise (if any) has no effect on the pricing cascades and positive or negative cascades do not lead to crowd of negative herding.

The alternative hypotheses are as follows:

(i) In the empirical regression model (1) the explanatory variable $\boldsymbol{h_t}$, which represents the time lag in seconds for impounding new, uncorrelated and generally available information, would have significant coefficient values for 'a_1', 'a_2' and 'a_3'.

(ii) In the empirical regression model (2), the explanatory variable $\Delta \boldsymbol{f_t}$ which represents recent change in market sentiment or information would have significantly positive or negative coefficient values for 'g_1', 'g_2', and 'g_3'.

(iii) In the empirical regression model (3), the explanatory variable $\Delta \boldsymbol{f_t}$ which represents recent change in market sentiment or information would have significant coefficient values for 'g_1', 'g_2', and 'g_3'.

(iv) In the empirical regression model (3), the explanatory variable $\Delta \boldsymbol{f_t}$ which represents recent change in market sentiment or information would have significant coefficient value for 'k_1', 'k_2', and 'k_3'.

Results and Findings

The results on the regression models (1), (2), (3), and (4) are presented in Tables 3, 4, 5, and 6 respectively for observations with the BSE market data. Tables 3 and 4 depict effects of proxy variable of time interval h_t i.e., the new, uncorrelated and generally available information (recent change in market sentiment or information, $\Delta \boldsymbol{f_t}$) on price changes that is proportional return data, $PR_{t+1,t}$ for the said market Tables 5 and 6 show effects of proxy variable of recent change in stock's market sentiment or information, $\Delta \boldsymbol{f_t}$) on possible positive (or negative) crowd of herding as envisaged in stocks' price changes that is the proportional return data, $PR_{t+1,t}$ for the said market.

Results on Transaction Time Interval (h_t)

Table 3 shows that the explanatory variable of transaction time interval h_t, proxy for new, uncorrelated, and generally available information can (cannot) explain the return data for the four (or six) scripts of ACL.LTD, ASSIANPAINT.LTD, BAZAZHIND.LTD, and BPCL.LTD (ACC.LTD, AXISBANK.LTD, BHEL.LTD, BOB.LTD, CARIN.LTD, and BHARATIARTL.LTD). In these stated four scripts, the explanatory h_t can be explained up to 1.15297%, 0.3309%, 0.4975%, and 1.3644% respectively with mostly confidence level of 96%, 77%, 83%, and 97%. That is, there is huge unexplained part of the return data that include noise. In these four cases the estimation is stable at linear level for ACL.LTD and at quadratic level for ASSIANPAINT.LTD, BAZAZHIND.LTD and BPCL.LTD and their both (or either of) intercept and coefficients is dynamically significant at satisfactory levels of significance. These observations thus confirm that two consecutive time interval incorporates meaningful

