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# Foreign Investors under Stress: Evidence from India

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# Foreign Investors under Stress: Evidence from India*

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**Abstract**

Emerging market policy makers have been concerned about the financial stability implications of financial globalisation. These concerns are focused on behaviour under stressed conditions. Do tail events in the home country trigger off extreme responses by foreign investors – are foreign investors `fair weather friends'? In this, is there asymmetry between the response of foreign investors to very good versus very bad days? Do foreign investors have a major impact on domestic markets through large inflows or outflows – are they 'big fish in a small pond'? Do extreme events in world markets induce extreme behaviour by foreign investors, thus making them vectors of crisis transmission? We propose a modified event study methodology focused on tail events, which yields evidence on these questions. The results, for India, do not support the skeptical perspective on financial globalisation.

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*All these countries have spent 40 years trying to build up their economies and a moron like Soros comes along with a lot of money to speculate and ruins things.*

– Mahathir Mohammad
Prime Minister of Malaysia, January 1998

## *1. Introduction*

The impact of international capital flows on emerging markets has occupied the attention of policy makers and economists for many decades. While developing countries have eased capital controls in recent decades, the debate is not settled, and many policy makers continue to be concerned about the problems associated with financial globalisation. These concerns have become more prominent after the global crisis, with the suggestion by the IMF that capital controls should be viewed more favourably under certain situations.

A significant international finance literature has explored the role of foreign investors in emerging markets. The emphasis of these explorations has been on the extent to which foreign investors are a 'stabilising' or a 'destabilising' influence in emerging equity markets, in the following sense – do foreign investors trade in a manner that push prices away from the fundamental value (in which case they are viewed as 'destabilising')? Alternatively, do foreign investors forecast prices better than domestic investors, and thus enhance market efficiency (in which case they are viewed as 'stabilising')? A considerable literature has developed on these questions, with mixed results.

The motivation for this paper lies in the distinction between this literature, and the concerns of policy makers in emerging markets. Emerging market policy makers are concerned about the financial stability consequences of foreign portfolio flows. However, their notions of stability may differ considerably from those expressed above. From the viewpoint of policy makers in emerging markets, four questions about the financial stability implications of foreign investment flows appear to loom large;

1. Do foreign investors exacerbate a domestic crisis by withdrawing capital on a large scale?
2. In this, is there asymmetric behaviour, 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 equity or currency market of an illiquid emerging market?
4. When there is stress in the global financial system, 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. These questions are thus distinct from those that have occupied the existing literature.

These four questions of interest to policy makers are focused almost exclusively on behaviour in extreme events. The first question is about the behaviour of foreign investors when there are extreme events in the local economy. The second question is about potential asymmetries in response to large positive shocks versus large negative shocks in the local economy. The third question is about days with extreme events in foreign investment and, the fourth question is about extreme days in the world economy.

In the existing literature, many studies have examined the interaction between foreign investors and emerging economy stock markets through estimation of linear relationships in the data, through VARs and VECMs. The estimated parameters then reflect the overall average relationship between the variables of interest. However, there may be an ordinary regime, i.e. the behaviour of foreign investors on ordinary days, and alongside it there may be different behaviour in the tails. While a $100 million sale may not destabilise a currency market, a $1 billion sale might. In the policy discourse, the concern is seldom about the overall average effects, but about behaviour under stressed conditions. If extreme behaviour by foreign investors is found under tail events, this is relevant to policy makers, regardless of what the overall average estimates show. Estimators based on averaging across all observations may tend to give misleadingly reassuring answers to policy makers, by underplaying extreme behaviour in the tails. The estimation of linear models on the overall data may yield benign results, but it may mask nonlinearities in the tail response, which need to be uncovered and brought into the policy discourse.

The contribution of this paper lies in adapting the workhorse of empirical finance, the event study, so as to directly address the above four policy-relevant questions, and in showing results for a large emerging market, India. Our methodology focuses on extreme events, allowing for the possibility that what happens under stressed market conditions may differ from day-to-day outcomes, and measures relationships of interest under stressed conditions. While the behaviour associated with extreme events can be estimated through parametric models, we adapt the non-parametric 'event study' methodology. As an example, we identify events consisting of extreme movements of the domestic stock market index. Surrounding these dates, we analyse the fluctuations of foreign investment 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 the paper, for India, are relatively benign. We find that on very good days in the local economy, foreign investors exacerbate the boom by bringing in additional capital. However, there is asymmetric behaviour and on very bad days in the local economy, no significant effects are found. Foreign investors exacerbate the boom on very good days in India, and appear to be indifferent to very bad days. 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, either on the currency market or on the equity market. Finally, very positive days on the S&P 500 trigger off 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 off exit by foreign investors. Foreign investors are not a vector of crisis transmission into India.

While the results for one large emerging market – India – are relatively benign, it could well be that in other countries, different results are obtained. Alongside cross-sectional variation by country, there may also be substantial cross-sectional variation in the impact of foreign investors upon different securities within a country. Foreign investors may not be big fish in a small pond when it comes to the Indian stock market index – but such problems may be present either with illiquid Indian securities or with the stock market indexes of countries with an illiquid equity market. Both these dimensions constitute possibilities for future research.

The remainder of the paper is organized as follows. In section 2, we summarise 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, looking beyond the traditional event study involving events about firms. Finally, we relate our approach to the 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 concludes.

## *2. Related Literature*

The question of impacts of capital flows by foreign institutional investors ("FII")[1] has exercised policymakers in India for some time, and attracted corresponding academic attention. A variety of authors have approached these questions using vector auto regressions (VAR). 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 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

[1] 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 FII.

(e.g., Rakshit, 2006). Chakrabarti (2006) also points out that there is evidence of a structural break in the data around April 2003, implying 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: the conclusions of those studies would not be an effective guide to more recent concerns of Indian policymakers.

More recent work includes that of Anshuman, Chakrabarti and Kumar (2010) who bring high frequency data and the tools of modern market microstructure analysis to address these questions. They find that the aggregate trading of FIIs dampens the volatility of the Indian stock market. Furthermore, positive shocks in trading volume have greater impacts than negative shocks, while trading between FIIs and domestic investors increases volatility.

Finally, Stigler, Shah and Patnaik (2010) estimate a VAR involving five variables: net FII investment, the Nifty index,[2] the S&P 500 index, the ADR premium index and the INR/USD exchange rate. Causality tests indicate that a shock to net FII flows does not cause the Nifty index returns, 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, and does not distinguish between "normal" and "extreme" days on the market.

We now turn to the significant literature 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.

On the other hand, different analyses, including that of Choe, Kho and Stulz (1998, 2001), find that other data is more consistent with the price pressure story. More recently, Jotikasthira, Lundblad and Ramadorai (2011) 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 behaviour, 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 those causes, their first-order concern is about the strength of the relationship between

[2] The Nifty index is India's major stock market index, analogous to the S&P 500 index in the US.

foreign flows and domestic market returns. Moreover, their interest is not so much in the normal or average relationship, but in what happens under stress. Therefore, our focus is on obtaining an estimation strategy, which illuminates the relationships in extreme circumstances, rather than in an information interpretation. In order to do this, we adapt the event study to suit our present objectives.

