Dynamics of Noise Traders' Risk in the NSE and BSE Markets

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Abstract

In Financial Economics, the "noise" and "noise traders" play critical roles in stocks' equilibrium pricing mechanism. It includes economic and non-economic aspects. The paper empirically explores the nature and magnitude of noise traders' risk in India during the present recovery phase. Besides the daily trading data, it utilizes intra-day 1D and 5D trade-prices, trade-volumes, and trade-times of the Nifty-Fifty firms listed both in the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE). The study utilizes the NSE-Nifty and the BSE-Sensex indices for market return data. It examines whether stocks' return variations incorporate noise traders' risk or not and whether informed traders' short-run arbitrage forces them to long-short positioning for hedging or not.

The study argues that noise has systematic and firm-specific components those vary over time. These components include idiosyncratic and noise aspects. At lag-periods, traders' long-short positions over these markets can hedge fundamental systematic and fundamental firm-specific shocks and may detach noise shocks. Once stocks are traded at long - short horizons, traders' long-short returns expose the noise aspects across stocks The study also compares the results for the current price-volume-trade time data with those of two years earlier. The findings suggest that intra-day returns from 1D and 5D data impound significant noise while daily (weekly) returns show its high (moderate) exposures. The conditional volatilities of long-short returns in the GARCH models show that the time-varying idiosyncratic noise is highly persistent at presence of noise traders. The study confirms that stocks' prices impound information and noise during the trading days.

Keywords: Pricing Equilibrium, Economic Recovery, Noise Trading, Systematic Noise, Idiosyncratic Noise, GARCH Models

Introduction

How do investors process information in stock markets? What does rule their strings of thoughts? What do they characterize? In the standard finance, the former query sets forth financial economists defining the market microstructure theories viz., the Capital Asset Pricing Model, the Arbitrage Pricing Theory, the Mean Variance Portfolio Theory, and the Expected Utility Theory etc. In these theorists, the capital markets are informationally efficient (Fama, 1970). The latter query advances that the investors are rational and risk-averse. Both beliefs lie at presence of the arbitrage forces where market participants with new relevant information set in the equilibrium price. It aggregates new information and stocks' prices are assumed to be mostly at their fundamental values.

The algorithm - the market is efficient if stocks' prices are rational and not behavioral - is too simple to be completed. It may be efficient at no systematic way to beat the market by an investor or mechanism (Statman, 1999). The condition of arbitrage is not a sufficient one for market efficiency. Arbitrage happens at mispricing. At equilibrium, both arbitrage and mispricing co-exist (Lee, 2001). If stocks' prices adjust the restless inflow of new information, then 'market efficiency' should imply as a journey not destination itself (Lee, 2001; p. 237). On the supply side, the arbitrage forces are state variables not means. On the demand side, the investors are open to risk -adjusted returns.

In contrast to the neo-classical market microstructures, in Behavioral Finance investors are human beings with psychological and value-expressive characteristics and not with rational utilitarian characteristics. Instead of normative and analyzable postulations, the theorists

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forward investors' dynamics behavioral choices, where "noise" or pseudo information has a presence (theorem 5, Grossman & Stiglitz, 1980). A competitive equilibrium system is incompatible with informationally efficient markets (theorem 6, Grossman & Stiglitz, 1980). At any given version of information θ of informed traders, the pricing system reveals a noisy version of θ.

In contrast to information, noise restricts knowing stocks' unobservable fundamental prices and true expected returns. It makes financial markets viable and imperfect as well (Black, 1985). A more liquid market entails to be less efficient. Noise is created if trades happen on already incorporated information or pseudo information or non-information. Noise attracts both opportunity and threats. In contrast to the axioms of expected utility, stock traders takes different positions at prospective losses and prospective gains (Tversky & Kahneman, 1981).

Possible arbitrage by the informed traders does not eliminate noise in the market and the "noise traders … create their own space" (DeLong, et al., 1990; p. 705). With the dispersion of daily net initiated order flow across brokers as proxy measure of level of noise trading, Berkman & Koch (2007) have showed that the noise trading is positively related to the trading volume and market depth. Noise traders distract stocks' prices far from their fundamental values. Given the abundance of noise traders in the markets, how noise is reflected into stocks' prices and what its risk is? Does the noise traders' risk show a mean reverting behavior?

The rest of study seeks to answer these queries mentioned in this Introduction, Section-I. The literature review is presented in section-II in brief to standard finance but at specific to behavioral finance. It is followed by the objectives, the methodology, and the propositions in section-III. The results and findings are showed in section-IV. Finally, a short conclusion is done in section-IV.

Literature Review

In the standard finance, the costs for new information thrust investors to different levels of market efficiency. Better information has edges for arbitrage benefits against noise traders while noise traders eventually disappear from the market (read with Fama, 1965; and Friedman, 1953; p. 175) and the stock market behaves as per the Efficient Market Hypothesis (EMH). Thus, investors' market portfolios face systematic risk only while otherwise they face the fundamental risks also. In the EMH, an investor is rational; he updates his beliefs correctly once he receives new information and at given beliefs, his choose to maximize subjective expected utility (Barberis & Thaler, 2003).

But, the risk exposures to investors are not as simplified as it is propagated in the EMH. In Akerlof (1970), at information asymmetry about stocks' fundamental values between firms and investors, the primary capital markets are piled up with lemons and there are some better products even if the lemons persist. But, if the price does not suit the informed traders, then they would face the adverse selection problem and would not trade with other informed traders (Bagehot, 1971). Hence, how can the informed traders recover their information costs? The information cost requires exogenously motivated (noise) traders to make its presence viable in the market. The equilibrium pricing mechanism includes both noise and information rather the fundamental value only. Stocks' prices are inefficient (Grossman & Stiglitz, 1980). Noise traders provide "camouflage" to informed insider traders to exercise monopolistic power in the market (Kyle, 1985; p. 1316).

In Kyle (1985), noise traders are randomly distributed in the market and are independent of informed traders. Informed traders make profit at expenses of noise trader. In Grossman & Stiglitz (1980), noise traders are neither randomly distributed nor independent of informed traders' expectations and hence, they set limits to the arbitrage benefits of the latter. An informed trader, who pays for information on long-term expectations, is not alone in the market and it makes difficult to exploit the rest in the market whether or not they predominate (Keynes, 1936; p. 157).

Noise traders and informed traders have different risk exposures in the stock markets (DeLong, et. al., 1990a). The former faces noise traders' risk but no fundamental risk while the latter faces both fundamental and noise traders' risks. If today's pessimistic (optimistic) noise traders become more bearish (bullish) tomorrow, then arbitrageurs buying (selling) at their long (short)-positions against noise traders would suffer losses. Arbitrage does not eliminate noise rather the reverse and noise traders create their own space while they possibly earn higher returns than the informed counterparts (DeLong, et. al, 1990b; p. 705-706). In contrast to the objections of

Friedman (1953) and Figlewski (1978), however, the noise traders exist in the market and survive in the long run. DeLong, et al., (1989) show that noise traders' risk reduce the size of capital market and consumptions of the economy. DeLong, et al. (1991) have showed that at one period investment, noise traders as a group can earn excess return than rational traders. They survive in the long-run and dominate the market.

But, what does motivate noise traders to stay in the market? In technical analysis, noise traders identify phases of stocks' price movements and respond to the phases based on popular models (Smith, 1968). They may be naïve traders in the markets (Black, 1986). At miss-pricing, informed arbitrageurs face fundamental risk on sell (buy) at high (low) prices above (bellow) the fundamental value of stocks (Shleifer & Summers, 1990). On sensational opportunities, thus, optimistic (pessimistic) noise traders can force informed arbitrageurs to liquidate their short (long) positions at too early (late) at losses. The limits of arbitrage by informed traders thus pave spaces for noise traders to exploit stocks' prices in the market (Shleifer & Vishny, 1997). If informed traders force their agents to trade rather than staying at idle, then agency conflict forces noise trading and market distortion by their active agents (Dow & Gorton, 1997).

How do noise traders make trading decisions? Economic men are very unlikely to be real men (Edwards, 1954, p. 382) and investors show bounded rationality (see, Simon, 1955; 1982, 1983, 1997). In the psychological judgment, investors in the stock markets are irrational i.e., noisy in nature. Based on mental frameworks (Tversky & Kahneman, 1981; Kahneman & Tversky, 1984), noise traders make choices intuitively and show heuristics (Tversky & Kahneman, 1974). Mental frameworks are usually socially shared and can be manipulated (Ellul, 1965). Investors are risk averse (taker) at sure profits (losses) (Kahneman & Tversky, 1979). On selling winner stocks early and holding the looser ones, their behavior is unsuitable for tax reasons (Shefrin & Statman, 1985). Their perceptions to risk-taking vary with changing fortunes (March & Shapira, 1992). At harsh price volatility, they myopically shy away in short horizons (Benartzi & Thaler, 1995).

Finally, what does a trader trade in the market? Is it noise or value that is information or both? Traders usually commit (trade) cognitive errors (i.e., mental mistakes), which cause systematic errors in stocks' consensus (equilibrium) prices in the markets (Shefrin & Statman, 1994). Investors' investments in portfolios are strictly segmented at multiple layers of their investment pyramids (Shefrin & Statman, 2000). Their consensus market prices are far deviated from fundamental values. Market prices have fundamental and noise components. Holding cost limits arbitrageurs' positions in the market and miss-pricing continues since arbitrageurs cannot hedge idiosyncratic risk (Pontiff, 2006). In the next section the objectives, methodology, and propositions of the thesis are stated.

Objectives, Methodology and Propositions

The presence of information and holding costs limits the arbitrage opportunities of informed traders. It makes trade happen in the stock markets. Both noise traders, the creatures and informed traders, the lions continuously supply fuel in the pricing system (Lee, 2001). But, what makes noise trading in fact worthy? Answers to this query as yet are missing in behavioral finance but cautioned as follows.

The (stock) market is not a weighing machine, on which the value of each issue is recorded by an exact and impersonal mechanism - Rather - the market is a voting machine, whereon countless individuals register choices which are the product partly of reason and partly of emotion. - Graham & Dodd (1934, p. 23).

I. Objectives

Keeping the warning of Graham & Dodd (1934) as living in investors' hearts (emotions) and minds (frames), the study seeks to reveal the dynamics of noise traders' risks in the stock markets. It entails developing an ingenious theoretical model and its empirical tests. The objectives in addressing the said missing link specifically are exploring (i) the returns to noise traders, (ii) their risks, and (iii) the dynamic nature of the both in the pricing mechanism.

II. Methodology

In this sub-section, firstly a theoretical model with presence of informed traders and noise traders and trading costs (information and holding costs) is forwarded and the theoretical propositions are identified. In the next, an empirical framework is settled up. Finally, the empirical methodology is designed.

1. **Theoretical Model:** Let us consider two stock markets (the National Stock Exchange, NSE latter assumed as 'A' and the Bombay Stock Exchange, BSE latter assumed as 'B') with both informed and uninformed traders. Let us also assume that in the internet based competitive order system at information and holding costs, there are n-types of informed traders. The distribution function and parameters of i-th informed trader with information set of Yi are thus different from that of j-th informed trader along with his information set of Yj. Again assume that there are perfect substitutes of the stocks across the markets (since there is dual listing of stocks across the NSE and the BSE Stock markets) but not within the same market. Informed traders, however, know the true underlying probability distribution of stocks' price generations. Based on new information, they can identify under or over-priced stocks. They take a long (short)-buy or short (long)-sell position if stocks are over (under)-priced currently. Noise traders take the current prices contain information and observing prices they perceive the probability distributions of price generations.

At a random trade time *t*, the quoted offer price P_{it} for possible buy (sale) position of *i*-th trader is thus different form that of P_{jt} of *j*-th trader for possible sale (buy) position. At presence of these two informed traders in the market, instantaneously there would be a "no trade" situation if the past observed price P_{0t-1} includes all information at time *t*-1 (Grossman & Stiglitz, 1980). At trade time *t*, trade would happen at price of P_{0t} if P_{0t-1} is already miss-priced and if the price P_{0t} is different from both P_{it} and P_{jt}. That is, trades among informed traders necessarily require price deviations from the perceived fundamental value/s (μ) to informed traders. The price P_{0t} reveals a noisy version of θ always. This noise is arising out of distrust to information itself and / or to its source. If α_i (α_j) and β_i (β_j) are the probabilities of receiving information θ_i (θ_j) at time *t* by an *i*-th (*j*-th) trader and it being true respectively, then $\alpha_i\beta_i$ ($\alpha_j\beta_j$) is the probability of perceived θ_i (θ_j) is being a true version of θ. Again, $\alpha_i\beta_i$ ($\alpha_j\beta_j$) for θ_i (θ_j) being believed to be true by *i*-th (*j*-th) informed trader has an ex-ante lower confidence (i.e., $\alpha\beta < \alpha$ & $\alpha\beta < \beta$ $\forall i,j$) always. For a single trade between the two (*i*-th and *j*-th) informed traders, the magnitude of its probability is $(\alpha_i\beta_i)(\alpha_j\beta_j)$. For *n* informed traders, the magnitude shrinks to $\Pi\alpha_i\beta_i$ (for all *i*-s, and *j*-s and $i \neq j$) while the probability of contamination or distrust to new information θ resulting into noise is $[1- \Pi\alpha_i\beta_i]$. Noise is, thus, pervasive even in a classical theoretical framework with only informed traders not only being a rational investor but also along with hearts and minds.

Besides the presence of *n*-type of informed traders in the stock market, let us now further assume that there are-types of noise traders. Observing stocks' prices in the markets these noise traders try to perceive the true version of θ and thus the true value of P_{0t}. They know that if P_{0t} is not the true price at time *t* (currently), then P_{0t+1} would also not be a true price at time *t* +1. It would include informed traders' price distrust, ε and noise traders' perceived price deviation, δ.