Table 3: Stocks' Returns Explained by Consecutive Trades' Time Interval (h_t)*

Regression Model		$PR_{t+1,t} = c_0 + a_1\,ht + a_2\,ht^2 + a_3\,ht^3 + ut$						
Coefficients		*Unstandardised Coefficients*	*Std. Error*	*Standardised Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std. Error)*	*F – Value (Sig. Lev.)*
ACC.Ltd*	Intercept (c_0)	-0.2503	0.432857		-0.57824	0.56369	0.01062 (1.806217)	0.218698 (0.883361)
	a_1	0.001359	0.009304	0.064369	0.146047	0.884018		
	a_2	-7.2E-09	4.92E-05	-0.00015	-0.00015	0.999884		
	a_3	-1.3E-09	6.79E-08	-0.01208	-0.01844	0.985301		
ACL.Lt8d	Intercept (c_0)	-0.04803	0.031573		-1.52119	0.129723	0.015297 (0.30824)	4.262218 (0.040204)
	a_1	0.000459	0.000223	0.141371	2.064514	0.040204		
	a_2							
	a_3							
ASSIAN PAINTS.Ltd	Intercept (c_0)	0.295868	0.14803		1.998705	0.046548	0.003309 (0.725093)	1.498022 (0.225251)
	a_1	-0.00454	0.003029	-0.24898	-1.49812	0.135162		
	a_2	1.42E-05	1.28E-05	0.183549	1.104433	0.270296		
	a_3							
AXISBANK .Ltd*	Intercept (c_0)	0.026114	0.641438		0.040711	0.967551	0.00832 (1.857622)	0.105628 (0.956758)
	a_1	0.005044	0.024436	0.079474	0.206413	0.836599		
	a_2	-9.5E-05	0.000287	-0.26782	-0.3328	0.7395		
	a_3	4.13E-07	9.83E-07	0.200158	0.419937	0.674811		
BAZA-ZHIND .Ltd	Intercept (c_0)	0.012445	0.014043		0.886232	0.376188	0.004975 (0.067926)	1.769999 (0.172073)
	a_1	-0.00046	0.00031	-0.26584	-1.49462	0.136043		
	a_2	2.56E-06	1.43E-06	0.316861	1.781461	0.075829		
	a_3							
BHEL .Ltd*	Intercept (c_0)	-0.11105	0.231944		-0.4788	0.632369	0.00746 (0.399453)	0.09664 (0.96186)
	a_1	0.00477	0.009732	0.188362	0.490073	0.624378		
	a_2	-5.7E-05	0.00013	-0.33236	-0.43564	0.663353		
	a_3	1.84E-07	5.09E-07	0.15768	0.362227	0.717393		
BOB .Ltd*	Intercept (c_0)	0.320176	0.5685		0.563195	0.573658	0.00323 (1.320024)	0.616337 (0.604803)
	a_1	-0.01273	0.024048	-0.2082	-0.52919	0.597004		
	a_2	0.000188	0.000317	0.483342	0.592464	0.553917		
	a_3	-9.1E-07	1.22E-06	-0.35733	-0.74595	0.45619		
BPCL .Ltd	Intercept (c_0)	0.270238	0.108122		2.499382	0.012878	0.013644 (0.683823)	3.545284 (0.029856)
	a_1	-0.00812	0.00326	-0.3304	-2.49141	0.013166		
	a_2	4.94E-05	2.56E-05	0.255522	1.926776	0.054781		
	a_3							
CARIN..Ltd*	Intercept (c_0)	0.056723	0.06666		0.850926	0.395417	0.00196 (0.348472)	0.669557 (0.512617)
	a_1	-0.00164	0.001419	-0.15228	-1.15673	0.248206		
	a_2	6.52E-06	6.27E-06	0.136843	1.039457	0.299339		
	a_3							
BHARATI ARTL .Ltd*	Intercept (c_0)	0.020363	0.083895		0.242717	0.808387	0.00837 (0.314432)	0.144559 (0.933116)
	a_1	-0.0005	0.002399	-0.066	-0.20684	0.836276		
	a_2	6.01E-07	1.9E-05	0.020934	0.031659	0.974764		
	a_3	1.96E-09	4.02E-08	0.019686	0.048824	0.961092		

* Marked Stocks' proportional returns are not being explained at all by traders' consecutive transaction time interval ***h***

Table 4: Stocks' Returns Explained by Consecutive Trades' Transaction Volume (Δf_t)#