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 can be traced back to Fama et al. (1969), followed by the early statistical analysis of 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 statistically examined. For example, abnormal 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 here has two key strengths. First, it imposes no functional form upon the responses surrounding event date: the data guides a non-parametric functional form about effects before and after event date. Second, there is a clear causal interpretation interlinking events and financial market responses. While event studies date back to 1969, the identification strategy of the event study is consistent with modern approaches at exploiting natural experiments in quasi-experimental econometrics (Angrist and Pischke, 2010).

While the event study methodology was invented in order to analyse the response of stock prices to events, 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 behaviour 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 behaviour 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.[3] The data is quarterly, and covers 2003:Q1 to 2009:Q2. The Broner et al. study finds that crises do matter, and affect the behaviour 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.[4]

Turning to the question of behaviour in the tails, an extensive literature has built up, on the analysis of tail behaviour using extreme value theory. The questions of this paper could potentially be approached through these tools, as has been done by Harmann et. al. (2004). Our approach adapts a familiar tool (the event study) to yield results which are easily

[3] 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.

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

interpreted, with a methodology which can be easily applied by researchers worldwide. For an analogy, estimation of stock betas using OLS was adapted to focus on estimation of OLS regressions using only the tail observations, to obtain the `tail beta', which is proving to be a useful element of the analysis of financial crises (Engle and Richardson, 2012). In our case, we would interpret the application of the event study methodology, with tail events, as yielding a result analogous to an impulse response function (from a VAR) computed in the tails.

## *3. Data and Methodology*

We use daily data for Indian stock market returns, net FII inflow, and the US S&P 500. We also observe the `call money rate', as a measure of the domestic interest rate. This data is available for the period 15 February 2000 to 29 July 2011, a period of more than 11 years, giving a unique dataset with 3561 observations of daily data. Summary statistics for all the series used in this paper are presented in Table 1.

### *FII Data*

FIIs in the Indian context can include a range of financial institutions, including banks, asset management 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). FIIs are required to settle through custodian banks.[5] Custodian banks are required to supply data to the government, and this is the source of our data. This yields a daily time-series of the activities of foreign investors on the equity market. The raw data is shown in Figure 1. This data is clearly non-stationary, reflecting the dramatic growth of India's equity market in this period, owing to which the dollar value of foreign investment has risen sharply. To correct for this, we divide this by the market capitalization of the CMIE Cospi index. This yields Figure 2 (the units of the vertical axis are multiplied by 10,000), which suggests that the scaled series (FII/MktCap) is stationary. This is confirmed by standard tests for stationarity.

### *Stock Market Data*

Our analysis uses the `Nifty' stock market index for India (Shah & Thomas, 1998), and the S&P 500 index for the US. Each of these indexes dominates the index derivatives and index fund industries of its respective country. 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.

### *Interest and Exchange Rates*

Our main interest is in the behaviour of FII flows and the stock market, but policymakers are also concerned with the response of interest rates and exchange rates to sharp movements in

[5] For institutional details about capital controls and foreign investment into India, see Shah & Patnaik (2007, 2011).

FII flows.[6] The interest rate we use is the call money rate, expressed as a percentage per annum rate. The rate used is a weighted (by volume of trades) average of rates for all reported trades, as calculated by the Reserve Bank of India. We also use first differences to deal with non-stationarity. The exchange rate is simply the nominal Rupee – US Dollar rate. Again, we use percent changes in the rate to avoid non-stationarity. Negative changes are therefore cases of nominal appreciation of the Rupee against the US Dollar.

### *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. For the purposes of this paper, 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 itself 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 favoured by going out into the tails) versus adequacy of data size.

Table 2 summarises the time pattern of the distribution of extreme events. The simple time pattern itself is revealing. As one would expect, a large proportion of the extreme values occur in 2008 and 2009, especially for the return variables. However, the Nifty and S&P 500 also display differences in time patterns of extreme daily returns, with, for example, 2002 being much more volatile for the S&P 500 in the sense of having a large number of tail values.[7] The distribution of FII tail values is much more even across years than in the case of returns, and its time pattern does not completely match that of Nifty returns. For example, 2005 has only 8 tail values for Nifty returns, but 33 for FII flows.[8]

There are two further issues to consider. First, matters are complicated by the fact that 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.

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6 We are grateful to Subir Gokarn for emphasizing this point.

7 In general, and not surprisingly, extreme values of returns on the Nikkei 225 index (not reported here) are more highly coincident with the S&P 500 than is the case for the Nifty.

8 In fact, the difference in time patterns between Nifty returns and FII flows is even more striking in the case of 2.5% tails.

We approach this problem through two paths. 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 have 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, as an second, alternative estimation strategy, we isolate what we term as "uncontaminated" single-day events where, within the event window, there is no other event. We define events using 5% tails rather than 2.5% tails of the distributions, so as to obtain adequate observations. For example, in the case of Nifty returns, these choices give us 65 events in the upper 5% tail, where there is no other event in the five days on either side of the event. These alternative results are presented as a sensitivity analysis, in the Appendix.

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 behaviour). 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. At the same time, our results are not qualitatively modified by shifting to a 20-day window, i.e. with 10 days on each side of the event.

Table 3 summarises the number of events (including the clustered events) that we obtain in this manner, for each of the three main variables – Nifty returns, S&P 500 returns and normalized net FII flows – as well as the three subsidiary variables. Roughly 60% of the 99 or 100 extreme events in each tail are uncontaminated, in the sense of there not being another tail event in the pre-event or post-event window. The resulting sample sizes of 36 to 66 for the main variables are sufficiently large to obtain considerable statistical precision, as is demonstrated ahead.

### *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 these '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 statistical efficiency. In this paper, such adjustment is not relevant since the object of interest is not features about individual firms but the overall macro time-series.

It must be emphasised that controlling for other factors is only a tool for increasing statistical efficiency. Whether adjustment is done or not does not undermine the basic logic of an event study; adjustment is a technique for increasing statistical power by reducing the variance of each CAR series. Further, macroeconomic series, such as the stock market index or the exchange rate, generally have low volatility compared with *adjusted* individual stock returns. Hence, the statistical power that we obtain with a given number of events, using unadjusted returns, is likely to be superior to that obtained in an event study with a similar number of firms where daily stock returns were re-expressed as market model residuals.

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 errors can arise from inference procedures based on standard assumptions.

One method for obtaining superior inference lies in harnessing the bootstrap. 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 methodology 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. We do 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 behaviour of foreign investors during crises that might not be captured in a model of average behaviour. To illustrate this difference, we conduct a Monte Carlo experiment, with two white-noise series where there is no relationship in the tails (Case I), and another case where an induced relationship exists in the tails (Case II). The sample

[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).

