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Foreign institutional investments in India: An empirical analysis of dynamic interactions with stock market return and volatility

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Abstract This paper investigates interactions of foreign institutional investments with market returns and market volatility in India using both static and dynamic models based on daily data. The findings of both models show foreign investors as positive feedback traders while investing in the Indian market, and as negative feedback traders during their withdrawal. Using the impulse response functions based on vector autoregression, we find strong evidence that foreign institutional investments destabilise the market, particularly with selling activities, as they significantly increase the volatility.

Introduction

Foreign investment flows to the Indian capital market have surged after the global financial crisis due to continuous stimulus measures from the US Federal Reserve in the form of quantitative easing. India has witnessed the highest inflow of foreign institutional investments (FIIs) in 2010 and 2012 in the aftermath of the opening of the liquidity taps, which did not happen during 2006 or 2007 (the boom years). During November 2013, Nifty climbed over the level of 6415.25, when FIIs purchased more than US$51.67 million of Indian stocks in just three months.[1] When Ben Bernanke, the chairman of the Federal Reserve of the USA, triggered hints about the cutbacks in monthly bond purchase during first week of January, the market drifted below 6000 level on the ground and FIIs started liquidating long positions and created short positions

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[1] Bureau, ET. Busting myths: Why it makes little sense to worry over FII selling. *The Economic Times*. Retrieved from http://articles.economictimes.indiatimes.com/2013-11-26/news/44486803_1_net-sellers-fiis-indian-stocks.

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of over US$16.67 million in the Futures & Options market.[2]

Along with some of the Emerging Market Economies (EMEs) like Brazil, China and Korea, India witnessed a preponderance of portfolio flows due to liberal investment regimes, rapid growth of economy, and strong macro-economic fundamentals. According to a survey conducted by the Japan Bank of International Corporation (JBIC), India has been ranked as the most preferred destination for future investments, with Indonesia and China at second and third ranks respectively.[3] The rapid increase in global liquidity and the large scale net portfolio flows to emerging countries have raised serious concerns in the recipient countries about the adverse effects. These include the danger of overheating, inflationary pressure on consumer and asset prices, exchange rate appreciation pressures, and risk of financial instability. Foreign institutional investors commenced investing in India in 1990, and since then they have been dogged by the perception that one day they will leave the country in search of newer emerging markets. It became a matter of concern in policy making circles, in particular because of the upward pressure on real exchange rates and monetary aggregates that made portfolio inflows potentially as destabilising as outflows (Calvo, Leiderman, & Reinhart, 1993). This perception turned into panic during 2008–2009 when FIIs withdrew US$142,635 million. The FIIs behaved like a flock of geese, which flee at the sound of the first gun shot. In much of the literature, international capital flows are portrayed as the main culprit (Calvo, 1998; Stiglitz, 1999; Taylor & Sarno, 1997), as sudden reversal of such flows potentially destabilises the financial market in the recipient country and spreads through contagion effect and spillovers to other countries. There seems to be consensus amongst market experts and academicians that capital inflow in the form of FIIs is temporary and short lived, and does not indicate the financial strength of any economy.[4] Another concern of the capital market authority (Security and Exchange Board of India) has been the substantial decline in domestic investments by home country corporations and individual investors since 2007–2008.

Given this background the study focuses on relationships between foreign institutional investment flows and domestic (Indian) equity returns and volatility in India. It deals with two questions: (1) Do foreign investors pursue feedback trading strategies? (2) Do FIIs adversely affect the performance of the Indian capital market in terms of volatility? While several studies have been carried out to understand the behaviour of foreign portfolio flows towards emerging markets, to the best of our knowledge, this paper is the first in-depth study attempting to explain such a relationship of FIIs with both capital market returns and volatility in India. Further, it also determines and delineates the effects of futures trading activities of FIIs on the Indian capital market along with their gross trading activities (cash plus derivatives). Another contribution of this study stems from the data, as it uses longitudinal data on a daily basis from January 2004 to September 2012, which has been bifurcated into six types of flows (series). Such extensive data, particularly data set related to FIIs futures trading activities, we submit, have not been utilised in any previous research.

The paper is structured as follows. The second section summarises several key studies and relevant literature review briefly. The third section explains data and empirical methodology. The empirical findings of the study are discussed in the fourth section and conclusions follow in the fifth section.

Literature review

Earlier studies predominantly typecast foreign institutional investors in capital markets as feedback traders or portfolio rebalancers. Much of the literature suggests the existence of positive correlation between foreign institutional investment flows and lagged local equity returns, which portrays foreign investors as positive feedback traders. For instance, Brennan and Cao (1997) using quarterly data, Clark and Berko (1997), Stulz (1999) and Bekaert, Harvey, and Lumsdaine (2002) using monthly data, and Froot, O'connell, and Seasholes (2001) using daily data support the same findings irrespective of the data they utilised. Choe, Kho, and Stulz (2001) also report that foreign investors indulged in negative feedback trading during the Asian crisis. Bohn and Tesar (1996) argue that capital flows are motivated by "chasing" high expected returns rather than portfolio rebalancing motives. They enter the market that possesses high expected returns and run away from the market that yields low expected returns. Richards (2005) opined that observed feedback trading might be due to behavioural factors rather than portfolio rebalancing. On the other hand, Griffin, Nardari, and Stulz (2004) find portfolio rebalancing effects and argue that foreign investors are likely to increase their holdings in emerging economies following increase in prices of assets in their home markets. Much academic literature has concentrated on similar relationships in the Indian capital market. Chakrabarti (2001); Mukherjee, Bose, and Coondoo (2002); Ahmad, Ashraf, and Ahmed (2005); and Kumar (2009) detect that foreign equity flows are highly correlated with market returns in India, and they are more likely to be the effect than the cause of these returns. These findings are in line with findings of research in Asian markets discussed earlier. The dependence of net FII flows on daily return in the domestic equity market, at a day's lag, is suggestive of foreign investors' feedback trading behaviour. Gordon and Gupta (2003) uncover significant negative relationship between monthly flows and lagged returns. This suggests negative feedback trading. The result of Ananthanarayanan, Krishnamurti, and Sen (2009) is consistent with the

[2] Baruah, Biswajit. FIIs start building shorts, sell longs in futures. *The Economic Times*. Retrieved from http://articles.economictimes.indiatimes.com/2014-01-09/news/46029966_1_long-positions-bank-nifty-nifty-futures.

[3] Bureau, The Hindu Business Line. Japanese manufacturers rank India as most preferred investment destination. Retrieved from http://www.thehindubusinessline.com/economy/japanese-manufacturers-rank-india-as-most-preferred-investment-destination/article6793679.ece.

[4] See, for instance, G. A. Calvo (1998), Dornbusch and Werner (1994) and Dornbusch, Goldfajn, Valdés, Edwards, and Bruno (1995).

base-broadening hypothesis,[5] but does not find compelling confirmation regarding momentum or contrarian strategies being employed by FIIs. Further, they reject the claim that foreign investors destabilise the market. Foreign investors have the ability to play as market makers given their volume of investments (Suresh Babu & Prabheesh, 2008), and there exists unidirectional causality running from FII to stock returns only during post 2003 (Takeshi, 2008), which is in contrast to past studies carried out on the Indian economy.