Regression Model		$PR_{t+1,t} = d_0 + b_1 \Delta f_t + b_2 \Delta f_t^{\,2} + b_3 \Delta f_t^{\,3} + v_t$..............(2)						
Coefficients		Unstandardised Coefficients	Std. Error	Standardised Coefficients	t - value	Sig. Lev.	Adj. R^2 (Std. Error)	F – Value (Sig. Lev.)
ACC.Ltd	Intercept (d_0)	0.796428	0.518052		1.537352	0.125644	0.006655 (1.790711)	1.498024 (0.215989)
	b_1	-0.01053	0.006325	-0.84763	-1.66527	0.097282		
	b_2	1.96E-05	1.5E-05	1.653985	1.304033	0.193585		
	b_3	-9.8E-09	8.77E-09	-0.92668	.	.		
ACL.Ltd#	Intercept (d_0)	0.001559	0.038309		0.040698	0.967576	0.01086 (0.312308)	0.247847 (0.86281)
	b_1	4.67E-05	0.000201	0.08521	0.23165	0.817039		
	b_2	-8.3E-08	1.83E-07	-0.46391	-0.45511	0.649506		
	b_3	1.84E-11	3.75E-11	0.353477	.	.		
ASSIAN PAINTS.Ltd	Intercept (d_0)	-0.09849	0.083922		-1.1736	0.241494	0.009182 (0.722953)	1.926712 (0.125282)
	b_1	0.001177	0.000625	0.619877	1.882445	0.060753		
	b_2	-1E-06	7.45E-07	-1.08938	-1.36853	0.17218		
	b_3	2.36E-10	2.13E-10	0.582311	.	.		
AXISBANK .Ltd#	Intercept (d_0)	-0.03031	0.144881		-0.20924	0.834395	0.00066 (1.850551)	0.892369 (0.410692)
	b_1	0.000441	0.00056	0.085694	0.787894	0.431337		
	b_2	-1.9E-08	1.52E-07	-0.01384	-0.12723	0.898838		
	b_3							
BAZAZHIND .Ltd	Intercept (d_0)	0.002138	0.004707		0.454248	0.649971	0.011822 (0.067692)	4.684667 (0.031204)
	b_1	-2.4E-06	1.1E-06	-0.1226	-2.16441	0.031204		
	b_2							
	b_3							
BHEL .Ltd	Intercept (d_0)	-0.0188	0.034473		-0.54546	0.585771	0.003636 (0.397247)	1.445167 (0.229327)
	b_1	5.02E-05	3.99E-05	0.273393	1.259113	0.208799		
	b_2	-1.1E-08	8.59E-09	-0.73977	.	.		
	b_3	3.93E-13	3.96E-13	0.426106	.	.		
BOB .Ltd	Intercept (d_0)	-0.05263	0.086954		-0.60522	0.545419	0.005153 (1.314501)	2.854162 (0.092011)
	b_1	0.000201	0.000119	0.089059	1.689427	0.092011		
	b_2							
	b_3							
BPCL .Ltd	Intercept (d_0)	-0.14471	0.074311		-1.94735	0.052259	0.069106 (0.664319)	10.10635 (2.07E-06)
	b_1	0.000123	4.35E-05	0.758754	2.817869	0.005098		
	b_2	-1.9E-08	4.99E-09	-2.46247	.	.		
	b_3	6.25E-13	1.41E-13	1.937888	.	.		
CARIN .Ltd	Intercept (d_0)	-0.03037	0.020097		-1.51129	0.13165	0.009361 (0.346498)	4.193798 (0.041347)
	b_1	2.26E-05	1.1E-05	0.110867	2.047876	0.041347		
	b_2							
	b_3							
BHARATI ARTL .Ltd	Intercept (d_0)	0.011384	0.022079		0.515608	0.6065	0.00373 (0.312539)	1.578385 (0.207977)
	b_1	-5.8E-05	3.39E-05	-0.204	-1.71795	0.086814		
	b_2	7.33E-09	4.25E-09	0.204896	.	.		
	b_3							

Marked Stocks' returns' data are not being explained by traders' consecutive transaction time interval, Δf_t at all

informational inputs in the pricing mechanism such that quick or delayed stock-trade may result in price differential but this strategy is subject to dynamic trade-off cost, which may be security transaction costs etc. The dynamic trade-off cost for ACL.LTD (ASSIANPAINT.LTD, BAZAZHIND.LTD and BPCL.LTD) is apprehensible with significant negative (or positive) intercept along with positive (or negative) coefficients for h_t at different orders. In contrast, the table shows that the return data of the other six scripts cannot be explained by h_t. There is huge noise in consecutive trading of these six scripts. A presence of noise is confirmed in Table 4 and explained in the following.

