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# Foreign Investors under Stress

## Evidence from India

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# Foreign Investors under Stress: Evidence from Indian Firms[*]

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**Abstract**

Emerging market policy makers have been concerned about the financial stability implications of financial globalization. These concerns are focused particularly on behavior under stressed conditions. Do tail events in the home country trigger off extreme responses by foreign investors and is there any asymmetry between the responses of foreign investors to very good versus very bad days? Do foreign investors have a major impact on domestic markets through large movements of funds? Do extreme events in world markets induce extreme behavior by foreign investors, thus making them vectors of crisis transmission? We examine these questions for India, using a modified event study methodology focused on tail events. We analyze data for individual companies, and find that, while in some cases, foreign investors do exacerbate extreme movements in stock price returns, in other cases they seem to lean against the wind, potentially stabilizing prices. Hence, there is no clear evidence for the presumption that foreign portfolio investors exhibit herd behavior that is uniformly destabilizing.

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## *1. Introduction*

In the past year, India's nascent growth miracle appears to have stalled, and there has been heightened attention to the role of possible economic reforms in reversing a slowdown that is feared to be structural and long-term in nature. An important dimension of economic reforms has been to modulate the role of foreign capital in providing investment for growth. The most prominent recent example of this has been the debate over foreign direct investment (FDI) in multi-brand retailing. FDI is often viewed as more beneficial than portfolio investment, being longer term and more stable. The Governor of India's central bank, the Reserve Bank of India, recently took this position, stating, "The other concern is the way we are financing it. We are financing our CAD through increasingly volatile flows. Instead, we should ideally be getting as much of FDI as possible to finance the CAD. On the other hand, what we are getting is a lot of volatile flows to finance it."[1] In practice, the distinction between FDI and portfolio investment can be blurry at the margin, and, more generally, the alleged destabilizing impacts of international portfolio flows in the Indian context have not been systematically examined.

In Patnaik, Shah and Singh (PSS, 2012), we rectified this omission to some extent, by analyzing the interplay between foreign portfolio flows and India's overall stock market performance. In contrast to earlier work that examined "average" relationships through a vector autoregression (VAR) model (Stigler, Shah and Patnaik, 2010), PSS focused on impacts in extreme cases, defined as cases where the value of the variable in question (stock index returns or levels of portfolio flows) lay in the tail of its distribution.

The results in PSS paint a fairly benign picture of the impact of international portfolio flows on the Indian stock market. Such flows did not appear to cause or exacerbate large movements in the market, on days when market behavior was extreme, in the aforementioned sense of being in the tail of the distribution. From a macroeconomic perspective, this kind of result on aggregate behavior is of potential comfort to policy makers, especially in the context of current debates on the merits of financial globalization. The global crisis, in particular, led to a rethinking of the value of capital controls. For example, the IMF (IMF, 2012; Ostry et al., 2010) has taken a new position that capital controls should be viewed more favorably in certain situations, as compared with its previous view that capital controls were an inadmissible tool of economic policy.

While the PSS results suggest that macroeconomic impacts of international portfolio flows may not be too worrying in the Indian context, there is still the possibility that stocks of individual companies may be affected in ways that cause concern. For example, a significant international finance literature has explored the role of foreign investors in emerging equity markets, with an emphasis on whether such investors are a 'stabilizing' or a 'destabilizing' influence in these

[1] Quoted in Indian Express (2013).

markets. This literature has emphasized two alternatives. Foreign investors could trade in a manner that pushes away from fundamental value -- viewed as 'destabilizing'. Alternatively, foreign investors forecast prices better than domestic investors, and thus enhance market efficiency -- viewed as 'stabilizing'. A considerable literature has developed on these questions, with mixed results.

As is the case for the aforementioned literature, we focus here on individual stocks, or groups of stocks, rather than on aggregate effects. Hence, unlike PSS (2012), the current analysis does not address financial stability consequences of foreign portfolio flows at the macroeconomic level. However, the concept of stability underlying the present analysis is in line with our previous work, and does not try to incorporate any notion of fundamental value, even at the level of the shares of individual companies. At the individual company level, four questions about the financial stability implications of foreign investment flows appear to be of interest from the viewpoint of regulators and policy makers in emerging markets:

1. Do foreign investors worsen negative performance of the shares of a domestic company by withdrawing capital on a large scale?
2. In this, is there asymmetric behavior, with different responses to very good versus very bad days in the local economy?
3. Are foreign investors big fish in a small pond – do their large transactions kick off substantial temporary mean-reverting distortions in the stock returns of an emerging market company?
4. When there are stressed conditions in the global financial systems, do foreign investors withdraw capital on a large scale, and thus act as a vector of crisis transmission?

Alternative answers to these questions could potentially be consistent with alternative findings in the existing international finance literature. As an example, emerging market policy makers care about flight of foreign capital in a domestic crisis – regardless of whether or not it brings prices closer to fundamental value. In this sense, these questions are distinct from those which have occupied the existing literature. Further, the questions of interest to policy makers are focused almost exclusively on behavior in extreme events, specifically, on the behavior of foreign investors when there are extreme events either in the domestic or in the global economy.[2]

[2] Many studies, including Stigler, Shah and Patnaik (2010), have examined the interaction between foreign investors and emerging economy stock markets through estimation of linear relationships in the data (e.g. using VARs or VECMs). The estimated parameters then reflect the overall average relationship. However, there may be an ordinary regime, i.e. the behavior of foreign investors on ordinary days, and alongside it there may be different behavior in the tails. In the policy discourse, the concern is seldom about the overall average effects, but about the behavior under stressed conditions. If extreme behavior by foreign investors is found in the tails, this is relevant to policy makers, regardless of what the overall average estimates show.

The contribution of this paper lies in directly addressing the above four policy-relevant questions, about the financial stability implications of foreign investors in an emerging market. Our methodology focuses on extreme events, allowing for the possibility that what happens in stressful market conditions may differ from day-to-day outcomes, and measures relationships of interest under stressful conditions. While the behavior associated with extreme events can be estimated through parametric models, we adapt a non-parametric 'event study' methodology. As an example, we identify events consisting of extreme movements of the shares of individual listed Indian companies. Surrounding these dates, we analyze the fluctuations of foreign investment in these companies using the event study methodology. This gives us evidence about the inter-linkages between foreign investment and stock market fluctuations in the tails, without needing to assume linearity.

The findings of this paper extend our earlier aggregate results. There, we found that foreign investors possibly amplified a boom in the stock market, but did not have a mirror effect on bad days, by taking out large sums. In looking at a handful of individual firms, we find that the positive and negative impacts vary across firms, and that there is also evidence of foreign investors buying on dips for some stocks, representing a potentially stabilizing force for those stocks. These results are the first to uncover such varying patterns of FII behavior across different Indian companies.

The remainder of the paper is organized as follows. In section 2, we summarize several strands of literature that are relevant for our analysis. We discuss a few key studies that empirically analyze the relationship between foreign institutional investment and stock market performance in India, using linear parametric methods. We also discuss recent examples of event studies in the context of international trade and capital flows more broadly. Finally, we relate our approach to an existing literature in finance on international information transmission in financial markets. Section 3 gives an overview of the data and the event study methodology. Section 4 presents our results, and Section 5 offers a summary conclusion.

## *2. Related Literature*

We begin with the empirical literature on India, and then turn to literature for other countries, with respect to cross-border portfolio flows. We also review the literature on event studies in the context of financial markets and international finance.

The question of impacts of portfolio flows by foreign institutional investors ("FII")[3] has exercised policymakers in India for some time, and consequently attracted academic attention. A

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[3] Foreign portfolio investment into India has to be channeled through qualified institutions, which must register with a government agency. These institutions are referred to as FIIs. The definition is discussed further in Section 3.

variety of authors have approached these questions using VARs. Chakrabarti (2001) uses monthly and daily data to estimate a VAR and test for Granger causality. He concludes that in the post-Asian crisis period, Indian stock market performance was the sole driver of FII flows in and out of India, though there may have been some reverse causality in the pre-Asian crisis period. Similar results were obtained by Mukherjee et al. (2002), using daily data from 1999-2002. Those authors also found an asymmetry between selling by FIIs and buying, with only the former being driven by stock returns. Gordon and Gupta (2003) analyzed monthly data over the period 1993-2000 and found that FII flows were *negatively* related to lagged stock market returns, suggesting negative feedback trading. However, monthly data may not be appropriate for identifying such effects (e.g., Rakshit, 2006). Chakrabarti (2006) also finds evidence of a structural break in the data around April 2003, suggesting the need for separate analysis of more recent data. This point is reinforced by the significant growth in FII flows in the period subsequent to these early studies.

More recently, Anshuman, Chakrabarti and Kumar (2010) analyze high frequency data to address these questions. They find that the aggregate trading of FIIs dampens the volatility of the Indian stock market on an intra-day level. Furthermore, positive shocks in trading volume have greater impacts than negative shocks, while trading between FIIs and domestic investors increases volatility. The focus on intra-day volatility is different than the questions examined in our analysis, and presumably less important from the perspective of policymakers who may care less about stock price movements within a day than about market swings over days, weeks or months that are driven by foreign capital.[4]

Stigler, Shah and Patnaik (2010) estimate a VAR involving five variables: net FII investment, the Nifty index,[5] the S&P 500 index, the ADR premium and the INR/USD exchange rate. Causality tests indicate that a shock to net FII flows does not cause the Nifty index, but the reverse causality does hold. In fact, shocks to net FII flows do not feed through to any of the other four variables, whereas positive shocks to the exchange rate, ADR premium and S&P 500 all affect net FII flows. As is the case for the other models surveyed above, this paper also uses a linear times series model, therefore not distinguishing between "normal" and "extreme" days on the market.

PSS (2012) use an event study methodology, rather than a VAR – this has the advantage of being nonparametric, and, in particular, not imposing linearity. It also admits the possibility that behavior in extreme situations is driven by different relationships than is the case for normal days. The findings of the paper, for India, are relatively benign. PSS find that on very good days in the local economy, foreign investors do accentuate the boom by bringing in additional capital.

[4] Of course, market volatility matters from the perspective of institutional design and regulation, but the implication for policy in that context would be devices such as circuit breakers, which are neutral with respect to the identities or characteristics of traders.

[5] The Nifty index is India's broader-based stock market index, analogous to the S&P 500 index in the US. Again, see Section 3 for further detail.

However, behavior is asymmetric, and on very bad days in the local economy no significant effects are found. Foreign investors do not seem to be big fish in a small pond: extreme days of foreign investment in India do not kick off short-term price distortions with mean-reversion in following days. Finally, very positive days on the S&P 500 trigger additional capital flowing into India, but there is no evidence of the reverse: international crises (with very poor days for the S&P 500) do not trigger exit by foreign investors. Foreign investors are not a vector of crisis transmission for India.

Turning to studies for other countries, the literature is obviously much more extensive, and we report on a small, relevant subset. There is a significant amount of work on the role of information transmission in international portfolio flows. For example, Froot and Ramadorai (2001, 2008) directly examine the forecasting power of international portfolio flows for local equity markets, attempting to attribute it to either better information about fundamentals on the part of international investors, or to price pressure irrespective of fundamentals. Their data is consistent with the information story, but not the price pressure story. They do, however, find evidence of trend-following in cross-border flows based on absolute, though not relative, returns. Therefore, international portfolio flows seem to be stabilizing with respect to notions of relative, but not absolute, value.

Analyses with different data, such as Choe, Kho and Stulz (1998, 2001), find results that are more consistent with the price pressure story. A recent example of this conclusion is the work of Jotikasthira, Lundblad and Ramadorai (2011), who note that movements in outside investors' flows to developed-country-based global funds force significant changes in these funds' portfolio allocations to emerging markets. These forced portfolio allocation shifts drive temporary movements in emerging market equity returns. They find that the data are consistent with performance chasing by outside investors and 'push' effects from the home country, rather than to any private information about emerging market returns.

Given the possibility that multiple factors can drive international investor behavior, in our analysis, we side-step the issue of precise causes of observed connections between foreign equity flows and domestic stock returns. While policymakers will ultimately be interested in causes, their first-order concern is with the strength of the relationship between foreign flows and domestic market returns. Moreover, their interest is not so much in the normal or average relationship, but in what happens in extreme cases. Therefore, our contribution is in focusing on the strength of relationships in extreme circumstances, rather than in precisely identifying the drivers of those relationships. We adapt event study methodology to this task.

The event study is a workhorse of empirical financial economics. Event studies were originally conceived of in the context of the impact of public announcements on stock returns. Precursors of the modern event study approach focused on stock splits (Dolley, 1933; Myers and Bakay, 1948). The current style of analysis goes back to Fama et al. (1969) and Brown and Warner (1980). In these and other similar studies, the variable of interest is a price or rate of return, such as a stock price, exchange rate, or bond price. The event of interest can be a merger, earnings announcement or regulatory change. Performance before and after the event is examined using statistical tools. For example, abnormal – as identified by statistical analysis – movements in a stock price, before a merger announcement can indicate the use of insider information, or leakage of the news to the market. The event study methodology as implemented in our analysis has two key strengths. First, it imposes no functional form upon the responses surrounding event date. Second, there is a clear causal interpretation interlinking news, event, and financial market responses.