That is, at a random trade time *t* for *k*-th stock, its price P_{0t} would be as in identity (1):

$$P_{0t} = \mu_{k,t} + \varepsilon_{k,t} + \delta_{k,t} \tag{1}$$

Let us again assume that an informed (noise) trader's perceived price distrust (deviation), ε (δ) have systematic component $u_{k,t}$ ($\eta_{k,t}$) and firm-specific component $\acute{\omega}_{kt}$ ($\acute{\upsilon}_{kt}$). At a random trade time *t* for *k*-th stock's price P_{0t} would be as in the identity (2). The 2nd (3rd) part in the right hand side of identity (2) is equal to $\varepsilon_{k,t}$ ($\delta_{k,t}$) where $\mu_{k,t}$ is the stock's unknown fundamental value.

$$P_{0t} = \mu_{k,t} + [u_{k,t} + \acute{\omega}_{kt}] + [\eta_{k,t} + \acute{\upsilon}_{k,t}] \tag{2}$$

Now, let us assume that the two markets are A and B. The *k*-th stock in the market *A*, K_A is a perfect substitute of K_B, the *k*-th stock in the market B, and vice-versa. There is no firm-specific fundamental ($\acute{\omega}_{kt}$) difference between K_A and K_B. Let us also assume that the *i* (*j*) th trader believes that stocks K_A (K_B) over (under)-priced currently. Again, assume that the confident informed arbitrators engage into monopolistic short buy and short sell trading over the two markets and hence, noise traders find scope for long-short trading over the time horizon over the markets only. Since θ_i and θ_j are different, *i*-th informed trader, on his own expectation of that prices will go down in the near future, takes up long-buy (short-sell) trade position over the time period *dt* (*dz*) in the market A (B) against *j*-th informed trader, on his own expectation of that prices will go up in future, with long-sell (short-buy) trade position over the time period *dz* (*dt*) in the market A (B). Further assume that both the investors have less general elements in their information generation functions. For simplicity in the empirical models in the bellow, however, an equal time interval for *dt* and *dz* will lead to robust presence of noisy environment. Noise arising out of distrust to information itself or to its source to *i*-th trader is u_{kit} and that to *j*-th trader is u_{kjt}. These distrust / noises lead to trade at price P_{Akt} (P_{Bkt}) at time *t* in the stock market A (B). Thus, a trade is finally happened at presence of non-identical systematic component of distrust u_{kit} and u_{kjt}.

At this stage, let us invoke the presence of noise traders. On perceiving of u_{kit} and u_{kjt} they frame up systematic (firm-specific) noise references η_{Akt} and η_{Bkt} ($\acute{\upsilon}_{Ak,t}$ and $\acute{\upsilon}_{Bk,t}$) to the above prices of P_{Akt} and P_{Bkt} for stocks K_A and K_B respectively. If these biases are shared by many noise traders, even if their magnitudes are not necessarily be the same, these would impinge noise on the trade prices. A long-short price differential $\Delta P_{AB,t}$ at time *t* of K_A over K_B for the time horizons *dt* and *dz* respectively is given in identity (3). An ex-post price differential $\Delta P_{AB,t}$ at time *t* is noticeable even if its elements are unobserved. Here if it is assumed that fundamental firm-specific information, both private and public, are impounded into stocks' prices simultaneously in two different markets, *idiosyncratic fundamental shocks* at long-short positioning are perfectly hedged and cancelled out. However since noise shocks differ at noise traders' perceptions and *systematic fundamental shocks* differ at different markets, both the noise shocks and systematic fundamental shocks are not perfectly hedged and cancelled out.

$$\Delta P_{AB,kt} = P_{Akt} - P_{Bkt} = [u_{Akt} - u_{Bkt}] + [\eta_{Akt} - \eta_{Bkt}] + [\acute{\upsilon}_{Akt} - \acute{\upsilon}_{Bkt}] \quad (3)$$

Here, $\Delta P_{ABk,t}$ shows relative changes in noise traders' as well as informed traders' sentiment between the two market *A* and *B*. Here, ($\Delta u_{kt} = u_{Akt} - u_{Bkt}$) indicates relative changes in informed traders' systematic return component, ($\Delta\eta_{kt} = \eta_{Akt} - \eta_{Bkt}$) is relative change in the noise traders' systematic return component, and ($\Delta\acute{\upsilon}_{kt} = \acute{\upsilon}_{Akt} - \acute{\upsilon}_{Bkt}$) is the contribution in terms of return of other idiosyncratic noise. Δu_{kt} represents *systematic fundamental shocks* in the pricing due to innovations in macro-economic risk factors. This shock (Δu_{kt}) is *non-diversifiable*. In addition, $\Delta\eta_{kt}$ represents *systematic noise shocks* due to change in noise traders' sentiments. It is orthogonal to fundamental news regarding *k* th stock and correlated with changes in noise traders' sentiment regarding other stocks. This shock is *non-diversifiable* to that extent where such shocks are correlated across stocks. $\Delta\acute{\upsilon}_{kt}$ is *idiosyncratic noise shock*. It includes firm-specific component of change in noise traders' sentiment about the *k* th stock and includes possible microstructure effects and other idiosyncratic noises. *Idiosyncratic noise shocks* are *diversifiable*. At presence of heterogeneous traders Δu_{kt}, $\Delta\eta_{kt}$, and $\Delta\acute{\upsilon}_{kt}$ as mentioned earlier are not perfectly hedged at trading over the markets A and B.

Now, let us transform the above price differential $\Delta P_{AB,kt}$ in the identity (3) into the rate of return in the identity (4) with reference to *i* th trader and the identity (5) with reference to *j* th trader for their buy positions as follows. However, if sock K_A (K_B) prices are over (under)-priced currently, the long-short returns in the identity (4) would show positive correlation and that in identity (5) negative correlation.

$$R_{i,AB,kt} = (\Delta P_{AB,kt}) / P_{Akt} = \Delta u_{kt} / P_{Akt} + \Delta\eta_{kt} / P_{Akt} + \Delta\acute{\upsilon}_{kt} / P_{Akt} \quad (4)$$

$$R_{j,AB,kt} = (\Delta P_{AB,kt}) / P_{Bkt} = \Delta u_{kt} / P_{Bkt} + \Delta\eta_{kt} / P_{Bkt} + \Delta\acute{\upsilon}_{kt} / P_{Bkt} \quad (5)$$

But, the firm-specific fundamental information (private and public) may not be impounded into stocks' prices in the two markets simultaneously. The adjustment to private information is subject to different adjustments speeds at different times. The speed depends on informed traders' nature as well as density in the markets. In Kyle (1985), private information vests strategic monopoly power to behave. In Grossman & Stiglitz (1980) and Holden & Subrahmanyam (1992), multiple informed traders involve in competition and result in quicker adjustment of private information. If there are differences in trading costs and market makers' behaviour etc., the strategic informed traders may vary across the markets and in such cases, private vis-à-vis public information would be revealed at different rates. For simplicity, we assume that for *i* th (*j* th) investor the *k* th stock adjust firm-specific fundamental information fully and immediately in the market A (B) but not that in the market *B* (A) fully and λ (γ) is the fraction that impounds immediately and the rest one period later as given in the identities (6) [(7)] as if it is *idiosyncratic fundamental shock*.

$$\acute{\omega}_{B,kt} = \lambda * \acute{\omega}_{A,kt} + (1-\lambda) * \acute{\omega}_{A,kt-1} \quad (6)$$

$$\acute{\omega}_{A,kt} = \gamma * \acute{\omega}_{B,kt} + (1-\gamma) * \acute{\omega}_{B,kt-1} \quad (7)$$

Therefore once incorporated the effects of identities (6) and (7) into identity (2), identity (3) can be rewritten as identity (8), identity (9) respectively as follows including the effects of *i* th (*j* th) investor. Therefore, identity (4) and identity (5) could be rewritten as identity (10) and identity (11) as in the following. However, the components in right hand side of these three identities are not observable while left parts are only visible.

$$\Delta P_{i,AB,kt} = (1-\lambda)\acute{\omega}_{A,kt} - (1-\lambda)\acute{\omega}_{A,kt-1} + [u_{Akt} - u_{Bkt}] + [\eta_{Akt} - \eta_{Bkt}] + [\acute{\upsilon}_{Akt} - \acute{\upsilon}_{Bkt}] \quad (8)$$

$$\Delta P_{j,AB,kt} = (1-\gamma)\acute{\omega}_{A,kt} - (1-\gamma)\acute{\omega}_{A,kt-1} + [u_{Akt} - u_{Bkt}] + [\eta_{Akt} - \eta_{Bkt}] + [\acute{\upsilon}_{Akt} - \acute{\upsilon}_{Bkt}] \quad (9)$$

$$R_{i,AB,kt} = (\Delta P_{AB,kt}) / P_{Akt} = (1-\lambda)\acute{\omega}_{A,kt} / P_{Akt} - (1-\lambda)\acute{\omega}_{A,kt-1} / P_{Akt} + \Delta u_{kt} / P_{Akt} + \Delta \eta_{kt} / P_{Akt} + \Delta\acute{\upsilon}_{kt} / P_{Akt} \quad (10)$$

$$R_{j,AB,kt} = (\Delta P_{AB,kt}) / P_{Bkt} = (1-\gamma)\acute{\omega}_{B,kt} / P_{Bkt} - (1-\gamma)\acute{\omega}_{B,kt-1} / P_{Bkt} + \Delta u_{kt} / P_{Bkt} + \Delta \eta_{kt} / P_{Bkt} + \Delta\acute{\upsilon}_{kt} / P_{Bkt} \quad (11)$$

2. **Theoretical Propositions:** If investors' long-short positions over the markets A and B impound information and noise as propagated in the identities (8) and (9), their returns as shown in the identities (10) and (11) would reveal first-order negative serial correlation along with premiums or discounts for the other components. The thesis forwards the following theoretical propositions.

Proposition 1: If there is dynamic pricing equilibrium at presence of both information and noise and if it either persists or reversed over the consecutive trading days, *the returns would be different at different habitats of investors.*

Proposition 2: If there is dynamic pricing equilibrium at presence of both information and noise and if it either persists or reversed over the consecutive trading days, *the return volatility would be different at different habitats of investors.*

3 **The Equilibrium Pricing Mechanism:** All the investors in the stock markets for a stock (ACC.LTD for example) is segregated in two separate groups: the i th traders and the j th traders. The i th traders believe that the stock is under (over)-priced currently in the BSE (NSE) market while the j th traders believe that the stock is under (over)-priced in the NSE (BSE) market. Such a belief only would not lead to dynamic trading in the markets. It needs different expectations within both the i th and j th traders' groups about the future price movements. For example, the *i* th trader's trading strategy of [SB(B)$_i$ LS(N)$_i$] that is, a Short Buy in the BSE immediately and Long Sell in the NSE, is subject to the expectation that in the near future the present overvaluation in the NSE market will persist. Again, for the other group, the strategy of [SB(N)$_j$ LS(B)$_j$] that is, a Short Buy in the NSE immediately and Long-Sell in the BSE is subject to the expectation that in the near future the present overvaluation in the BSE market will persist. These strategies lead to excess demand in the short-run in both markets simultaneously and excess supply in the long-run as well. Investors with only of these two these hedging strategies will destroy the market themselves leaving no seller in the short run and no-buyer in the long run. The both strategies disrupt the property of generality that if the overvaluation could persist in future in both the markets, then undervaluation should also be alive presently in both the markets rather than the same in any one of the markets.

The said complexity could be removed with presence of heterogeneity assumption that some other *i* th traders have the trading strategy of [SS(N)$_i$ LB(B)$_i$]/that is, a Long Buy in the BSE immediately and Short Sell in the NSE, is subject to the expectation that in the near future the present undervaluation in the BSE market will persist. On the other hand, at presence expectation that in the near future the present undervaluation in the NSE market will persist with heterogeneous *j* th traders. Here the strategy of [SS(B)$_j$ LB(N)$_j$]/that is, a Short Sell in the BSE and Long-Buy in the NSE is subject to the expectation that in the near future the present undervaluation in the NSE market will persist. That is, the presence of heterogeneous traders' expectations at the both positions within the same group of investors about the persistency of present undervaluation or overvaluation in one market resolve the problem of demand-supply mismatch. Hence, intraday equilibrium pricing for trades with long-short position would take place dynamically with the both groups in the two ways (i) [SB(B)$_i$ LS(N)$_i$] x [SS(B)$_j$ LB(N)$_j$]/and (ii) [SB(N)$_j$ LS(B)$_j$] x [SS(N)$_i$ LB(B)$_i$]/ for two separate prices in the markets.

4. **Empirical Methodology, Proxy Variables, and Data:** The components in the theoretical models (10) and (11) are unobservable. It is complex to define their specific proxies. The paper makes an in-

genious effort of principal component analysis on this regard in the following four steps. Firstly, out of the stock's return data ($R_{j,\,AB,\,kt}$ and $R_{i,\,AB,\,kt}$) at long-short positions over the markets, noise components of idiosyncratic fundamental shocks [$(1\text{-}\lambda)\acute{\omega}_{A,\,kt\text{-}1}$ / P_{Akt} and $(1\text{-}\,\gamma)\acute{\omega}_{B,\,kt\text{-}1}/P_{Bkt}$ in identity (10) and (11)] are sorted out empirically in regression models 12.A and 12.B. In the second step, the residuals ("first residuals" $\acute{U}_{j,\,AB,\,kt}$ and $\acute{U}_{i,\,BA,\,kt}$) in 12.A and 12.B are explained by systematic fundamental shocks [Δ_{ukt}/P_{Akt} and Δ_{uk}/P_{Bkt} in identity (10) and (11)] in regression models 13.A and 13.B. The residuals in 13.A and 13.B, "second residuals" $\hat{U}_{j,\,AB,\,kt}$ and $\hat{U}_{i,\,BA,\,kt,}$ in the third stage, are explored by systematic noise shocks [$\Delta\,\eta_{kt}$ / P_{Akt} and $\Delta\,\eta_{kt}/P_{Bkt}$] in models 14.A and 14.B. The residuals in 14.A and 14.B, "third residuals" $\bar{U}_{j,\,AB,\,kt}$ and $\bar{U}_{i,\,BA,\,kt,}$ in the forth step, are regressed by idiosyncratic noise shock [$\acute{\upsilon}_{kt}/P_{Akt}$ and $\Delta\acute{\upsilon}_{kt}/P_{Bkt}$] in models 15.A and 15.B. Moreover to mention that, since there is two separate data set for two separate heterogeneous investors' groups, an estimation methodology within the family of ARIMA (p,d,q) with $AR(p)$, $I(d)$, and $MA(q)$ or VAR is not applicable and amenable as well from the perspective of estimation and noise determination. Since one groups' game decision depends on the others' choice, here we apply simultaneous regression methodology to study the time series nature of the empirical data.

Since the trading strategies of [$SB(B)_i$ $LS(N)_i$] x [$SS(B)_j$ $LB(N)_j$]/ and $SB(N)_j$ $LS(B)_j$] x [$SS(N)_i$ $LB(B)_i$]/ result into single prices for each of the two markets, as discussed earlier, either of [$SB(B)_i$ $LS(N)_i$] and [$SS(B)_j$ $LB(N)_j$]/ cannot explain one another and similarly, either $SB(N)j$ $LS(B)_j$] and [$SS(N)_i$ $LB(B)_i$]/ cannot explain one another. However, one trading data from the first set of [$SB(B)_i$ $LS(N)_i$] and [$SS(B)_j$ $LB(N)_j$]/ may explain (and also can be explained by) any one from the second set of $SB(N)_j$ $LS(B)_j$] and [$SS(N)_i$ $LB(B)_i$]/ and may identify the role of noises.