Another aspect of the study is to analyse the effect of FIIs on stock market volatility, an area where little work has been done. Stulz (1999) finds weak evidence of adverse effect of foreign investments on performance of the equity market. Hamao and Mei (2001) suggest that foreign investors improve market liquidity but find little evidence of increase in market volatility. Wang and Shen (1999) support the same findings that foreign investments mildly increase the volatility of the Taiwan stock market and show existence of destabilising effect. James and Karoglou (2010), after identifying structural break using CUSUM (cumulative sum) test, suggest that stock market volatility decreased after the opening of the stock market to foreign participants and increased at the time of the Asian crisis. Ananthanarayanan et al. (2009) do not find any substantiation for the claim that foreign investors destabilise the Indian market.

Given this background, this study improves upon several aspects of previous studies. (1) Prior research in the Indian context concentrated only on trading–return interactions; this study considers trading–volatility (of index return) interactions along with the trading–return interactions. (2) The study utilises Threshold generalised autoregressive conditional heteroscedasticity (TARCH) model to measure return volatility, which accounts for time varying (conditional) volatility with leverage effects. (3) To check the destabilising effect, it considers impulse response function for both trading-return and trading-volatility interactions.

Data and methodology

To provide a comprehensive account of the FII trading activities, stock market return and its volatility, daily data have been analysed. India has an efficient and permanent system of capital controls (Patnaik & Shah, 2012). The Security Exchange Board of India (SEBI) compiles the FII-related data on the basis of reports submitted by the custodian banks, National Stock Exchange of India (NSE) and Bombay Stock Exchange of India (BSE). Data related to FII trading activities have been bifurcated broadly into gross flows[6] and futures flows.[7] Further, the gross flows of FIIs are categorised as inflow (FIII), outflow (FIIO) and net flow (FIIN), and FII flows in futures market are categorised into futures buy (FIIFB), futures sell (FIIFS) and futures open interest (FIIFOI). The analysis uses Nifty index for computing Indian stock market return and its volatility, as it dominates the index derivatives and is termed as the benchmark index representing the whole of the Indian capital market. Nifty return is computed using logarithmic difference of closing price on a daily basis. The data set consists of 2121 observations for the period ranging from 1 January 2004 to 30 September, 2012 for seven series or variables, viz. FIII, FIIO, FIIN, FIIFB, FIIFS, FIIOI and Nifty (returns). Only working days are considered in the sample.

As the time series analysis necessitates fulfilling stationarity assumption, stationarity has been checked using augmented Dickey-Fuller and Phillips-Perron unit root tests. Results of both tests suggest that all FIIs series are trend stationary, whereas Nifty is stationary at first difference. Therefore, FIIs series can be represented as *I(0)* and Nifty as *I(1)*. Further, Ljung–Box *Q*-statistic is used to verify that there are no significant autocorrelations among the residuals. Optimal lag length is determined using Akaike information criterion (AIC) and Schwarz Bayesian criterion (BIC).

To analyse the trading-volatility interactions, the volatility of Nifty return has been estimated using ARMA–TARCH model, as the series possesses volatility clusters. ARMA is an autoregressive integrated moving average model, which estimates the mean equation. TARCH stands for threshold autoregressive conditional heteroscedasticity model, which measures the conditional (time varying) variance. The volatility estimation model for Nifty returns is as follows.

The daily return r_t for Nifty index has a statistically significant lag-1 autocorrelation suggesting Nifty series as *AR(1)*[8] process.

$$r_t = \phi_0 + \phi_1 r_{t-1} + a_t \tag{1}$$

where $\{a_t\} \sim iid\ N(0, \sigma_a^2) =$ white noise.

AR(1) model implies that, conditional on past return r_{t-1}, we have

$$E(r_t | r_{t-1}) = \phi_0 + \phi_1 r_{t-1}, \tag{2}$$

$$Var(r_t | r_{t-1}) = Var(a_t) = \sigma_a^2 \tag{3}$$

That is, given the past return r_{t-1} the current return is centred around $\phi_0 + \phi_1 r_{t-1}$ with standard deviation σ_a. To put the volatility models in proper perspective and to capture clustering effect, the conditional mean and variance of r_t, given r_{t-1}; is,

$$\mu_t = E(r_t | r_{t-1}) = \frac{\phi_0}{1-\phi_1} \tag{4}$$

[5] The theory behind the base-broadening hypothesis suggests that the expansion of investor base to include foreign investors leads to increased diversification followed by reduced risk and consequently the lowering of the required risk premium. Thus there is a permanent increase in the equity share price through risk pooling (Merton, 1987).

[6] Gross flow is an aggregate flow towards Indian capital market irrespective of primary or secondary market and cash or derivatives segment.

[7] Here only FIIs trading activities in index futures have been considered, because their long or short positions in index futures clearly defines what they perceive about overall Indian economy, whether bullish or bearish.

[8] Box and Jenkins' (1976) strategy is adopted for appropriate selection of ARMA model.

$$\sigma_t^2 = Var(r_t|r_{t-1}) = E\left[(r_t - \mu_t)^2 \middle| r_{t-1}\right] \quad (5)$$

The ARCH model of Engle (1982) provides a systematic framework for volatility modelling. The underlying idea is that the shock a_t of an asset return is serially uncorrelated, but dependent and dependence of a_t is a simple quadratic function of its lagged values. For ARCH*(m)* model,

$$a_t = \sigma_t \epsilon_t,\ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots \alpha_m a_{t-m}^2 \quad (6)$$

where $\{\epsilon_t\}$ is a series of independent and identically distributed random variables with mean 0 and 1, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$.

$$a_t = \epsilon_t \sqrt{\alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2} = \epsilon_t \sqrt{h_t},\ \text{where } h_t = \sigma_t^2 \quad (7)$$

ARCH model suffers from several weaknesses (Tsay, 2002), so to overcome some of them Bollerslev (1987) proposed an extension to ARCH, known as generalised ARCH (GARCH) model. For a log return series r_t, let $a_t = r_t - \mu_t$, be the innovation at time t. Then a_t follows a GARCH*(m,s)* model, if

$$a_t = \sigma_t \epsilon_t,\ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \quad (8)$$

where $\{\epsilon_t\}$ follows the same properties as discussed for ARCH model, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ for $i > 0$, and $\sum_{i=1}^{max(m,s)} (\alpha_i + \beta_j) < 1$; the latter constraint on $\alpha_i + \beta_j$ implies that the unconditional variance of a_t is finite, whereas conditional variance σ_t^2 evolves over time.

The superiority of GARCH over ARCH model is that the model provides a simple parametric function that is more parsimonious than ARCH*(m)* and can be used to describe the volatility evolution, but it encounters the same weakness as the ARCH model. For instance, it responds equally to positive and negative shocks, and does not capture the leverage effect, which is obvious for price of financial assets. To overcome this weakness Glosten, Jagannathan, and Runkle (1993) proposed threshold GARCH (or TGARCH/TARCH) model. Table 1 shows the superiority of TARCH model over ARCH and GARCH models as the log likelihood and adjusted R-squared values are highest for TARCH*(1,1)* model.