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

size used in this simulation is identical to the size of our dataset. Under Case I, where there is no special tail response, the impulse response results from the standard VAR framework (left hand top panel of Figure 3) do not differ from results using our approach (left hand bottom panel of Figure 3). However, in Case II, the impulse response from a VAR model, which represents the overall average relationship, fails to pick up the relationship in the tails (right hand top panel) whereas the event study methodology does so clearly (right hand bottom panel).[11]

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

*Do foreign investors exacerbate a domestic crisis by withdrawing capital on a large scale?* We analyse this question using an event study, which measures the behaviour of foreign investors surrounding extreme events for the domestic stock market index.

*Is there asymmetric behaviour, 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 an illiquid emerging market?* 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 market index.

*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 market index.

## *4. Results*

For each type of 11-day window (the event and five days before and after), we construct a confidence interval for cumulative values.[12] Figure 4 shows the results for the case where the extreme events are defined using Nifty returns, and the responses of net FII flows are measured. In this figure, and subsequent ones for other cases, the confidence interval is constructed beginning from the first day of the 11-day window.

We start with the evidence about very positive days for Nifty returns (left pane of Figure 4). Prior to days with large positive Nifty returns, there is no unusual activity in FII investment. This suggests that unusually large positive Nifty returns are not the consequence of price

[11] Details of this simulation, and full source code, are available from the authors on request.

[12] 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.

pressure caused by prior buying by FIIs for exogenous reasons. On the event date, when Nifty has an unusually large positive value, FII investment also has a statistically significant positive value. The location estimator shows +2 basis points (of the overall market capitalization) as the net purchase of FIIs on the event date, and that the null hypothesis of 0 can be rejected. This may be interpreted as a situation where both foreign investors and Nifty are responding to positive news.

In the days after the event date, there is evidence of slow or positive feedback trading by FIIs. Net foreign investment continues to be positive in the following days. The point estimator adds another 2 basis points (of the overall market capitalization) in the four trading days after the event date.

Turning to very bad dates for Nifty (the right pane of Figure 4), there is no evidence of foreign investors selling *prior* to the event date. After the event date, unlike in the case of very good dates, there is no evidence of positive feedback trading. There is, in fact, slight evidence of foreign investment being positive in the event window.

These results suggest that there is not a simple relationship between Nifty returns and FII flows. 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.[13] 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. Thus, the casual perceptions of the dangers of "hot money" in the context of FII flows do not find empirical support here. On the other hand, those who have been concerned about excessive inflows might argue that Figure 4 raises concerns about positive feedback – the point estimate being 1.5 times the standard deviation of daily returns on the series, with a 95% confidence band from 0.64 to 2.4 standard deviations.

Figure 5 shows the reverse relationship to the previous figure. How do Nifty returns respond to extreme values of FII flows? The pattern for positive extremes is similar to what was observed for the obverse case. Nifty returns rise before the very good day for FII flows. This is likely to reflect both foreign investors and the stock market responses to good news. This is consistent with a positive feedback interpretation of the behaviour of foreign investors; large inflows from FIIs are associated with an extremely positive day for Nifty. After the event date, the cumulative returns on Nifty flatten out, which is consistent with an efficient response to the extreme event. There is no evidence of overshooting. One kind of extreme response that may have possibly arisen is one where Nifty rises sharply on the day of an extremely large FII inflow, after which mean reversion takes place. Such behaviour is not observed. Very bad days for FII flows, i.e., large outflows, do not seem to be preceded by

[13] 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.

large drops in Indian stock market returns, nor do they seem to trigger further negative returns, since the cumulative graph is relatively flat after the sharp outflow. After the event date, the flat event study response is the pattern expected in an efficient market. On the day of such sharp outflows, there is a drop in Nifty of one standard deviation of the daily series (reflecting that both Nifty and foreign investors respond to news), but it does not get exacerbated in subsequent days. Consistent with the interpretation of Figure 4, the pattern in Figure 5 does not suggest that sharp declines in FII flows trigger large and persistent domestic stock market declines.

As noted earlier, the relationship between Indian stock market returns and FII flows is of direct interest to policymakers, especially when there are large changes in either variable. From that simple perspective, the results illustrated in the Figures 4 and 5 should be somewhat comforting. However, the question of causality remains. Hence, it is useful to examine how FII flows respond to extreme values of an exogenous variable. S&P 500 returns are an obvious choice for capturing the impact of global shocks. To the extent that the US stock market is the most globalized and responsive to new information, S&P 500 returns can be considered to aggregate this global information. Furthermore, the size of the US market makes it unlikely to be affected by the Indian market, or by FII flows in and out of India.

Figure 6 shows the response of FII flows to extreme events as measured by S&P 500 returns. Very good days on the S&P 500 appear to be associated with a striking pattern of strong FII inflows worth at least twice its standard deviation into India, both before the event and after the event. The response seen here is much stronger than that observed in the impact of domestic events (i.e. very positive events for the Nifty). FIIs are a vector of transmission of good news on the S&P 500 into India. In the case of very bad days on the S&P 500, there does not seem to be any marked impact on FII flows, the pattern being not dissimilar to the "response" to very bad days for the Nifty index. There is an interesting asymmetry visible here; FIIs seem to communicate the extremely good days on the S&P 500 into India in the form of large purchases, but they do not behave symmetrically with large negative days on the S&P 500.

Figure 7 shows the response of Nifty returns when there are extreme events on the S&P 500. This event study is effectively an exploration of the linkages between India and the US, as seen in the tails. It is important to keep in mind a news-based explanation: Good news for the S&P 500 is likely to be good news for India, and vice versa. Consistent with this, we see an impact on Nifty on event date in both directions, and an approximately flat event study trajectory after that.

Finally, we explore the "knock-on" impacts of FII flows on other variables of interest to macroeconomic policymakers. We have argued that the evidence does not suggest that extreme events, either exogenous (as measured by the behaviour of the US stock market) or endogenous (as measured by the Indian market) trigger extreme responses by FIIs that would lead to a crisis; nor does FII behaviour in extreme situations (large inflows or outflows) trigger precipitous changes in the Indian stock market. If we turn to the effect of large FII inflows or outflows on interest rates and exchange rates, we do see some impact on the latter, in the expected directions.

Figure 8 shows the behaviour of the call money rate around extreme movements of FII flows. Exceptionally large FII inflows (the left hand side of the figure) have imperceptible effects on the interest rate. FII outflows appear to be followed by some rise in interest rates, but the confidence interval grows very wide, and therefore this effect is uncertain. It must also be borne in mind that endogenous policy responses to sharp FII outflows could be part of the phenomenon being observed, rather than a pure market response.