Now, for the first step in 12.A as follows, the dependent variable in the terms of returns for the j th traders' short-buy in the BSE ($SS(N)_j$) and long-sell in the NSE ($LS(N)_j$) that is, [$SB(B)_j$ $LS(N)_j$] are generated and explained by the independent variable in the terms of returns for the i th traders' long-buy in the BSE ($LB(B)_i$) and short-sell in the $NSE(SS(N)_i)$ that is, by the data of [$LB(B)_i$ $SS(N)_i$]. On the other hand in 12.B as follows, the dependent variable in the terms of returns for the i th traders' long-buy in the BSE ($LB(B)_i$) and short-sell in the NSE ($SS(N)_i$) that is, the data of [$LB(B)_i$ $SS(N)_i$] are generated and explained by the independent variable in the terms of returns for the j th traders' short-buy in the BSE ($SB(B)_j$) and long-sell in the NSE ($LS(N)_j$) that is, the data of [$SB(B)_j$ $LS(N)_j$]. Further, the lag variables along with the lead variables of the independent return variables are used to serve proxy in identifying the impacts of idiosyncratic fundamental shocks.

For the second step, in 13.A and 13.B, *first residuals* are explained by proxy variables of $\beta_{\,i,AB,kt}$ and $\beta_{\,j,BA,kt}$ respectively for *systematic fundamental shocks.* It represents systematic (that is, market wise) information distrust about firm's fundamentals and it is caused by innovations in macro-economic risk factors. It also serves for informed traders' heterogeneity across the two markets. The variable $\beta_{i,AB,kt}$ ($\beta_{j,BA,kt}$) is defined as *i* (*j*) th investor's long-short systematic risk coefficient in market A (B) over B (A). In developing long-short systematic risk, it is assumed that an instrument for exchange of market index could be imagined and be made available for long-short trading over their fluctuations. At ex-ante, ex-post the long-short market returns over the markets A and B are unobservable. With historical intraday trading data over dates, long-short market returns are used to regress *i* (*j*) th investor's long-short stock returns in order to generate the dynamic long-short systematic risk data over past 20 transactions in market A (B) over B (A).

For the third step in 14.A and 14.B, *second residuals* are explained by proxy variables of $\gamma_{i,\,AB,kt}$ and $\gamma_{j,BA,kt}$ for *systematic noise shocks* respectively. Since these proxy variables are orthogonal to fundamental news regarding *k* th stock and correlated with changes in noise traders' sentiment regarding other stocks, these variables for *i* th and *j* th investors are defined as the time varying dynamic coefficients of stock's aggregate dynamic noise at long-short positioning (Sİ) derived as residuals in the second step (i.e., historical long-short return of stocks less their expected long-short return as adjusted for their respective intercepts and $\beta_{i,AB,kt}$ or $\beta_{j,BA,kt}$ coefficients in a simple linear regression model) and once the said noises are being explained by the market's long-short stochastic returns as observed for the *j* th and *i* th traders' positioning.

Finally in the regression models 15.A and 15.B, the residuals generated from 14.A and 14.B are explained by the *idiosyncratic noise shocks*. In order to proxy for the *j* th (*i* th) investor's *idiosyncratic noise shocks*, the concept of volatility clustering is convenient to explain investors' behaviours. It is argued that greater (lesser) degrees of investor's *idiosyncratic noise shocks* should set forth higher (lower) numbers of heterogeneous or homogeneous crowds in the market. In order to proxy for the *idiosyncratic homogeneous* (*heterogeneous*) *noise shocks* viz., the set of variables of $\gamma_{1j,AB,kt}$ and $\gamma_{1i,BA,kt}$ ($\gamma_{2j,AB,kt}$ and $\gamma_{2i,BA,kt}$) in model 15.A and 15.B are defined as the coefficients of squared error term in the lag time (the lagged conditional variances) in a GARCH (1,1) process of the residuals $\ddot{U}_{j,BA,kt}$ ($\ddot{U}_{i,AB,kt}$) at some continuous lag, and given that $\ddot{U}_{j,AB,kt}$ and $\ddot{U}_{i,BA,kt}$ follow a **Markov first-order autoregressive scheme**. Therefore, last two models are specified as error free model. The effect of any error term is assumed to be contained in the constant term in the models.

$$R_{j,AB,kt} = \alpha_j + \theta_{-1j} R_{i,AB,kt-1} + \theta_{0j} R_{i,AB,kt} + \theta_{1j} R_{i,AB,kt+1} + U_{j,AB,kt} \quad (12.A)$$

$$R_{i,BA,kt} = \alpha_i + \theta_{-1i} R_{j,BA,kt-1} + \theta_{0i} R_{j,BA,kt} + \theta_{1i} R_{j,BA,kt+1} + U_{i,BA,kt} \quad (12.B)$$

$$\acute{U}_{j,AB,kt} = \alpha_j + \phi_{-1j} \beta_{i,AB,kt-1} + \phi_{0j} \beta_{i,AB,kt} + \phi_{1j} \beta_{i,AB,kt+1} + \hat{U}_{j,AB,kt} \quad (13.A)$$

$$\acute{U}_{i,BA,kt} = \alpha_i + \phi_{-1i} \beta_{i,BA,kt-1} + \phi_{0i} \beta_{i,BA,kt} + \phi_{1i} \beta_{i,BA,kt+1} + \hat{U}_{i,BA,kt} \quad (13.B)$$

$$\hat{U}_{j,AB,kt} = \alpha_j + \varphi_{-1j} \Upsilon_{i\ i,AB,kt-1} + \varphi_{0j} \Upsilon_{i,AB,kt} + \varphi_{1j} \Upsilon_{i,AB,kt+1} + \ddot{U}_{j,AB,kt} \quad (14.A)$$

$$\hat{U}_{i,BA,kt} = \alpha_j + \varphi_{-1i} \Upsilon_{j,BA,kt-1} + \varphi_{0i} \Upsilon_{j,BA,kt} + \varphi_{1i} \Upsilon_{j,BA,kt+1} + \ddot{U}_{i,BA,kt} \quad (14.B)$$

$$\sigma_{jt}^2 (\ddot{U}_{j,AB,kt}) = \alpha_j + \aleph_{1j} \gamma_{1j,AB,kt} + \aleph_{2j} \gamma_{2j,AB,kt\ t} \quad (15.A)$$

$$\sigma_{it}^2 (\ddot{U}_{i,BA,kt}) = \alpha_i + \aleph_{1i} \gamma_{1i,BA,kt\ t} + \aleph_{2j} \gamma_{2j,BA,kt} \quad (15.B)$$

Now, if the stated two propositions hold true then the above ten regression models from 12.A and 12.B to 15.A and 15.B would find robust and significant coefficients.

The empirical exploration in the research has incorporates the intraday one minute trading data (1D data) for four days over ten scripts listed both in the BSE and the NSE. These scripts are ACC.LTD, ACL.LTD, ASSIANPAINTS.LTD, AXISBANK.LTD, BAZAZHIND.LTD, BHEL.LTD, BOB.LTD, BPCL.LTD, CARIN.LTD, and BHARATIARTL.LTD. The trading dates are 27.09.2013, 30.09.2013, 04.10.2013, and 07.10.2013. The intraday trading data of these ten 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. The data set also includes the index data for the 1D BSE-SENSEX and 1D NSE-NIFTY. However, since the data generation procedure takes huge manual efforts, the study limits its scope with in four days trading within the two markets over ten scripts.

Results and Findings

The study depicts the results on the regression models 12.A, and 12.B in Table-1 and Table-2 respectively. The same on the regression models 13.A and 13.B are showed in the tables Table-3 and Table-4. The observation and findings on the regression model 14.A and 14.B are laid in the Table-5 and Table-6 while the same on regression model 15.A and 15.B are given in the tables Table-7 and Table-8. However, in the following sub-heading firstly an overall observations of all these eight regression models are discussed and then a separate sub-heading is dedicated for general discussion for the observations with regard to the regression models 12.A and 12.B.

I. Overall Observations

The results in ***Table-1*** for the regression model 12.A show that the *j* th trader's long-short return could be explained by the *i* th trader's long-short returns, the lead returns, and the lag returns from 63.85 % (for BAZAZ HIND.LTD) to 96.58 % (for BHARATIARTL.LTD) significantly. Their coefficients are significant at 1% level of significance except for two cases of ACC.LTD and BPCL.LTD. Here, in the first case of ACC.LTD, in explaining the *j* th trader's long-short returns ($R_{j,AB,kt}$) by the independent long-short returns of the *i* th (i.e., $R_{i,AB,kt}$) the coefficient is significant at 32.14 % level of significance while *j* th trader's lead long-short return variable ($R_{i,AB,kt+1}$) and lag long short return variable ($R_{i,AB,kt-1}$) result in significant coefficients and these explain 83.56 % of the dependent variable $R_{j,AB,kt}$. In the other case of BPCL.LTD, the intercept is significant at 11.69 % level of significance and the

Table 1: Idiosyncratic Fundamental Shocks on [$SB(B)_j$ $LS(N)_j$] Explained by [$LB(B)_i$ $SS(N)_i$]

Regression Model		$R_{j,AB,kt} = \alpha_j + \theta_{-1j} R_{i,AB,kt-1} + \theta_{0j} R_{i,AB,kt} + \theta_{1j} R_{i,AB,kt+1} + Ú_{j,AB,kt}$ ……..(12.A)						
Coefficients		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t - value	Sig. Lev.	Adj. R^2 (Std. Error)	F - Value
ACC.Ltd	Intercept (α_j)	0.021164	0.00188		11.25839	4.09E-23	0.835679 (0.00364)	346.825
	$R_{i,AB,kt-1}$	-1.00479	0.043664	-0.71316	-23.0119	3.12E-58		
	$R_{i,AB,kt}$	-0.05175	0.052069	-0.03097	-0.99392	0.321459		
	$R_{i,AB,kt+1}$	-0.77766	0.039229	-0.56605	-19.8234	3.52E-49		
ACL.Ltd	Intercept (α_j)	0.012215	0.001681		7.266218	8E-12	0.86052 (0.00291)	420.523
	$R_{i,AB,kt-1}$	-0.46638	0.042065	-0.39625	-11.087	1.35E-22		
	$R_{i,AB,kt}$	0.506479	0.048409	0.357263	10.46259	9.91E-21		
	$R_{i,AB,kt+1}$	-0.31181	0.031834	-0.33746	-9.79478	9.1E-19		
ASIAN PAINTS Ltd.	Intercept (α_j)	-0.00742	0.001301		-5.70634	4.09E-08	0.845271 (0.002398)	372.479
	$R_{i,AB,kt-1}$	-0.2686	0.031833	-0.26301	-8.43788	6.32E-15		
	$R_{i,AB,kt}$	0.554099	0.04292	0.557857	12.91009	3.64E-28		
	$R_{i,AB,kt+1}$	-0.34634	0.041414	-0.34423	-8.36288	1.01E-14		
AXIS BANK Ltd.	Intercept (α_j)	0.013905	0.003424		4.061277	6.99E-05	0.959552 (0.002269)	1614.18
	$R_{i,AB,kt-1}$	-0.15792	0.036544	-0.06614	-4.32134	2.44E-05		
	$R_{i,AB,kt}$	0.741203	0.06047	0.607755	12.25741	3.71E-26		
	$R_{i,AB,kt+1}$	-0.38168	0.049713	-0.38134	-7.67763	6.93E-13		
BAZA-ZHIND Ltd.	Intercept (α_j)	0.021909	0.001694		12.93005	2.57E-27	0.638502 (0.004639)	106.387
	$R_{i,AB,kt-1}$	-0.57658	0.040884	-0.69889	-14.103	1.04E-30		
	$R_{i,AB,kt}$	0.004062	0.001046	0.18174	3.883454	0.000146		
	$R_{i,AB,kt+1}$	-0.91861	0.058243	-0.79638	-15.7722	1.66E-35		
BHEL .Ltd	Intercept (α_j)	-0.01251	0.002662		-4.70031	4.82E-06	0.959961 (0.002159)	1631.32
	$R_{i,AB,kt-1}$	-0.2689	0.049158	-0.13603	-5.47012	1.33E-07		
	$R_{i,AB,kt}$	0.907008	0.027454	0.822776	33.03728	3.63E-83		
	$R_{i,AB,kt+1}$	-0.0874	0.023859	-0.06689	-3.66336	0.000318		
BOB .Ltd	Intercept (α_j)	0.008605	0.002027		4.245216	3.34E-05	0.961109 (0.002383)	1681.45
	$R_{i,AB,kt-1}$	-0.37983	0.061722	-0.12349	-6.15396	4.02E-09		
	$R_{i,AB,kt}$	0.537387	0.047877	0.464204	11.22442	5.18E-23		
	$R_{i,AB,kt+1}$	-0.6157	0.052491	-0.44189	-11.7297	1.52E-24		
BPCL .Ltd	Intercept (α_j)	0.002106	0.001337		1.574555	0.116932	0.817511 (0.003545)	305.625
	$R_{i,AB,kt-1}$	-0.14492	0.027708	-0.18464	**-5.23034**	4.23E-07		
	$R_{i,AB,kt}$	0.958066	0.047516	0.816182	**20.16313**	3.61E-50		
	$R_{i,AB,kt+1}$	-0.01523	0.026302	-0.02241	-0.57912	0.563158		

Regression Model		$R_{j,AB,kt} = \alpha_j + \theta_{-1j} R_{i,AB,kt-1} + \theta_{0j} R_{i,AB,kt} + \theta_{1j} R_{i,AB,kt+1} + Ú_{j,AB,kt}$ ....(12.A)						
Coefficients		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std. Error)*	*F - Value*
CARIN Ltd.	Intercept (α_j)	0.010162	0.000742		13.69552	1.37E-30	0.822817 (0.002025)	316.784
	$R_{i,AB,kt-1}$	-0.66437	0.05596	-0.40611	-11.8722	5.59E-25		
	$R_{i,AB,kt}$	0.431201	0.043043	0.443414	10.01787	2.03E-19		
	$R_{i,AB,kt+1}$	-0.19965	0.02864	-0.2759	-6.97107	4.42E-11		
BHARATI-AIRTEL Ltd.	Intercept (α_j)	-0.00426	0.00164		-2.60031	0.010006	0.965879 (0.002404)	1925.92
	$R_{i,AB,kt-1}$	-0.1531	0.039214	-0.05581	-3.90414	0.000129		
	$R_{i,AB,kt}$	0.794412	0.043497	0.704591	18.26347	1.44E-44		
	$R_{i,AB,kt+1}$	-0.46721	0.062612	-0.28209	-7.46205	2.52E-12		

coefficient for *j* th trader's lead long-short return variable ($R_{i,AB,kt+1}$) is significant at 57.91 % level of significance while the other independent variables are significant at 1% level of significance.