Results on Change in Stock's Market Sentiment or Information (Δf_t)

In Table 4, the results show that the explanatory proxy variable of recent change in stock's market sentiment or information, Δf_t has significant impact on returns for all of the scripts except of ACL.LTD and AXISBANK.LTD, where the regression model (2) is not stable. The values of the Adj. R^2 statistics show that model could explain to an extent of 0.6655%, 0.9182%, 1.1822%, 0.3636%, 0.5153%, 6.9106%, 0.9361%, and 0.373% ACC.LTD, ASSIANPAINT.LTD, BAZAZHIND.LTD, BHEL.LTD, BOB.LTD, BPCL.LTD, CARIN.LTD, and BHARATIARTL.LTD. In these nine cases, the signs of the intercept and coefficients in our cubic specification of the explanatory variable Δf_t show that stocks' market sentiment or information as envisaged by the trade-volume data results in a trade-off relationship in the pricing mechanism. If the return data includes significant positive (or negative) intercept that is, constant benefit (or cost), there is significant negative (or positive) coefficient for Δf_t implying presence of incremental cost (or benefit) effect in acquiring new and relevant information. It suggests that in order to obtain significant price differential, a higher volume can be transacted only at excess access of information or at information costs or costs for search technology. Informational efficiency can explain a little while there is huge noise and unexplained component within the return data. It is interesting to note that both regression model (1) and (2) are not stable for AXISBANK.LTD. This suggests that there is robust noise for this script's trade in the market.

Results on Positive Herding (CH^+)

Here, we discuss whether transaction volume could explain the presence of crowd of positive herding in the return data. Here, presence of positively (or negatively) significant coefficients for the explanatory variable suggest for crowd of positive herding caused by information (or noise) cascades.

Table 5 shows that the explanatory variable of recent change in stock's market sentiment or information, Δf_t has significant impact on the presence of crowd of positive herding of the return data for the seven scripts out of the ten sample firms except of three scripts - ACL.LTD, AXISBANK.LTD, and BAZAZHIND.LTD. In these three cases, however, the regression model (3) is not stable. The Adj. R^2 shows that the model could explain to an extent of 0.804%, 3.223%, 1.10272%, 2.187%, 1.5414%, 1.0584%, and 7.7271% for ACC.LTD, ASSIANPAINT.LTD, BHEL.LTD, BOB.LTD, BPCL.LTD, CARIN.LTD, and BHARATIARTL.LTD respectively. In these seven cases, further, the signs of the intercept and coefficients in our cubic specification of the variable Δf_t show that stocks' market sentiment or information envisaged by trade-volume data results in dynamic progressive relationship. The positive herding includes significant positive intercept in these seven cases. These suggest for stock-specific market sentiments as observed in higher or lower transaction volume and this have enduring effects on pricing behaviours. The coefficients of Δf_t for these scripts are positively (or negatively) significant at the first order of the explanatory variable (i.e., equivalent to a linear specification) for ASSIANPAINT.LTD, BOB.LTD, BPCL.LTD, and CARIN.LTD (ACC.LTD, BHEL.LTD, and BHARATIARTLLTD) while positively (or negatively) significant at the second order of the variable (equivalent to quadratic specification) for ACC.LTD, BHEL.LTD, CARIN.LTD, and BHARATIARTLLTD (ASSIANPAINT.LTD, and BOB.LTD). These observations sought support for the alternative hypothesis that crowd of positive herding is portrayed by the investors in the markets and is caused by both information and noise cascades.