It is observed that volatility tends to increase more when the stock market index decreases than when it increases by the same amount. Cappiello, Engle, and Sheppard (2006) state that asymmetric volatility can be explained by two models: leverage effect and time-varying risk premium (volatility feedback). The reason for such a phenomenon may be when the equity price falls, the debt remains constant in the short term and increases the debt/equity ratio. The firm becomes highly leveraged, making the future of the firm quite uncertain, thus the equity price becomes more volatile (Black, 1976). Alternatively Campbell and Hentschel (1992) and Wu (2001) argue that if volatility is priced, an expected increase in volatility raises the required return on equity, leading to an immediate stock price decline. Bekaert and Wu (2000) show that when combining these two explanations in an empirical model, often the coefficient linking volatility to expected return is insignificant, and the sign is different depending on the study. And also, that the leverage effect alone does not adequately explain the changes in volatility after a decrease in the asset price. Finally, De Goeij and Marquering (2004) give a third explanation, described as herd effect based on psychological behaviour. Investors might pay less attention to the market fundamentals during a stock market crash, and therefore sell their stocks if others are selling. Bae, Kim, and Nelson (2007) also explain the negative relationship between stock returns and volatility.

Table 1 Diagnostic check of estimated models for volatility of Nifty returns.

Models	ARCH(4)	GARCH(1,1)	TARCH(1,1)
AIC	−5.5818	−5.6098	−5.6298
SBC	−5.5605	−5.5964	−5.6138
Log likelihood	5921.9650	5948.5710	5970.7670
Adjusted R-squared	−0.0002	0.0005	0.0018

Note: AIC, Akaike information criterion; SBC, Schwarz Bayesian criterion.

For TARCH(m,s) model,

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s} (\alpha_1 + \gamma_1 N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2 \quad (9)$$

where N_{t-i} is an indicator for negative a_{t-i}, that is,

$$N_{t-i} = \begin{cases} 1, & if\ a_{t-i} < 0 \\ 0, & if\ a_{t-i} \geq 0 \end{cases}$$

α_i, β_j, and γ_i are non-negative parameters satisfying the conditions similar to those of GARCH models. Hence, positive a_{t-i} contributes $\alpha_i a_{t-i}^2$ to σ_t^2, whereas negative a_{t-i} has larger impact $(\alpha_i + \gamma_i) a_{t-i}^2$ with $\gamma_i > 0$. Zero is used as a threshold to separate the impacts of past shocks. Volatility of Nifty returns is modelled as TARCH(*1,1*) process and takes the following form:

$$\sigma_t^2 = V_t = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1}) a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (10)$$

Volatility series of Nifty returns so obtained is used for analysing trading-volatility interactions. To achieve the aforesaid objectives, the following models are estimated, where "*R*" represents the Nifty returns, "*F*" represents all six types of foreign flows and "*V*" represents the volatility of Nifty returns estimated through TARCH (*1,1*) model.

Flow–return interactions

Feedback trading (return chasing) using simple regression

Warther (1995) proposed the following methodology to investigate feedback trading. Feedback trading argues that current FII flows are affected by past equity returns as FIIs chase returns in foreign markets.

$$F_t = \Theta_0 + \psi_t R_{t-1} + \theta_t \quad (11)$$

where Θ_0 is a k-dimensional vector, ψ_t is a $k \times k$ matrix, and $\{\theta_t\}$ is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix Σ. Positive feedback trading requires $\psi_t > 0$, and negative feedback trading requires $\psi_t < 0$.

Contemporaneous cross-correlation

The cross-correlation matrices are used to measure the strength of linear dependence between FII flows and Nifty return series. The lag-l cross-covariance matrix of R_t is defined as

$$\Gamma_l \equiv [\Gamma_{ij}(l)] = E[(F_{i,t} - \mu)(R_{j,t-l} - \mu)'] \quad (12)$$

where μ is the mean vector of F_t. Therefore, the (i, j)th element of Γ_l is the covariance between $F_{i,t}$ and $R_{j,t-l}$. The cross-covariance matrix Γ_l is a function of l, not the time index t. The lag-l cross-correlation matrix of $F_{i,t}$ is defined as

$$\rho_l \equiv [\rho_{ij}(l)] = D^{-1}\Gamma_l D^{-1} \quad (13)$$

where D is the diagonal matrix of standard deviations of the individual series $F_{i,t}$ and correlation coefficient ρ_l of (i, j)th element is

$$\rho_{ij}(l) = \frac{\Gamma_{ij}(l)}{\sqrt{\Gamma_{ii}(0)\Gamma_{jj}(0)}} = \frac{Cov(F_{i,t}R_{j,t-l})}{std(F_{i,t})std(R_{j,t-l})} \quad (14)$$

If $\rho_{ij}(l) \neq 0$ and $l > 0$, it implies that the series $R_{j,t}$ leads the series $F_{i,t}$ at lag l. Similarly, $\rho_{ji}(l)$ measures the linear dependence of $R_{j,t}$ and $F_{i,t}$, and it suggests that the series $F_{i,t}$ leads the series $R_{j,t}$ at lag l if $\rho_{ji}(l) \neq 0$ and $l > 0$.

Static analysis using Granger causality

To eliminate the possibility of a simultaneity bias in the model, Granger causality test is used. It uses standard F-test of restriction:

$$a_{21}(1) = a_{21}(2) = a_{21}(3) = \ldots = a_{21}(p) = 0 \quad (15)$$

In a two equation model with p-lags, $R_{j,t}$ does not Granger cause $F_{i,t}$, if and only if all the coefficients of the polynomial $A_{ij}(L)$ are equal to zero, where $A_{ij}(L)$ represents the coefficients of lagged values of variable j on variable i.

Dynamic analysis using bivariate vector autoregression (BVAR)

For checking flow-return interactions BVAR(2) model is estimated. It consists of the following equations:

$$F_t = \phi_{10} + \psi_{11}F_{t-1} + \psi_{12}F_{t-2} + \pi_{11}R_{t-1} + \pi_{12}R_{t-2} + \Omega_t \quad (16)$$

$$R_t = \phi_{20} + \psi_{21}F_{t-1} + \psi_{22}F_{t-2} + \pi_{21}R_{t-1} + \pi_{22}R_{t-2} + \Omega_t \quad (17)$$

where ϕ_0 is a 2-dimensional vector, ψ is a 2×2 matrix, and $\{\Omega_t\}$ is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix Σ. ψ_{ij} and π_{ij} are the (i, j)th element of ψ and π, respectively. Based on the first equation, π_{11} and π_{12} denote the linear dependence of F_t on R_{t-1} and R_{t-2} in the presence of F_{t-1} and F_{t-2}. Similarly, ψ_{21} and ψ_{22} denote the linear dependence of R_t on F_{t-1} and F_{t-2} in the presence of R_{t-1} and R_{t-2}.