While the event study methodology was invented for analyzing high frequency financial returns, it has been extended to an array of fields including the study of households, firms and countries. More recently, event studies have been applied to the behavior of quantities as well as prices. Two recent studies are noteworthy in the context of our research, since both focus on international capital flows. Broner et al. (2010) examine the behavior of gross capital flows of foreigners and domestic investors before and after financial crises. They use panel data, with annual observations covering 1970-2009 and 103 countries (segmented by income classes). IMF (2010) includes an event study of the impact of capital control introductions on 37 "liquidity receiving" countries.[6] The data is quarterly, and covers 2003:Q1 to 2009:Q2. The Broner et al. study finds that crises do matter, and affect the behavior of foreign and domestic investors differently but predictably. On the other hand, the IMF study finds little impact of capital control introductions on capital inflows. Hence, an event study can provide useful information whether or not the event in question has "significant" effects on the variable of interest: results do not have to be "significant" to be of interest.[7]

## *3. Data and Methodology*

We use daily data for returns on selected Indian company stocks, net FII inflows at the individual company level, and the US S&P 500. The Indian data is available for the period 2002 to 2011, but there are very few observations on individual transactions prior to 2003.

### *FII Data and Firms*

India has a comprehensive system of capital controls (Patnaik & Shah, 2012). In the case of portfolio equity flows, the capital controls work as follows. There is no quantitative restriction. Foreign investment can only be undertaken by "foreign institutional investors" (FIIs). FIIs in the Indian context can include a range of financial institutions, including banks, asset management

[6] These are defined to be "countries where the crisis did not originate, with the primary challenge being an upside risk of inflation expectations in goods and asset markets." They include the emerging market economies, as well as several developed economies.

[7] Other examples that apply the event study methodology to international trade and finance questions include Pynnonen (2005) and Manova (2008).

firms, hedge funds and even trusts and foundations. Qualified FIIs are registered with India's stock market regulator, the Securities and Exchange Board of India (SEBI). The ownership by all foreign investors cannot exceed a certain proportion of the company. This proportion is set to 24% by default, but can be raised by a resolution of the shareholders of the company up to 98%.[8] In practice, this has meant that FIIs have nearly complete convertibility. The results observed in this paper largely reflect the unconstrained actions of foreign investors.

FIIs are required to settle through custodian banks. Custodian banks are required to supply data to the government, and this is the source of our data on FII flows. In previous work (PSS, 2012), we used aggregate data made available through SEBI, which collects, validates and aggregates the data on individual transactions. For the present study, we obtained, for the first time, access to individual transaction data, with the identity of individual FIIs being kept confidential. Table 1 summarizes the nature of the data collected and reported by SEBI.

**Table 1** Variables reported by SEBI

| | |
|---|---|
| Custodian code | Report date |
| Transaction ID | FII registration number |
| Scrip name | Sub account registration number |
| ISIN code | Broker registration number |
| Transaction date | Transaction type |
| Stock exchange code | Settled code |
| Transaction date | Transaction type |
| Transaction rate | Transaction quantity |
| Instrument type | Value of transaction |
| Reporting type | Reason for delay in report |
| Reason for amendment | |

We aggregated the transaction data to the daily level, to construct our FII series for each of about 2000 individual company stocks. However, the daily series, when aggregated over time, does not always match a quarterly series that is made public by SEBI. In some cases, the discrepancies are large, and there has been no explanation forthcoming as to the source of the discrepancies. We next describe our procedure for aggregating and normalizing the data, as well as dealing with discrepancies between aggregated transactions and quarterly reports, which show up as extreme outliers in our data series.

The transaction level data is converted to daily series by summing all the transactions on a particular day. This gives us gross purchases, gross sales and net purchases on a daily basis. We get quarterly FII share holding of the firm from the Centre for Monitoring Indian economy

[8] Of the over 5000 listed companies, at any point in time, there are no more than 20 firms where FIIs lack headroom for additional purchases. Hence, for almost all firms, the limit of 24 per cent has not been reached, or the shareholder resolution has come about which raises the limit beyond 24 per cent. When it comes to selling, there are no restrictions.

(CMIE) database. We next use daily FII estimated series of net purchases and quarterly FII holding to estimate daily FII series for each firm. We take quarterly FII holding as the initial or seed value, we have the next day's net purchases and we add that to the seed value and estimate the next day's FII holding. We iterate this for each day and estimate the daily FII holding (*dfh*) in each firm. The expression for this daily FII holding is given by

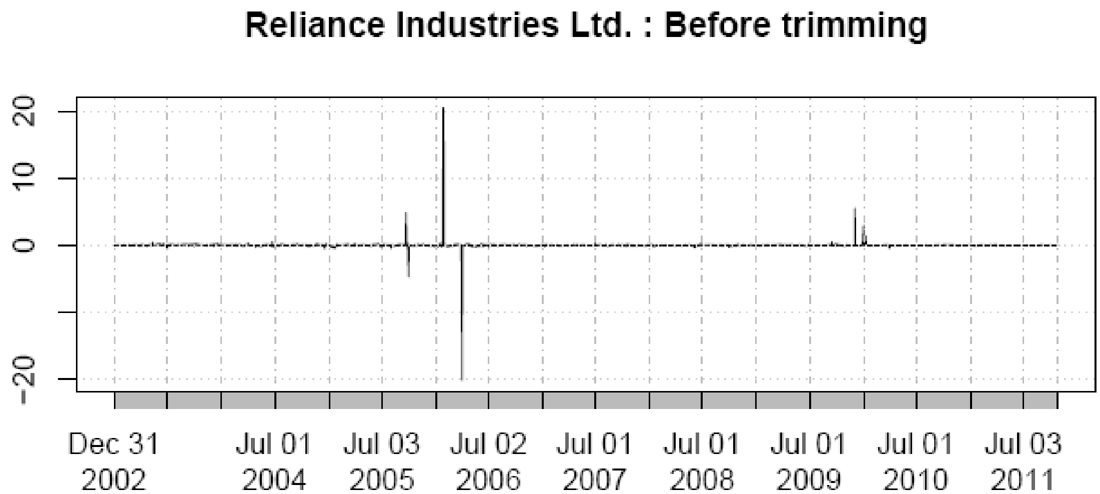
$$fii = \frac{dfh_t - dfh_{t-1}}{ts_t}$$

We define *fii* as the ratio of change in FII holding to daily total shares (ts). The daily total shares figure is extracted from the CMIE database. There are a handful of extreme outliers in the *fii* series for each firm due to unexplained reasons, with very high positive or negative changes in the FII holding. We remove such points by trimming the data. We expurgate and clean the data by removing 0.3% of the observations in each tail, and keeping the remaining 0.3% to 99.7%. The final series used for FII is therefore the trimmed daily *fii* series. Figure 1 shows the effect of trimming for Reliance Industries, a large firm with some particularly extreme outliers.

There are close to 2000 firms for which there is FII activity in our dataset. Overall summary statistics for trading are presented in Table 2, below. Despite the large volumes and numbers of transactions, trading is heavily skewed toward a relatively small number of companies. If we set a minimum standard of being traded by FIIs on at least 85 percent of the approximately 220 trading days, typically less than 100 companies meet this standard in any given year, with the most active being India's largest company by market capitalization, Reliance Industries. Conversely, 75 percent of the companies traded by FIIs have trades on less than 13 percent of the trading days in the sample.

Alternatively, one can also look at the volume of trading. Table 3 displays the year wise number of firms for various levels of cutoff of the total volume of trading in a given year. Thus, in 2011, the number of firms that represented 85 percent of total trading volume, when ranked from most to least active, was 92. The number of firms that encompassed 99 percent of the traded volume in that year was 384, or roughly 20 percent of the total number of firms. The remaining 80 percent of firms represented only 1 percent of FII trading volume. We therefore focus on these 384 firms, since the remainder are too thinly traded by FIIs to provide enough data that can be analyzed usefully.

**Table 1: Reliance Industries – Effect of Trimming**



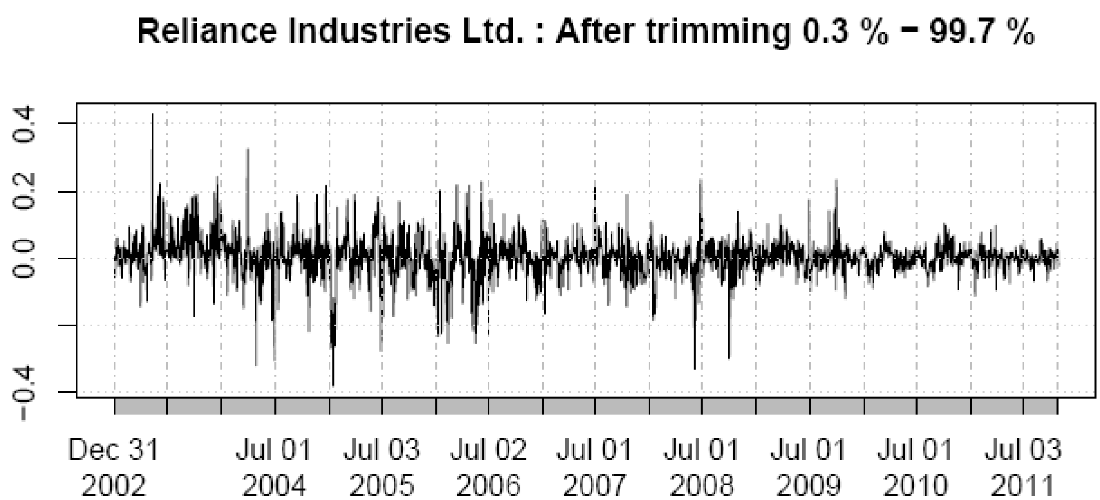




**Table 2: FII Trading in Indian Shares**

| | Mean | Median |
|---|---|---|
| Daily purchase transactions | 1017 | 944 |
| Daily sales transactions | 965 | 969 |
| Quantity of shares traded daily | 136 million | 125 million |
| Value of shares traded daily | INR 38 billion | INR 36 billion |

**Table 3: Number of firms comprising 'x' percent of FII trade value (by year)**

| | 85 percent | 90 percent | 99 percent |
|---|---|---|---|
| 2003 | 21 | 26 | 81 |
| 2004 | 29 | 38 | 114 |
| 2005 | 51 | 74 | 246 |
| 2006 | 61 | 85 | 303 |
| 2007 | 82 | 117 | 367 |
| 2008 | 73 | 105 | 341 |
| 2009 | 68 | 95 | 297 |
| 2010 | 105 | 144 | 428 |
| 2011 | 92 | 128 | 384 |

In our first stage of analysis, we examine and compare the behavior of the top and bottom deciles of the 384 firms identified as our core sample. In each case, we pool the data for firms within their respective deciles, to increase the number of data points and improve our confidence intervals. Tables 4 and 5 list the firms in the top and bottom deciles of the core sample, respectively. In the bottom decile, six firms are omitted because of gaps in the data.

**Table 4: Top Decile Firms**

| | |
|---|---|
| Allahabad Bank | Indian Overseas Bank |
| Andhra Bank | Larsen and Toubro Ltd. |
| Axis Bank Ltd. | N T P C Ltd. |
| Bank Of Baroda | Oil and Natural Gas Corpn. Ltd. |
| Bank Of India | Oriental Bank Of Commerce |
| Bharat Heavy Electricals Ltd. | Power Finance Corpn. Ltd. |
| Bharat Petroleum Corpn. Ltd. | Power Grid Corpn. Of India Ltd. |
| Bharti Airtel Ltd. | Punjab National Bank |
| Canara Bank | Reliance Communications Ltd. |
| Central Bank Of India | Reliance Industries Ltd. |
| Corporation Bank | Rural Electrification Corpn. Ltd. |
| Essar Oil Ltd. | State Bank Of India |
| H D F C Bank Ltd. | Steel Authority Of India Ltd. |
| Hindustan Petroleum Corpn. Ltd. | Syndicate Bank |
| Housing Development Finance Corpn. Ltd. | Tata Steel Ltd. |
| I C I C I Bank Ltd. | Uco Bank |
| I D B I Bank Ltd. | Union Bank Of India |
| Indian Bank | United Bank Of India |
| Indian Oil Corpn. Ltd. | Vijaya Bank |

**Table 5: Bottom Decile Firms**

| | |
|---|---|
| Acropetal Technologies Ltd. | K P I T Cummins Infosystems Ltd. |
| Allied Digital Services Ltd. | Karuturi Global Ltd. |
| B F Utilities Ltd. | Kokuyo Camlin Ltd. |
| Cox and Kings Ltd. | Lovable Lingerie Ltd. |
| Delta Corp Ltd. | N I I T Technologies Ltd. |
| Den Networks Ltd. | New Delhi Television Ltd. |
| Dynamatic Technologies Ltd. | Onmobile Global Ltd. |
| Eclerx Services Ltd. | Orient Green Power Co. Ltd. |
| Eicher Motors Ltd. | P T C India Financial Services Ltd. |
| Eros International Media Ltd. | Persistent Systems Ltd. |
| Ess Dee Aluminium Ltd. | Prime Focus Ltd. |
| Everest Kanto Cylinder Ltd. | Sterling International Enterprises Ltd. |
| Everonn Education Ltd. | Sumeet Industries Ltd. |
| Gateway Distriparks Ltd. | Sunteck Realty Ltd. |
| Genesys International Corpn. Ltd. | T D Power Systems Ltd. |
| Info Edge (India) Ltd. | T T K Prestige Ltd. |
| Jindal South West Holdings Ltd. | Talwalkars Better Value Fitness Ltd. |
| Jubilant Foodworks Ltd. | Tv18 Broadcast Ltd. |
| Jyothy Laboratories Ltd. | Voltamp Transformers Ltd. |

In the second stage of our analysis, we use data for individual companies that are listed on the Indian stock market. We have chosen five firms, based on data quality. Table 6 lists these companies, and provides summary statistics for each of them, in terms of overall trading and stock price movements. Two of the companies are banks (Axis and ICICI), two are information technology companies (Infosys and TCS), and one is an engineering firm (Larsen & Toubro).

