Foreign Investors under Stress:
Evidence from India[*]

Ila Patnaik
National Institute for Public
Finance and Policy

Ajay Shah
National Institute for Public
Finance and Policy

Nirvikar Singh
University of California,
Santa Cruz

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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 suggest that financial globalisation has induced instability on the equity market.

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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 during the crisis?

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 economy?

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 economy policy makers care about flight of foreign capital in a domestic crisis – regardless of whether or not it brings prices closer to fundamental value. The four policy-relevant questions articulated above are thus distinct from those that have occupied the existing literature.

These four questions are almost exclusively about 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 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 that average across all observations might give misleadingly reassuring answers to policy makers, by underplaying extreme behaviour in the tails. Linear models estimated using the overall data may yield benign results, but 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. 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 potentially be estimated through parametric models, our approach avoids the need to make parametric assumptions by extending the non-parametric event study methodology.

As an example, we identify events consisting of extreme movements of the domestic stock market index. These dates are treated as events, and an event study is conducted in order to measure how foreign investment behaves surrounding these dates. This gives us evidence

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about the inter-linkages between foreign investment and stock market fluctuations in the tails, without requiring parametric assumptions about tail behaviour.

We illustrate the proposed methodology by analyzing data for one large emerging market, India. The findings of the paper, for India, are relatively benign. We find that on very good days in the local economy, foreign investors seem to exacerbate the boom by bringing in additional capital. However, there is asymmetric behavior: on very bad days in the local economy, no significant effects are found[1]. 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 the Indian equity market.

Future research can explore extensions in three dimensions. The results presented here pertain to one large emerging equity market, India. It would be interesting to explore (a) The relationships observed in other countries, particularly relatively small countries and those less integrated into financial globalisation; (b) Other asset classes including debt capital, which have been an important source of concern in international financial crises; (c) Cross-sectional variation between multiple firms traded in the Indian equity market. Foreign investors may not be `big fish in a small pond' when it comes to the overall Indian stock market index – but

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[1] One has to be careful about causality in the interpretation of the results, since, even though there is temporal directionality that is consistent with so-called "Granger causality," both variables are endogenous and subject to simultaneous exogenous effects. Rakesh Mohan has commented to us that this statement is not consistent with the large FII outflows and Indian stock market price fall in 2008-09. There are several possible reasons for the difference. First, the level of aggregation and the time scale are completely different when one looks at daily behavior versus annual aggregates. Second, our procedure does "average" across different extreme events, and is not specific to a single temporal episode, such as the worst days of 2008 or 2009.

may kick off problems either with illiquid Indian securities or with the stock market indexes of countries with an illiquid equity market. The stance of foreign investors towards debt securities may differ considerably. In order to assist replication, downstream research, and methodological advances, the full source code developed for this paper has been released into the public domain.

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 analyse 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 traditional event studies that involve 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")[2] 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

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[2] 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.

Mukherjee et al. (2002), using daily data from 1999-2002. Those authors also found asymmetry between buying and selling by FIIs, with only the latter 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, low-frequency data such as monthly data may not be appropriate for identifying such effects (e.g., Rakshit, 2006). 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 powerful tools of 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 observed at the daily frequency: net FII investment, the Nifty index,[3] 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 research 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

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

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 sidestep the issue of precise causes of observed connections between foreign equity flows and domestic stock returns. While policymakers will ultimately be interested in the *causes*, their first-order concern is about 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 under stress. Therefore, our focus is on an estimation strategy, which illuminates the reduced form 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). There is renewed interest in event studies as a part of the toolkit of modern causal econometrics, in areas well beyond traditional finance applications.

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. 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,

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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.[4] 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.[5]

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). While this work is important and potentially yields greater statistical efficiency, our approach adapts a familiar non-parametric tool (the event study) to yield results which are easily interpreted, with a methodology which can be easily applied by researchers worldwide.

For an analogy, the 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; Acharya et. al. 2010). Our proposal consists of interpreting the application of the event study methodology, with tail events, as yielding a result analogous to a `tail IRF': an impulse response function computed in the tails, while avoiding the assumption of linearity.

3. Data and Methodology

We use daily data for Indian stock market returns, net FII inflow, and the US S&P 500. We

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[4] 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.

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

also observe the `call money rate', as a measure of the domestic interest rate. Our dataset covers the period from 15 February 2000 to 29 July 2011, a period of more than 11 years, giving 2,035 observations of daily data. Summary statistics for all the series used in this paper are presented in Table 1.