The results in Table-2 read with the regression model 12.B show that the *i* th trader's long-short return could be explained by the *j* th trader's long-short returns, the lead returns, and the lag returns from 44.63 % (for ACC.LTD) to 97.41 % (for BHARATIARTL.LTD) significantly. Their coefficients are significant at 1% level of significance except for three cases of ASSIANPAINTS.LTD, BHEL.LTD, and BHARATIARTL.LTD. Here, in the first case of ASSIANPAINTS.LTD, in explaining the *i*

Table 2: Idiosyncratic Fundamental Shocks on [$LB(B)_i$ $SS(N)_i$] Explained by [$SB(B)_j$ $LS(N)_j$]

Regression Model		$R_{i,BA,kt} = \alpha_i + \theta_{-1i} R_{j,BA,kt-1} + \theta_{0i} R_{j,BA,kt} + \theta_{1i} R_{j,BA,kt+1} + Ú_{i,BA,kt}$ ....(12.B)						
Coefficients		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F - Value*
ACC.Ltd	Intercept (α_i)	0.020018	0.001421		14.0849	8.53E-32	0.446341 (0.004)	55.819
	$R_{j,BA,kt-1}$	-0.34956	0.05192	-0.35573	-6.73274	1.71E-10		
	$R_{j,BA,kt}$	0.198014	0.031982	0.330904	6.19152	3.3E-09		
	$R_{j,BA,kt+1}$	-0.47428	0.05212	-0.47962	-9.09976	9.01E-17		
ACL.Ltd	Intercept (α_i)	0.018798	0.001245		15.10055	6.19E-35	0.711353 (0.00295)	168.58
	$R_{j,BA,kt-1}$	-0.23125	0.04794	-0.18811	-4.82369	2.78E-06		
	$R_{j,BA,kt}$	0.359449	0.034686	0.509578	10.36295	1.96E-20		
	$R_{j,BA,kt+1}$	-0.38727	0.050794	-0.36437	-7.62431	9.55E-13		
ASIAN PAINTS.Ltd	Intercept (α_i)	-0.00266	0.001814		-1.46876	0.14346	0.796259 (0.00277)	266.75
	$R_{j,BA,kt-1}$	-0.06393	0.041534	-0.0522	-1.53913	0.125345		
	$R_{j,BA,kt}$	0.715716	0.044874	0.710895	15.94931	1.51E-37		
	$R_{j,BA,kt+1}$	-0.32103	0.058818	-0.23698	-5.45796	1.41E-07		
AXISBANK .Ltd	Intercept (α_i)	0.027213	0.001647		16.51917	2.72E-39	0.972854 (0.00152)	2437.96
	$R_{j,BA,kt-1}$	-0.19092	0.026197	-0.0887	-7.28781	7.05E-12		
	$R_{j,BA,kt}$	0.441737	0.028166	0.538731	15.68346	9.91E-37		
	$R_{j,BA,kt+1}$	-0.41259	0.030867	-0.45857	-13.3667	1.42E-29		

Regression Model		$R_{i,BA,kt} = \alpha_i + \theta_{-1i} R_{j,BA,kt-1} + \theta_{0i} R_{j,BA,kt} + \theta_{1i} R_{j,BA,kt+1} + Ú_{i,BA,kt}$ ….(12.B)						
Coefficients		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t - value	Sig. Lev.	Adj. R^2 (Std.-Error)	F - Value
BAZAZHIND .Ltd	Intercept (α_i)	0.014501	0.002081		6.967791	9.85E-11	0.721492 (0.00307)	131.39
	$R_{j,BA,kt-1}$	-0.52491	0.033552	-0.82274	-15.6448	3.56E-33		
	$R_{j,BA,kt}$	0.264139	0.036161	0.338458	7.304636	1.59E-11		
	$R_{j,BA,kt+1}$	-0.59414	0.043017	-0.76577	-13.8116	2.12E-28		
BHEL .Ltd	Intercept (α_i)	-0.00684	0.002757		-2.48109	0.013919	0.9531 (0.00212)	1382.88
	$R_{j,BA,kt-1}$	-0.23092	0.053711	-0.10564	-4.29926	2.67E-05		
	$R_{j,BA,kt}$	0.80142	0.025626	0.883467	31.27426	3.72E-79		
	$R_{j,BA,kt+1}$	-0.01275	0.023037	-0.01146	-0.55326	0.580699		
BOB .Ltd	Intercept (α_i)	0.013288	0.001571		8.460298	5.48E-15	0.960352 (0.00208)	1648.11
	$R_{j,BA,kt-1}$	-0.30433	0.050605	-0.1117	-6.01386	8.42E-09		
	$R_{j,BA,kt}$	0.453506	0.032619	0.525002	13.90315	3.11E-31		
	$R_{j,BA,kt+1}$	-0.51046	0.044904	-0.39879	-11.3677	1.91E-23		
BPCL .Ltd	Intercept (α_i)	0.009369	0.000865		10.83244	7.82E-22	0.85355 (0.00271)	397.32
	$R_{j,BA,kt-1}$	-0.0659	0.02297	-0.09184	-2.86881	0.00456		
	$R_{j,BA,kt}$	0.625041	0.029463	0.733697	21.21462	3.4E-53		
	$R_{j,BA,kt+1}$	-0.17144	0.018315	-0.29345	-9.36036	1.63E-17		
CARIN .Ltd	Intercept (α_i)	0.008038	0.000791		10.15939	7.8E-20	0.869521 (0.00178)	454.155
	$R_{j,BA,kt-1}$	-0.53661	0.037784	-0.44294	-14.2022	3.7E-32		
	$R_{j,BA,kt}$	0.369992	0.03797	0.359801	9.744431	1.27E-18		
	$R_{j,BA,kt+1}$	-0.31351	0.026377	-0.36946	-11.8853	5.1E-25		
BHARATI ARTL .Ltd	Intercept (α_i)	-0.0019	0.001294		-1.46582	0.14426	0.97417 (0.00185)	2565.58
	$R_{j,BA,kt-1}$	-0.17403	0.030963	-0.06686	-5.62058	6.3E-08		
	$R_{j,BA,kt}$	0.613747	0.023853	0.691988	25.73088	1.6E-65		
	$R_{j,BA,kt+1}$	-0.51456	0.044635	-0.30482	-11.5282	6.23E-24		

th trader's long-short returns ($R_{i,AB,kt}$) by independent lag long-short returns of the *j* th (i.e., $R_{j,AB,kt-1}$), the coefficient is significant at 12.53 % level of significance while the intercept is significant at 14.34 % level of significance while the other independent variables are significant at 1% level of significance. In the second case of BHEL.LTD, the intercept is significant at 1.39 % level of significance and the coefficient of the lead long-short return variable (i.e., $R_{j,AB,kt+1}$) is insignificant at 20 % level while the other independent variables are significant at 1% level. In the third case of BHARATIARTL.LTD, the intercept is significant at 14.42% level of significance while the other independent variables are significant at 1% level.

In exploring the *systematic fundamental shocks* component, the results in ***Table-3*** for the regression model 13.A show that the first residual of the *j* th trader's long-short return could be explained by the *i* th trader's long-short systematic risk coefficient (viz., $\beta_{i,AB,kt}$), its lag variable and the lead variable. The explanatory powers of the said specification in regression model 13.A in the terms of Adj. R^2 values (along with significant F-values) are found to be 3 % for ACC.LTD, 17.99 % for ACL.LTD, 9.23 % for BAZAZHIND.LTD, 10.87 % for BOB.LTD, 9.37 % for BPCL.LTD, 11.32 % for CARIN.LTD, and 9.17 % for BHARATIARTL.LTD. However, for ASSIANPAINTS.LTD (AXISBANK.LTD) the explanatory power is low and 1.229 % (0.78 %) with the F-value 1.767 (1.486) being significant at 16% (22%) level of significance while for BHEL.LTD. the model is unstable even at 25 % level of confidence. Further, the table shows that the coefficient of the lag-variable (that is,) is negatively (positively) significant for ACC.LTD, BPCL.LTD, CARIN.LTD, and BHARATIARTL.LTD (ACL.LTD, BAZAZHIND.LTD, and BOB.LTD) while the coefficient of the lead-variable (that is,) is positively significant for AXISBANK.LTD, BPCL.LTD, and BHARATIARTL.LTD and negatively insignificant for all of the firms. Here, the coefficient of the variable $\beta_{i,AB,kt}$ is negatively (positively) significant for the scripts of ACL. LTD, and ASSIANPAINTS.LTD (BOBL.LTD, BPCL. LTD, CARIN.LTD, and BHARATIARTL.LTD). These observations suggest that the *systematic fundamental shock* has dynamicity in framing investors' perception about prices and therefore about their returns in the long-short positions.

In ***Table-4*** in exploring the *systematic fundamental shocks* for the regression model 13.B, it is observed that

Table 3: Systematic Fundamental Shocks with First Residuals in Table-1

Regression Model	$\acute{U}_{j,AB,kt} = \alpha_j + \phi_{-1j}\beta_{i,AB,kt-1} + \phi_{0j}\beta_{i,AB,kt} + \phi_{1j}\beta_{i,AB,kt+1} + \hat{U}_{j,AB,kt}$ …….(13.A)							
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F – Value (Sig. Lev)*
ACC.Ltd	Intercept (α_j)	-0.00032	0.000244		-1.30787	0.192567	0.030005 (0.003264)	2.907546 (0.036021)
	$\beta_{i,AB,kt-1}$	-0.00063	0.000217	-0.22698	-2.89135	0.004303		
	$\beta_{i,AB,kt}$	-9.6E-05	0.000216	-0.03434	-0.44533	0.65661		
	$\beta_{i,AB,kt+1}$	-7E-05	0.00019	-0.0272	-0.368	0.713303		
ACL.Ltd	Intercept (α_j)	0.000213	0.000188		1.132182	0.259047	0.179906 (0.002497)	14.52797 (1.59E-08)
	$\beta_{i,AB,kt-1}$	0.000249	0.000144	0.155337	1.73337	0.084724		
	$\beta_{i,AB,kt}$	-0.00063	0.000155	-0.30375	-4.07892	6.76E-05		
	$\beta_{i,AB,kt+1}$	0.000123	0.000141	0.074338	0.868677	0.386168		
ASIAN PAINTS.Ltd	Intercept (α_j)	0.000375	0.000163		2.305401	0.022272	0.012291 (0.002149)	1.767396 (0.154996)
	$\beta_{i,AB,kt-1}$	-4.7E-05	0.000106	-0.03377	-0.4456	0.656414		
	$\beta_{i,AB,kt}$	-0.00044	0.000193	-0.17382	-2.29842	0.022675		
	$\beta_{i,AB,kt+1}$	-3.4E-05	0.000152	-0.01626	-0.22086	0.825451		
AXIS-BANK .Ltd	Intercept (α_j)	0.000248	0.000204		1.219498	0.224233	0.007829 (0.00164)	1.486618 (0.219709)
	$\beta_{i,AB,kt-1}$	-2.1E-06	0.000109	-0.0015	-0.01937	0.984569		
	$\beta_{i,AB,kt}$	-8.6E-05	0.000119	-0.06363	-0.72327	0.470441		
	$\beta_{i,AB,kt+1}$	0.000294	0.000151	0.179924	1.952431	0.052421		
BAZA-ZHIND .Ltd	Intercept (α_j)	-0.00023	0.000459		-0.49603	0.620717	0.092319 (0.003907)	5.475193 (0.001422)
	$\beta_{i,AB,kt-1}$	0.00062	0.000169	0.34434	3.672326	0.000351		
	$\beta_{i,AB,kt}$	6.98E-05	0.00039	0.020288	0.178829	0.858352		
	$\beta_{i,AB,kt+1}$	0.000261	0.000265	0.103546	0.987546	0.325224		
BHEL .Ltd	Intercept (α_j)	0.000194	0.000185		1.044152	0.2978	0.00927 (0.001868)	0.433632 (0.729176)
	$\beta_{i,AB,kt-1}$	1.93E-05	0.000115	0.013325	0.166889	0.867643		
	$\beta_{i,AB,kt}$	5.67E-05	0.000111	0.051999	0.511136	0.609875		
	$\beta_{i,AB,kt+1}$	2.66E-05	8.32E-05	0.033076	0.319934	0.749386		
BOB .Ltd	Intercept (α_j)	0.000942	0.00025		3.769236	0.000221	0.108742 (0.002003)	8.523895 (2.51E-05)
	$\beta_{i,AB,kt-1}$	0.000852	0.000188	0.356087	4.527547	1.08E-05		
	$\beta_{i,AB,kt}$	0.000431	0.000129	0.296425	3.342246	0.001009		
	$\beta_{i,AB,kt+1}$	2.91E-05	0.000113	0.020443	0.257272	0.79726		

Regression Model		$\acute{U}_{j,AB,kt} = \alpha_j + \phi_{-1j}\beta_{i,AB,kt-1} + \phi_{0j}\beta_{i,AB,kt} + \phi_{1j}\beta_{i,AB,kt+1} + \hat{U}_{j,AB,kt}$ ....(13.A)						
Coefficients for variables		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t - value	Sig. Lev.	Adj. R^2 (Std.-Error)	F – Value (Sig. Lev)
BPCL .Ltd	Intercept (α_j)	0.000197	0.000317		0.622204	0.534587	0.09372 (0.003421)	7.377038 (0.000108)
	$\beta_{i,AB,kt-1}$	-0.00025	0.000148	-0.12241	-1.67831	0.095002		
	$\beta_{i,AB,kt}$	0.000308	0.00015	0.151753	2.052403	0.041562		
	$\beta_{i,AB,kt+1}$	0.000292	9.68E-05	0.214477	3.018502	0.002905		
CARIN .Ltd	Intercept (α_j)	6.92E-05	0.000142		0.488618	0.6257	0.113214 (0.00177)	8.87283 (1.61E-05)
	$\beta_{i,AB,kt-1}$	-0.00055	0.000137	-0.28248	-4.03765	7.95E-05		
	$\beta_{i,AB,kt}$	0.000605	0.000215	0.194749	2.807262	0.005541		
	$\beta_{i,AB,kt+1}$	0.000103	0.000151	0.047594	0.680362	0.49714		
BHARATI ARTL .Ltd	Intercept (α_j)	0.000281	0.000145		1.934826	0.054562	0.091738 (0.001647)	7.228576 (0.000131)
	$\beta_{i,AB,kt-1}$	-0.00014	0.000101	-0.09843	-1.39833	0.163716		
	$\beta_{i,AB,kt}$	0.000241	7.28E-05	0.238449	3.305326	0.001143		
	$\beta_{i,AB,kt+1}$	0.000232	0.000113	0.147186	2.045397	0.042255		

the first residual of the *i* th trader's long-short return could be explained by the *j* th trader's long-short systematic risk coefficient (viz., $\beta_{j,AB,kt}$), its lag variable and the lead variable. The explanatory powers of the said specification in regression model 13.B in the terms of Adj. R^2 values are found to be 17.53 % for ACC.LTD, 31.21 % for ACL.LTD, 14.96 % for ASSIANPAINTS.LTD, 2.27 % for AXISBANK.LTD, 5.74 % for BAZAZHIND. LTD, 5.58% for BHEL.LTD, 5.09 % for BOB.LTD, 2.64 % for BPCL.LTD, 16.91 % for CARIN.LTD, and 7.65 % for BHARATIARTL.LTD. There are significant F-values at mostly 1% level of significance and at 7% level of significance for AXISBANK.LTD, at 2% level for BAZAZHIND.LTD, and at 5% level for BPCL. LTD. Therefore, the model 13.B is stable at 90 % level of confidence. The table also shows that the coefficients of the lag and lead variables of the long-short systematic risk coefficient are negatively and positively significant dynamically over the scripts except those of AXISBANK. LTD and BHARATIARTL.LTD where only the lead coefficient is significant. These observations reveal that the *systematic fundamental shock* has dynamicity in framing investors' perception about prices and about their returns in the long-short positions.