**Table 6: Summary Statistics for Analyzed Firms**

| | Axis Bank | ICICI | Infosys | TCS | L&T |
|---|---|---|---|---|---|
| Returns Range | (-21.7,18.3) | (-22.7,20.7) | (-30.8,14.8) | (-11.3,14.4) | (-12.3,21.9) |
| Stock price range | (1322,1357) | (1113,1139) | (2267,2295) | (1218,1245) | (1648,1682) |
| Volume | 120701 | 534343 | 59847 | 63469 | 134453 |
| M.cap.(Rs Cr) | 57759 | 131038 | 130759 | 242878 | 100732 |
| M.cap.% of Nifty | 1.05 | 2.42 | 2.40 | 4.48 | 1.85 |

Stock market returns are calculated using differences in logs of stock prices. To capture the impact of exogenous events, we use the S&P 500 index for the US, as a sufficiently broad index. The daily index is used to calculate daily returns. In the case of holidays, we assume that the index remains the same for the holiday, implying a zero return for such days. This allows us to avoid problems which arise from the fact that there are different holidays in the two markets. Furthermore, in lining up Indian and US data, while for a particular calendar date, the Indian market is open before the US market, and closes before the US market opens, the likely chain of causality runs from the US market to the Indian market. Therefore we line up the previous calendar day of US data with the Indian data.

***Event Definition***

In the traditional event study in finance, the event is an identifiable action at a specific point in time, such as an announcement of a merger or stock split. In more recent applications, events may also be more spread out, such as trade liberalization or introductions of capital controls. Hence, an event window may not coincide with the time unit of the data. In addressing the questions posed in this study, we define event dates as those on which extreme values of returns or flows are observed. As an example, we would scan the time-series of returns on the S&P 500, and identify the dates on which one-day returns were in the tails.

This approach is unlike that seen with the typical event study paper, in that the definition of the event is one of the choices faced in devising the estimation strategy. How extreme should our extreme cases be? We might define extreme values to be those in the upper and lower 2.5% tails of the distribution. This would be in keeping with the statistical tradition of using 5% as the standard level of significance in hypothesis testing. However, in this application a different perspective is appropriate. The choice of the tail probability reflects a tradeoff between identifying the truly extreme events (which is favored by going out into the tails) versus adequacy of data size.

There are two further issues to consider. First, matters are complicated by the fact that such extreme (tail) values may cluster: for example, there may be two or three consecutive days of very high or very low daily returns, or these extremes may occur in two out of three days. If the extreme values are all in the same tail of the distribution, it might make sense to consider the cluster of extreme values as a single event. The main results of the paper are based on fusing all consecutive extreme events, of the same direction, into a single event. In event time, date +1 is then the first day after the run of extreme events, and date -1 is the last day prior to the start of the cluster. This strategy avoids losing observations of some of the most important crises, which involve clustered extreme events in the same direction. On the other hand, the interpretation of event studies is cleanest when there is no other extreme event in the pre-event or post-event window. In order to address this, one can isolate what we term as "uncontaminated" single-day events where, within the pre- and post-event windows, there is no other event. This alternative is analyzed by PSS (2012), along with the clustering approach.

The second issue is the length of the period of interest around each event. In the case of announcing a merger or a policy change, there might be interest in some period before the event (to examine whether the information was leaked or the event was somehow anticipated), and some other period after the event (to examine the impact of the event on subsequent behavior). In all these examples, as well as in our case, there is some degree of arbitrariness in the choice of the pre-event and post-event periods. Again, the issue of clustering determines our choice, and we go with pre-event and post-event windows of five market days each, that is, a calendar week each. Five days seems a sufficiently long time in the context of stock market data to pick up either anticipatory or reactive movements for extreme events.

***Methodology***

Early event studies, which were focused on stock market returns on individual firms, used a regression-based approach for identifying abnormal returns. An estimation window that precedes the event is used to estimate a relationship between individual stock returns and some explanatory variable, typically market returns. This relationship is then used to calculate residuals from the pre-event or post-event window, and these residuals (individually or cumulatively) are subjected to a statistical test to see if they are significantly different from zero. The advantage of dealing with market model residuals, rather than raw returns, is that to the extent that the systematic factor (the stock market index) is controlled for, there is a reduction in variance, which improves the precision of the event study. Controlling for other factors is only a tool for increasing statistical precision: whether adjustment is done or not does not undermine the basic logic of an event study.

Inference procedures in traditional event studies were based on classical statistics. Subsequently, there have been concerns raised about the distributional assumptions required for this procedure, including normality and lack of serial correlation. It has been demonstrated that serious biases can arise in inferences based on standard assumptions. One method for obtaining superior inference lies in harnessing the bootstrap.

Here we focus on a bootstrap approach to statistical inference for our extreme events. The choice of this approach influences our choices of pre-event and post-event windows, and of the probability value of the tails, as discussed earlier in this section. The bootstrap approach avoids imposing distributional assumptions such as normality, and is also robust against serial correlation – the latter being particularly relevant in the context of FII flows.[9]

The observed data $x_1, x_2, \dots x_n$ is treated as a random sample from the unknown underlying distribution $F$.

$$x_1, x_2, \dots x_n \xrightarrow{iid} F$$

The parameter of our interest is $\theta$, which is estimated from the following statistical function.

[9] For general discussions of the advantages of the bootstrapping approach to event study analysis, see, for example, Kothari and Warner (2007), and Lefebvre (2007).

$\theta = t(F)$

$t(F) = \int xdF(x)$

The estimate of $\theta$ is $t = t(\hat{F})$. We have to replace unknown $F$ by $\hat{F}$ which can be obtained by parametric or non-parametric approach. In parametric approach, the distribution is assumed to be normal or exponential to get the estimate. While in a non-parametric approach using empirical distribution of original data $x_1, x_2, \ldots x_n$, we generate random samples.

$x_1^*, x_2^*, \ldots x_n^* \xrightarrow{iid} \hat{F}$

Further we compute $\hat{\theta}_r$, using $x_1^*, x_2^*, \ldots x_n^*$ where;

$r = 1, \ldots R$

R is number of iterations to be done which should be more than 1000 to get more accurate estimator. From the above process we will have R estimates for the parameter $\theta$.

$\theta_1^*, \theta_2^*, \ldots \theta_r^*$

The properties of the unknown parameter $\hat{\theta}$, are determined using the bootstrap replicates. Confidence interval is constructed using normal approximation to the distribution of T, random value of which t is the observed value. The true bias and the variance of T are

$b(F) = E(T|F) - \theta$

$b(F) = E(T|F) - t(F)$

$v(F) = var(T|F)$

then for large samples we get

$$Z = \frac{T - \theta - b(F)}{v(F)^{1/2}} \sim N(0,1)$$

In the above case the confidence interval for $\theta$ is

$t - b(F) - z_{1-\alpha} v(F)^{1/2},\ t - b(F) - z_{\alpha} v(F)^{1/2}$

where z is the $\alpha$ quantile of the standard normal distribution. After replacing $F$ by $\hat{F}$, we get our estimates of variance and confidence interval.

The bootstrap inference strategy that we use is as follows:[10]

1. Suppose there are $N$ events. Each event is expressed as a time-series of cumulative returns ($CR$) (or cumulative quantities in the case of FII flows) in event time, within the event window. The overall summary statistic of interest is the $\overline{CR}$, the average of all the $CR$ time-series.
2. The bootstrap stage consists of sampling with replacement *at the level of the events*. Each bootstrap sample is constructed by sampling with replacement, $N$ times, within the dataset of $N$ events. For each event, its corresponding $CR$ time-series is taken. This yields a time-series $\overline{CR}$ which is one draw from the distribution of the statistic.
3. This procedure is repeated 1000 times in order to obtain the full distribution of $\overline{CR}$. Percentiles of the distribution are shown in the graphs reported later, giving bootstrap confidence intervals for our estimates.

To the extent there is a difference between normal times and tail events, our methodology will provide a glimpse into the behavior of foreign investors during crises that might not be captured in a model of average behavior.

Before turning to the results, we summarize precisely how we use the data and the event study approach to analyze the four questions we posed in the introduction.

*Do foreign investors worsen negative performance of the shares of a domestic company by withdrawing capital on a large scale?* We analyze this question using an event study which measures the behavior of foreign investors surrounding extreme events for the domestic stock market.

*Is there asymmetric behavior, with different responses to very good versus very bad days in the local economy?* We measure this by conducting separate event studies for very positive and very negative days for the local stock market index.

*Are foreign investors big fish in a small pond – do their large transactions kick off substantial temporary mean-reverting distortions in the stock returns of an emerging market company?* We measure this by conducting an event study where extreme events are defined as days with very positive or very negative foreign capital inflows, and observe the outcomes for the domestic stock returns.

*Finally, when there are stressed conditions in the global financial system, do foreign investors withdraw capital on a large scale, and thus act as a vector of crisis transmission?* We measure this by conducting an event study focusing on extreme days in terms of the S&P 500, and focus on the outcomes seen in terms of foreign capital inflows and the domestic stock returns.

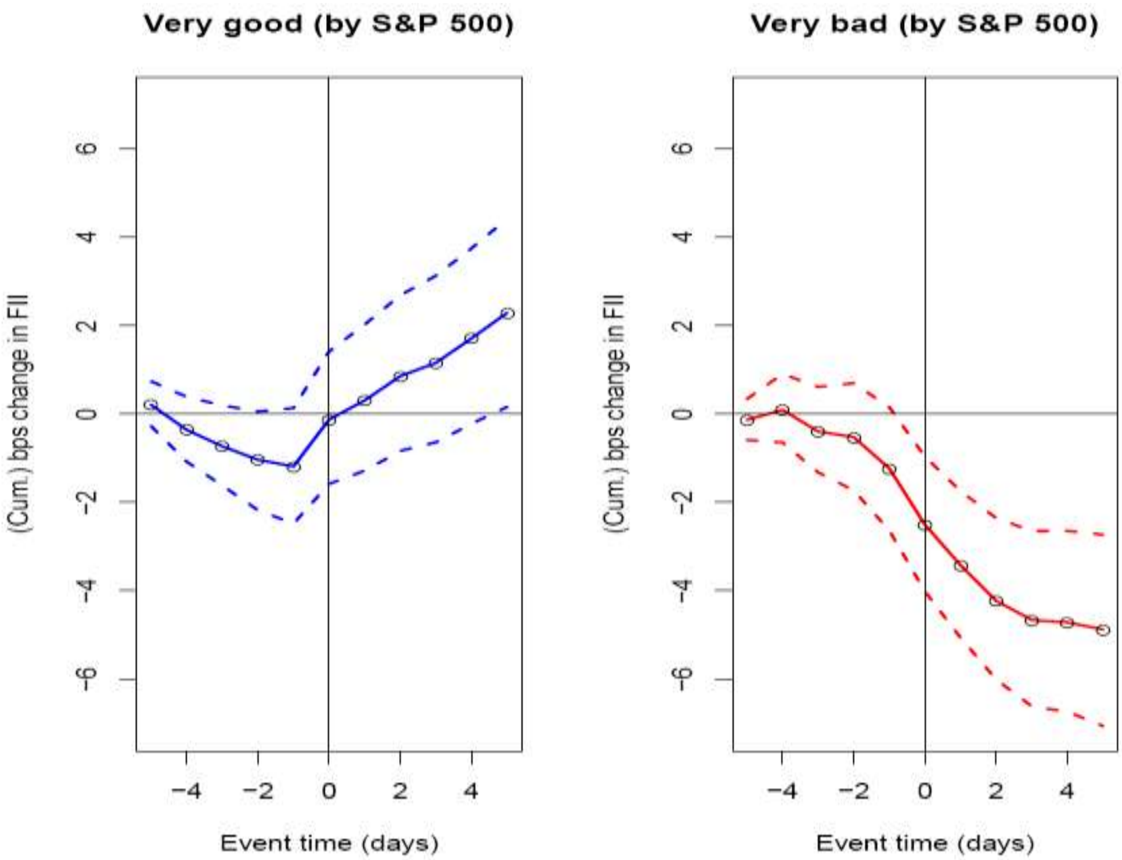
[10] The specific approach used here is based on Davison, Hinkley, and Schectman (1986).

*4. Results*

***Top and Bottom Deciles***

For each type of 11-day window (the event and five days before and after), we construct a confidence interval for cumulative values.[11] For responses of FIIs to extreme changes in the S&P 500, Figure 2 shows that in the case of the top decile of firms, there is not a statistically significant response. On the day of a positive event, there is actually no response in the investment of FIIs, with a positive trend in the days after, though not statistically significant. In the case of a negative global shock, the FII response is significant, but it does not seem to persist in a dramatic manner after the event itself – the negative trend is mild.