Impulse response function

The impulse response function (IRF) is used to analyse the impact of innovations from all the explanatory variables to produce the time path of the dependent variables in the VAR. If the system of equations is stable, any shock should decline to zero or die out gradually. An unstable system would produce an explosive time path. Choleski decomposition is used to trace the time path of the effect of structural shocks on the dependent variables of the model. For this model IRF is based on Equation (16).

Flow-volatility interactions

Flow–volatility interactions are analysed using the above models, by replacing Nifty returns series R_t with volatility series of Nifty returns V_t (estimated as TARCH(1,1)). The difference is with regard to the research objective—earlier models described feedback trading behaviour, while the latter attempted to analyse destabilising effects.

Destabilising effect

To check the contemporaneous destabilising effect, F_t is included as an exogenous variable in the estimated variance equation for Nifty returns using TARCH (*1,1*) model in Equation (10). Thus, the model is represented as follows:

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1})a_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \delta_t F_t \quad (18)$$

Contemporaneous cross correlation

Cross correlation coefficients are estimated as follows:

$$\rho_{ij}(l) = \frac{\Gamma_{ij}(l)}{\sqrt{\Gamma_{ii}(0)\Gamma_{jj}(0)}} = \frac{Cov(F_{i,t}V_{j,t-l})}{std(F_{i,t})std(V_{j,t-l})} \quad (19)$$

Static analysis using Granger causality

Similarly, Granger causality checks for lead-lag relationship between the two variables $F_{i,t}$ and $V_{j,t}$ are carried out.

Dynamic analysis using bivariate vector autoregression (BVAR)

The following pair of equations have been estimated to see the effect of variables ($F_{i,t}$ and $V_{j,t}$) on each other at lag 1 and 2 in the presence of their own two lags.

$$F_t = \phi_{10} + \psi_{11}F_{t-1} + \psi_{12}F_{t-2} + \pi_{11}V_{t-1} + \pi_{12}V_{t-2} + \Omega_t \quad (20)$$

$$V_t = \phi_{20} + \psi_{21}F_{t-1} + \psi_{22}F_{t-2} + \pi_{21}V_{t-1} + \pi_{22}V_{t-2} + \Omega_t \quad (21)$$

Impulse response function

Impulse response function is based on the estimated Equation (21).

Empirical findings

Flow-return interactions

Feedback trading (return chasing) using simple regression

Table 2 represents the results of feedback trading behaviour of FIIs. The results suggest the existence of concurrent relationship between FIIs and Nifty returns. FIII and FIIN reflect positive feedback trading by foreign investors. When it comes to selling activities, irrespective of cash segment or futures

Table 2 Feedback trading for foreign institutional investments and Nifty returns.

Exogenous variable	Endogenous variables	
	Intercept(Θ_0)	$R_{t-1}(\psi_t)$
FIII	−2.03692	5483.003*
FIIO	5.072859	−8048.78*
FIIN	−7.12371	13559.41*
FIIFB	−0.04629	958.194
FIIFS	6.075432	−11192.5*
FIIFOI	7.781944	−7180.3

Note: Test results for feedback trading are based on the following equation: $F_t = \Theta_0 + \psi_t R_{t-1} + \theta_t$. Here F_t represents different daily FII series viz as FIII (inflow), FIIO (outflow), FIIN (net flow), FIIFB (futures buy), FIIFS (futures sell) and FIIFOI (futures open interest) at time t, R_{t-1} represents daily Nifty returns at time *t-1*, Θ_0 is intercept coefficient and ψ_t is slope coefficient. "*" indicates significant value at 5% level.

segment, they are negative feedback traders, while no concurrent relationship is noticed for FIIFB (long position in futures market) and FIIFOI (open interest in futures market) from Nifty returns.

Contemporaneous cross-correlation

Table 3 shows the cross correlation coefficients estimated up to 10 leads and lags of FIIs. Negative and positive integers in the first column refer to the lags and leads of FIIs. Lag (*i*) refers to the number of times FIIs lag stock returns, which implies that the return of Nifty at time *(t-1)* influences the FIIs at time t. Likewise, Lead (*i*) refers to number of times FIIs lead stock returns implying that the FIIs at time *(t-1)* influence the Nifty return at time t. The results show the statistically significant lead coefficients of FIII, FIIFB and FIIFS, FIIO and FIIN have both lead and lag significant cross correlation coefficients implying cause and effect relationship coming from both variables, FIIs and Nifty. The only statistically significant cross correlation coefficient at lag 1 for FIIO and FIIN exhibit their behaviour as feedback traders. The reason for the results of FIII, FIIFB and FIIFS might be the herd effect (De Goeij & Marquering, 2004). Tayde and Rao (2011) also support the findings that FIIs exhibit herding and positive feedback trading while investing in India.

Static analysis using Granger causality

Table 4 provides the results of Granger causality test based on bivariate VAR framework. The results show the presence of unidirectional causality from Nifty returns to FIII and FIIFS, whereas there is bidirectional causality running between FIIO and Nifty returns, and FIIN and Nifty returns. The null hypothesis "Nifty does not Granger cause FII flows" is rejected for FIII, FIIO, FIIN and FIIFS. This suggests that Nifty contains useful information for FII flow and that the FIIs are involved in feedback trading.

Dynamic analysis using bivariate vector autoregression (BVAR)

Table 5 shows the results of vector autoregression for different FII series and Nifty returns. The results show that all the series are better explained by their own lagged values.

Table 3 Contemporaneous cross-correlation between foreign institutional investments and Nifty returns.

Lag/Lead (*k in* $F_{i,t\pm k}$)	$\rho_{i,j}(l)$					
	FIII	FIIO	FIIN	FIIFB	FIIFS	FIIFOI
−10	−0.0154	−0.0376	0.0289	−0.0279	−0.0214	−0.0288
−9	−0.0364	−0.048*	0.0091	0.0077	−0.0239	−0.0219
−8	−0.0328	−0.0428*	0.0088	0.0046	−0.0149	−0.0187
−7	−0.0268	−0.0465*	0.0235	−0.0229	−0.0265	−0.0176
−6	−0.0064	−0.0321	0.0331	−0.0046	0.0057	−0.0146
−5	−0.0277	−0.0265	−0.0066	−0.0119	−0.0004	−0.015
−4	−0.0292	−0.0303	−0.0045	0.0134	0.0359	−0.0143
−3	0.0046	−0.0108	0.0213	0.0023	0.0171	−0.0191
−2	−0.0034	−0.0242	0.0284	0.025	0.024	−0.0288
−1	−0.0119	−0.0476*	0.0497*	0.0241	−0.0096	−0.0319
0	0.0722*	−0.1258*	0.289*	0.016	−0.1142*	−0.0351
1	0.0705*	−0.1169*	0.2735*	0.009	−0.1297*	−0.026
2	0.0323	−0.0537*	0.1244*	−0.0234	−0.064*	−0.0239
3	0.0294	−0.0505*	0.1166*	−0.0276	−0.0393	−0.0171
4	0.0207	−0.0315	0.0774*	−0.0509*	−0.0358	−0.0103
5	0.008	−0.0385	0.0722*	−0.0599*	−0.0349	−0.0064
6	0.0261	−0.0016	0.0446*	−0.0079	−0.0171	0.004
7	0.0371	−0.0192	0.0833*	−0.0415	−0.0264	−0.0017
8	0.0522*	−0.0054	0.0872	−0.0387	−0.0198	−0.0027
9	0.0368	0.0091	0.0451	−0.0472*	−0.0173	0.0091
10	0.0427*	0.0118	0.0509	−0.0159	−0.002	0.0067

Note: Asymptotic standard error for the cross correlation coefficients is ±0.04256. First column of the table denoted as "k" represents the lags/leads of FIIs. Here correlation is between R_t and $F_{t\pm k}$ and is denoted as $\rho_{i,j}(l)$. "*" represents significant cross correlation coefficient.