In ***Table-5***, the study reports the results obtained for

Table 4: Systematic Fundamental Shocks with First Residuals in Table-2

Regression Model		$\acute{U}_{i,BA,kt} = \alpha_i + \phi_{-1i}\beta_{i,BA,kt-1} + \phi_{0i}\beta_{i,BA,kt} + \phi_{1i}\beta_{i,BA,kt+1} + \hat{U}_{i,BA,kt}$ .....(13.B)						
Coefficients for variables		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t - value	Sig. Lev.	Adj. R^2 (Std.-Error)	F – Value
ACC.Ltd	Intercept (α_i)	-0.00011	0.000267		-0.39873	0.690559	0.175324 (0.003473)	14.11018 (2.61E-08)
	$\beta_{i,BA,kt-1}$	0.001068	0.000255	0.287152	4.186379	4.41E-05		
	$\beta_{i,BA,kt}$	-0.00134	0.000338	-0.28151	-3.96015	0.000107		
	$\beta_{i,BA,kt+1}$	0.00034	0.000198	0.119417	1.719478	0.087228		

Regression Model		$\acute{U}_{i,BA,kt} = \alpha_i + \phi_{-1i}\beta_{i,BA,kt-1} + \phi_{0i}\beta_{i,BA,kt} + \phi_{1i}\beta_{i,BA,kt+1} + \hat{U}_{i,BA,kt}$ .....(13.B)						
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F – Value*
ACL.Ltd	Intercept (α_i)	0.000235	0.000192		1.224137	0.222483	0.312162 (0.002202)	28.98618 (2.28E-15)
	$\beta_{i,BA,kt-1}$	-0.00027	0.000198	-0.08614	-1.36031	0.175414		
	$\beta_{i,BA,kt}$	0.000834	0.00016	0.321438	5.212293	5.03E-07		
	$\beta_{i,BA,kt+1}$	-0.00102	0.000122	-0.53509	-8.36514	1.54E-14		
ASSIAN PAINTS.Ltd	Intercept (α_i)	-4.8E-05	0.000224		-0.21408	0.83072	0.14964 (0.002459)	11.85164 (3.98E-07)
	$\beta_{i,BA,kt-1}$	-0.00062	0.00016	**-0.26353**	**-3.86077**	0.000157		
	$\beta_{i,BA,kt}$	0.000345	0.00019	**0.123837**	**1.817107**	0.070846		
	$\beta_{i,BA,kt+1}$	0.000825	0.000174	**0.323509**	**4.734803**	4.4E-06		
AXISBANK .Ltd	Intercept (α_i)	**0.000362**	0.000181		**1.998838**	0.047114	0.022731 (0.001272)	2.43438 (0.066377)
	$\beta_{i,BA,kt-1}$	0.000137	0.000115	0.091258	1.19965	0.231835		
	$\beta_{i,BA,kt}$	-1.2E-05	8.23E-05	-0.0112	-0.15089	0.880229		
	$\beta_{i,BA,kt+1}$	-0.00027	0.000107	**-0.1999**	**-2.57518**	0.010813		
BAZA-ZHIND .Ltd	Intercept (α_i)	**-0.00041**	0.000283		**-1.45288**	0.148686	0.05749 (0.002966)	3.683847 (0.013814)
	$\beta_{i,BA,kt-1}$	0.000289	0.000157	**0.160742**	**1.840514**	0.067991		
	$\beta_{i,BA,kt}$	-0.00041	0.000191	**-0.19558**	**-2.14907**	0.033496		
	$\beta_{i,BA,kt+1}$	0.000128	0.000141	0.085081	0.911596	0.363682		
BHEL .Ltd	Intercept (α_i)	0.000105	0.000165		0.637858	0.524368	0.058006 (0.001743)	4.797272 (0.00306)
	$\beta_{i,BA,kt-1}$	0.000365	0.000152	**0.192011**	**2.405208**	0.017165		
	$\beta_{i,BA,kt}$	-0.0002	8.57E-05	**-0.23235**	**-2.37535**	0.018572		
	$\beta_{i,BA,kt+1}$	0.00014	7.05E-05	**0.204483**	**1.981857**	0.049001		
BOB .Ltd	Intercept (α_i)	-1.6E-05	0.000218		-0.07344	0.941535	0.050983 (0.001844)	4.312822 (0.005763)
	$\beta_{i,BA,kt-1}$	0.000126	0.000148	0.062391	0.853012	0.394774		
	$\beta_{i,BA,kt}$	0.000255	7.66E-05	**0.241378**	**3.327949**	0.001059		
	$\beta_{i,BA,kt+1}$	-8.5E-06	0.000125	-0.00493	-0.06793	0.945919		
BPCL .Ltd	Intercept (α_i)	-0.0002	0.000221		-0.90231	0.368086	0.026445 (0.002529)	2.675093 (0.048671)
	$\beta_{i,BA,kt-1}$	-0.00021	0.000146	**-0.10754**	**-1.46788**	**0.143862**		
	$\beta_{i,BA,kt}$	3.71E-05	8.89E-05	0.030332	0.417407	0.676873		
	$\beta_{i,BA,kt+1}$	0.000271	0.000105	**0.190067**	**2.590177**	**0.010369**		
CARIN .Ltd	Intercept (α_i)	0.000129	0.000122		1.058368	0.29129	0.169134 (0.001384)	13.55304 (5.08E-08)
	$\beta_{i,BA,kt-1}$	-0.00054	0.000175	**-0.21481**	**-3.09633**	0.002269		
	$\beta_{i,BA,kt}$	0.0007	0.00017	**0.342793**	**4.10297**	6.15E-05		
	$\beta_{i,BA,kt+1}$	-0.0007	0.00015	**-0.38095**	**-4.68989**	5.35E-06		
BHARATI ARTL .Ltd	Intercept (α_i)	**0.000323**	0.000119		**2.71068**	0.007357	0.076515 (0.001526)	6.1094 (0.000555)
	$\beta_{i,BA,kt-1}$	-0.00014	0.000132	-0.07916	-1.09514	0.274902		
	$\beta_{i,BA,kt}$	5.94E-06	9.26E-05	0.005312	0.064128	0.948939		
	$\beta_{i,BA,kt+1}$	-0.00047	0.000129	**-0.30976**	**-3.67486**	0.000313		

the regression model 14.A. Here, the *second residuals* obtained from *j* th trader's long-short return in order to explain the component of *systematic noise shocks*. The residuals are explained by the *i* th trader's time varying dynamic coefficients of stock's aggregate dynamic noise at long-short positioning for market's long-short stochastic returns (viz., $\gamma_{i\ i,AB,kt}$). The explanatory powers of the said specification in regression model in the terms of Adj. R^2 values are found to be 28.8 % for ACC.LTD, 1.74 % for ACL.LTD, 15.89 % for ASSIANPAINTS.LTD, 4.15 % for AXISBANK.LTD, 13.69 % for BAZAZHIND.LTD, 0.043 % for BHEL.LTD, 7.87 % for BOB.LTD, 12.147 % for BPCL.LTD, 0.7 % for CARIN.LTD, and 0.297 % for BHARATIARTL.LTD. These observations have significant F-values at mostly 1% level of significance and at 12 % level of significance for ACL.LTD and at 2% level for AXISBANK.LTD while for BHEL.LTD, CARIN. LTD, and BHARATIARTL.LTD the model is unstable respectively at 60%, 75%, and 50% level of confidence. The coefficients of the variable $\gamma_{i\ i,AB,kt-1}$ and its lag and lead variables are negatively and positively significant dynamically over the scripts except those cases where the

Table 5. (Prev Page): Systematic Noise Shocks with Second Residuals in Table-3

Regression Model	$\hat{U}_{j,AB,kt} = \alpha_j + \varphi_{-1j}\,\gamma_{i\ i,AB,kt-1} + \varphi_{0j}\,\gamma_{i,AB,kt} + \varphi_{1j}\,\gamma_{i,AB,kt+1} + \breve{U}_{j,AB,kt}$ ....(14.A)							
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F - Value*
ACC.Ltd	Intercept (α_j)	-0.00101	0.000252		-3.99468	9.79E-05	0.288056 (0.002781)	23.38816 (1.21E-12)
	$\gamma_{i\ i,AB,kt-1}$	-3E-06	0.000211	-0.00093	-0.01395	0.988886		
	$\gamma_{i,AB,kt}$	-0.00133	0.000199	-0.44262	-6.69424	3.33E-10		
	$\gamma_{i,AB,kt+1}$	-0.00119	0.000209	-0.37923	-5.67079	6.33E-08		
ACL.Ltd	Intercept (α_j)	-0.00018	0.000222		-0.82733	0.409258	0.017462 (0.002196)	1.983399 (0.118521)
	$\gamma_{i\ i,AB,kt-1}$	0.000416	0.000181	0.192692	2.293517	0.023095		
	$\gamma_{i,AB,kt}$	0.00011	0.000243	0.036451	0.452573	0.651458		
	$\gamma_{i,AB,kt+1}$	-7.4E-05	0.000125	-0.05089	-0.59422	0.55319		
ASIAN PAINTS.Ltd	Intercept (α_j)	-0.00069	0.000221		-3.09583	0.002311	0.158921 (0.002022)	11.45517 (7.43E-07)
	$\gamma_{i\ i,AB,kt-1}$	0.000819	0.000184	0.327009	4.453229	1.56E-05		
	$\gamma_{i,AB,kt}$	-0.00069	0.000268	-0.19286	-2.58893	0.010498		
	$\gamma_{i,AB,kt+1}$	-0.00054	0.000152	-0.25591	-3.52977	0.000541		
AXISBANK .Ltd	Intercept (α_j)	0.000412	0.000197		2.091134	0.038067	0.041516 (0.001689)	3.396709 (0.019308)
	$\gamma_{i\ i,AB,kt-1}$	-0.00055	0.000229	-0.19606	-2.38858	0.018057		
	$\gamma_{i,AB,kt}$	7.14E-06	0.00033	0.002095	0.021675	0.982734		
	$\gamma_{i,AB,kt+1}$	-0.00019	0.000149	-0.11846	-1.30627	0.193303		
BAZAZHIND .Ltd	Intercept (α_j)	-0.00148	0.000459		-3.23326	0.00162	0.136907 (0.003502)	6.921929 (0.000262)
	$\gamma_{i\ i,AB,kt-1}$	-0.00094	0.000268	-0.35047	-3.51112	0.00065		
	$\gamma_{i,AB,kt}$	-0.00019	0.000199	-0.09296	-0.94362	0.34745		
	$\gamma_{i,AB,kt+1}$	0.00079	0.000376	0.207668	2.102548	0.037808		
BHEL .Ltd	Intercept (α_j)	-0.00019	0.000149		-1.27151	0.20536	0.00043 (0.001871)	0.976393 (0.405386)
	$\gamma_{i\ i,AB,kt-1}$	0.000317	0.000188	0.135935	1.685417	0.093822		
	$\gamma_{i,AB,kt}$	-3.6E-05	0.000116	-0.02496	-0.31153	0.755795		
	$\gamma_{i,AB,kt+1}$	-3.6E-05	0.000103	-0.02923	-0.35219	0.725151		

Regression Model		$\hat{U}_{j,AB,kt} = \alpha_j + \varphi_{-1j}\,\gamma_{i\ i,AB,kt-1} + \varphi_{0j}\,\gamma_{i,AB,kt} + \varphi_{1j}\,\gamma_{i,AB,kt+1} + \breve{U}_{j,AB,kt}$ ……………....(14.A)						
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F - Value*
BOB .Ltd	Intercept (α_j)	0.000243	0.000196		1.242182	0.215954	0.078721 (0.001982)	5.728119 (0.000944)
	$\gamma_{i\ i,AB,kt-1}$	-0.00066	0.0002	-0.24839	-3.29241	0.001218		
	$\gamma_{i,AB,kt}$	0.000631	0.000248	0.189904	2.545781	0.011831		
	$\gamma_{i,AB,kt+1}$	7.73E-05	0.000137	0.04254	0.563247	0.574041		
BPCL .Ltd	Intercept (α_j)	-0.00018	0.000266		-0.68684	0.493159	0.121472 (0.003185)	8.650804 (2.32E-05)
	$\gamma_{i\ i,AB,kt-1}$	0.000144	0.000307	0.03451	0.469987	0.638993		
	$\gamma_{i,AB,kt}$	-0.00114	0.000239	-0.3527	-4.77918	3.9E-06		
	$\gamma_{i,AB,kt+1}$	0.000522	0.000222	0.175244	2.353318	0.0198		
CARIN .Ltd	Intercept (α_j)	-8.9E-05	0.000137		-0.65185	0.515415	0.007104 (0.001516)	1.395924 (0.245971)
	$\gamma_{i\ i,AB,kt-1}$	-5.3E-06	0.000198	-0.0021	-0.02679	0.978662		
	$\gamma_{i,AB,kt}$	0.00047	0.000303	0.121068	1.547741	0.123624		
	$\gamma_{i,AB,kt+1}$	0.000153	0.000115	0.103743	1.338464	0.182609		
BHARATI AIRTEL .Ltd	Intercept (α_j)	9E-05	0.000178		0.505521	0.613876	0.00297 (0.00181)	0.83625 (0.475789)
	$\gamma_{i\ i,AB,kt-1}$	0.00018	0.000196	0.077188	0.917818	0.36007		
	$\gamma_{i,AB,kt}$	0.000121	0.000143	0.076025	0.844469	0.399645		
	$\gamma_{i,AB,kt+1}$	-7.6E-05	0.000153	-0.04133	-0.494	0.621969		

model is unstable.