**Figure 2: Top Decile -- Event on S&P500 and response of FII**




Responses of FIIs to the domestic market are more noticeable on the positive side. A very positive day as measured by returns on the stocks in this group is reflected in an increase in FII inflows. In fact, the increase begins before the extreme positive event. The trend after the event is not particularly strong, however, with the central value on the day of the event remaining in

[11] For expositional convenience, we refer to a cluster of consecutive extreme events as a single day. In reality, some of the periods may therefore be longer than 11 days.

the confidence interval for the next few days. In the case of extreme negative returns, the pattern is somewhat similar, but considerably smaller in magnitude.

**Figure 3: Top Decile -- Event on stock returns and response of FII**

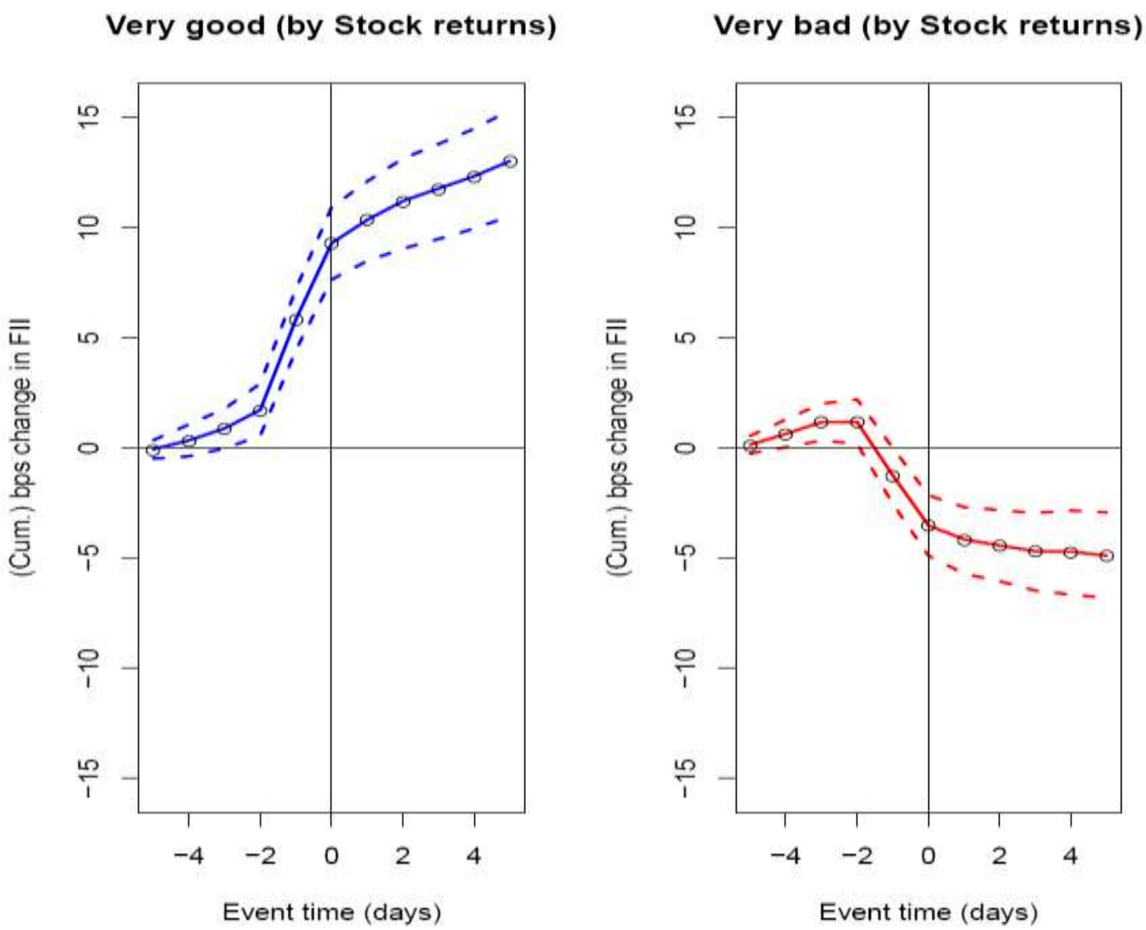
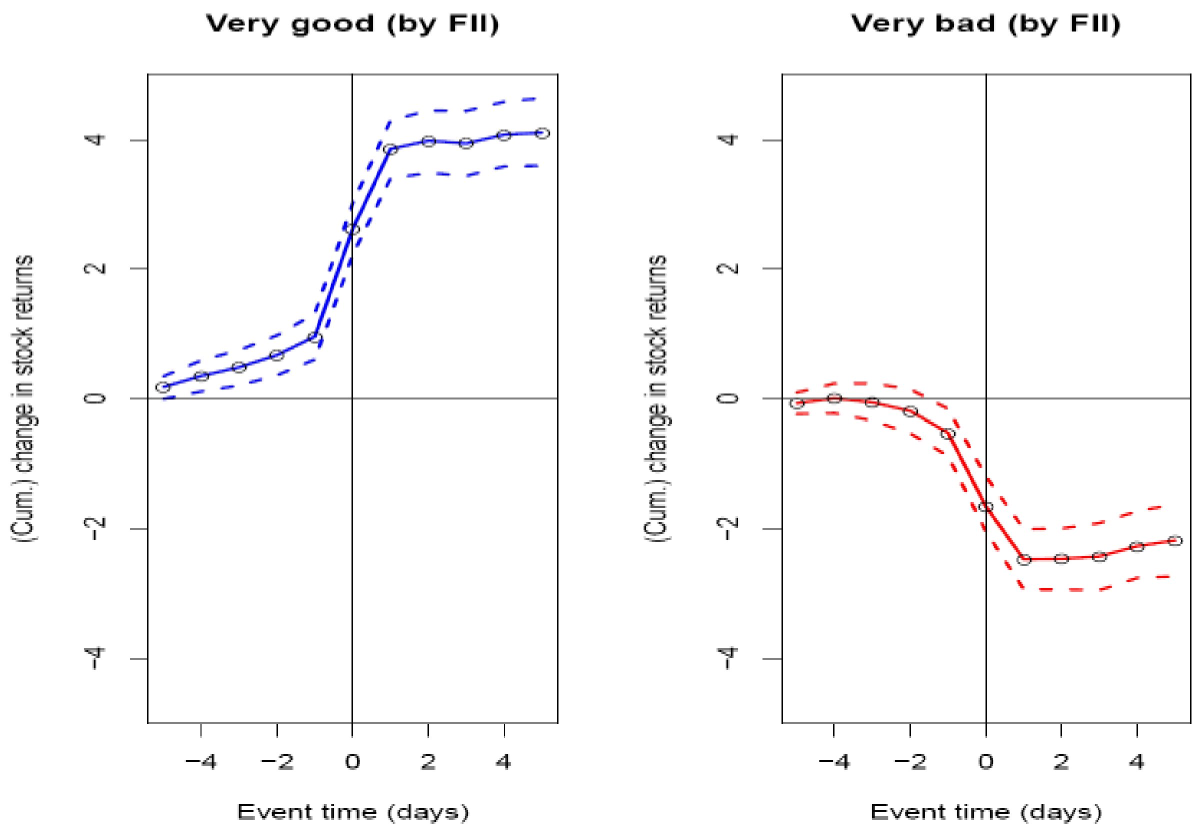


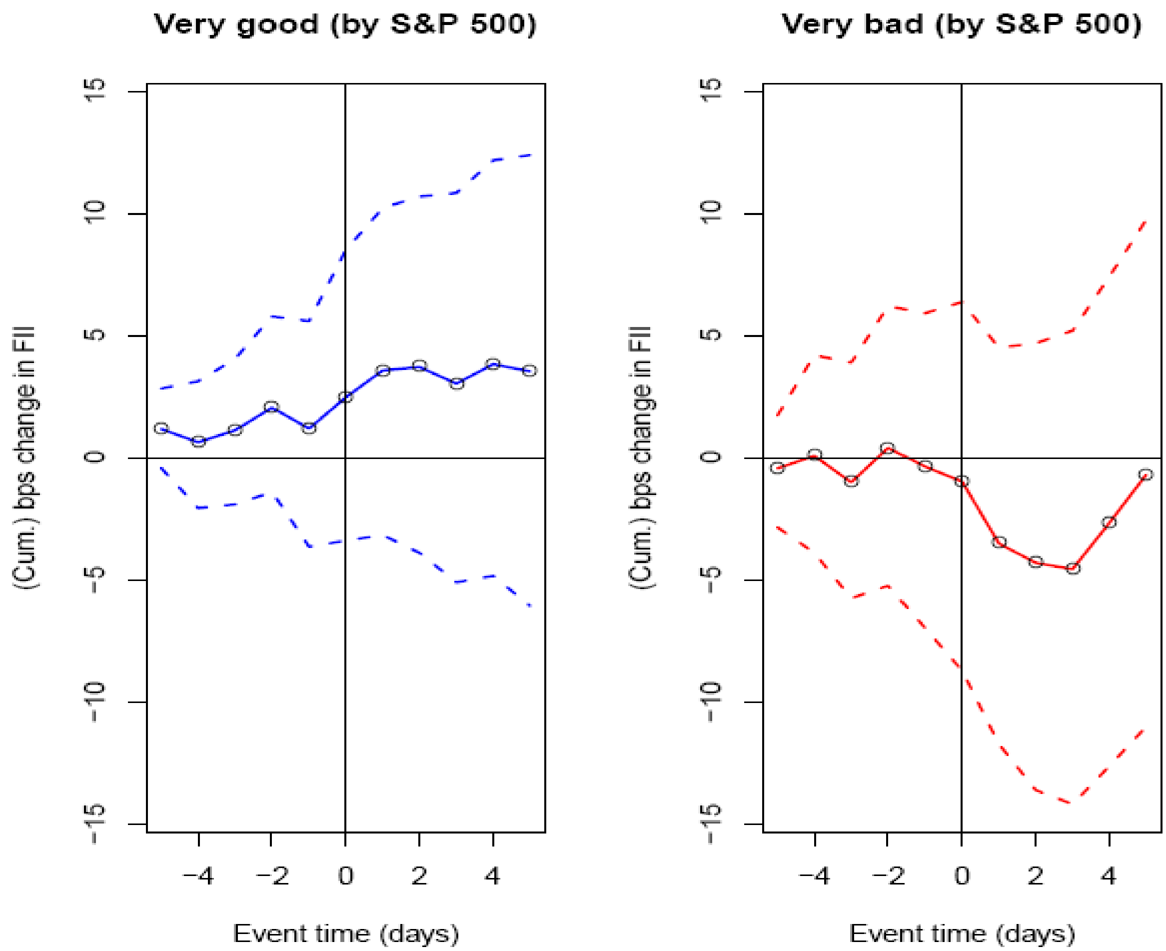

Figure 4 shows the response of daily stock returns to extreme events with respect to FII flows. The responses to positive and negative extreme events in FII flows for the set of companies in the top decile are quite similar. There is a foreshadowing of the event in the trend of data before the event, then a continuation the day after the event, but then a flattening out, so that the cumulative effect changes little in the days following. The magnitudes of the changes are not inordinately large.

**Figure 4: Top Decile -- Event on FII and response of stock returns**



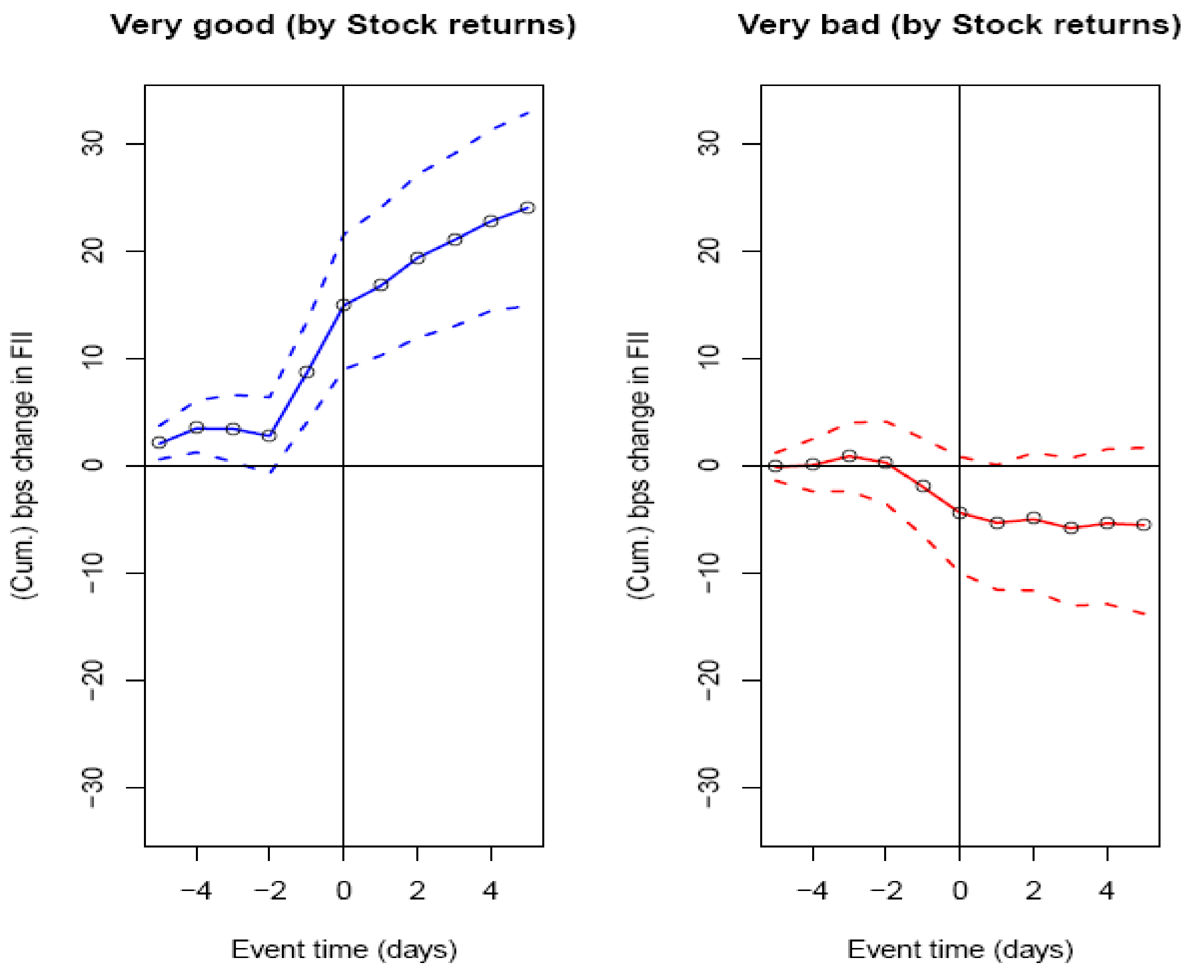

Turning to the group of companies in the bottom decile of the subset of firms actively traded by FIIs, we find that the patterns are less decisive and not subject to clear interpretation because of the width of the confidence intervals. The wider confidence intervals may partly reflect the fact that this bottom decile is less actively traded, so the tails of the distribution are less populated, and the sample size for the bootstrapping method is smaller. The confidence intervals are particularly wide for the responses of FIIs to extreme movements in the S&P 500, however, and in this case, the tails of the distribution of the S&P 500 are not any different. However, the fact that these firms are less actively traded is what leads to wide confidence intervals for the FII responses.