FII Data

India has a comprehensive and permanent system of capital controls (Patnaik & Shah, 2012). With 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), who are required to register with the securities regulator in India. FIIs can include a range of financial institutions, including banks, asset management firms, hedge funds, trusts and foundations. The ownership by all foreign investors in a given firm cannot exceed a certain proportion. This proportion is set to 24% by default, but can be raised by a resolution of the shareholders of the company up to 98%.[6] In practice, this has meant that FIIs have nearly complete convertibility. The results observed in this paper thus largely reflect the unconstrained actions of foreign investors.

FIIs are required to settle their trades through custodian banks.[7] Custodian banks are required to supply aggregate 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, alongside which the dollar value of foreign investment

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[6] 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. There are no restrictions on selling or repatriating capital.

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

has risen sharply. To correct for this, we divide this by the market capitalisation of the CMIE Cospi index.[8] 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. This is a somewhat unusual setting in that there is no overlap in the trading time of the two countries. Hence, lining up the two time-series requires one ad-hoc choice. While for a particular calendar date, the Indian market opens and closes *before* the start of trading in the US market, the causal relationship of interest 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 FII flows.[9] 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

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[8] Chakrabarti (2006) points out that there is evidence of a structural break in the net FII time-series around April 2003 (and Figure 1 suggests similarly). In our analysis, once net FII investment is rescaled, this problem is addressed (see Figure 2), thus permitting a greater span of the data.
[9] We are grateful to Subir Gokarn for emphasising this point.

therefore cases of nominal appreciation of the Rupee against the US Dollar.

Methodology

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. In 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 the tradeoff between identifying the truly extreme events (which is favoured by going out into the tails) versus adequacy of data size and thus statistical precision. We are assisted in this by the large dataset of 2,035 observations which permits reaching into the tails and still having adequate power.

Table 5 summarises the time pattern of the distribution of extreme events. As an example, it shows that of the 67 upper tail events for the S&P 500, 8 were in 2000. The median value of these 8 upper tail events for 2000 was a return of +3.02%. As one would expect, a large

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proportion of the extreme values occur in 2008 and 2009, especially for the return variables.[10] The distribution of FII tail values is 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 4 tail values for Nifty returns, but 16 for FII flows.[11] This suggests that extreme events for FII investment are not strongly related with extreme events for Nifty. Few extreme events on the rupee are observed prior to 2007. This reflects the structural break in the Indian exchange rate regime of 23 March 2007, that is identified by the methodology of Zeileis, Shah and Patnaik, 2010.

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.

We approach this problem through two paths. On one hand, we analyse a clean dataset with only uncontaminated events, i.e. those where there is no other event within the event window. In addition, we also analyse a modified dataset where we *fuse 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 run. This strategy avoids losing observations of some of the most important crises, which have clustered extreme events in the same direction. Sometimes, the event window is contaminated (in that it contains more than one extreme event) and fusing is infeasible (in that we lack a run of extreme events in one direction surrounded by non-extreme days). Those events are not used

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[10] 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.
[11] In fact, the difference in time patterns between Nifty returns and FII flows is even more striking in the case of 2.5% tails.

in the analysis.

We define events using 5% tails rather than 2.5% tails of the distributions, so as to obtain adequate observations. As an example (the right hand top of Table 2), in the case of FII returns, the lower 5% tail contains 102 extreme events. Of these, 57 are uncontaminated. There are 6 clustered events which are used by our strategy of fusing. That leaves 39 extreme events which are not used in the analysis. Our ability to utilise clustered extreme events is related to the extent to which runs of extreme events are found. Table 3 shows the distribution of run length. In some other series, the strategy of fusing runs of extreme events is much more effective. As an example, with the lower tail of the FII series, in Table 2, there are 56 uncontaminated events. In addition, we are able to use 41 clustered extreme events, leaving only 5 unutilised.

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. 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 2 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.

Extreme events methodology #1: Uncontaminated events only

Consider the analysis of upper tail events for Nifty. We denote the Nifty returns time-series (expressed as log differences) as x_t, t = 1, …, T. For a quantile q of interest, we identify $Q(x,q)$ such that $Pr(x_t > Q(x,q) = q$. This yields the set of dates in the upper tail:

$$E^+ = \{i\} \quad s.t. \ x_i > Q(x,q)$$

Alongside this is E^-, the set of left tail extreme events and $E = E^+ \cup E^-$, the set of all extreme events.