Table 4 Granger causality test between foreign institutional investments and Nifty returns.

Lags		$F_{i,t}$					
		FIII	FIIO	FIIN	FIIFB	FIIFS	FIIFOI
$R_{j,t}$	1	-	↔	↔	-	↑	-
	2	↑	↔	■	-	↑	-

Note: Single sided arrow shows unidirectional causality running from Nifty returns ($R_{j,t}$) to FIIs ($F_{i,t}$), and two-way arrow shows bidirectional causality between particular FII flow and Nifty returns. "-" indicates the absence of causal relationship at particular lag. Arrows represent significant F-statistics at 5% or 10% level. No. of lags have been determined using BIC criterion.

Table 5 Vector autoregression for foreign institutional investments and Nifty returns.

Endogenous variables	$FIII_t$ with R_t		$FIIO_t$ with R_t		$FIIN_t$ with R_t		$FIIFB_t$ with R_t		$FIIFS_t$ with R_t		$FIIFOI_t$ with R_t	
	$FIII_t$	R_t	$FIIO_t$	R_t	$FIIN_t$	R_t	$FIIFB_t$	R_t	$FIIFS_t$	R_t	$FIIFOI_t$	R_t
ϕ_{10}	0.0916		0.8024		−4.1235		2.9833		2.338		−0.9250	
ϕ_{20}		0.0005		0.000509		0.00052		0.000504		0.000505		0.000504
ψ_{11}	0.4805*		0.5304*		0.3017*		0.3964*		0.70255*		0.7673*	
ψ_{21}		−2.59E-07		−7.61E-07		9.11E-07		1.51E-07		−5.00E-07		−1.72E-07
ψ_{12}	0.1951*		0.2144*		0.1548*		0.1179*		−0.0327		0.2007*	
ψ_{22}		1.63E-07		1.04E-07		5.40E-07		1.64E-07		5.64E-07		6.07E-08
π_{11}	3055.5*		−2879*		8894.9*		175.53		−4378.1*		1975.68	
π_{21}		0.05492*		0.04735*		0.039959		0.05269*		0.04886*		0.05227*
π_{12}	−1372.63		2577.18*		−597.09		−3076.23		2226.0		767.99	
π_{22}		−0.04606*		−0.05141*		−0.0659*		−0.04687*		−0.04626*		−0.04708*
Adj.R^2	0.3826	0.00312	0.4831	0.005101	0.2151	0.006047	0.2115	0.00367	0.4680	0.004215	0.924	0.003869
log like.	−17759.5	5584.718	−17313.2	5586.819	−17060.1	5587.826	−18675.5	5585.30	−17822.9	5585.875	−18225.8	5585.508

Note: Test results for vector autoregression are based on the following equation: $F_t = \phi_{10} + \psi_{11}F_{t-1} + \psi_{12}F_{t-2} + \pi_{11}R_{t-1} + \pi_{12}R_{t-2} + \Omega_t$, and $R_t = \phi_{20} + \psi_{21}F_{t-1} + \psi_{22}F_{t-2} + \pi_{21}R_{t-1} + \pi_{22}R_{t-2} + \Omega_t$. Here, F_t represents different daily FII flows at time t and R_t represents daily Nifty returns at time t. No. of lags has been determined using BIC criterion. "*" indicates significant value at 5% level.

FIII, FIIO, FIIN, and FIIFS are also significantly affected by the first lag of Nifty returns in the presence of their own lagged values up to lag 2. This provides robust evidence of feedback trading behaviour of the foreign investors. Further, as the statistically significant coefficients' values (π_{11}) for FIIO and FIIFS are negative, their liquidating activities prove them to be negative feedback traders. Low past Nifty returns motivate FIIs to be involved in a feedback trading process by redeeming their stake in the Indian market. However, the coefficients' values for FIII and FIIN are positive, depicting them to be positive feedback traders. In summary, stock market returns contain additional information about FIIs flow (spot and futures), while FIIs do not contain any additional information about the market returns implying that FIIs respond to changes in market returns.

Impulse response function

Fig. 1 presents the impulse response function for the estimated Equation (16) in the bivariate VAR model. Since the dynamic dependence of the FIIs on Nifty returns is moderate, the impulse response functions exhibit simple patterns and decay quickly almost at 5th lag for FIII, FIIO, FIIN and FIIFS. FIIFB and FIIFOI trace out the effect of one standard deviation shock to Nifty returns. The graph undoubtedly proves that FIIs in terms of FIII and FIIN are positive feedback traders, as F_t rises in period t and dies out slowly, whereas for FIIO and FIIFS, the negative off-diagonal elements of π for Nifty returns prove foreign investors to be negative feedback traders. The impact to Nifty returns is stronger in case of FIIO, FIIFS and FIIN, which supports the investor sentiment that it is easier to supply liquidity to a seller than to a buyer.

Flow-volatility interactions

Destabilising effect

Table 6 represents the contemporaneous relationships between the different FII flow series represented as F_t and estimated volatility series V_t for Nifty returns. The model is based on the estimated TARCH (*1,1*) process for Nifty returns, where FIIs are considered as one of the regressors in variance equation. All the considered exogenous variables in the equation are significant, which proves the existence of contemporaneous relationship between F_t and V_t. This implies FIIs affect the volatility of Nifty returns.