**Figure 5: Bottom Decile -- Event on S&P500 and response of FII**



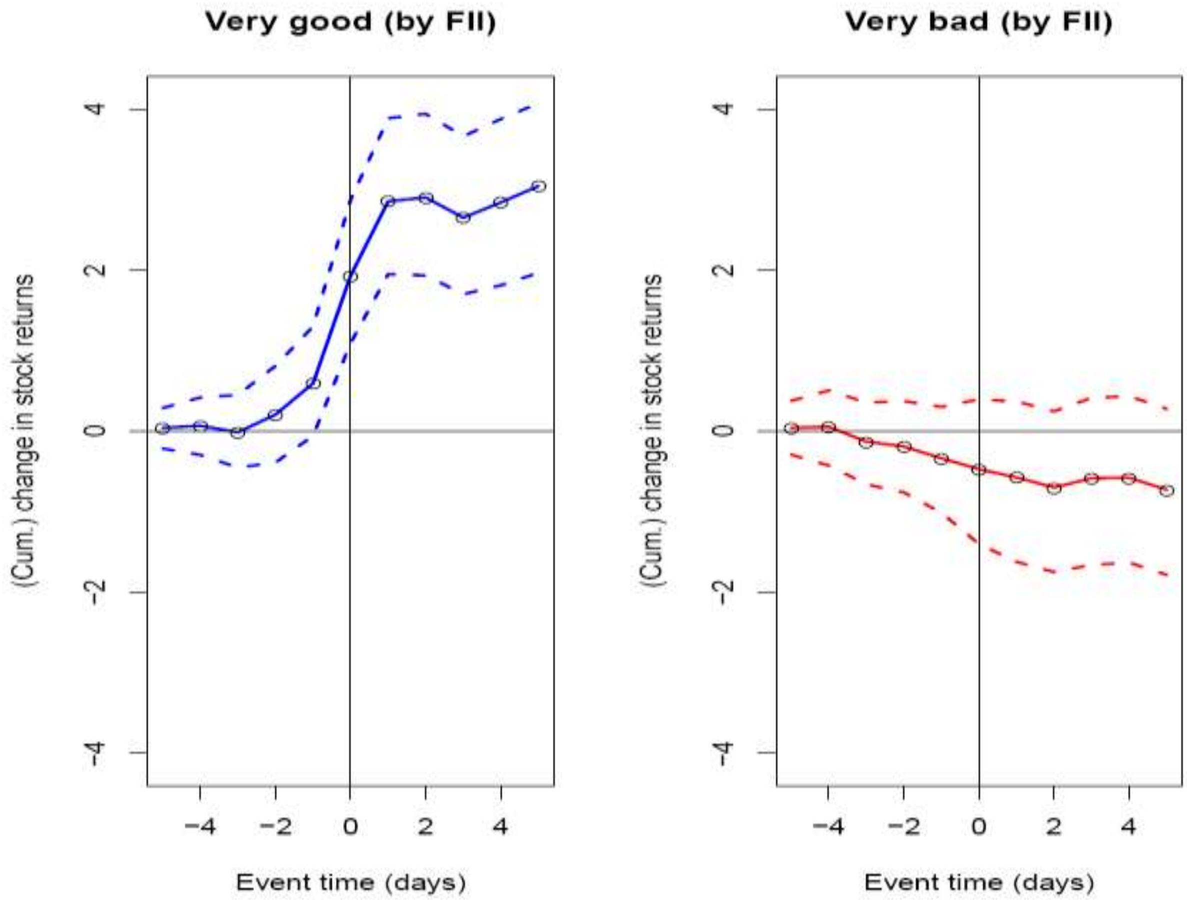

The case of FII responses to extreme movements in stock returns for the group of companies in the bottom decile is interesting, in that positive events display significant responses, but negative events have responses that are smaller in magnitude and not even significantly different from zero. The wider confidence intervals here, as well as the somewhat smaller magnitude of response, distinguish this from the top decile case, but otherwise, there are some similarities in the responses of FIIs to extreme movements in the stock returns of the top and bottom decile groups. Of course, this comparison is already across a restricted set of firms, but it does suggest some degree of uniformity across responses to different classes of Indian companies. The asymmetry with respect to positive and negative events does not have an obvious explanation, but bears further investigation.

**Figure 6: Bottom Decile -- Event on stock returns and response of FII**




Finally, the case of extreme events in FII flows for the bottom decile of firms, and the responses of stock returns, is presented in Figure 7. As for the top decile, there is a clear asymmetry between responses to positive and negative events, and the magnitude of the responses in the negative case is smaller and no longer statistically significant after the event. The fact that the confidence intervals in Figures 6 and 7, while wider than those for the top decile firms, are narrow enough to provide statistical significance, suggests that the wide confidence intervals in the case of Figure 5 are indicative of some difference in how these bottom decile firms are viewed by FIIs versus the top decile firms. In particular, it may be reflective of different classes of FIIs investing in these smaller companies versus the big marquee names.

**Figure 7: Bottom Decile -- Event on FII and response of stock returns**




***Individual Firms***

Next we turn to the results for individual firms. Figure 8 shows the results for Axis Bank, where the extreme events are in the tails of S&P 500 returns, and the responses of net FII flows are considered. In this figure, and subsequent ones for other cases, the confidence interval is constructed beginning from the first day of the 11-day window. There is some evidence that FII flows for this firm lead extreme S&P 500 returns, but the confidence intervals are too wide for this to be treated as statistically significant. Furthermore, there is evidence of persistence after the event: net FII flows stay positive (negative), and in the latter case, the cumulative graph maintains a downward slope. The confidence interval for the 11-day window includes zero, for both the positive and negative shock cases.

**Figure 8: Axis Bank -- Event on S&P500 and response of FII**

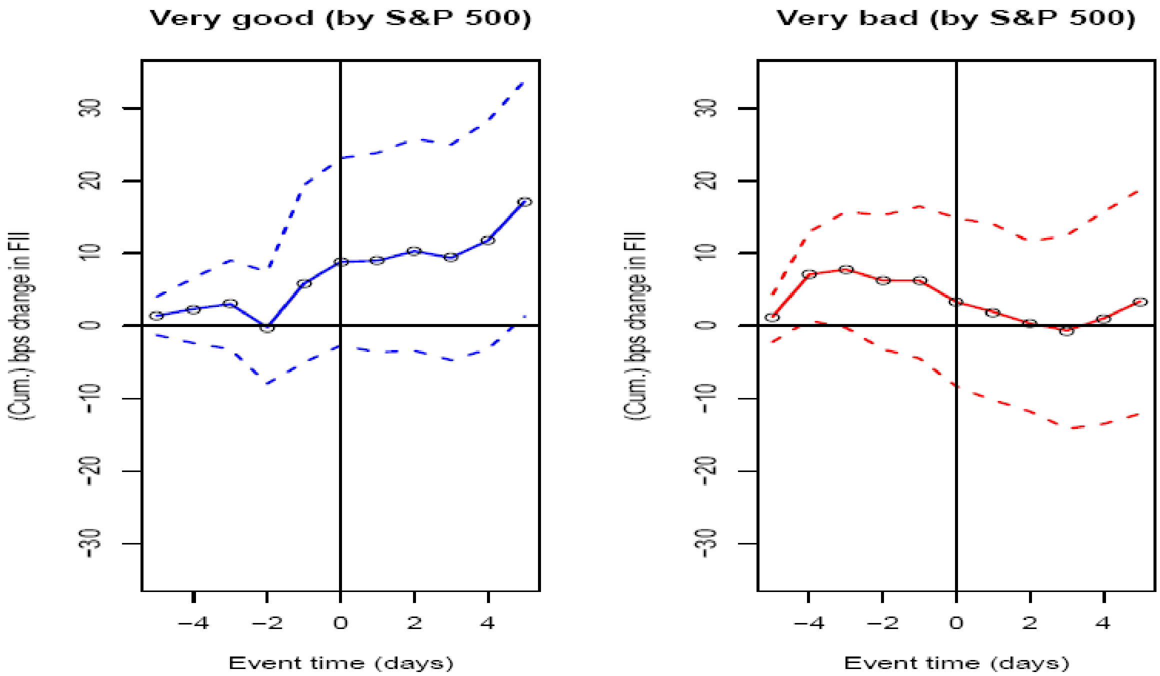



Figure 9 shows the response of FII flows to extreme events defined by being in the tail of the distribution of stock returns of Axis Bank. In this case, the event is not exogenous, as can be assumed for the S&P 500 index, so the causality is not as clear cut in this case. However, the behavior of FII investments in the stock of Axis Bank in response to extreme values of stock returns is not too dissimilar to the behavior in response to extreme events in the S&P 500 index. However, the confidence intervals are narrower, and the responses of FII flows to positive extreme events show some momentum.

**Figure 9: Axis Bank -- Event on stock returns and response of FII**

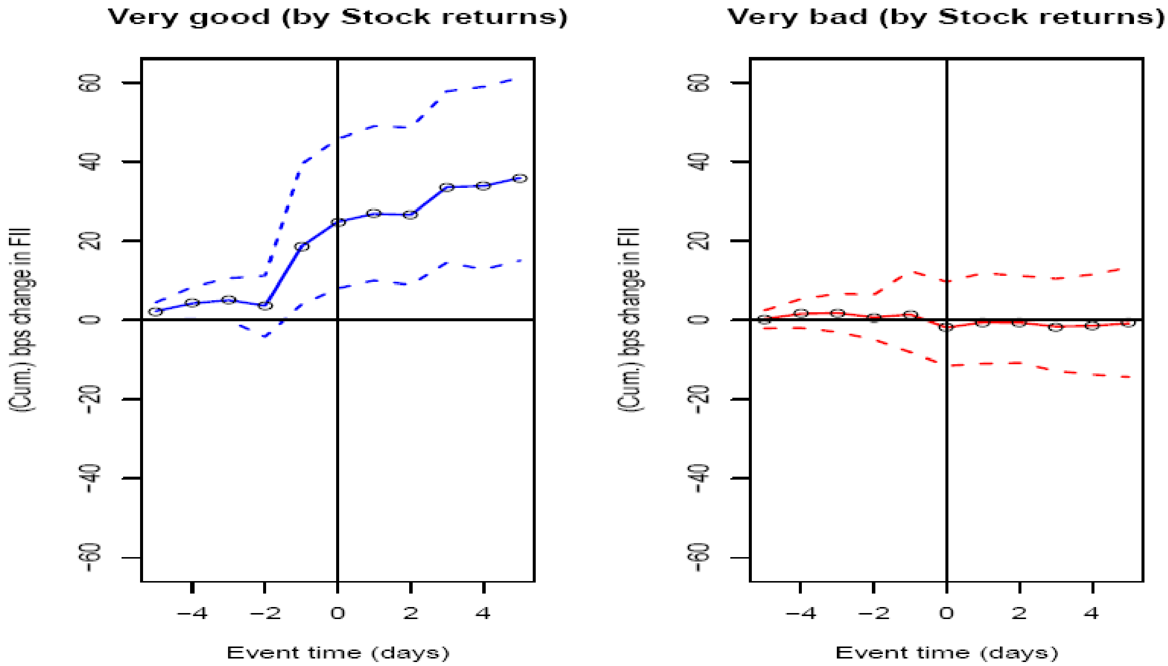
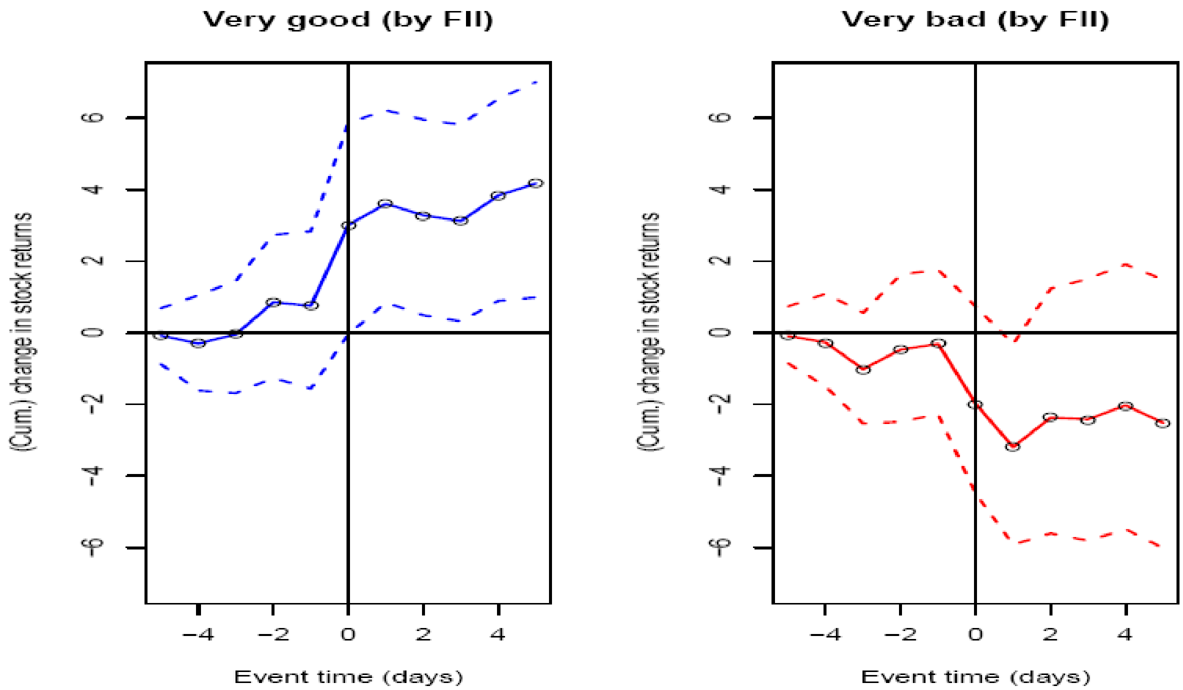