Results on Negative Herding (CH^-)

In parallel to the above findings on presence of information and noise in stocks' pricing equilibrium, trade-volume can also explain the presence of crowd of negative herding. A presence of positively (or negatively) significant coefficients for the explanatory variable here suggest for crowd of negative herding as contributed by information (or noise) cascades.

Table 5: Stocks' Positive Herding (CH^+) Explained by Consecutive Trade Volume (Δf_t)$

Regression Model		$CH^+ = h^+_0 + g_1 \Delta f_t + g_2 \Delta f_t^2 + g_3 \Delta f_t^3 + w_t$ ……….…..(3)						
Coefficients		*Unstandardised Coefficients*	*Std. Error*	*Standardised Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std. Error)*	*F – Value (Sig. Lev.)*
ACC.Ltd	Intercept (h^+_0)	**1.529363**	0.412052		3.711582	0.000261	0.00804 (1.411842)	1.599745 (0.190383)
	g_1	-0.0108	0.005028	-1.09554	-2.14738	0.032862		
	g_2	2.39E-05	1.19E-05	2.567396	2.018083	0.044802		
	g_3	-1.3E-08	6.92E-09	-1.59419	.	.		
ACL.Ltd$	Intercept (h^+_0)	0.764798	0.103221		7.409297	3.13E-12	0.00027 (1.247716)	0.942584 (0.332742)
	g_1	-0.00016	0.000163	-0.06717	-0.97087	0.332742		
	g_2							
	g_3							
ASSIAN PAINTS.Ltd	Intercept (h^+_0)	0.558544	0.131641		4.242951	2.95E-05	0.03223 (1.521204)	5.978799 (0.002847)
	g_1	0.001476	0.000612	0.365807	2.410633	0.016532		
	g_2	-3.9E-07	3.02E-07	-0.19808	-1.30532	0.192795		
	g_3							
AXISBANK .Ltd$	Intercept (h^+_0)	0.834006	0.159097		5.242124	2.82E-07	0.00595 (2.067051)	0.003846 (0.996161)
	g_1	-2.2E-05	0.000627	-0.0037	-0.03446	0.972531		
	g_2	1.21E-08	1.7E-07	0.007588	0.070731	0.943654		
	g_3							
BAZAZHIND .Ltd$	Intercept (h^+_0)	0.830351	0.115373		7.197097	4.84E-12	0.000984 (1.30235)	1.100818 (0.349032)
	g_1	4.51E-05	8.73E-05	0.121804	0.516489	0.605888		
	g_2	-1.3E-08	1.26E-08	-0.57484	-1.01881	0.309105		
	g_3	5.53E-13	4.17E-13	0.514	.	.		
BHEL .Ltd	Intercept (h^+_0)	0.801252	0.124175		6.45261	3.53E-10	0.010272 (1.418743)	2.262712 (0.080858)
	g_1	-0.00029	0.000146	-0.42059	-1.98997	0.047347		
	g_2	6.8E-08	3.19E-08	1.200831	2.132533	0.033636		
	g_3	-2.8E-12	1.45E-12	-0.77803	.	.		
BOB .Ltd	Intercept (h^+_0)	0.379566	0.092163		4.11841	4.75E-05	0.02187 (1.170976)	4.991093 (0.007283)
	g_1	0.000667	0.000235	0.327596	2.842533	0.004734		
	g_2	-1.5E-07	7.87E-08	-0.21967	-1.90603	0.057454		
	g_3							
BPCL .Ltd	Intercept (h^+_0)	0.370783	0.101299		3.660304	0.000289	0.015414 (0.902895)	2.915119 (0.034266)
	g_1	6.01E-05	5.95E-05	0.273506	1.009467	0.313421		
	g_2	-1.1E-08	6.83E-09	-1.07904	.	.		
	g_3	4.07E-13	1.92E-13	0.916518	.	.		
CARIN .Ltd	Intercept (h^+_0)	**0.435759**	0.066832		6.520234	2.59E-10	0.010584 (1.042812)	2.802481 (0.062082)
	g_1	0.000159	7.19E-05	**0.259325**	**2.209598**	**0.027809**		
	g_2	-6E-09	3.8E-09	-0.18397	.	.		
	g_3							
BHARATI ARTL .Ltd	Intercept (h^+_0)	**0.811405**	0.111256		7.293108	2.63E-12	0.077271 (1.3718)	9.597543 (4.5E-06)
	g_1	-0.00058	0.000288	**-0.4422**	**-2.03218**	**0.043002**		
	g_2	3.59E-07	9.68E-08	**2.196447**	**3.712159**	**0.000244**		
	g_3	-2.7E-11	6.83E-12	-1.72266	.	.		