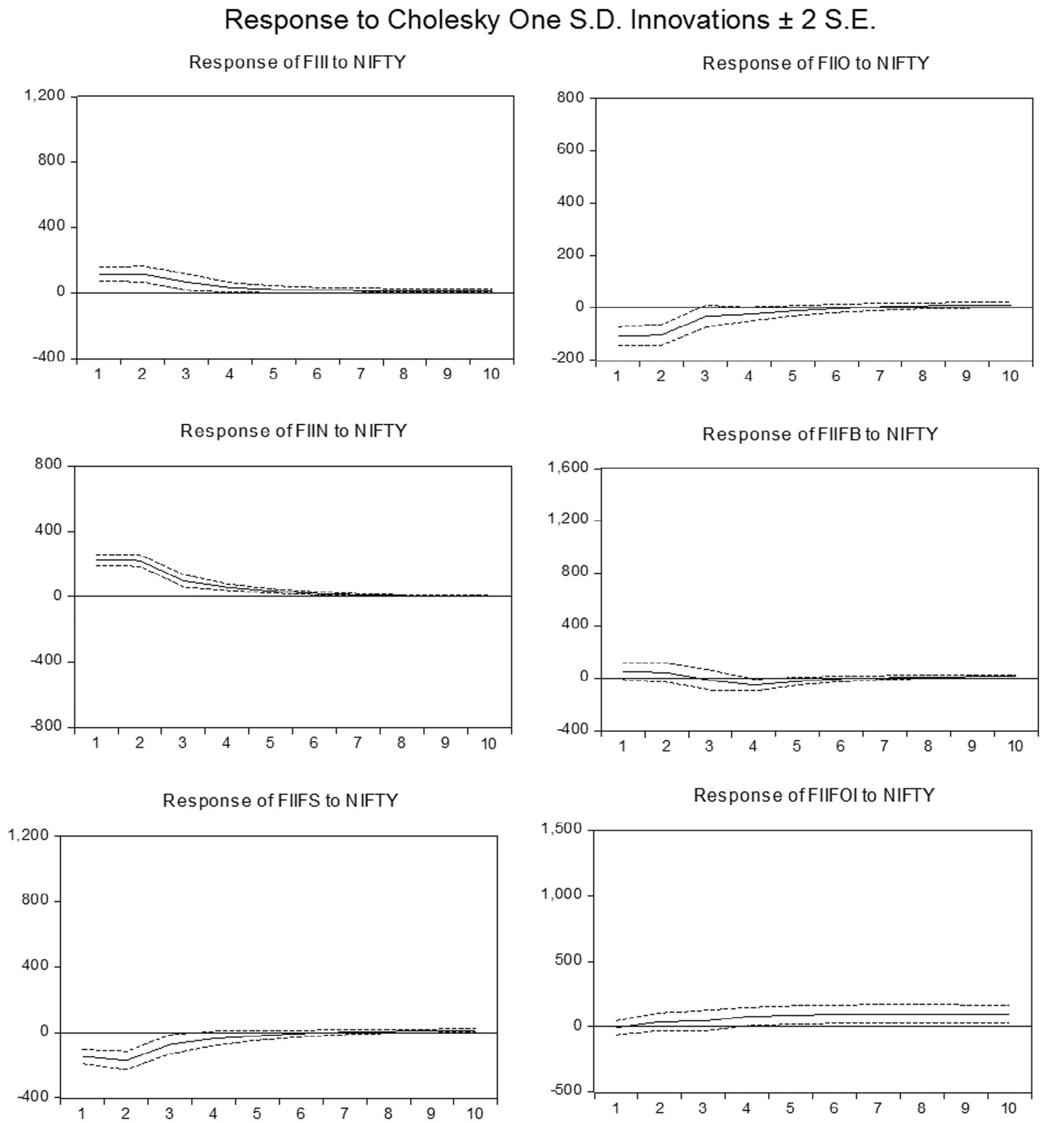

Figure 1 Response to Cholesky one S.D. innovation ± 2 S.E. Note: S.D. = Standard Deviation, S.E. = Standard Error.

Table 6 Destabilising effect of Nifty returns measured as TARCH (*1,1*).

V_t {TARCH(*1,1*)	α_0	α_1	γ_1	β_1	δ_t	SBC	Log like.
FIII $\rightarrow V_t$	6.65E-06	0.030198	0.152347	0.870073	3.13E-09	–5.62	5981.21
FIIO $\rightarrow V_t$	8.51E-06	0.039474	0.13723	0.860933	4.54E-09	–5.623	5984.29
FIIN $\rightarrow V_t$	7.47E-05	0.15	0.05	0.599997	–2.13E-08	–5.484	5837.54
FIIFB $\rightarrow V_t$	7.12E-06	0.03995	0.152323	0.860173	1.55E-09	–5.612	5972.32
FIIFS $\rightarrow V_t$	7.60E-06	0.041767	0.145244	0.859407	2.73E-09	–5.615	5976.43
FIIFOI $\rightarrow V_t$	6.87E-06	0.039428	0.149572	0.862298	3.76E-10	–5.613	5973.82

Note: Test results for destabilising effect are based on the following equation: $\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1})a_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \delta_t F_t$. Here, F_t represents different daily FII flows at time t and V_t represents volatility of daily Nifty returns measured as TARCH (*1,1*) process at time t. α_0, α_1, γ_1, and β_1 represent coefficients for intercept, ARCH effect, TARCH effect and GARCH effect, respectively.

Table 7 Contemporaneous cross-correlation between FIIs and volatility of Nifty returns.

Lag/Lead (k in $F_{i,t\pm k}$)	$\rho_{i,j}(l)$					
	FIII	FIIO	FIIN	FIIFB	FIIFS	FIIFOI
−10	0.0975*	0.2394*	−0.1813*	0.0804*	0.1059*	0.1467*
−9	0.0915*	0.2381*	−0.1889*	0.0789*	0.106*	0.1441*
−8	0.0837*	0.2355*	−0.1975*	0.0827*	0.1127*	0.1424*
−7	0.0766*	0.2315*	−0.203*	0.0849*	0.1176*	0.1409*
−6	0.0717*	0.2299*	−0.2085*	0.0925*	0.1264*	0.1391*
−5	0.0704*	0.2347*	−0.2172*	0.0972*	0.1322*	0.1366*
−4	0.0677*	0.234*	−0.2205*	0.1068*	0.1404*	0.1329*
−3	0.0572*	0.2281*	−0.2288*	0.1095*	0.14*	0.1266*
−2	0.0559*	0.2214*	−0.2213*	0.1129*	0.1369*	0.1172*
−1	0.0463*	0.2073*	−0.2168*	0.1208*	0.1382*	0.1097*
0	0.0403*	0.178*	−0.1854*	0.1227*	0.1209*	0.1023*
1	0.0172	0.1363*	−0.1638*	0.1167*	0.0958*	0.0945*
2	0.0041	0.1069*	−0.1435*	0.1064*	0.0851*	0.0886*
3	−0.0033	0.0844*	−0.1236*	0.1029*	0.0821*	0.0831*
4	−0.0098	0.0697*	−0.1135*	0.09*	0.0699*	0.08*
5	−0.0188	0.0596*	−0.1137*	0.0751*	0.0533*	0.0774*
6	−0.0197	0.0564*	−0.1106*	0.0619*	0.0443*	0.0763*
7	−0.0241	0.0492*	−0.1076*	0.0507*	0.0323	0.0753*
8	−0.0279	0.0372	−0.0969*	0.0406	0.0228	0.0705*
9	−0.0324	0.0326	−0.0976*	0.0255	0.0097	0.0693*
10	−0.0384	0.0286	−0.1013*	0.0235	0.0085	0.0665*

Note: Asymptotic standard error for the cross correlation coefficients is ±0.04256. First column of the table denoted as "k" represents the lags/leads of FIIs. Here correlation is between V_t and $F_{t\pm k}$ and is denoted as $\rho_{i,j}(l)$. "*" represents significant cross correlation coefficient.