However, in these cases of unstable regressions for model 14.A, the lag-variable is positively significant at 10% level of significance. These observations lead for the apprehension that systematic noise shocks have positive thrusts to be carried forward from the earlier days. That is, systematic noise is cumulative in nature and its dynamicity involves in equilibrium pricing mechanism.

In order to explain the component of *systematic noise shocks*, in ***Table-6***, the paper reveals the results of regression model 14.B. The *second residuals* in *i* th trader's long-short return is explained by *j* th trader's time varying dynamic coefficients of stock's aggregate dynamic noise at long-short positioning for market's long-short stochastic returns (viz., $\gamma_{jj,AB,kt}$). The explanatory powers of the said specification in regression model in the terms of Adj. R^2 values are found to be 5.5 % for ACC.LTD, 6.03 % for ACL.LTD, 1.44 % for ASSIANPAINTS.LTD, 2.75 % for AXISBANK.LTD, 21.59 % for BAZAZHIND.LTD, 1.17 % for BHEL.LTD, 20.34 % for BOB.LTD, 1.78 % for BPCL.LTD, 0.08 % for CARIN.LTD, and 11.14 % for BHARATIARTL.LTD. These observations have significant F-values at mostly 1% level of significance and at 15 % level of significance for ASSIANPAINTS.LTD and at 6% level for AXISBANK.LTD while for BHEL.LTD and CARIN.LTD the model is unstable respectively at 25%, and 60% level of confidence. The coefficients of variable $\gamma_{i\ i,AB,kt-1}$ and its lag and lead variables are negatively and positively significant dynamically over the scripts where the model is robustly sound with regard to the magnitudes of the F-value and the coefficients are static in nature with significant intercept where the regression model is not so robust or unstable. These observations confirm that systematic noise has effects of temporary as well as permanent components.

Now, the study discusses the observations on the fourth component of *idiosyncratic noise shocks* specified in the models 15.A and 15.B. The third residuals are explained by the *idiosyncratic homogeneous as well as heterogeneous noise shocks* defined by the coefficients of lagged squared error term and the lagged conditional variances in a GARCH (1, 1) process. Since the models are specified as error term free and it is assumed effects of the other residual factors might be explained by the intercepts of the regression results, the ***Table-7*** and ***Table-8*** need special care on explanations. The tables show that the intercepts are significant at acceptable level

Table 6: Systematic Noise Shocks with Second Residuals in Table-4

Regression Model		$\hat{U}_{i,BA,kt} = \alpha_j + \varphi_{-1i}\gamma_{j,BA,kt-1} + \varphi_{0i}\gamma_{j,BA,kt} + \varphi_{1i}\gamma_{j,BA,kt+1} + \bar{U}_{i,BA,kt}$ ….(14.B)						
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F – Value (Sig. Lev)*
ACC.Ltd	Interceptpt (α_j)	-0.0002	0.000259		-0.7876	0.432074	0.055023 (0.002937)	4.221896 (0.006621)
	$\gamma_{j,BA,kt-1}$	0.000473	0.000247	0.153498	1.912175	0.057608		
	$\gamma_{j,BA,kt}$	0.000383	0.000334	0.101182	1.148463	0.25246		
	$\gamma_{j,BA,kt+1}$	-0.00063	0.000207	-0.2526	-3.0331	0.002817		
ACL.Ltd	Intercept (α_j)	-1.8E-05	0.000174		-0.10127	0.919458	0.060324 (0.002009)	4.552201 (0.004314)
	$\gamma_{j,BA,kt-1}$	0.000349	0.000168	0.171435	2.074737	0.039582		
	$\gamma_{j,BA,kt}$	-4.9E-05	0.000183	-0.01994	-0.26484	0.791467		
	$\gamma_{j,BA,kt+1}$	-0.00087	0.000239	-0.30025	-3.63414	0.000373		
ASIAN PAINTS. Ltd	Intercept (α_j)	1.61E-05	0.000229		0.070367	0.943988	0.014458 (0.002611)	1.811743 (0.147073)
	$\gamma_{j,BA,kt-1}$	0.000309	0.000288	0.085883	1.071121	0.285699		
	$\gamma_{j,BA,kt}$	-0.0004	0.00024	-0.13287	-1.65484	0.099881		
	$\gamma_{j,BA,kt+1}$	6.02E-05	0.000276	0.017064	0.218026	0.827681		
AXIS-BANK .Ltd	Intercept (α_j)	0.000111	0.000122		0.910556	0.363874	0.027529 (0.001337)	2.56638 (0.056394)
	$\gamma_{j,BA,kt-1}$	0.000176	0.000112	0.123295	1.568366	0.118735		
	$\gamma_{j,BA,kt}$	-1E-04	9.7E-05	-0.0836	-1.02732	0.305793		
	$\gamma_{j,BA,kt+1}$	0.000389	0.000208	0.155763	1.867242	0.063663		
BAZA-ZHIND .Ltd	Intercept (α_j)	-0.00081	0.000271		-2.97782	0.003473	0.215961 (0.002463)	13.02787 (1.77E-07)
	$\gamma_{j,BA,kt-1}$	-0.00041	0.000122	-0.31774	-3.39227	0.000923		
	$\gamma_{j,BA,kt}$	-6.1E-05	0.000241	-0.02387	-0.25239	0.801144		
	$\gamma_{j,BA,kt+1}$	0.000812	0.000169	0.394898	4.800269	4.34E-06		
BHEL .Ltd	Intercept (α_j)	-6.2E-05	0.00015		-0.41567	0.678198	0.01179 (0.001768)	0.355136 (0.785483)
	$\gamma_{j,BA,kt-1}$	9.19E-05	0.000188	0.039137	0.48824	0.626036		
	$\gamma_{j,BA,kt}$	5.68E-05	9.08E-05	0.050845	0.625569	0.532472		
	$\gamma_{j,BA,kt+1}$	4.55E-05	8.84E-05	0.042818	0.515068	0.607203		
BOB .Ltd	Intercept (α_j)	-0.00018	0.000156		-1.16163	0.247086	0.203449 (0.001709)	15.13278 (9.81E-09)
	$\gamma_{j,BA,kt-1}$	0.000381	0.000169	0.162386	2.260035	0.025143		
	$\gamma_{j,BA,kt}$	-0.00024	9.11E-05	-0.19037	-2.602	0.010122		
	$\gamma_{j,BA,kt+1}$	0.000933	0.000168	0.401156	5.566958	1.05E-07		
BPCL .Ltd	Intercept (α_j)	4.08E-05	0.000205		0.198804	0.842664	0.017842 (0.00251)	2.005173 (0.115307)
	$\gamma_{j,BA,kt-1}$	0.000332	0.000162	0.15761	2.041263	0.042837		
	$\gamma_{j,BA,kt}$	0.000155	0.000202	0.06615	0.76803	0.44358		
	$\gamma_{j,BA,kt+1}$	-0.00023	0.00019	-0.10464	-1.21871	0.224716		
CARIN .Ltd	Intercept (α_j)	3.17E-07	0.00011		0.002877	0.997708	0.00082 (0.001344)	0.954493 (0.415774)
	$\gamma_{j,BA,kt-1}$	-0.00017	0.000168	-0.08538	-1.02649	0.30618		
	$\gamma_{j,BA,kt}$	-0.00013	0.000147	-0.08117	-0.85565	0.393445		
	$\gamma_{j,BA,kt+1}$	-1.6E-05	0.000186	-0.00813	-0.08621	0.931407		

Regression Model		$\hat{U}_{i,BA,kt} = \alpha_j + \varphi_{-1i}\, \gamma_{j,BA,kt-1} + \varphi_{0i}\, \gamma_{j,BA,kt} + \varphi_{1i}\, \gamma_{j,BA,kt+1} + \bar{\ddot{U}}_{i,BA,kt}$ ….(14.B)						
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F – Value (Sig. Lev)*
BHARATI AIRTEL .Ltd	Intercept (α_j)	-0.00021	0.000118		-1.8018	0.073424	0.111492 (0.001444)	7.943358 (5.63E-05)
	$\gamma_{j,BA,kt-1}$	0.000132	0.000117	0.089063	1.134882	0.258091		
	$\gamma_{j,BA,kt}$	-0.00049	0.000136	-0.33512	-3.63099	0.000378		
	$\gamma_{j,BA,kt+1}$	-8.7E-05	0.000196	-0.04313	-0.44243	0.658762		

of significance for all firms except for BAZAZHIND. LTD, BHEL.LTD, BPCL.LTD, and CARIN.LTD for model 15.A and ASSIANPAINTS.LTD, BHEL.LTD, and BPCL.LTD for model 15.B. These confirm that the intercept has least explanatory power and the dynamicity is needed to be addressed by the noise shocks.

The results on model 15.A are depicted in ***Table-7*** and the same on model 15.B are showed in Table-8. In explaining the *j* th traders return residuals (that is, third residuals), Table-7 shows that the Adj. R^2-values lie within the range of 0.818 percent (for BAZAZHIND.LTD) to 11.3762 percent (ACL.LTD). Here, the *idiosyncratic homogeneous noise* shock coefficient is significant for five firms out of the ten sample firms and these are ACC.LTD, ACL.LTD, AXISBANK.LTD, and CARIN.LTD. The *idiosyncratic*

Table 7: Idiosyncratic Noise Shocks with Third Residuals in Table 5

Regression Model		$\sigma_{jt}^{2}\, (\bar{\ddot{U}}_{j,AB,kt}) = \alpha_j + \aleph_{1j}\, \gamma_{1j,AB,kt} + \aleph_{2j}\, \gamma_{2j,AB,kt\,t}$ ……………(15.A)						
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F - Value*
ACC.Ltd	Intercept (α_j)	0.003119	0.001419		**2.197673**	0.029418	0.043759 (0.003092)	4.683797 (0.010557)
	$\gamma_{1j,AB,kt}$	-0.00421	0.001749	**-0.19228**	**-2.40838**	0.017168		
	$\gamma_{2j,AB,kt\,t}$	-0.00183	0.001529	**-0.09535**	**-1.19429**	0.234144		
ACL.Ltd	Intercept (α_j)	**0.005496**	0.001863		**2.949789**	0.00366	0.113762 (0.002426)	11.33334 (2.5E-05)
	$\gamma_{1j,AB,kt}$	-0.0064	0.001974	**-0.24324**	**-3.24008**	0.001455		
	$\gamma_{2j,AB,kt\,t}$	-0.00583	0.001974	**-0.22168**	**-2.95282**	0.003627		
ASIAN PAINTS.Ltd	Intercept (α_j)	**-0.0067**	0.0017		**-3.94159**	0.000121	0.102975 (0.002799)	10.24107 (6.55E-05)
	$\gamma_{1j,AB,kt}$	-0.00147	0.002363	-0.05224	-0.62051	0.535811		
	$\gamma_{2j,AB,kt\,t}$	0.008395	0.00197	**0.358786**	**4.26162**	3.47E-05		
AXISBANK .Ltd	Intercept (α_j)	**-0.00179**	0.000992		**-1.802**	0.073439	0.044245 (0.002875)	4.726636 (0.010138)
	$\gamma_{1j,AB,kt}$	0.00366	0.003176	**0.094785**	**1.152366**	0.2509		
	$\gamma_{2j,AB,kt\,t}$	0.002731	0.001205	**0.186442**	**2.266691**	0.024757		
BAZA-ZHIND .Ltd	Intercept (α_j)	0.00139	0.001382		1.005983	0.316736	0.00818 (0.003405)	0.565658 (0.569708)
	$\gamma_{1j,AB,kt}$	-0.00144	0.001548	-0.09198	-0.93155	0.353704		
	$\gamma_{2j,AB,kt\,t}$	-0.00116	0.001712	-0.06666	-0.67511	0.501093		
BHEL .Ltd	Intercept (α_j)	-0.00077	0.001231		-0.62518	0.532747	0.011 (0.001877)	0.124492 (0.883031)
	$\gamma_{1j,AB,kt}$	-0.00024	0.001469	-0.01314	-0.16477	0.869336		
	$\gamma_{2j,AB,kt\,t}$	0.000719	0.00148	0.038768	0.486259	0.627453		
BOB .Ltd	Intercept (α_j)	**-0.00292**	0.001837		**-1.58952**	0.113929	0.01329 (0.003311)	2.084235 (0.127788)
	$\gamma_{1j,AB,kt}$	-0.00123	0.002589	-0.03815	-0.47455	0.635759		
	$\gamma_{2j,AB,kt\,t}$	0.004421	0.002165	**0.164129**	**2.041655**	0.042839		

Regression Model		$\sigma_{jt}^2\ (\bar{U}_{j,AB,kt}) = \alpha_j + \aleph_{1j}\ \gamma_{1j\ ,AB,kt} + \aleph_{2j}\ \gamma_{2j,AB,kt\ t}$..............(15.A)						
Coefficients for variables		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t - value	Sig. Lev.	Adj. R^2 (Std.-Error)	F - Value
BPCL .Ltd	Intercept (α_j)	0.000933	0.001727		0.540116	0.589873	0.00837 (0.003659)	0.331503 (0.718339)
	$\gamma_{1j\ ,AB,kt}$	-0.00197	0.002638	-0.05967	-0.74689	0.456232		
	$\gamma_{2j,AB,kt\ t}$	-0.00044	0.002019	-0.0175	-0.21906	0.826884		
CARIN .Ltd	Intercept (α_j)	-0.00018	0.000563		-0.32714	0.743993	0.008442 (0.001496)	1.685397 (0.188665)
	$\gamma_{1j\ ,AB,kt}$	-0.00161	0.000906	**-0.14328**	**-1.78219**	0.076627		
	$\gamma_{2j,AB,kt\ t}$	0.000512	0.000626	0.065728	0.817555	0.414835		
BHARATI AIRTEL .Ltd	Intercept (α_j)	**-0.00247**	0.001296		**-1.90325**	0.058815	0.032147 (0.003143)	3.673773 (0.027559)
	$\gamma_{1j\ ,AB,kt}$	-0.00012	0.001805	-0.00542	-0.06727	0.946455		
	$\gamma_{2j,AB,kt\ t}$	0.004015	0.00153	**0.211589**	**2.624273**	0.00953		

heterogeneous noise coefficient is significant for six firms out of the ten sample firms and these are ACC. LTD, ACL.LTD, ASSIANPAINT.LTD, AXISBANK. LTD, BOB.LTD, and BHARATIARTL.LTD. None of two coefficients are significant for BAZAZHIND.LTD, BHEL.LTD, and BPCL.LTD. These observations suggest that there is diverse distribution of *idiosyncratic* noise across the firms in the market. It is further interesting that the nature of the noise component and their magnitudes as well as direction of effects on return is of dynamic in nature. The coefficients are either positively or negatively significant.