In the case of the exchange rate (Figure 9), the impact of extreme FII inflows or outflows are as expected. Large inflows are associated with appreciation of the Rupee, whereas large outflows are associated with depreciation. The impacts are somewhat asymmetric, since appreciations tend to cumulate, both before and after the event. In the case of outflows ("very bad" days for FII flows), the depreciation appears to precede the extreme event, but there is no persistence, since the graph is flat in the days following the event. Interestingly, the period of our analysis includes several changes in the Reserve Bank of India's approach to exchange rate management, in the direction of greater flexibility of a managed float. Our results do indicate that capital flows affect the exchange rate, which is unsurprising. However, they do not support a view that large inflows or outflows trigger a panic with respect to the currency – the impact is at most 1.3 times (in both directions) the standard deviation of daily returns on the rupee.

Our main results, presented above, have fused a cluster of extreme events (of the same sign) into one. Through this, date +1 in the event study is always the first date after the last extreme event. As part of sensitivity analysis, we focus only on uncontaminated events: on a single day where an extreme event is observed, but no other day in the event window is an extreme event. These results are presented in the Appendix. The results are qualitatively similar to those shown above.

## *5. Conclusion*

Concerns about the financial stability implications of financial globalisation continue to be of considerable importance for emerging markets and LDCs. A significant finance literature has focused on the question of whether foreign investors contribute to market efficiency. This is an interesting and important question.

At the same time, policy makers in emerging markets focus on somewhat different questions focused on behaviour under stressed conditions. These questions are distinct and important. As an example, it is possible that a large exit by foreign investors in the aftermath of a domestic crisis brings prices closer to fair value. In the eyes of the existing finance literature on foreign investors, this would be viewed as a case where foreign investors are `stabilising' since they restore market efficiency. However, policy makers in emerging markets would view this quite differently.

In this paper, we have proposed a new methodology through which these questions can be directly addressed. Our innovation is analogous to the idea of the tail beta -- where OLS estimation of the beta is conducted in the tails -- in that we apply the familiar event study methodology in the tails. Bootstrap inference gives us a robust inference strategy without relying on parametric assumptions.

This approach has several advantages. We impose no functional form on the profile of response, prior or after days of extreme events. The event study traces out these impacts, with familiar interpretation given the long experience in the literature with event studies. The resulting event study is analogous to the impulse-response function of a VAR, with the difference that while the conventional VAR reports the average relationship across all values, the event study focuses on the relationships in the tails.

As an example, we apply this methodology to India. Our results are relatively benign. Many of the concerns expressed by skeptics about financial globalisation are not borne out in the analysis.

Further research can usefully proceed in three directions. First, refinements of the event study can be undertaken, drawing on the rich literature on the econometrics of event studies. Second, this methodology can be applied across multiple countries. While the tail behaviour of foreign investors in a relatively large and liquid market -- India -- is relatively benign, the results could potentially be quite different in countries faced with greater asymmetric information and illiquid markets. Third, this methodology could be applied across firms, aiming to uncover heterogeneity in the impact of foreign investors across different firms within a country.

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## Tables and Figures

**Figure 1: Net FII Flows**

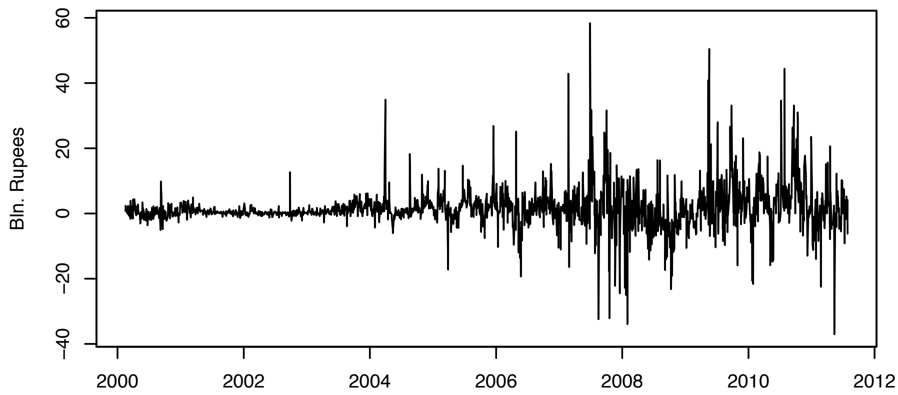
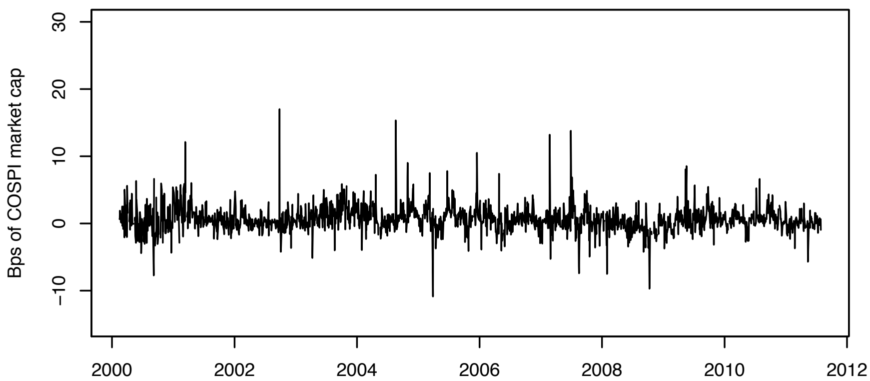
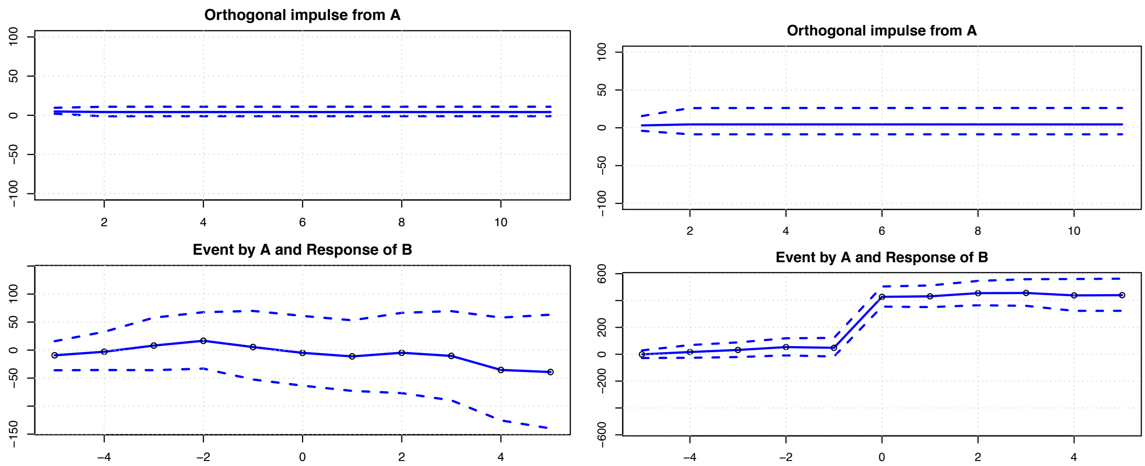