Contemporaneous cross-correlation

Table 7 shows the cross correlation coefficients estimated up to 10 leads and lags of FIIs with volatility of Nifty returns. The results show that most of the lead-lag statistics for cross correlations are significant except for a few in FIII, FIIO, FIIFB and FIIFS, which suggest robust positive contemporaneous cross correlation between FIIs and volatility of Nifty returns. The results are consistent with the results of Oh and Parwada (2007) for the Korean market. Further, these relationships are bidirectional and interdependent, and continue to exist even up to a minimum of five leads of FIIs except for FIII (where only lag coefficients of FIII are significant). These results also point towards the herd effect and feedback trading behaviour of FIIs (including FIII). Significant lead and lag coefficients of FIIs suggest that these flows might increase the volatility of market returns, and this increased volatility attracts more inflow/outflow of FIIs. The reason for this is that the increased volatility provides a better platform for the speculative activities of FIIs and these activities further increase the market volatility.

Static analysis using Granger causality

Table 8 provides the results of Granger causality test based on bivariate VAR framework for FIIs and volatility of Nifty returns. There is a unidirectional causality running from volatility of Nifty returns to FIII, which implies that the change in volatility does affect the aggregate inflow of FII into the market. There is a bidirectional causality running between FIIN and volatility of Nifty returns. These results of FIII and FIIN are in accordance with the explanations provided above that the FIIs engage in speculative activities and these flows are short lived. They take advantage of increased volatility and form the vicious circle that again boosts the volatility of market returns. These results also support the findings of Black (1986) and Lee, Shleifer, and Thaler (1991) that noise traders cause wide swings away from fundamentals and are an important factor in the overall market movement. Furthermore, the unidirectional causality from FIIO and FIIFS implies that the selling activities of FII certainly Granger cause the volatility of the Indian capital market, both to the cash and futures segments, providing evidence for the destabilising effects of FIIs.

Table 8 Granger causality test between FIIs and volatility of Nifty returns.

Lags		$F_{i,t}$					
		FIII	FIIO	FIIN	FIIFB	FIIFS	FIIFOI
$V_{j,t}$	1	→	←	↔	-	←	-
	2	→	←	↔	-	←	-

Notes: Single sided arrow shows unidirectional causality running from volatility of Nifty returns (represented as $V_{j,t}$) to FIII, and from FIIO and FIIFS to volatility of Nifty returns, and two-way arrow shows bidirectional causality for FIIN and volatility of Nifty returns. "-" indicates the absence of causal relationship at particular lag. Arrows represent significant F-statistics at the 5% or 10% level. Number of lags have been determined using BIC criterion.

Dynamic analysis using bivariate vector autoregression (BVAR)

Table 9 shows the results of vector autoregression for volatility of Nifty returns and different FII series. The R-squared

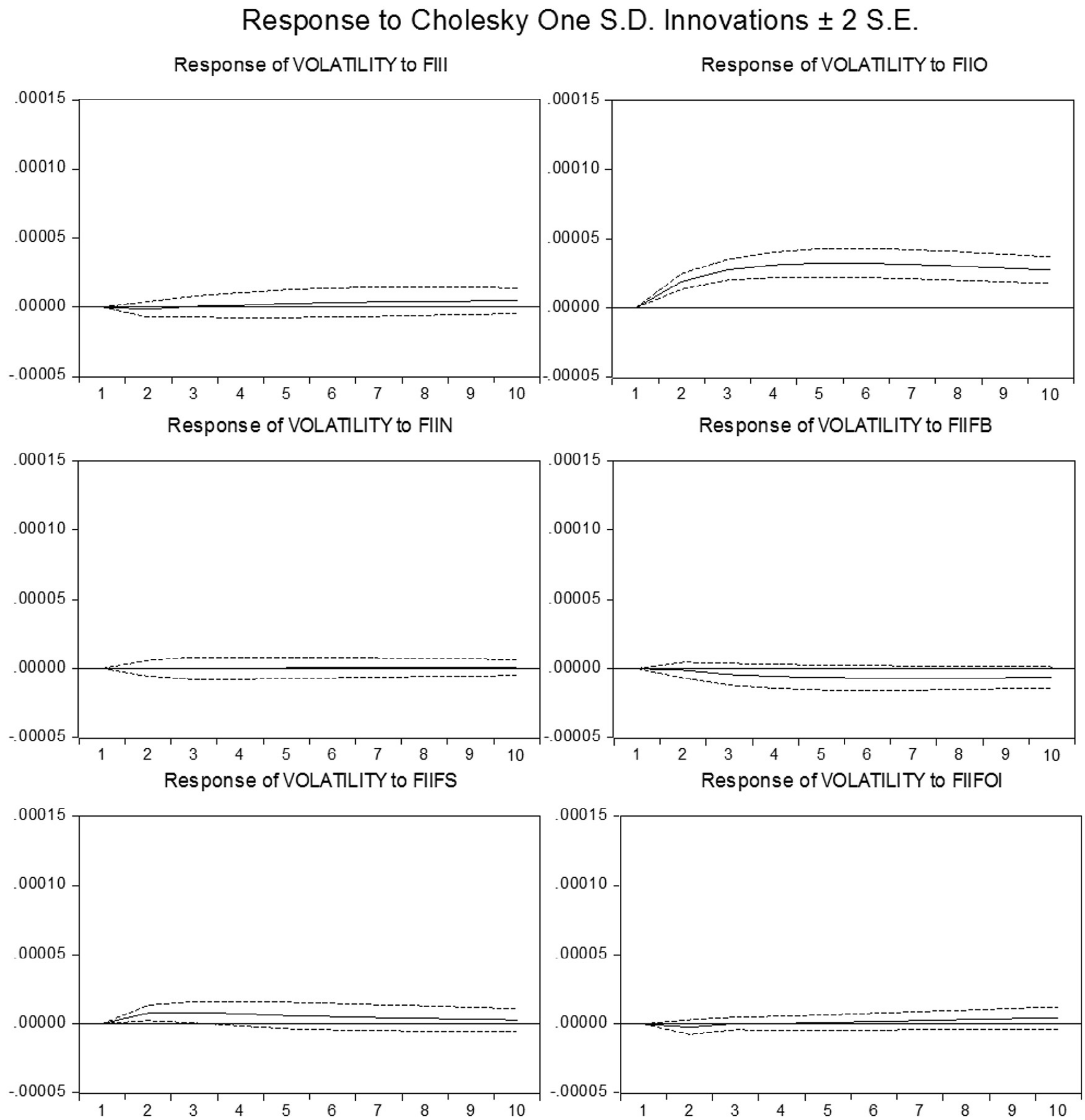

Figure 2 Response to Cholesky one S.D. innovation ± 2 S.E. Note: S.D. = Standard Deviation, S.E. = Standard Error.

values for all considered bivariate models are significantly high, which strongly supports the model. The results show that the variance of a particular series is mostly explained by its own lagged values, whereas the results of VAR using volatility of Nifty returns differ a lot from the results obtained using Nifty returns. The results, as discussed above, clarify feedback trading behaviour of FIIs getting affected by Nifty return. This reveals that FIIs do affect the volatility of Nifty returns, and volatility of Nifty returns is significantly affected by lagged values of FIIO, FIIN and FIIFS. FIII, FIIFB and FIIFOI do not exhibit such implications on volatility of Nifty returns. It is evident from Table 9 that almost 90 percent of volatility of Nifty returns is explained by the past volatility and lagged values of FIIO, FIIN and FIIFS. Further the coefficients of FIIO and FIIFS are positive which suggests that these flows increase the volatility of market returns. This signifies that selling activity of FIIs, in futures as well as equity market, has great impact on the variability of Nifty returns. It also ascertains the leverage effect or asymmetry prevailing in Nifty returns while treating the good and bad news. Bad news has significantly higher impact on volatility of Nifty returns.