On the other hand, the results in ***Table-8*** with regard to the regression model 15.B shows that the *i* th traders' return residuals could be explained by the two *idiosyncratic noise shocks* components. The coefficient of *idiosyncratic homogeneous noise* shock coefficient is significant for six firms ACC.LTD, ASSIANPAINT.LTD, BAZAZHIND. LTD, BOB.LTD, BPCL.LTD, and CARIN.LTD while the *idiosyncratic heterogeneous noise* shock coefficient is significant for firms out of the ten sample firms and these are ACC.LTD, ACL.LTD, ASSIANPAINT.LTD, AXISBANK.LTD, BAZAZHIND.LTD, BOB.LTD, and BHARATIARTL.LTD. None of the two shocks are found to be significant for BHEL.LTD while only the *idiosyncratic heterogeneous noise* shock is significant for ACL.LTD, AXISBANK.LTD, and BHARATIARTL.LTD. These observations show that the proxy variables for the two *idiosyncratic noise shocks* can explain from 0.4 percent (BHEL.LTD) to 15.8635 percent (BHARATIARTL.LTD) in the terms of Adjusted R^2-value while the degree of explanatory power varies robustly for the different firms.

II. General Discussion

The observations in the earlier sub-section now need to be explained firm-specifically and the dynamicity could be explored. In the following sub-headings, the study reports the results on regression models 12.A and 12.B for their explanatory and explained variables as well. However, in order to save space, the present work avoids detailing the results in tables. The approach here is to get readers be well attended on the matter how diverse the relationships of the different groups of traders either homogeneous or heterogeneous are in their intra-day trading.

II. i. ACC LTD

For the case of ACC.LTD, in a cubic expression of forecasting, the lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 31.1152 percent while $R_{i,AB,kt}$ can explain the lead variable $R_{i,AB,kt+1}$ with the Adj. R^2 of 0.03932 percent. This suggests that in trading at presence of homogeneous *i* th group of investors with long-short strategy, today's perception serves little in tomorrow's decision choices while perception made in the past is more meaningful in today's choices. But, is the strategy of long-short positioning meaningful at presence of heterogeneous traders, that is, at presence of *i* th and *j*

Table 8: Idiosyncratic Noise Shocks with Third Residuals in Table 6

Regression Model		$\sigma_{it}^{2}\,(\bar{U}_{i,BA,kt}) = \alpha_i + \aleph_{1i}\,\gamma_{1i,BA,kt\ t} + \aleph_{2j}\,\gamma_{2j,BA,kt}$ ....(15.B)						
Coefficients for variables		*Unstandardized Coefficients*	*Std. Error*	*Standardized Coefficients*	*t - value*	*Sig. Lev.*	*Adj. R^2 (Std.-Error)*	*F - Value*
ACC.Ltd	Intercept (α_i)	0.003773	0.001672		2.256608	0.025395	0.070635 (0.002699)	7.118279 (0.001095)
	$\gamma_{1i,BA,kt\ t}$	0.004622	0.00157	0.224018	2.944134	0.003724		
	$\gamma_{2j,BA,kt}$	-0.00459	0.001825	-0.19149	-2.51664	0.012839		
ACL.Ltd	Intercept (α_i)	-0.00382	0.001459		-2.61506	0.00978	0.053319 (0.003138)	5.533933 (0.004749)
	$\gamma_{1i,BA,kt\ t}$	-0.00012	0.002313	-0.00435	-0.05197	0.958618		
	$\gamma_{2j,BA,kt}$	0.005091	0.001658	0.256811	3.070513	0.002514		
ASSIAN PAINTS.Ltd	Intercept (α_i)	-0.00185	0.002472		-0.7487	0.455147	0.035786 (0.005736)	3.987684 (0.020427)
	$\gamma_{1i,BA,kt\ t}$	-0.00827	0.003249	-0.20204	-2.54637	0.011835		
	$\gamma_{2j,BA,kt}$	0.004607	0.002628	0.1391	1.753109	0.081511		
AXIS-BANK .Ltd	Intercept (α_i)	-0.00259	0.001521		-1.70482	0.09018	0.024396 (0.003151)	3.012991 (0.051959)
	$\gamma_{1i,BA,kt\ t}$	-0.00306	0.002874	-0.08659	-1.06406	0.288915		
	$\gamma_{2j,BA,kt}$	0.004352	0.001794	0.197438	2.426251	0.016374		
BAZA-ZHIND .Ltd	Intercept (α_i)	0.002947	0.001215		2.425017	0.017015	0.081931 (0.002189)	5.774517 (0.004176)
	$\gamma_{1i,BA,kt\ t}$	-0.00296	0.00179	-0.16013	-1.65515	0.10088		
	$\gamma_{2j,BA,kt}$	-0.00354	0.001499	-0.22872	-2.36417	0.019909		
BHEL .Ltd	Intercept (α_i)	0.000826	0.000954		0.866322	0.387619	0.004 (0.001725)	0.679109 (0.508533)
	$\gamma_{1i,BA,kt\ t}$	0.000932	0.001384	0.055857	0.673675	0.501496		
	$\gamma_{2j,BA,kt}$	-0.00131	0.00118	-0.09212	-1.11107	0.268216		
BOB .Ltd	Intercept (α_i)	-0.00546	0.001565		-3.48833	0.000629	0.131314 (0.003077)	13.16866 (5.11E-06)
	$\gamma_{1i,BA,kt\ t}$	0.004187	0.00199	0.158622	2.103662	0.036982		
	$\gamma_{2j,BA,kt}$	0.007518	0.001841	0.308015	4.084913	6.97E-05		
BPCL .Ltd	Intercept (α_i)	-3.8E-05	0.000939		-0.04064	0.967633	0.038446 (0.00248)	4.21868 (0.016399)
	$\gamma_{1i,BA,kt\ t}$	0.005122	0.00188	0.230451	2.725389	0.007143		
	$\gamma_{2j,BA,kt}$	-0.0002	0.001071	-0.01587	-0.18767	0.851371		
CARIN .Ltd	Intercept (α_i)	0.001006	0.000488		2.060375	0.040992	0.009867 (0.001589)	1.802231 (0.168283)
	$\gamma_{1i,BA,kt\ t}$	-0.00144	0.001046	-0.10889	-1.37698	0.170455		
	$\gamma_{2j,BA,kt}$	-0.00061	0.000544	-0.08846	-1.11861	0.264993		
BHARATI AIRTEL .Ltd	Intercept (α_i)	-0.005	0.001109		-4.50693	1.27E-05	0.158635 (0.003124)	16.17783 (4.02E-07)
	$\gamma_{1i,BA,kt\ t}$	-0.00033	0.001872	-0.0132	-0.17528	0.861082		
	$\gamma_{2j,BA,kt}$	0.007098	0.001289	0.414722	5.505103	1.45E-07		

th groups of traders?

In model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 25.616 percent of the dependent variable $R_{j,AB,kt}$ while its lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 57.3628 (39.8326) percent. This suggests that in the long-short trading strategy for stock ACC. LTD over the two markets, the past's (future's) references (expectations) about events serve more relevance in the equilibrium price formation process. That is, past observation serves more relevance in formation of decision references that those of present's. But, how much new news contributes to the investors' decision making? The results show that the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ upto 40.5725 percent while the same explanatory variable along with its lag variable can explain about 57.6709 percent. Here again, the effect of today and yesterday is more powerful than the same of today and tomorrow. However, in an appraisal of the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises upto 83.5679 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 83.5689 percent. This shows that even though the independent variable $R_{i,AB,kt}$ has substantial information content in determining the long–short returns but its value becomes lost in the market place once the investors react with respect to their already framed references from past data and future expectations. In the other words, the news / market gossips and framing of the long-short positions about all of Mr. I *s* and all of Mr. J *s* contribute noises that "Today's News is Less Relevant to Yesterday's one" and "Today's News is Irrelevant to the joint effect of Yesterday's News and Tomorrow's Expectations". This observation is on the contrary of the EMH where the market has no memory and drastically, it impounds the information instantly.

In model 12.B on the contrary, in the cubic expression of forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 16.9491 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ with the Adj. R^2 of 4.8023 (4.4478) percent in a quadratic (cubic) expression of forecasting. This also confirms the presence of homogeneous *i* th group of investors with long-short strategy while today's observations serve little proxy for tomorrow and investors' past perception is robust in making today's decisions. At presence of heterogeneous traders, however, the results would be somewhat different. In model 12.B, the variable $R_{j,AB,kt}$ alone can explain 23.2222 percent of the dependent variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain the same up to 30.80 (17.8169) percent. This further confirms that past observations serves more relevance in determining decision references that those of the present. The results show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 32.4838 percent while the same explanatory variable along with its lag variable can explain about 38.7016 percent. That is, the effect of today and yesterday is less powerful than the same of today and tomorrow. This is however different from the same results obtained in 12.A. this suggests that there is substantial flow of noises within the two markets. The effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 44.6341 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 34.401 percent. This confirms that the effect of the independent variable $R_{i,AB,kt}$ is substantial in determining the long–short returns and it is not lost in the market place. The investors react not only with respect to their already framed references from past data and future expectations but also incorporate the present development in the market. These observations suggest that information and noise co-exists in the market.

II. ii. ACL LTD: For the case of ACL.LTD, in a cubic expression of forecasting, the lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 35.761 percent while $R_{i,AB,kt}$ in a linear setting can explain the lead variable $R_{i,AB,kt+1}$ about 30.2653 percent. This suggests that in trading at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves less in explaining tomorrow's decision choices and past perceptions are more meaningful in today's choices. On the long-short positioning at presence of heterogeneous traders, that is, in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 45.4338 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 65.5892 (59.8678) percent. The past's (future's) references (expectations) about events therefore serve greater relevance in the price formation process than the same at the present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 77.6333 percent while the same explanatory variable along with its lag variable can explain about 77.7853percent. That means, the effect of today along with that of yesterday is more powerful than the same along with tomorrow. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 86.052 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 78.5624 percent. In brief, this observation shows that variable $R_{i,AB,kt}$ has substantial information contents in the long–short returns and it persists in the market along with framed references and future expectations. These observations are in tune with the predictions of noise traders' risks.

In model 12.B, the cubic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 15.8203 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 37.2833 percent in a linear expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve much representation for tomorrow than that as served by past's observations to represent the future's decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 45.4338 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 9.8539 (47.8192) percent. The past (future) observations (expectations) serves less (more) relevance in determining decision references than that for the present. The results show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 67.9533 percent while the same variable along with its lag can explain about 58.3329 percent. Therefore, the effect of today and yesterday is less powerful than the same of today and tomorrow and this suggests that there are substantial flows of noises within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 71.1353 percent while lag variable along with the lead variable can explain up to 55.9326 percent. This showcases that the inputs in $R_{i,AB,kt}$ are substantial in determining the long–short returns and it has not been lost in the market place. The investors also incorporate the present development in the market. These observations suggest that information and noise co-exists in the market.

II. iii. ASIAN PAINTS. LTD

For the case of ASIAN PAINTS.LTD, in a cubic forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 19.5489 percent while $R_{i,AB,kt}$ in a linear setting can explain the lead variable $R_{i,AB,kt+1}$ about 48.6076 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves more in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On the long-short positioning at presence of heterogeneous traders, however in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 51.0607 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 20.0283 (51.5842) percent. These observations briefly suggest that past (future) references (expectations) about events therefore serve lesser (greater) relevance in the price formation process than that at the present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 79.1501 percent while the same explanatory variable along with its lag variable can explain about 76.9783 percent. That is, the effect of today along with that of tomorrow is more powerful than the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 84.5271 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 71.837 percent. In brief, this observation shows that variable $R_{i,AB,kt}$ has substantial effects in the long–short returns and it persists in the market along with framed references and future expectations. These observations are in tune with the predictions of noise traders' risks.

In model 12.B, the cubic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 8.734 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 42.0233 percent in a linear expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve much representation for tomorrow than that by past's observations to represent the todays' decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 63.8509 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 0.07008 (48.2259) percent. The past (future) observations (expectations) serves less (more) relevance in determining decision references than that for the present. The results show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 79.4879 percent while the same variable along with its lag can explain about 65.5541 percent. Therefore, the effect of today and yesterday is less powerful than the same of today and tomorrow and this suggests that there are substantial flows of expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 79.9256 percent while lag variable along with the lead variable can explain up to 54.0695 percent. Hence, the inputs in $R_{i,AB,kt}$ are substantial in determining the long–short returns and it has not been lost in the market place. The investors also incorporate present development in the market. These suggest that information and noise co-exists in the market.

II. iv. AXIS BANK. LTD

For the case of AXIS BANK.LTD, in a cubic forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 5.2385 percent while $R_{i,AB,kt}$ in a linear setting can explain the lead variable $R_{i,AB,kt+1}$ about 90.7959 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves huge in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On the long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 92.8621 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 2.1286 (91.0835) percent. These observations briefly suggest that past (future) references (expectations) about events therefore serve lesser (greater) relevance in the price formation process than that at the present. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 95.6013 percent while the same explanatory variable along with its lag variable can explain about 95.1718 percent. That is, the effect of today along with that of tomorrow is more powerful than the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 95.9552 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 92.9668 percent. This observation briefly shows that even if variable $R_{i,AB,kt}$ has less effects on long–short returns, it persists in the market along with framed references and future expectations. These observations confirm coexistence of noise and information.