$ Marked Stocks' Positive Herding are not being explained by traders' consecutive transaction time interval, Δf_t at all

Table 6 shows that the explanatory variable Δf_t has significant impact on presence of crowd of negative herding in stocks' pricing only for three scripts out of the sample firms, which are ACC.LTD, BAZAZHIND.LTD,

Table 6: Stocks' Negative Herding (CH^-) Explained by Consecutive Trade Volume (Δf_t)@

Regression Model		$CH^- = h^-_0 + k_1 \Delta f_t + k_2 \Delta f_t^2 + k_3 \Delta f_t^3 + x_t$……………(4)						
Coefficients		*Unstandardised Coefficients*	*Std. Error*	*Standardised Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.Error)*	*F – Value (Sig. Lev.)*
ACC.Ltd	Intercept (h^-_0)	**0.415479**	0.112373		3.69732	0.000275	0.014379 (1.222334)	4.238791 (0.040683)
	K_1	0.001174	0.00057	**0.137183**	**2.058832**	**0.040683**		
	K_2							
	k_3							
ACL.Ltd@	Intercept (h^-_0)	0.180924	0.0836		2.164154	0.031603	-0.00562 (0.678309)	0.610368 (0.608985)
	K_1	0.000513	0.000443	0.400407	1.158858	0.247856		
	K_2	-4.4E-07	4.03E-07	-1.0021	-1.08342	0.279889		
	k_3	7.67E-11	8.21E-11	0.609039	.	.		
ASSIAN PAINTS.Ltd@	Intercept (h^-_0)	0.239433	0.072541		3.300657	0.001082	-0.00151 (0.838265)	0.774279 (0.461964)
	K_1	0.000409	0.000337	0.187162	1.212424	0.226314		
	K_2	-1.7E-07	1.66E-07	-0.15729	-1.01889	0.309085		
	k_3							
AXISBANK .Ltd@	Intercept (h^-_0)	0.351961	0.063146		5.573788	5.13E-08	-0.00507 (0.820414)	0.150203 (0.860591)
	K_1	5.08E-05	0.000249	0.021865	0.203914	0.838545		
	K_2	-2.9E-08	6.76E-08	-0.0466	-0.43459	0.664139		
	k_3							
BAZAZHIND .Ltd	Intercept (h^-_0)	0.014393	0.037062		0.388359	0.69802	0.094274 (0.532943)	32.95474 (2.27E-08)
	K_1	4.96E-05	8.64E-06	0.311809	5.740622	2.27E-08		
	K_2							
	k_3							
BHEL .Ltd@	Intercept (h^-_0)	0.219626	0.062555		3.510944	0.000503	1.34E-05 (0.71471)	1.001631 (0.392147)
	K_1	0.000114	7.38E-05	0.32879	1.547643	0.122582		
	K_2	-2.5E-08	1.61E-08	-0.86447	-1.52731	0.127558		
	k_3	9.95E-13	7.31E-13	0.558338	.	.		
BOB .Ltd@	Intercept (h^-_0)	0.2273	0.078975		2.878114	0.004243	-0.00056 (0.816206)	0.933721 (0.424477)
	K_1	0.000482	0.000322	0.343138	1.494185	0.136018		
	K_2	-3.2E-07	2.33E-07	-0.6764	-1.3645	0.173278		
	k_3	4.33E-11	3.94E-11	0.354954	.	.		
BPCL .Ltd	Intercept (h^-_0)	0.293012	0.08373		3.499488	0.000524	0.012446 (0.967053)	3.312571 (0.037521)
	K_1	7.99E-05	3.15E-05	0.340175	2.53417	0.011689		
	K_2	-3.3E-09	1.51E-09	-0.29037	.	.		
	$\boldsymbol{k_3}$							
CARIN .Ltd@	Intercept (h^-_0)	0.281549	0.041811		6.733841	7.2E-11	-6.3E-05 (0.651631)	0.591812 (0.553901)
	K_1	-3.9E-05	4.5E-05	-0.1016	-0.86005	0.390375		
	K_2	1.08E-09	2.38E-09	0.053785	.	.		
	k_3							
BHARATI ARTL .Ltd@	Intercept (h^-_0)	0.210373	0.058944		3.569041	0.000416	-0.00679 (0.726783)	0.307353 (0.820073)
	K_1	8.38E-05	0.000152	0.124996	0.549924	0.582774		
	K_2	-3.8E-08	5.13E-08	-0.45697	-0.73936	0.460257		
	k_3	2.58E-12	3.62E-12	0.320032	.	.		