Impulse response function

Causality can also be studied by tracing out the effect of an exogenous shock or innovation in one of the variables or all the other variables through multiplier analysis. A closer analysis of information dissemination is required to identify effects that are long-term and effects that are short-term. Impulse response functions test this dynamic interrelationship between flows and returns, as discussed, and flow and volatility of returns. In Figs. 1 and 2, the solid line in the middle represents Impulse Response (IR) coefficients and the dash- lines around it represent bootstrapped 90 percent confidence band. X-axis shows the days and origin is the contemporaneous day. No graph starts from the 0 showing the lagged responses of dependent variable. The FIIs' responses to NIFTY return

Table 9 Vector autoregression for FIIs and volatility of Nifty returns.

Endogenous variables	$FIII_t$ with V_t		$FIIO_t$ with V_t		$FIIN_t$ with V_t		$FIIFB_t$ with V_t		$FIIFS_t$ with V_t		$FIIFOI_t$ with V_t	
	$FIII_t$	V_t	$FIIO_t$	V_t	$FIIN_t$	V_t	$FIIFB_t$	V_t	$FIIFS_t$	V_t	$FIIFOI_t$	V_t
ϕ_{10}	12.9562		3.078545		44.72		−69.5818		−19.8673		19.0342	
ϕ_{20}		1.73E-05*		0.000019*		1.9E-05*		−9.0E-10*		1.76E-05*		1.76E-05*
ψ_{11}	0.4844*		0.5352*		0.349*		0.39138*		0.71123*		0.76699*	
ψ_{21}		−3.10E-10		1.35E-08*		−2.1E-08*		1.30E-09		9.57E-09*		5.53E-10
ψ_{12}	0.1915*		0.20880*		0.1239*		0.1135*		−0.0425*		0.20133*	
ψ_{22}		3.71E-09		−6.80E-10		1.02E-09		0.000		−5.2E-09*		5.94E-10
π_{11}	7374.16		25412.16		−251737		466422.9		−195014		−219516	
π_{21}		1.031519*		1.014123*		1.02033*		1.03172*		1.02616*		1.03056*
π_{12}	−45965		−33390.9		108886		−238706		262866.9		160270.1	
π_{22}		−0.08703*		−0.07494*		−0.0825*		−0.0869*		−0.08251*		−0.08694*
Adj.R^2	0.38099	0.902026	0.480173	0.903226	0.2151	0.903566	0.213907	0.9019	0.465727	0.902539	0.923912	0.902064
log like.	−17754.4	15915.89	−17311.5	15928.93	−17085	15932.66	−18663.9	15914.8	−17819.5	15921.44	−18217.8	15916.29

Note: Test results for vector autoregression are based on the following equation: $F_t = \phi_{10} + \psi_{11}F_{t-1} + \psi_{12}F_{t-2} + \pi_{11}V_{t-1} + \pi_{12}V_{t-2} + \Omega_t$, and $V_t = \phi_{20} + \psi_{21}F_{t-1} + \psi_{22}F_{t-2} + \pi_{21}V_{t-1} + \pi_{22}V_{t-2} + \Omega_t$. Here, F_t represents different daily FII flows at time t and V_t represents daily volatility of Nifty returns at time t. No. of lags has been determined using BIC criterion. "*" indicates significant value at 5% level.

innovations decay rapidly, with the effects being complete after five days. This short-term response of FIIs is consistent with the herd effect because the responses approach zero quickly. The response of volatility of Nifty returns (presented as VOLATILITY in Fig. 2) to one standard deviation shock to FIIs is strong and long lived, which can be seen in Fig. 2. It does not die even after ten lags. The FIIs' selling activity in futures market and cash market exerts great impact on volatility of Nifty returns causing the market to be more volatile for a long period of time. The net flow of FIIs does not have any impact on volatility of Nifty returns and only long position of FIIs has stabilising effect as it reduces the volatility of Nifty returns. The FIIO is quite interesting, as it increases the volatility of the market drastically, which sustains for a long period of time, exhibiting herding behaviour (Batra, 2003) of FIIs.

Summary and conclusion

It is generally accepted that foreign capital flows, particularly portfolio flows, are very crucial to the financial markets of emerging economies. This study attempts to detect relationships among foreign institutional investments, stock market returns and its volatility in one of the most important markets of the Asia-Pacific region—India, on a daily basis. A strong relationship has been identified between FIIs and market returns, and FIIs and volatility of market returns. Gross flows have been divided into three categories: inflow, outflow and net flow. Investments in futures market is divided into (1) buy/long position, (2) sell/short position, and (3) futures open interest.

The FIIs in India are "return chasers" or "feedback traders". The FIIs exhibit positive feedback trading while investing in the Indian capital market. Their selling activities, irrespective of types of market, cash or futures, portray them as negative feedback traders. The results are supported by both static and dynamic models, as discussed in the analysis, and are consistent with the results of Chakrabarti (2001), Gordon and Gupta (2003), and Kumar (2009). The impulse response function reveals that innovation or shock to current return increases the FIIs significantly, but the impact is short lived and dies out at the 5th lag. These results also support the fact that FIIs indulge in information dissemination. Based on the results of VAR, it is clear that daily returns possess explanations for FIIs, but the reverse is not true.

The other objective of the study is to analyse the destabilising effect of FIIs. For this, volatility of the Indian capital market is estimated as TARCH (*1,1*) process of Nifty returns. The contemporaneous relationship is analysed by including FIIs as one of the regressors in estimated volatility equation, which suggests that FIIs influence the market volatility. It is interesting to note that FIIs do not cause any change in market returns, but they affect volatility of Nifty returns, particularly their selling activities. The Granger causality test and VAR support the findings strongly and are in line with the findings of Wang and Shen (1999), Stulz (1999), and James and Karoglou (2010). The results of impulse response function provide evidence that FIIs destabilise the Indian capital market, as the shock to FIIs increases volatility and this impact remains for more than 10 days. Furthermore, the results are robust for aggregate outflow from the Indian market and their short positions in the futures market. These results call for some preventive measures from stock market authority, especially for selling activities of FIIs at the time of crisis, when the outflow is more than the inflow.

In a nutshell, evidence strongly supports the argument that foreign investors are feedback traders and amplify the financial market volatility. The study clearly reveals the need for a deeper knowledge of the reasons for stock market returns, its volatility, foreign institutional investments and their rapidly changing composition. Foreign institutional investments (FIIs) have brought enormous positive changes in the working of the Indian capital market and have thus been considered a boon, while FIIs' tumultuous nature cannot be unheeded. The study provides policy makers with a chance to manage short term, non-debt creating flows to emerging economies in a pragmatic and improved manner. Appropriate action by the policy makers/emerging economies will, in turn, keep FIIS in check.

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