In model 12.B, the quadratic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 5.7206 percent while $R_{j,AB,kt}$ in a linear expression can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 87.4116 percent. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve much representation for tomorrow than that by past's observations to represent the todays' decisions. However, at presence of heterogeneous traders, the variable $R_{j,AB,kt}$ alone can explain 92.8621 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 3.6938 (91.7975) percent. The past (future) observations (expectations) serves less (more) relevance in determining decision references than that at present. The results show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 96.5851 percent while the same variable along with its lag can explain about 95.2578 percent. Therefore, the effect of today and yesterday is less powerful than that today and tomorrow. There are substantial flows of expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 97.3253 percent while lag variable along with the lead variable can explain up to 93.9933 percent. Hence, the inputs in $R_{i,AB,kt}$ has not been lost in the market place even if it has not enough power in determining the long–short returns. These confirm that information and noise co-exists in the market.

II. v. BAZAZHIND.LTD

In the case of BAZAZHIND.LTD, the quadratic forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 2.3433 percent while $R_{i,AB,kt}$ in a cubic setting can explain the lead variable $R_{i,AB,kt+1}$ about 19.6795 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves more in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On the long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 0.334 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 13.7149 (23.5369) percent. These observations briefly suggest that past (future) references (expectations) about events therefore serve greater relevance in the price formation process than that at the present. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 23.4328 percent while the same explanatory variable along with its lag variable can explain about 13.7344 percent. That is, the effect of today along with that of tomorrow is more powerful than the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 63.8502 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 60.9743 percent. This observation briefly shows that the variable $R_{i,AB,kt}$ has less effects on long–short returns and it persists minimally in the market along with framed references and future expectations. These observations confirm coexists of noise and information.

In model 12.B, the quadratic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 25.202 percent while $R_{j,AB,kt}$ in a linear expression can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 13.5133 percent. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve less representation for tomorrow than that by past's observations to represent today's decisions. However, at presence of heterogeneous traders, the variable $R_{j,AB,kt}$ alone can explain 19.8326 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 8.9439 (16.9214) percent. The past (future) observations (expectations) serve less relevance in determining decision references than that at present. The results show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 26.5862 percent while the same variable along with its lag can explain about 36.6795 percent. Therefore, the effect of today and yesterday is more powerful than that today and tomorrow. There is less flow of expectations but more flow of past reference within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 72.1492 percent while lag variable along with the lead variable can explain up to 62.3625 percent. Hence, the inputs in $R_{i,AB,kt}$ has not been lost in the market place and has much power in determining the long–short returns. These confirm that information and noise co-exists in the market.

II. vi. BHEL. LTD

For the case of BHEL.LTD, in a cubic forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 74.3122 percent while $R_{i,AB,kt}$ in a similar setting can explain the lead variable $R_{i,AB,kt+1}$ about 48.3383 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves less in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 95.7606 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 76.8147 (42.3665) percent. These observations briefly suggest that past (future) references (expectations) about events therefore serve lesser relevance in the price formation process than that at present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 95.4228 percent while the same explanatory variable along with its lag variable can explain about 96.5597 percent. That is, the effect of today along with that of tomorrow is more powerful than the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 95.9961 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 74.815 percent. This observation shows that variable $R_{i,AB,kt}$ has substantial effects in long–short returns and it persists in the market along with framed references and future expectations. These observations are in tune with the predictions of noise traders' risks.

In model 12.B, the cubic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 71.015 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 56.2312 percent in a cubic expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve less representation for tomorrow than that by past's observations to represent the today's' decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 95.7606 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 72.6411 (44.6434) percent. The past (future) observations (expectations) serve less relevance in determining decision references than that for the present. The results further show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 94.904 percent while the same variable along with its lag can explain about 96.4272 percent. Therefore, the effect of today and yesterday is less powerful than the same of today and tomorrow and this suggests that there are substantial flows of new expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 95.31 percent while lag variable along with the lead variable can explain up to 72.6241 percent. Hence, the inputs in $R_{i,AB,kt}$ are substantial in determining long–short returns and it has robust effects in the market place. The investors also incorporate present development in the market strongly. These suggest that information and noise co-exists in the market.

II. vii. Bharati Airtel.ltd

For the case of BHARATI AIRTEL. LTD, in a linear forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 38.165 percent while $R_{i,AB,kt}$ in a similar setting can explain the lead variable $R_{i,AB,kt+1}$ about 86.7493 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves more in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 89.0316 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 4.3577 (88.2456) percent. These observations suggest that past (future) references (expectations) about events therefore serve lesser relevance in the price formation process than that at present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 96.3473 percent while the same explanatory variable along with its lag variable can explain about 95.3851 percent. That is, the effect of today along with that of tomorrow is more powerful than the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 96.5879 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 90.9706 percent. This observation shows that variable $R_{i,AB,kt}$ has substantial effects in long–short returns but the same may be ignored if reference frames include observed past data and future expectations. These observations confirm the predictions of noise traders' risks.

In model 12.B, the linear forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 3.109 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 84.241 percent in cubic expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve more representation for tomorrow than that by past's observations to represent the today's' decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 89.0316 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 4.1484 (86.2929) percent. The past (future) observations (expectations) serve less relevance in determining decision references than that with the present. The results further show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 97.0258 percent while the same variable along with its lag can explain about 95.4478 percent. Therefore, the effect of today and yesterday is less powerful than the same of today and tomorrow and this suggests that there are substantial flows of new expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 97.417 percent while lag variable along with the lead variable can explain up to 88.9636 percent. Hence, the inputs in $R_{i,AB,kt}$ are substantial in determining long–short returns and it has robust effects in the market place. The investors also incorporate present development in the market strongly. These suggest that information and noise co-exists in the market.

II. viii. BOB Ltd

For the case of BOB. LTD, in a linear forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 50.6039 percent while $R_{i,AB,kt}$ in a similar setting can explain the lead variable $R_{i,AB,kt+1}$ about 86.4135 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves more in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 85.6253 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 54.9995 (90.9963) percent. These observations suggest that past (future) references (expectations) about events therefore serve lesser (greater) relevance in the price formation process than that at present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 95.401 percent while the same explanatory variable along with its lag variable can explain about 93.2629 percent. That is, the effect of today along with that of tomorrow is more powerful than the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 96.1109 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 93.7044 percent. This observation shows that variable $R_{i,AB,kt}$ has substantial effects in long–short returns but the same may be ignored if reference frames include observed past data and future expectations. These observations confirm the predictions of noise traders' risks.

In model 12.B, the linear forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 44.6001 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 84.0763 percent in similar expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve more representation for tomorrow than that by past's observations to represent the today's' decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 85.6253 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 46.5398 (89.442) percent. The past (future) observations (expectations) serve less (more) relevance in determining decision references than that with the present. The results further show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 95.345 percent while the same variable along with its lag can explain about 93.2869 percent. Therefore, the effect of today and yesterday is mostly equal powerful to the same of today and tomorrow and this suggests that there is little substantial flows of new expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 96.0352 percent while lag variable along with the lead variable can explain up to 92.2609 percent. Hence, the inputs in $R_{i,AB,kt}$ lost its robustness in determining long–short returns in the market place. The investors also incorporate present development in the market strongly. These suggest that information and noise co-exists in the market.

II. ix. BPCL.ltd

For the case of BPCL.LTD, in a cubic forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 13.0526 percent while $R_{i,AB,kt}$ in a similar setting can explain the lead variable $R_{i,AB,kt+1}$ about 35.4131 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves more in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 72.2179 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 19.1149 (16.2793) percent. These observations suggest that past (future) references (expectations) about events therefore serve greater (lesser) relevance in the price formation process than that at present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 79.3701 percent while the same explanatory variable along with its lag variable can explain about 79.0478 percent. That is, the effect of today along with that of tomorrow is mostly equivalent to the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 81.7511 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 45.1132 percent. This observation shows that variable $R_{i,AB,kt}$ has substantial effects in long–short returns and the same could not be ignored even if reference frames include observed past data and future expectations. These observations confirm the predictions of noise traders' risks.

In model 12.B, the cubic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 21.0165 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 28.6635 percent in similar expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve more representation for tomorrow than that by past's observations to represent the today's' decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 72.2179 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 13.4898 (32.4575) percent. The past (future) observations (expectations) serve less relevance in determining decision references than that with the present. The results further show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 84.8308 percent while the same variable along with its lag can explain about 76.7265 percent. Therefore, the effect of today and yesterday is higher than the same of today and tomorrow and this suggests that there is substantial flow of new expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 85.355 percent while lag variable along with the lead variable can explain up to 52.7981 percent. The inputs in $R_{i,AB,kt}$ submit its robustness in determining long–short returns in the market place. The investors also incorporate present development in the market strongly. These suggest that information and noise co-exists in the market.

II. x. Carin.LTD

For the case of CARIN.LTD, in a cubic forecasting, lag explanatory variable $R_{i,AB,kt-1}$ can explain the variable $R_{i,AB,kt}$ to an extent of Adj. R^2 of 27.0086 percent while $R_{i,AB,kt}$ in a similar setting can explain the lead variable $R_{i,AB,kt+1}$ about 44.2895 percent. That is, at presence of homogeneous *j* th group of investors with long-short strategy, today's perception serves more in explaining tomorrow's decision choices than the role of past perceptions for today's choices. On long-short positioning at presence of heterogeneous traders in model 12.A, the explanatory variable $R_{i,AB,kt}$ alone can explain 63.7231 percent of the variable $R_{j,AB,kt}$ while the lag (lead) variable viz., $R_{i,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain 43.5394 (43.0821) percent. These observations suggest that past (future) references (expectations) about events therefore serve lesser relevance in the price formation process than that at present events. On the contrary, the explanatory variable $R_{i,AB,kt}$ along with its lead variable can explain $R_{j,AB,kt}$ up to 70.0063 percent while the same explanatory variable along with its lag variable can explain about 77.3518 percent. That is, the effect of today along with that of tomorrow is mostly less equivalent to the same along with yesterday. Further, the effect of the variable $R_{i,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 82.2817 percent while it is interesting to note that the lag variable along with the lead variable can explain up to 73.5667 percent. This observation shows that variable $R_{i,AB,kt}$ has substantial effects in long–short returns and the same should be incorporated even if reference frames with regard to observed past data and future expectations explains the returns robustly. These observations confirm the predictions of noise traders' risks.

In model 12.B, the cubic forecasting, the lag explanatory variable $R_{j,AB,kt-1}$ can explain the variable $R_{j,AB,kt}$ to an extent of Adj. R^2 of 33.5656 percent while $R_{j,AB,kt}$ can explain the lead variable $R_{j,AB,kt+1}$ up to with the Adj. R^2 of 32.7715 percent in similar expression of forecasting. That is, at homogeneous traders of *j* th group of investors with long-short strategy, today's observations serve mostly equal representation for tomorrow with respect to that by past's observations to represent the today's' decisions. However, at presence of heterogeneous traders, the results are somewhat different. The variable $R_{j,AB,kt}$ alone can explain 63.7231 percent of the variable $R_{i,AB,kt}$ while its lag (lead) variable viz., $R_{j,AB,kt-1}$ ($R_{i,AB,kt+1}$) alone can explain about 50.2067 (45.4393) percent. The past (future) observations (expectations) serve less relevance in determining decision references than that with the present. The results further show that the explanatory variable $R_{j,AB,kt}$ along with its lead variable can explain $R_{i,AB,kt}$ up to 73.9879 percent while the same variable along with its lag can explain about 77.3349 percent. Therefore, the effect of today and yesterday is higher than the same of today and tomorrow and this suggests that there is less substantial flow of new expectations within the two markets. Further, the effect of the variable $R_{j,AB,kt}$ along with the lag and lead variables, the explanatory power raises up to 86.9521 percent while lag variable along with the lead variable can explain up to 80.8832 percent. The inputs in $R_{i,AB,kt}$ submit its robustness in determining long–short returns in the market place. The investors also incorporate present development in the market strongly. These suggest that information and noise co-exists in the market.

Conclusion

In explaining the investors' behaviors in their stock market trades with intraday trading data, the present study has followed an ingenious framework. It firstly described the issues involved in investors' decision marking from the behavioral points of arguments, and the methodologically developed a theoretical model, then defined the theoretical propositions, then specified the equilibrium pricing mechanism, and then the empirical methodology, proxy variables, and data. Theoretically the study argues that noise in pricing of assets is pervasive and it makes trades happen in the market place but restrict the "monopolistic power" of the informed traders. In the theoretical model the paper has put forward an innovative formulation for a trade in the market place at presence of information and noise. It further has decomposed the elements of noise to be systematic and firm-specific ones. Therefore with two group of informed traders (the *i* th and the *j* th) at presence of their homogeneous and heterogeneous classifications, it is theoretically showed that one trader's long-short position in a market for a stock with dual listing in two separate stock markets (the NSE and the BSE) could be explained by the other traders' long-short position in the other market. However, the necessary condition is that there must be perfect stocks to be traded in the two markets and the sufficient condition is that there are heterogeneous groups of the both group of traders to take position with the other groups. The novelty of the theory is that it suggests that keeping apart the standard finance concept of systematic risk as proposed in the Capital Asset Pricing Model (CAPM), stock trading and the returns and risk relationships could be explained by the risks of noise, which are (i) *idiosyncratic fundamental shock,* (ii) *systematic fundamental shocks,* (iii) *systematic noise shocks,* and (iv) *Idiosyncratic noise shocks.* Therefore, the study sets forth two theoretical propositions that at different habitats information and noise both persist in the stocks' intraday returns and volatility.

The empirical observations show that investors' intraday returns at long-short positions could be explained by the above shock components. The explanatory power of the *idiosyncratic fundamental shock* is robust and it could explain to an extent of 97.41 % to 96.58 % for BHARATIARTL.LTD. The second and third noise components that is, systematic *fundamental shocks* and *systematic noise shocks* can explain moderately to an extent of 25% to 30%. However, the *idiosyncratic noise shocks* can explain up to 15% of the returns. The findings of the paper with intra-day returns derived from 1D and 5D data are mostly similar in nature. Both impound a significant level of noise. However, with the daily return (weekly) returns the study observes high (moderate) exposures to noise. The findings of conditional volatilities of long-short returns from the GARCH models show that the estimate of time-varying idiosyncratic noise is highly persistent at presence of noise traders in the equilibrium pricing mechanism. The study therefore concludes that stocks' prices impound information as well as noise in the market places during four distinct trading days.

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