Figure 10 shows the reverse relationship to the previous figure. How do stock price returns respond to extreme values of FII flows in and out of the company's stock? Again, since both the return and quantity variables are endogenous, there is not a strict causal relationship to be inferred in this case. However, there is much more symmetry in the impact of large inflows and large outflows on stock returns, than was the case for the reverse direction of impacts (from stock returns to flows). However, extreme positive FII inflows into the stock seem to be preceded to some extent by positive stock performance, and to be followed by continued positive momentum. The confidence interval lies entirely above the horizontal axis of zero stock returns. In the case of extreme FII outflows, however, the performance of the stock is somewhat different – there is less of a prior effect, and no momentum of the negative event.

**Figure 10: Axis Bank -- Event on FII and response of stock returns**




Figures 11 through 13 follow the same sequence of interactions, but in this case for another major Indian bank. ICICI bank is one of the country's largest private banks, with a market capitalization more than double of Axis Bank. It also has American Depository Receipts (ADRs), traded on the New York Stock Exchange. As indicated in Table 6, it is proportionately more heavily traded than Axis Bank, even on the Indian market, aside from any ADR trading. The more globalized nature of investment in ICICI Bank is reflected in Figure 11. In contrast to Axis Bank (Figure 1), FII flows in and out of the stock respond more noticeably to extreme events on the S&P 500 index, though the wide confidence intervals still do not permit any inference of statistical significance.

The results for responses of FII flows to extreme events defined by tail values of daily stock price returns are also different for ICICI Bank versus its smaller competitor. In particular, poor stock price performance seems to trigger an outflow by FIIs. This pattern is mirrored in Figure 13, which displays the reverse relationship – extreme events defined by FII outflows in the tail of the distribution are preceded and followed by negative stock price returns. The contrast between the response of FII flows on the positive side to a global shock (proxied by movements in the S&P 500) and on the negative side to domestic factors, is also noteworthy, and deserving of further explanation.

**Figure 11: ICICI Bank -- Event on S&P500 and response of FII**

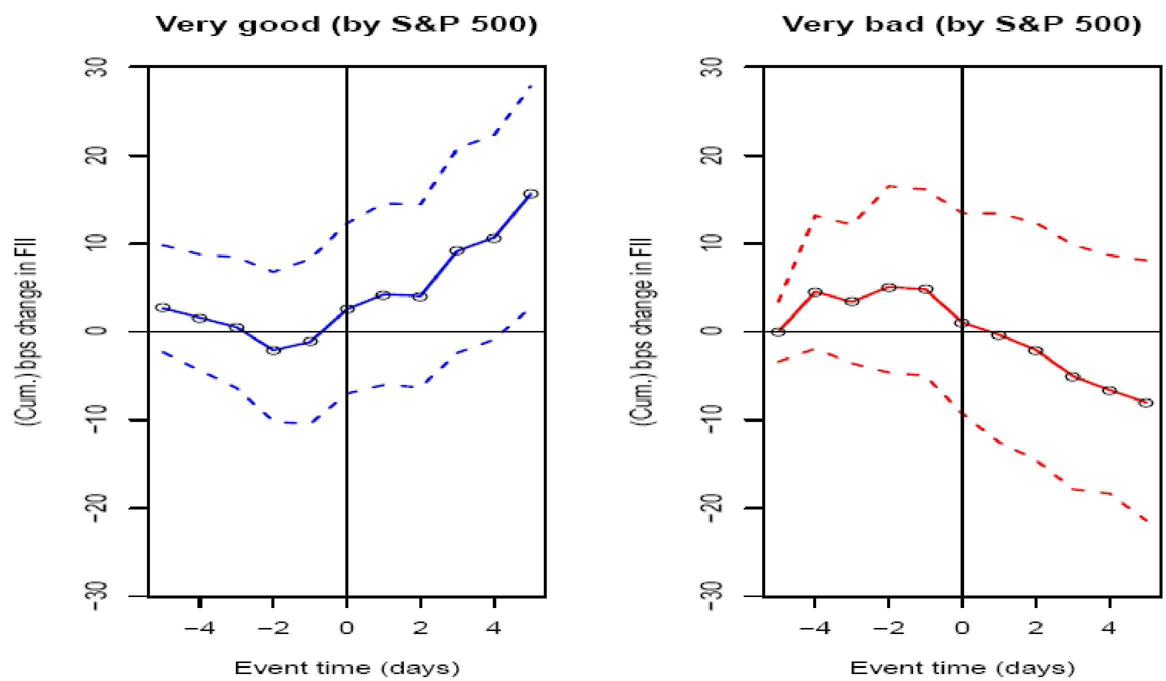



**Figure 12: ICICI Bank -- Event on stock returns and response of FII**

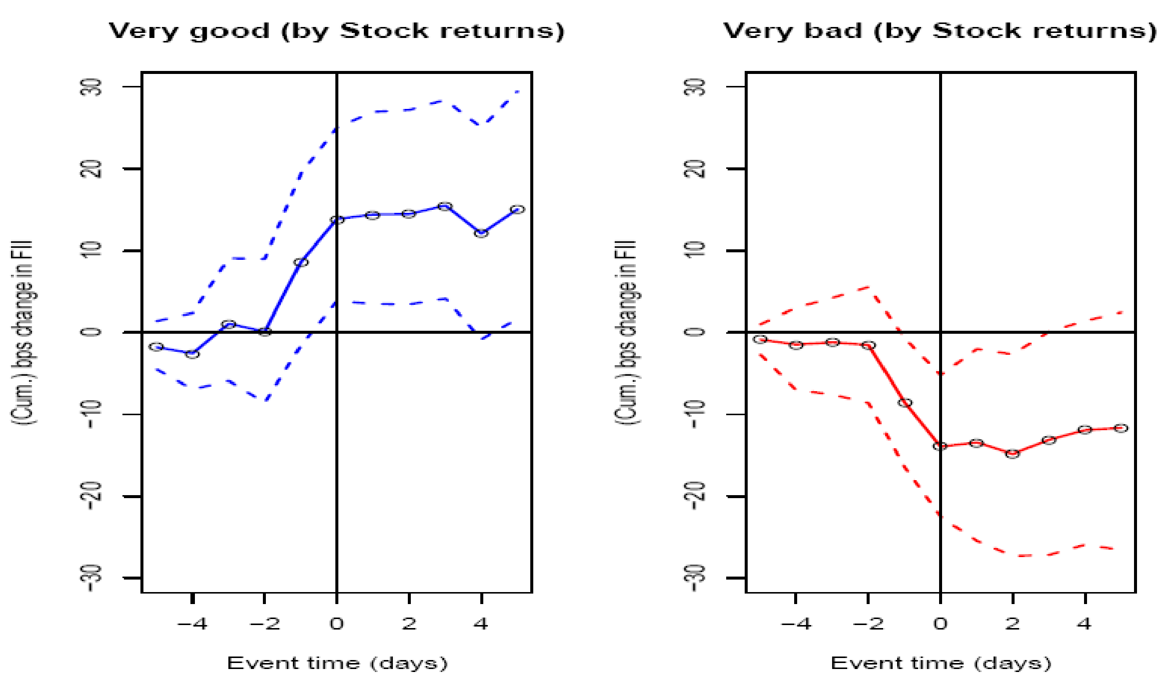
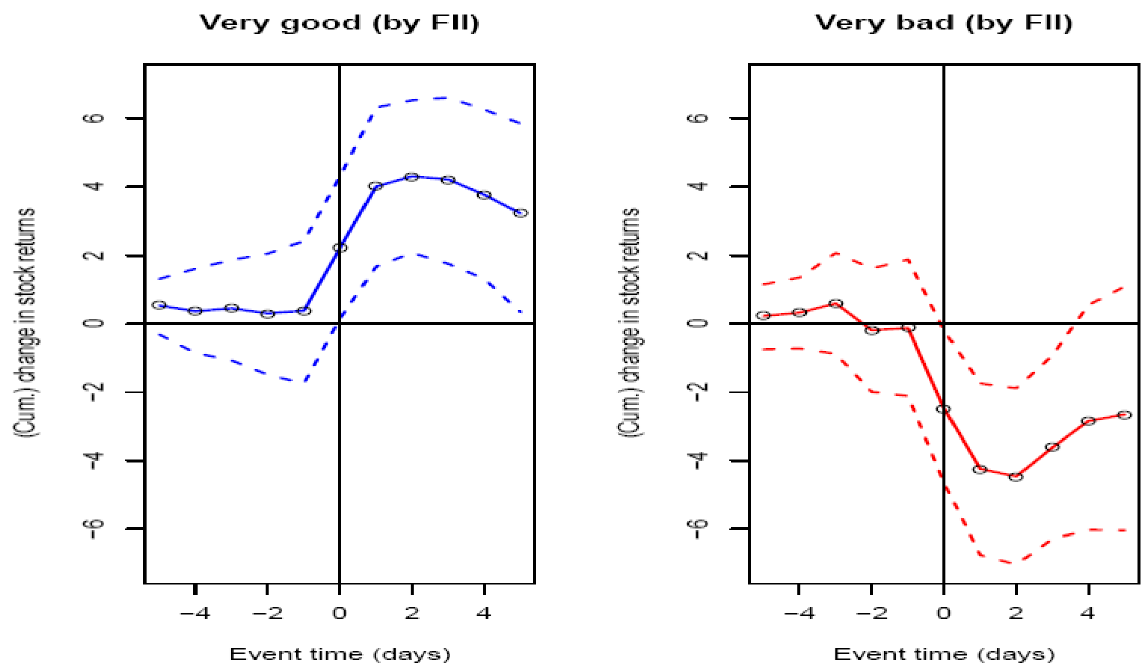


**Figure 13: ICICI Bank -- Event on FII and response of stock returns**




Figures 14 through 16 present the results for Infosys, one of India's iconic information technology companies, focusing on software services for export. Infosys also has ADRs traded on the US stock market. The patterns of responses in the case of Infosys are quite different than either of the bank stocks, and are puzzling in some respects. Although the confidence intervals are very wide in all cases, making statistical inference of limited usefulness, the average behavior of the response variables is surprising in some cases. Responses of FII inflows to positive extreme events in the S&P 500 index or the company's own stock price returns display some positive momentum, similar to the case of ICICI bank. However, FIIs seem to respond to negative tail events in stock price returns by treating these as a buying opportunity. In other cases, the behavior of FIIs is similar to that observed for the bank stocks, with momentum carrying over for a day after an extreme event, but not beyond that. One can offer some conjectures as to possible portfolio strategies of holders of Infosys stock, but in the absence of more detailed data, these would remain conjectures. However, one can at least note that there is not an obvious one-way effect of foreign investors magnifying trends in individual stocks, or simply amplifying fluctuations.