@ Marked Stocks' Positive Herding are not being explained by traders' consecutive transaction time interval, Δf_t at all

and BPCL.LTD. For these firms, the model (4) can explain 1.4379%, 9.4274%, and 1.2446% of the return data in the terms of Adj. R^2-value. In the other seven scripts, the model is not stable. In these cases, the results show that cubic specification of Δf_t is not sustained while the cubic specification is sound in producing relevant coefficients up to the first order of the variable only. The signs of intercept and coefficients in regression show that stocks' market sentiment as envisaged by trade-volume data results in dynamic progressive relationship. The negative herding portrays significant positive intercept. This suggests stock-specific market sentiments having enduring effects on the pricing behaviours. The coefficients of Δf_t are positively significant at first order of the explanatory variable for these three scripts. These findings sought support for the alternative hypothesis that crowd of negative herding is portrayed by the investors in the markets and is caused by both sentiments and information.

The said observation is based on the data for the BSE market. On the NSE market over the same date of trading, the observations are somewhat different in magnitudes with respect to the scripts but support the presence of herding. In order to save pages, the author abstracts from repetition in reporting.

Conclusion

On anomalies to standard finance prescriptions about the behaviours of the markets vis-à-vis investors, researchers in behavioural finance offer challenges and new explanations as well. This new area shows that investors are "normal" rather than "rational", they participate in stock markets in "crowd", they replicate others' behaviours, perceptions, expectations, beliefs, personal greed, fears, and corrections of attitudes etc. Extending Banerjee's (1992) and Bikhchandani, Hirshleifer, and Welch (1992)'s researches specifically on theory building, this paper puts forward ingenious model, where noise is pervasive in trading and both positive and negative cascades could be based on information and noise while both cascades are reversible. An empirical test of the model is avoided since the parameters α_i, β_i and γ_j, are not observable. Future works may survey on exploring their values.

However, with utilisation of intraday trading price-volume-timestamp data for ten sample scripts in the BSE market, the empirical results in the paper show that the trade-interval could explain the observed rapidness (or delay) in information (or noise) impounding process in stocks' pricing. The trade-volume data extend supports that recent change in stock market sentiment may explain the market's equilibrium pricing dynamics with large (or small) trade-volume for presence of information (or noise). The work finally confirms that crowds of positive and negative herding are influenced by informed vis-à-vis noise trades as defined by the trade-volume in the market. Future research further may extend our empirical derivation with the order book data for identifying presence of herding and noise as well and thereby, exploring their effects on the equilibrium pricing.

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