**Figure 2: Normalized Net FII Flows**

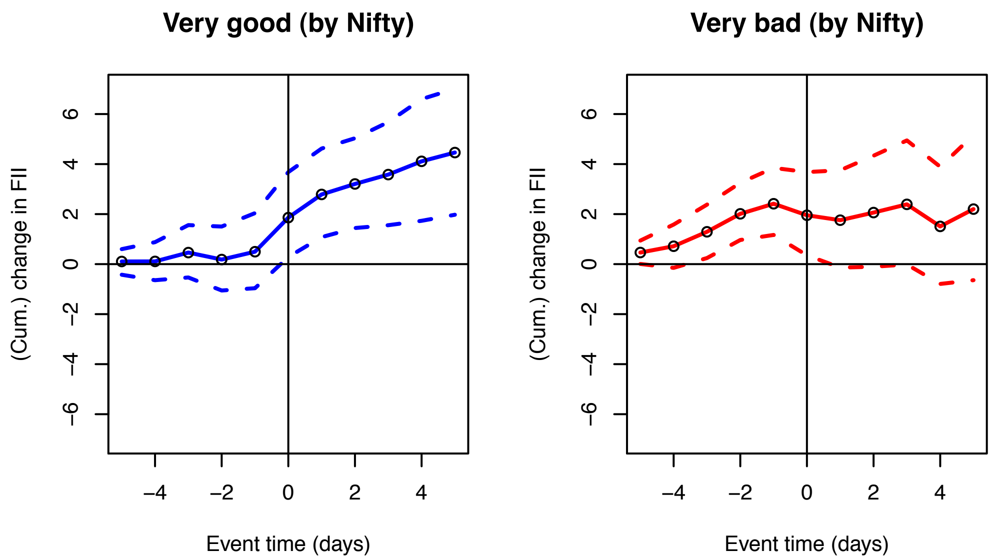


## Figure 3: Monte Carlo experiment

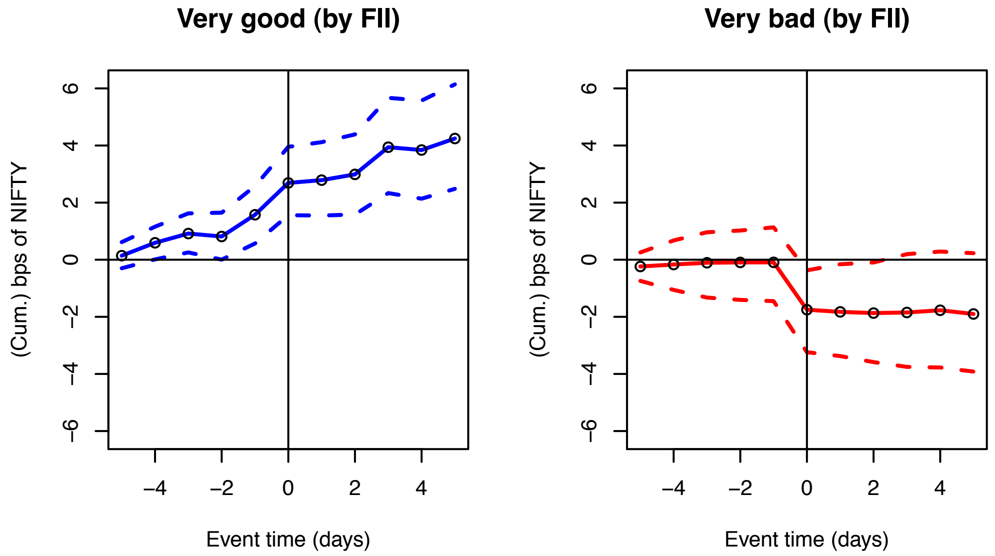
Case (I) Case (II)



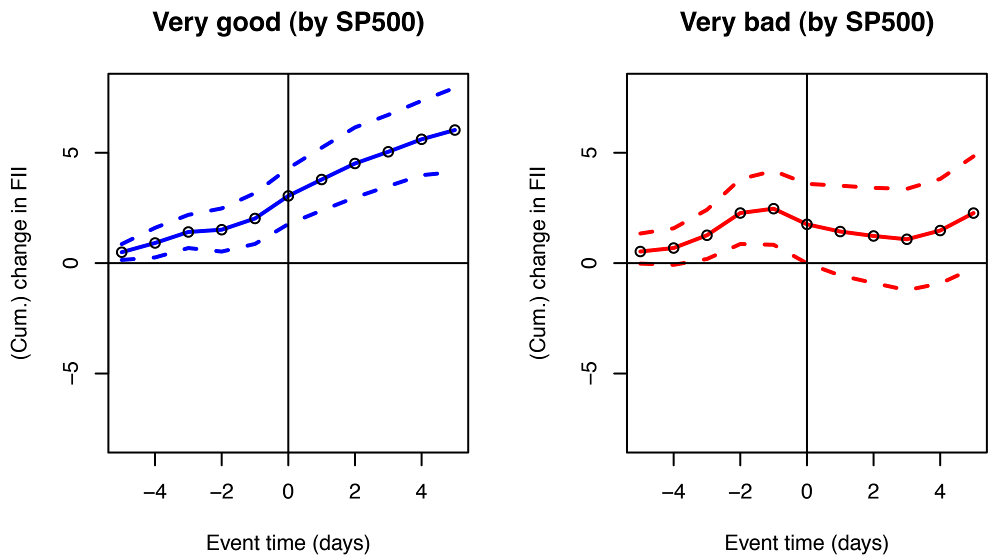

## Figure 4: Extreme event on Nifty and response of FII



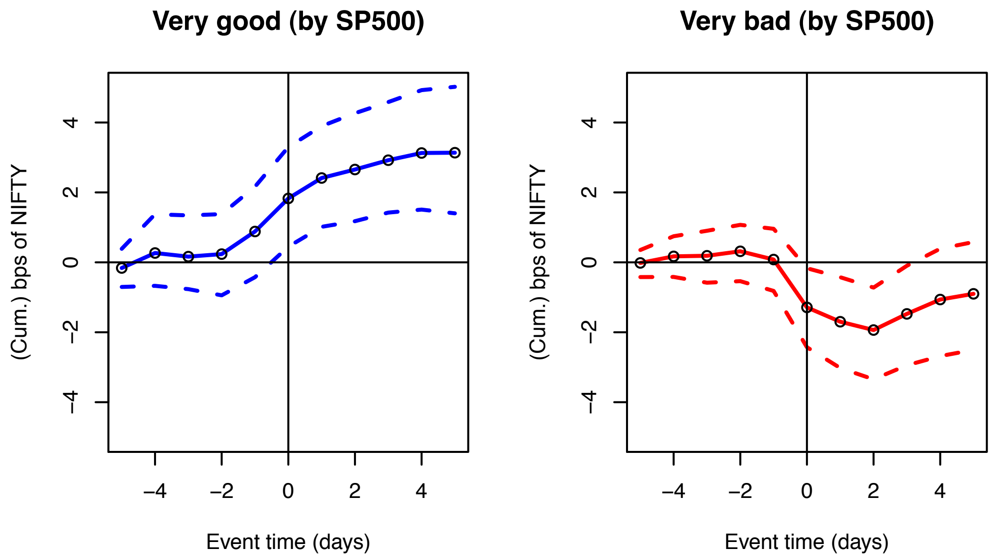
## Figure 5: Extreme event on FII and response of Nifty