**Figure 14: Infosys -- Event on S&P500 and response of FII**

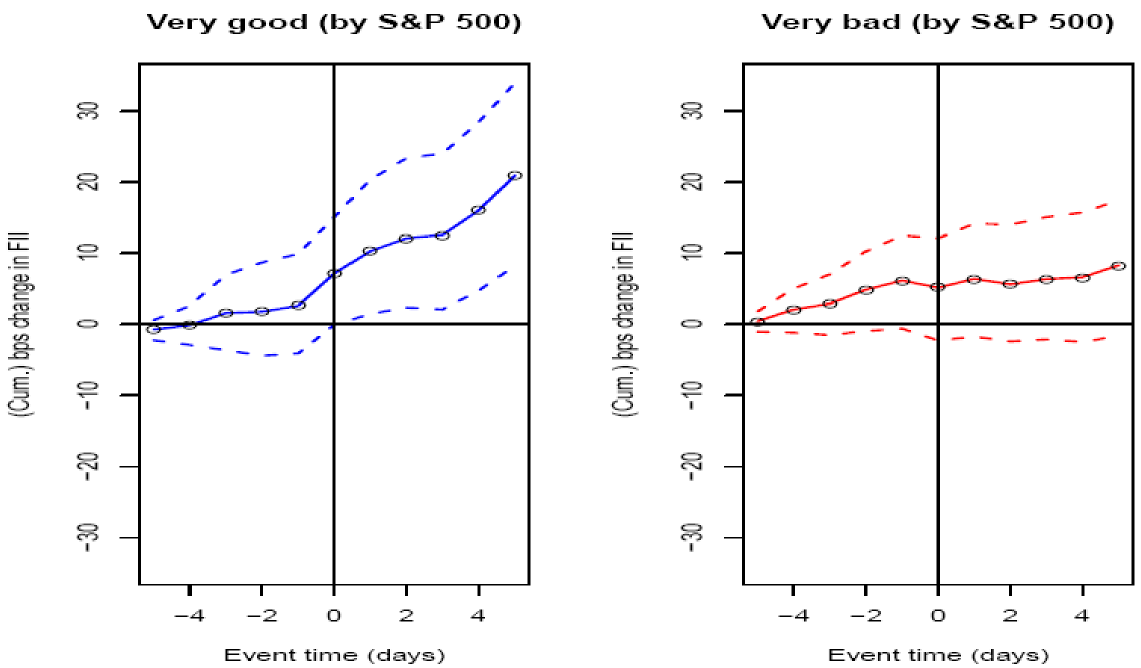



**Figure 15: Infosys -- Event on stock returns and response of FII**

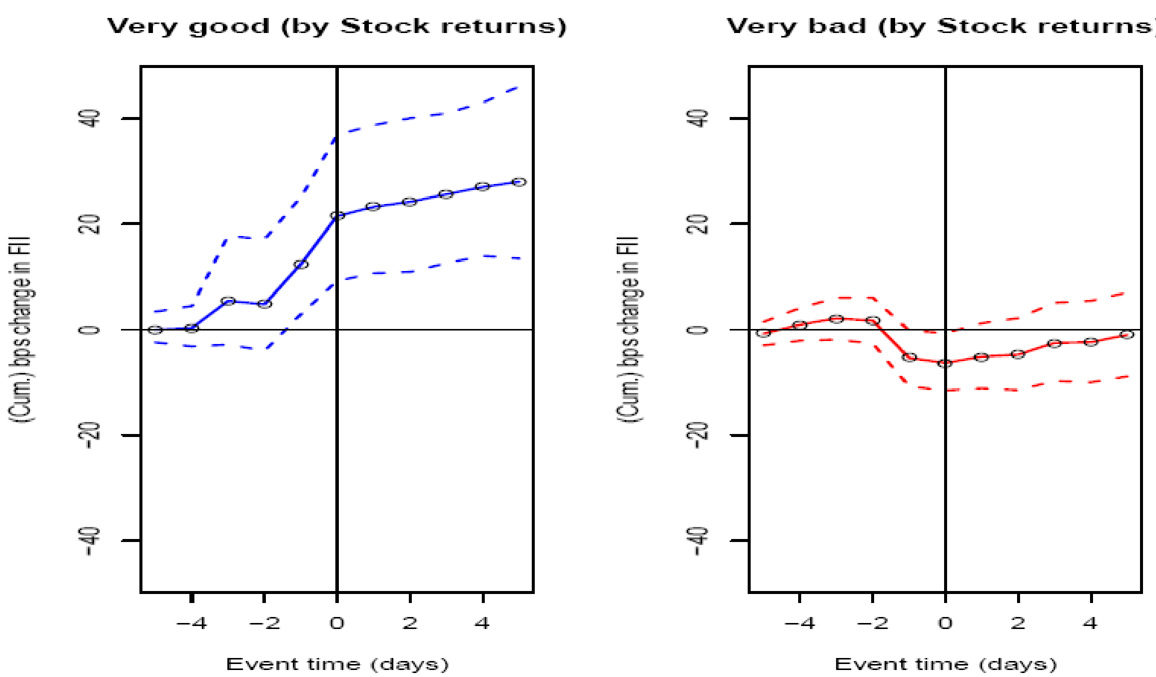
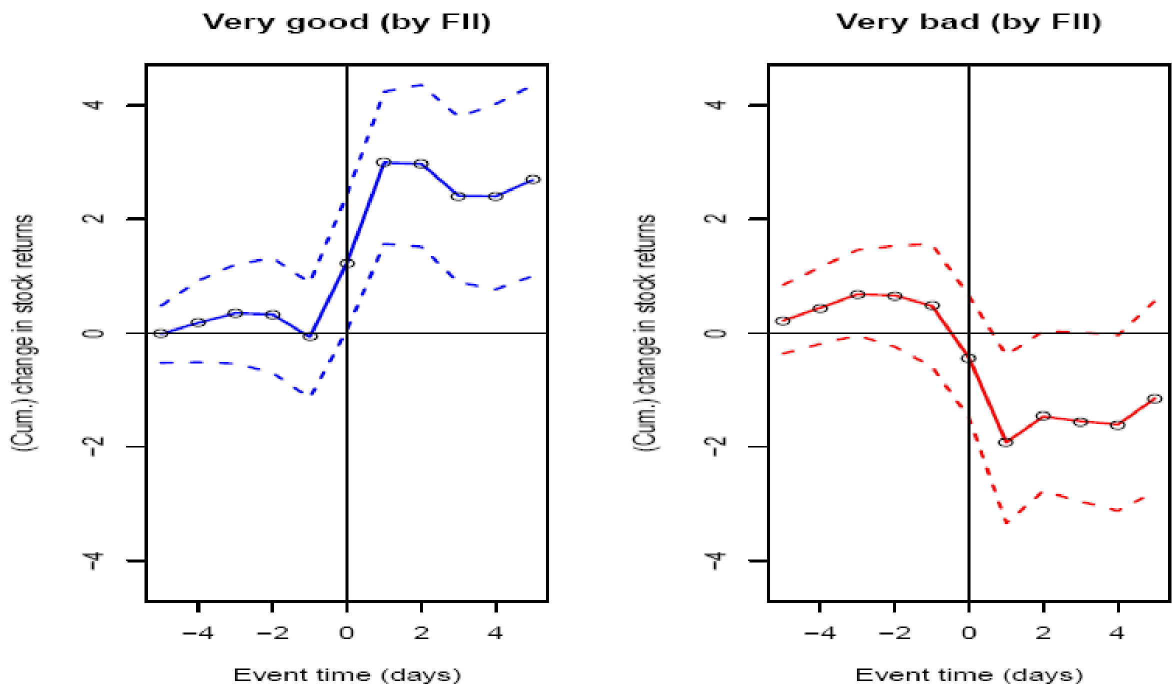


**Figure 16: Infosys -- Event on FII and response of stock returns**




Figures 17 through 19 illustrate the interactions between the variables for TCS, another important Indian information technology company – in fact the largest by sales and profits, with a market capitalization of over 4 percent of the Nifty stock market index. The behavior of FII flows in and out of the company's stock (Figure 17) in response to extreme global shocks display asymmetries somewhat reminiscent of the other firms considered. FII responses to extreme movements of the company's own stock are less symmetric between positive and negative shocks, and somewhat similar to the kind of behavior uncovered for Infosys. In the case of TCS, extreme inflows and outflows of FII investment into the stock seem to be less important in moving the stock return, even temporarily (Figure 19). Furthermore, negative returns precede an extreme FII inflow, suggesting a strategy of buying on dips. The obverse pattern is also visible in that FII outflows are immediately preceded by positive returns (though the confidence intervals are too wide to give statistical significance.