## Figure 6: Extreme event on S&P 500 and response of FII



## Figure 7: Extreme event on S&P 500 and response of Nifty




## Figure 8: Extreme event on FII and response of call money rate

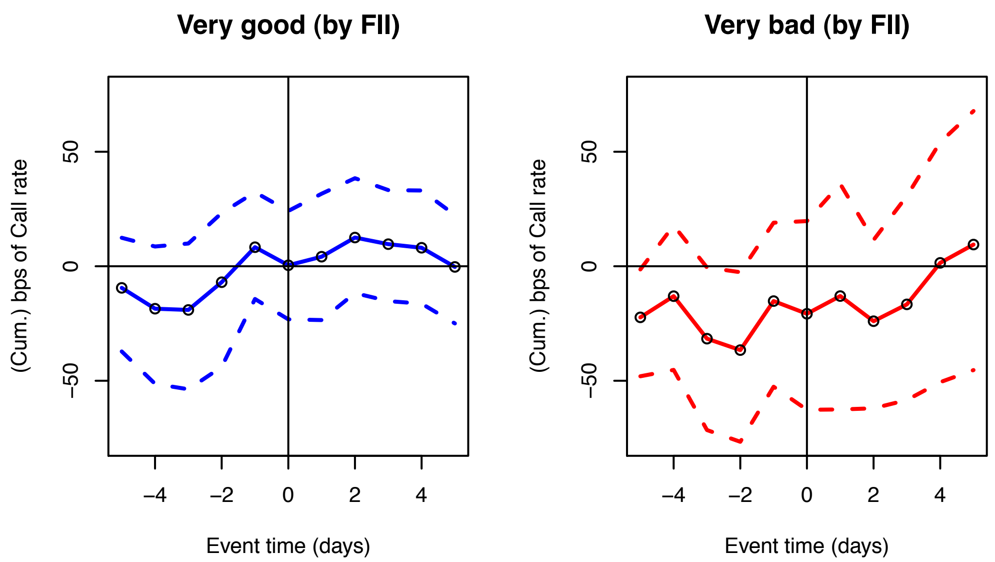


**Figure 9: Extreme event on FII and response of INR**

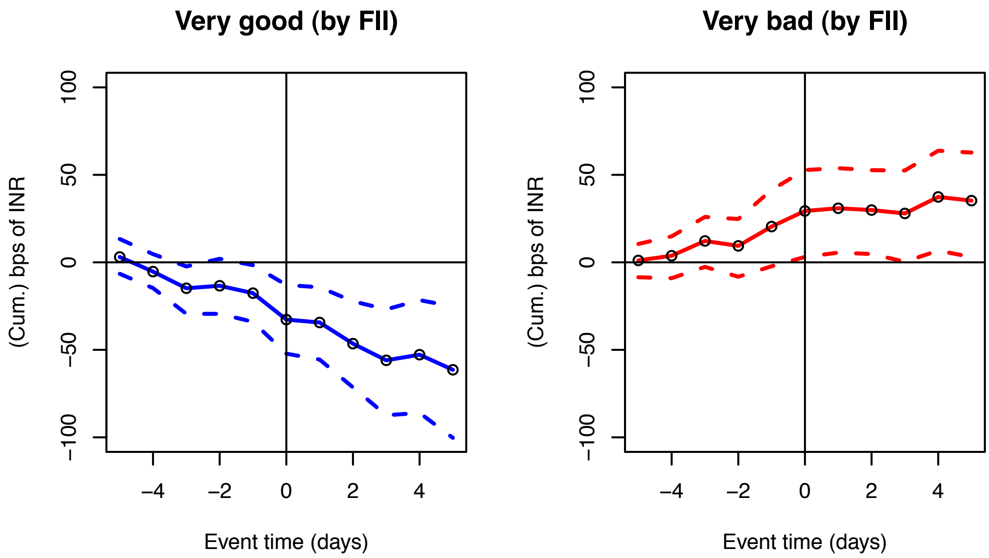



**Table 1: Summary Statistics**

| | FII | Nifty | NIKKEI | SP500 | INR | Call money rate |
|---|---|---|---|---|---|---|
| Mean | 0.62 | 0.09 | -0.03 | 0.02 | -0.01 | -0.72 |
| Median | 0.49 | 0.16 | 0.03 | 0.10 | 0.00 | 0.00 |
| Min | -10.87 | -13.97 | -17.53 | -9.47 | -4.17 | -1761.00 |
| Max | 17.01 | 16.23 | 9.99 | 6.98 | 2.87 | 1769.00 |
| Standard Deviation | 1.87 | 1.80 | 1.70 | 1.36 | 0.40 | 87.74 |

**Table 2: Yearly distribution of extreme values (5% tails)**

| | **S&P 500 (Returns)** | | | | **Nifty (Returns)** | | | | **FII (bps change)** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Good days** | | **Bad days** | | **Good days** | | **Bad days** | | **Good days** | | **Bad days** | |
| | No. | Median | No. | Median | **No.** | **Median** | **No.** | **Median** | **No.** | **Median** | **No.** | **Median** |
| **2000** | 11 | 0.03 | 10 | -0.03 | 12 | 0.03 | 13 | -0.05 | 13 | 4.99 | 16 | -2.88 |
| **2001** | 10 | 0.02 | 8 | -0.04 | 4 | 0.03 | 9 | -0.04 | 16 | 4.59 | 5 | -2.26 |
| **2002** | 16 | 0.03 | 17 | -0.03 | 5 | 0.04 | 2 | -0.04 | 3 | 4.79 | 3 | -3.65 |
| **2003** | 9 | 0.04 | 5 | -0.02 | 4 | 0.04 | 3 | -0.04 | 18 | 4.50 | 2 | -4.57 |
| **2004** | 1 | 0.02 | 2 | -0.02 | 6 | 0.03 | 9 | -0.04 | 11 | 5.25 | 3 | -2.31 |
| **2005** | 1 | 0.02 | 0 | | 3 | 0.04 | 4 | -0.03 | 10 | 4.68 | 10 | -2.39 |
| **2006** | 1 | 0.02 | 0 | | 8 | 0.04 | 4 | -0.04 | 6 | 3.75 | 8 | -2.96 |
| **2007** | 7 | 0.02 | 10 | -0.03 | 12 | 0.04 | 10 | -0.04 | 9 | 4.87 | 12 | -3.16 |
| **2008** | 14 | 0.03 | 19 | -0.03 | 17 | 0.04 | 28 | -0.04 | 0 | | 25 | -2.47 |
| **2009** | 19 | 0.03 | 19 | -0.03 | 23 | 0.03 | 11 | -0.03 | 7 | 5.45 | 8 | -2.27 |
| **2010** | 9 | 0.02 | 7 | -0.03 | 2 | 0.03 | 4 | -0.03 | 6 | 4.28 | 4 | -2.59 |
| **2011** | 1 | 0.02 | 2 | -0.02 | 3 | 0.04 | 2 | -0.04 | 0 | | 3 | -3.70 |
| | | | | | | | | | | | | |