**Figure 17: TCS -- Event on S&P500 and response of FII**

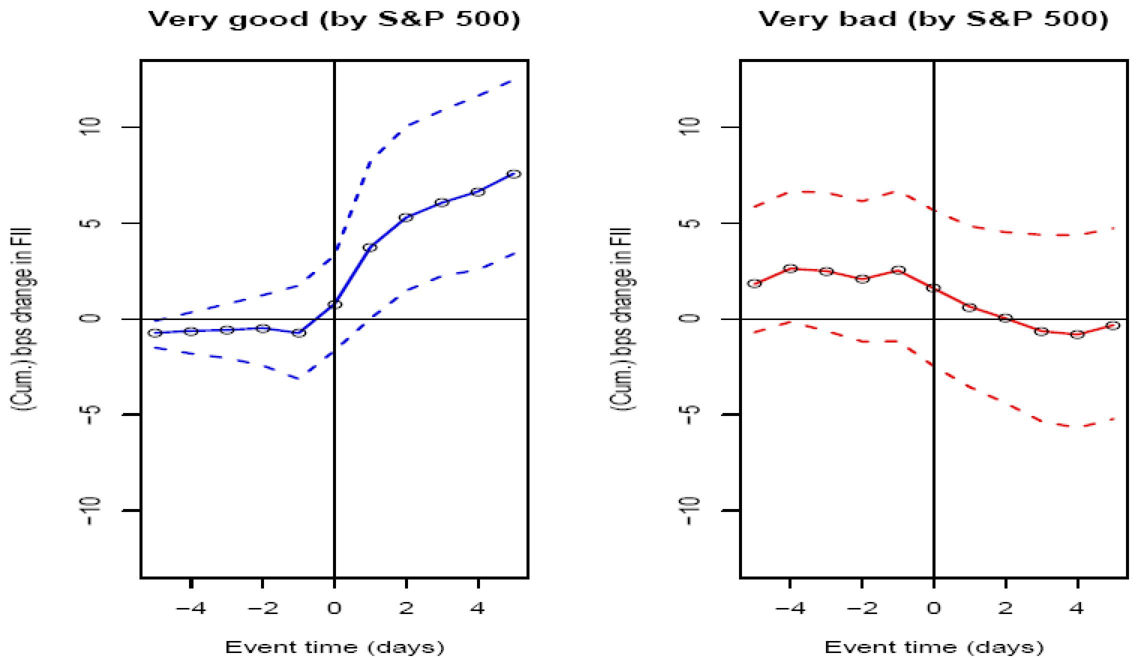



**Figure 18: TCS -- Event on stock returns and response of FII**

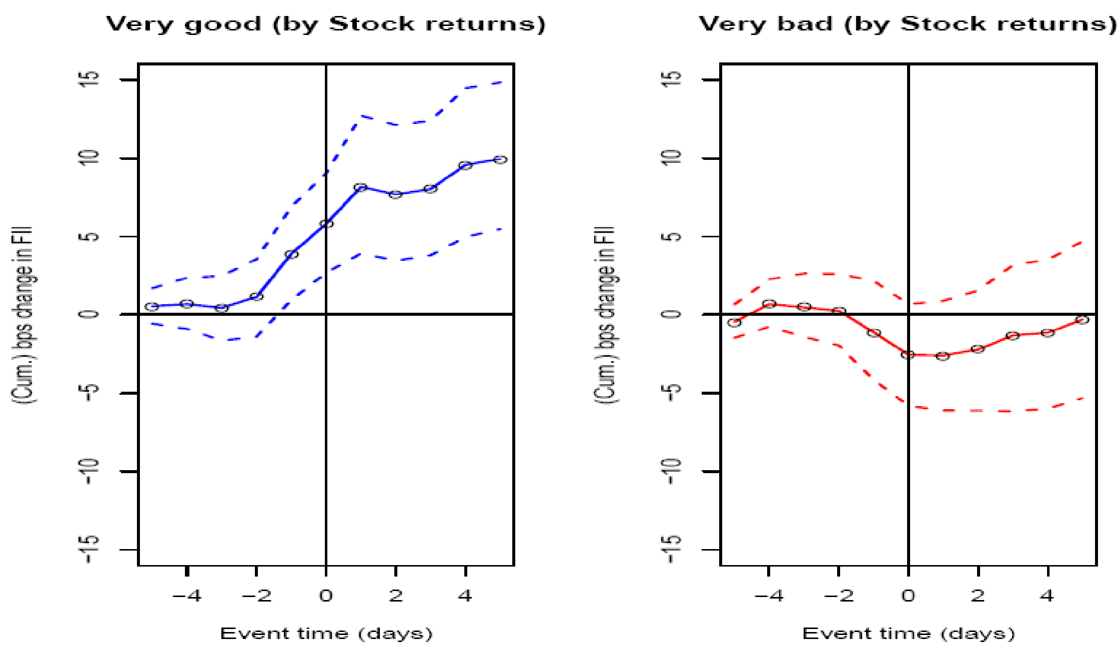
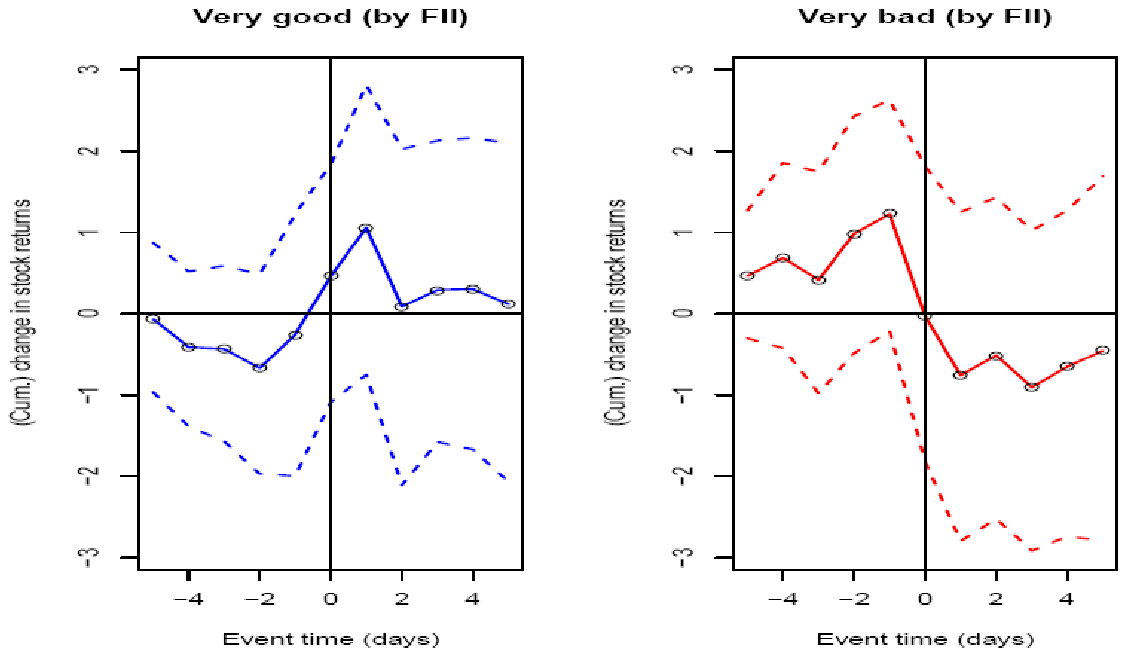


**Figure 19: TCS -- Event on FII and response of stock returns**




Finally, Figures 20 through 22 display the results for Larsen & Toubro (L&T), a major Indian engineering firm. In this case, responses of FII flows to global shocks as proxied by extreme events in the S&P 500 (Figure 20) are not as great as in the case of stocks such as ICICI Bank and Infosys, though the confidence intervals are also relatively wide in this case. There is considerable sensitivity of FII flows to movements in the stock price of the company itself (Figure 21), though with little suggestion of momentum after the event. In the case of extreme events as defined by FII inflows or outflows (Figure 22), negative stock returns seem to precede extreme cases of negative flows, rather than there being any momentum after the event of an extreme outflow by FIIs.

The result in some case, of positive FII inflows into the company following negative stock returns, suggests that there is not an obvious case that FIIs amplify stock price fluctuations, though in other cases such an impact is discernible. At a minimum, this suggests that, even at the level of individual stocks, the behavior of FIIs is heterogeneous, and subject to company-specific factors. This is comforting for policy makers who might worry about herd behavior or destabilization by FIIs as big fish in a small pond.

**Figure 20: L&T -- Event on S&P500 and response of FII**

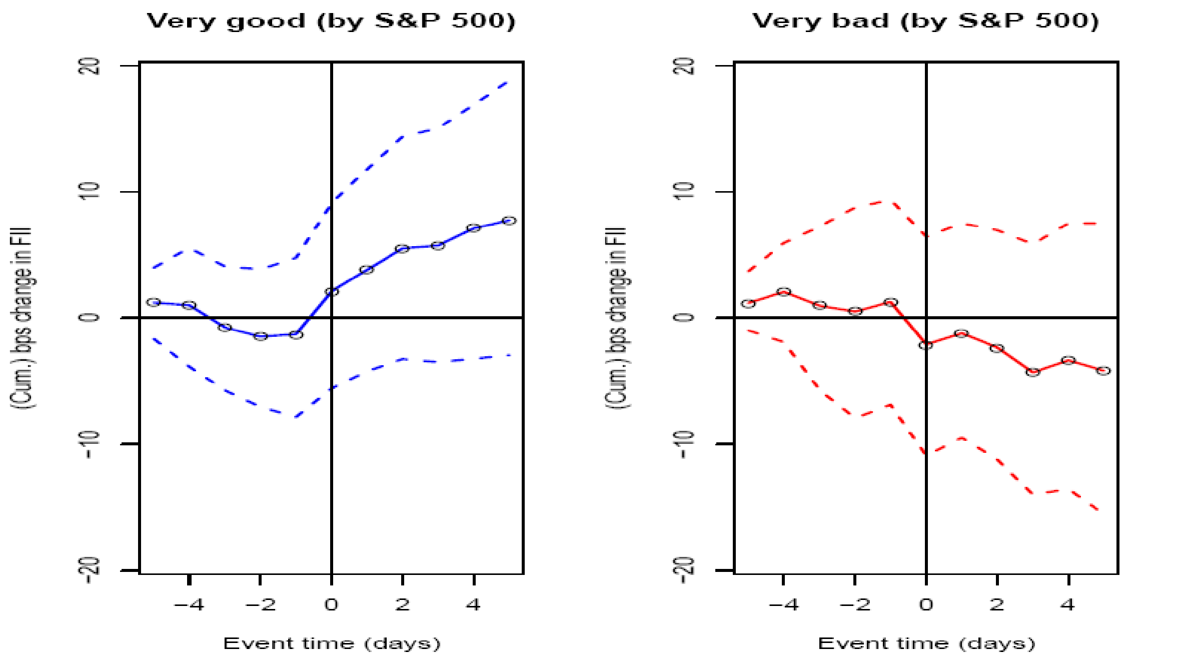



**Figure 21: L&T -- Event on stock returns and response of FII**

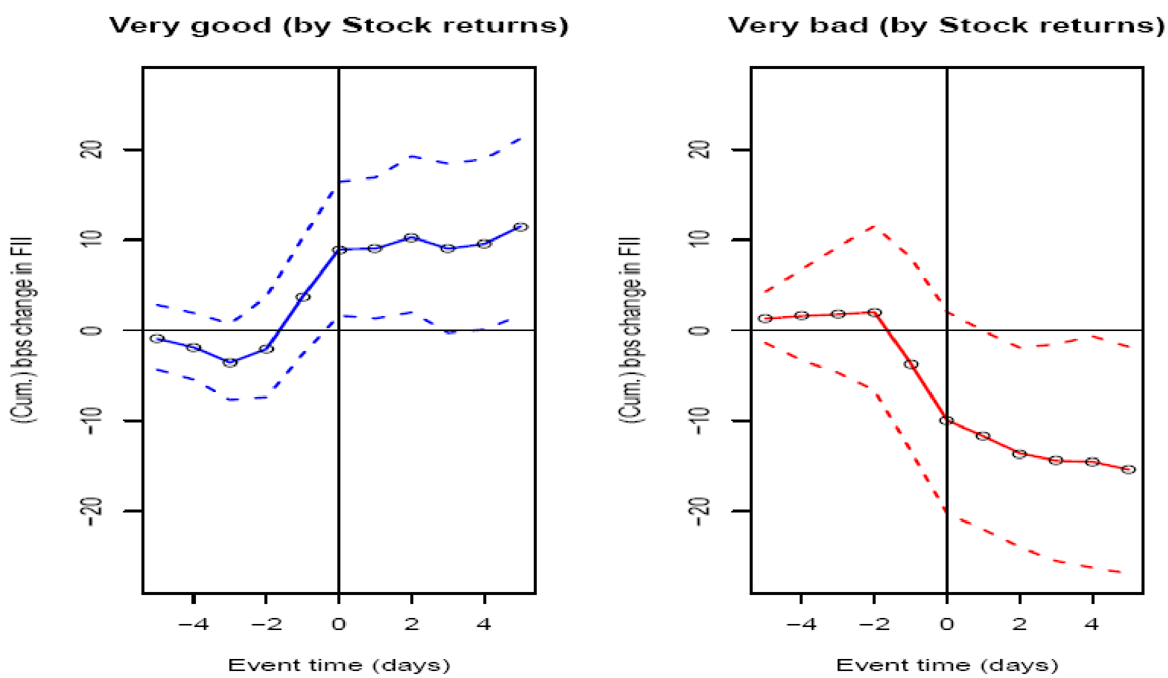
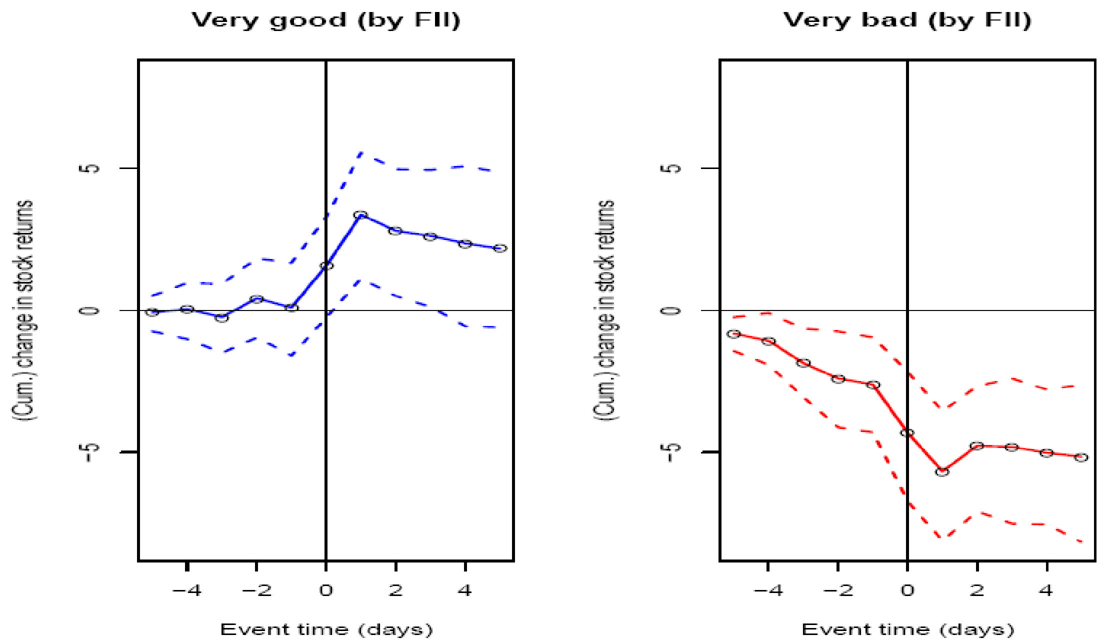


**Figure 22: L&T -- Event on FII and response of stock returns**




Overall, our results suggest that there is not a simple relationship between the returns on an individual stock and FII flows in and out of that stock. Even though the relationship here is not strictly causal (both variables could be – and probably are – moving because they are jointly affected by some exogenous variable), the difference in pattern between negative and positive cases suggests that there is not a single explanation in terms of information transmission or of price pressure: such general explanations should not depend on the sign of the movements.[12] Furthermore, there are differences across individual stocks that do not have a facile explanation in terms of general patterns of behavior.

From the perspective of a policymaker worried about FII outflows in response to very bad days in the Indian stock market going on to trigger a crisis, there is no evidence from this data and analysis that such a problem has occurred over this period, even at the level of individual stocks. Thus, the casual perceptions of the dangers of "hot money" in the context of FII flows do not find empirical support here, just as they did not in our earlier, aggregate analysis.

## *5. Conclusions*

While India has gradually decontrolled the capital account from 1992 onwards, there has been a spirited debate about the wisdom of allowing large FII inflows to India. Some have asserted that

[12] The asset fire sale analysis discussed in the literature review is an example of an exception to this directional independence of explanations, but it goes in the opposite direction to the pattern observed here.

FII inflows constitute a threat to the Indian economy, contributing to asset bubbles. At other times, concerns have been expressed about the damage caused by sharp FII outflows. There are complex issues of impacts on the exchange rate, exports, and inflation, but a major fear is also that sharp inflows and outflows destabilize the Indian stock markets. While policymakers have been much less concerned with the dangers of inflows, arguing that they can be managed properly as well as contribute to domestic growth, the basic empirical question of impacts of portfolio flows on domestic equities, and whether they have been factors in triggering bubbles and crashes, remains to be answered. This paper provides a further step in building the empirical underpinnings necessary for informed policy debate, by extending our earlier work to the analysis of the behavior of individual stocks.

A major contribution of this paper lies in focusing on extreme events. In particular, we do not find evidence in this data that sharp FII outflows destabilize the Indian stock market, in the sense of leading to further, cumulative declines in the prices of major stocks. In the case of some companies, there appear to be cumulative effects at work, such as might be associated with momentum trading. In other cases, however, drops in stock prices seem to be viewed by FIIs as buying opportunities. As we extend our work to incorporate additional firms, the prevalence of different types of FII behavior, and of differential impacts, will emerge more clearly.

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