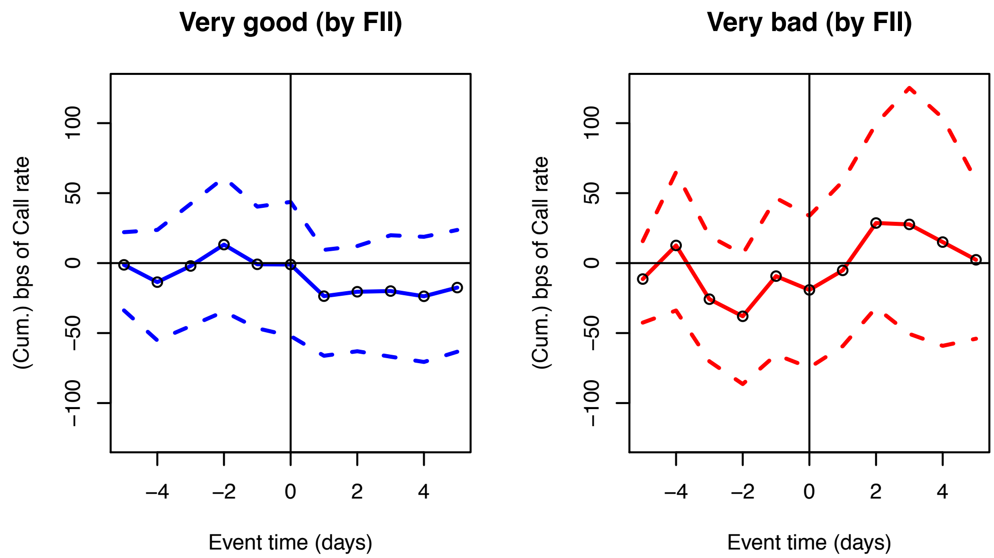
| | **INR (% change)** | | | | **Call rate (bps change)** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Good days** | | **Bad days** | | **Good days** | | **Bad days** | |
| | No. | Median | No. | Median | No. | Median | No. | Median |
| **2000** | 5 | 0.75 | 1 | -0.80 | 14 | 109.50 | 13 | -131.00 |
| **2001** | 2 | 1.16 | 0 | | 10 | 94.50 | 11 | -160.00 |
| **2002** | 0 | | 1 | -0.75 | 2 | 86.50 | 3 | -125.00 |
| **2003** | 6 | 0.90 | 7 | -0.97 | 2 | 96.50 | 5 | -111.00 |
| **2004** | 6 | 0.82 | 3 | -0.80 | 3 | 100.00 | 2 | -119.00 |
| **2005** | 4 | 0.99 | 5 | -0.80 | 1 | 87.00 | 1 | -124.00 |
| **2006** | 5 | 1.18 | 14 | -0.78 | 7 | 143.00 | 3 | -124.00 |
| **2007** | 30 | 0.83 | 19 | -0.79 | 11 | 194.00 | 15 | -146.00 |
| **2008** | 17 | 1.04 | 29 | -0.87 | 19 | 163.00 | 21 | -146.00 |
| **2009** | 16 | 0.88 | 17 | -0.84 | 11 | 117.00 | 10 | -127.00 |
| **2010** | 8 | 0.88 | 4 | -0.84 | 16 | 101.00 | 12 | -91.00 |
| **2011** | 5 | 0.75 | 1 | -0.80 | 6 | 111.5 | 3 | -138 |

## Table 3: Event Counts

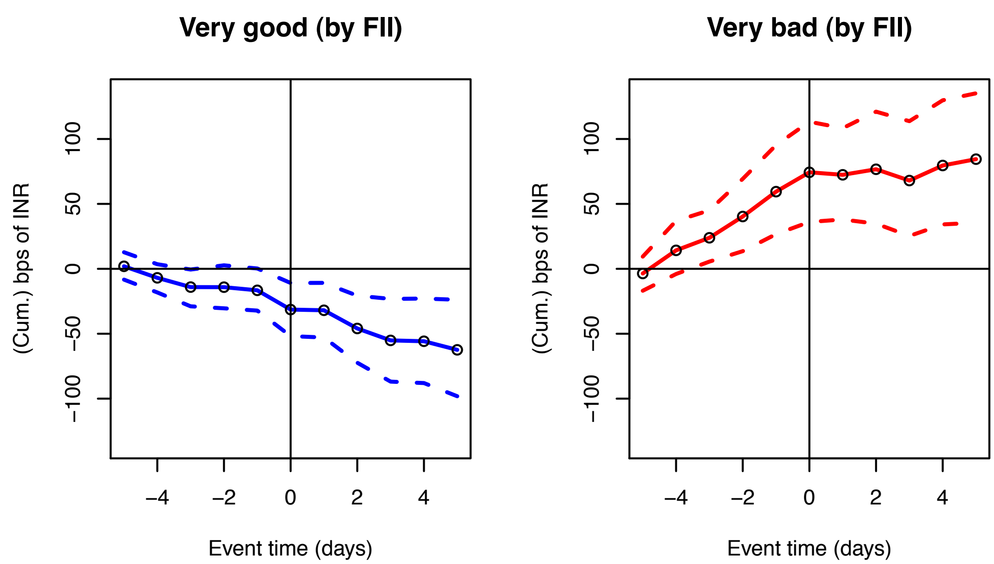
| Variable | 1.5% | | 2.5% | | 5% | |
|---|---|---|---|---|---|---|
| | No. | Median | No. | Median | No. | Median |
| **Nifty returns** | | | | | | |
| **Negative extremes** | 20 | 5.48 | 50 | 4.34 | 99 | 3.44 |
| **Uncontaminated** | 17 | 5.49 | 39 | 4.35 | 64 | 3.50 |
| **Positive extremes** | 20 | -5.85 | 50 | -4.44 | 99 | -3.70 |
| **Uncontaminated** | 19 | -6.00 | 41 | -4.34 | 65 | -3.63 |
| **S&P 500 returns** | | | | | | |
| **Negative extremes** | 20 | 4.16 | 50 | 3.41 | 99 | 2.80 |
| **Uncontaminated** | 15 | 4.16 | 37 | 3.28 | 62 | 2.62 |
| **Positive extremes** | 20 | -4.85 | 50 | -3.27 | 99 | -2.73 |
| **Uncontaminated** | 14 | -4.86 | 36 | -3.18 | 66 | -2.70 |
| **FII flows** | | | | | | |
| **Negative extremes** | 20 | 7.65 | 50 | 5.64 | 99 | 4.60 |
| **Uncontaminated** | 17 | 7.80 | 38 | 5.60 | 53 | 4.45 |
| **Positive extremes** | 20 | -4.67 | 50 | -3.58 | 99 | -2.74 |
| **Uncontaminated** | 17 | -4.36 | 35 | -3.54 | 57 | -2.77 |
| **INR returns** | | | | | | |
| **Negative extremes** | 20 | 1.52 | 50 | 1.14 | 100 | 0.90 |
| **Uncontaminated** | 18 | 1.52 | 31 | 1.14 | 50 | 0.87 |
| **Positive extremes** | 20 | -1.49 | 50 | -1.08 | 99 | -0.85 |
| **Uncontaminated** | 18 | -1.58 | 38 | -1.1 | 53 | -0.83 |
| **Call rate (bps change)** | | | | | | |
| **Negative extremes** | 20 | 282.5 | 50 | 165 | 99 | 118 |
| **Uncontaminated** | 11 | 215 | 26 | 153.5 | 36 | 98.5 |
| **Positive extremes** | 20 | -232.5 | 50 | -172 | 100 | -126 |
| **Uncontaminated** | 10 | -214 | 24 | -150 | 44 | -124 |

### Annex – I: Sensitivity analysis

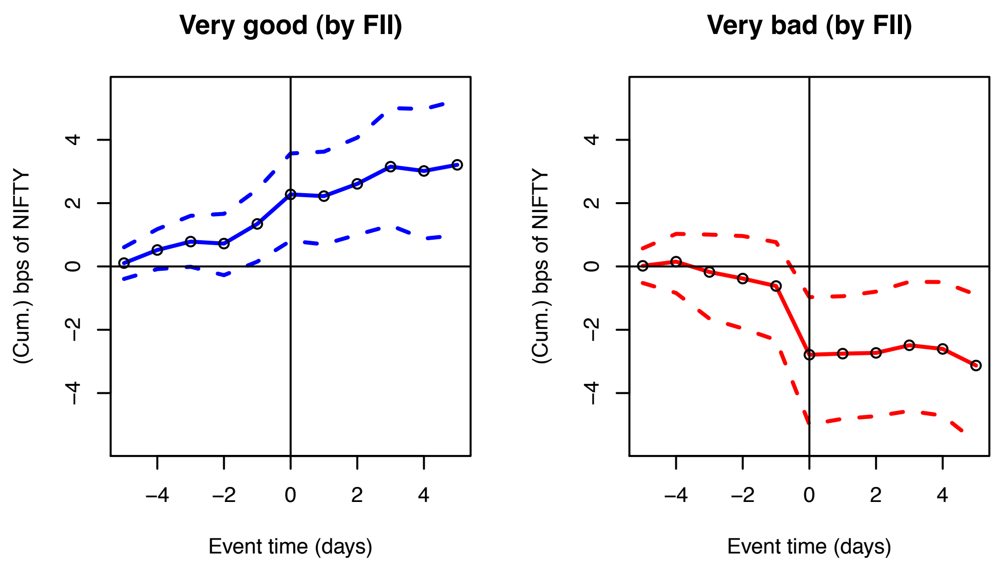
### Response of call rate to events on FII



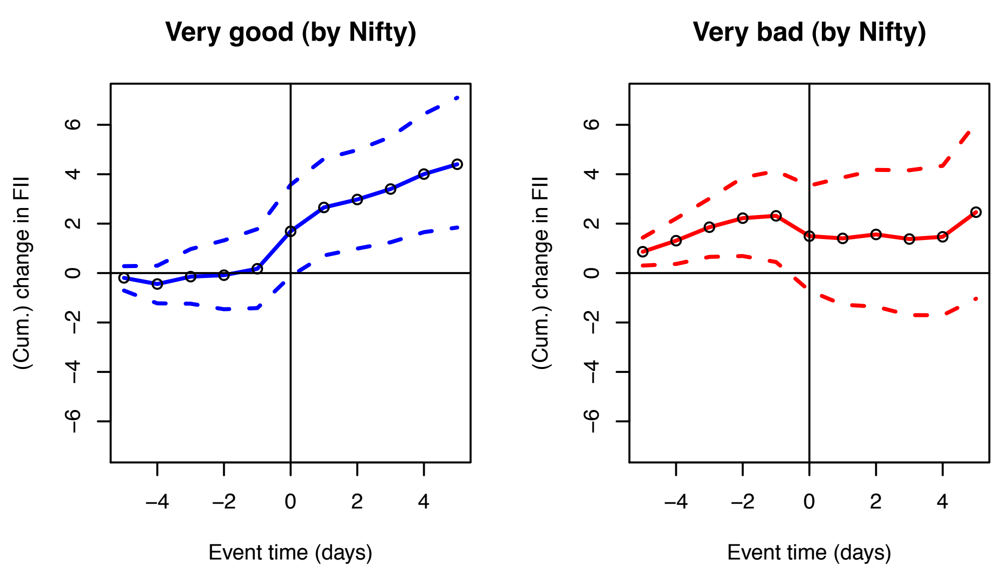

### Response of INR to events on FII



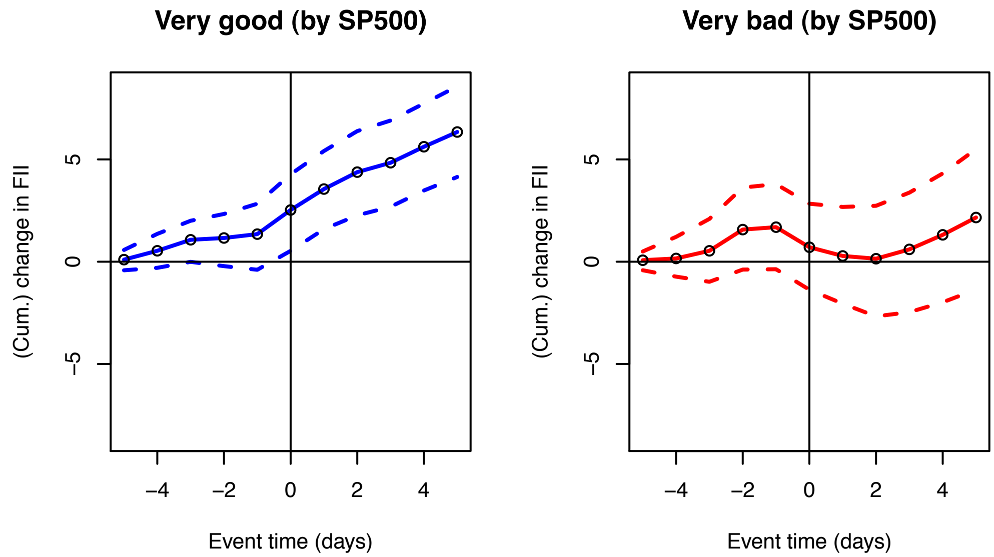
## Response of Nifty to events on FII




## Response of FII to events on Nifty



## Response of FII to events on S&P 500




## Response of Nifty to events on S&P 500