The event window of interest has a width of W days prior to and after the event date. We define the set of uncontaminated extreme events in the upper tail, E_u^+, as the dates {j} where:

$$j \in E^+$$

$$(j+k) \notin E \ \forall \, k \in \{-W, …, -1, 1, …, W\}$$

This is the set of event dates for our first event study: one where the event window is uncontaminated by any other extreme event.

Extreme events methodology #2: Some runs of extreme event also

We also identify runs of upper tail extreme events which are surrounded by a normal event window. An uncontaminated event of length R is a set of dates such that:

$$\{n, n+1, …, n+R\} \in E^+$$

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$$(j+k) \notin E \; \forall \, k \in \{-W, \ldots, -1, 1, \ldots, W\}$$

Returns on the days of the run are fused into a single big value $\sum_{i=n}^{n+r} x_i$, which is used as the event date return. This results in values for the event window of:

$$x_{n-W}, \; \ldots, \; x_{n-1}, \; \sum_{i=n}^{n+r} x_i, \; x_{n+R+1}, \; \ldots, \; x_{n+R+W}$$

In the class of contaminated windows, some satisfy the properties required above, and are thus merged into the event study analysis, alongside the un-contaminated events, giving the second event study. This reduces, but does not eliminate, the extent to which crises that are characterized by clustered extreme events are brought into the analysis.

Early event studies, which were focused on stock market returns on individual firms, used OLS regressions for computing 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.[12]

The bootstrap inference strategy that we use is as follows:[13]

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.

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[12] On the advantages of bootstrap inference in event studies, see, for example, Kothari and Warner (2007), and Lefebvre (2007).
[13] The specific approach used here is based on Davison, Hinkley, and Schectman (1986).

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.

There are interesting analogies between the impulse response function of a vector autoregression (VAR) and our event study perspective. Our attempt, at measuring the response to tail events, can be considered analogous to the IRF of a VAR in the tails. To illustrate this difference, we conduct a Monte Carlo experiment. We simulate a first case with two white-noise series where there is no relationship in the tails (Case I), and another case where a relationship exists in the tails only (Case II). The sample size used in this simulation is identical to the size of our dataset. Under Case I, where there is no special tail response in the data generating process, the impulse response results from the standard VAR framework (left hand top panel of Figure 3) do not differ from the event study in the tail (left hand bottom panel of Figure 3). The only difference is that the 95% confidence interval with the event study is inferior, since it only utilizes a small number of tail events.

The interesting differences arise in Case II, where the data generating process contains a response in the tails (only). 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). The 95% confidence interval is wider, reflecting the noise in the tails, but the null of no effect is not rejected. In contrast, the strategy of conducting an event study in the tails clearly picks up the tail response (right hand bottom panel).[14] In this sense, there is an analogy between an event study in the tails, and a tail-VAR impulse response function.

While the idea of event studies with tail events as articulated here is novel, it is related to

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

several strands of the existing literature. In the field of international finance, this work is related to Broner et. al., 2010, in terms of the questions. However, Broner et. al. 2010 work with annual data, while we harness high frequency (daily) data to analyse both cause (extreme events) and effect (behavior of foreign investors), which permits efficient identification of causal effects which would not be visible with low frequency data. In addition, they use a regression framework to think about events, while we build on the econometrics of event studies. In terms of the methodology of event studies, our work is related to Lasfer et. al. 2003, which uses an event-study in analyzing the performance of stock market indexes after extreme days of the stock market. More recently, Cumperayot et. al. 2006 analyse the linkages between extreme days on the stock market and extreme days on the currency market, though not in an event study framework. In related work, Lasfer et. al. 2012 examine the Chinese evidence, through similar approaches, and find that after extreme events, there is over-reaction on the B market (where foreign investors are permitted) but not on the A market (where they are not).

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.[15] 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). Table 4 shows us that these upper tail values have a mean of +4.25% and a median value of +3.8%. The events that we are analyzing comprise event days when Nifty went up by more than 2.96%, with the most extreme value at 16.23%. Figure 4 shows that prior to the event date, there is no unusual activity in FII investment. This suggests that unusually large positive Nifty returns are not the consequence of price pressure caused by prior buying by FIIs for exogenous reasons. On the event date, when Nifty has an unusually large positive value, FII

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[15] 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 in trading time.

investment also has a positive value. The location estimator increases by 1 basis point (of the overall market capitalization) as the net purchase of FIIs on a two-day horizon from 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 five trading days after the event date. As Table 1 shows that the standard deviation of the daily net FII inflow is 2.12 bps, the effects seen in the event study are not large.

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. Unusually large negative Nifty returns are not the consequence of price pressure caused by prior FII selling for exogenous reasons. 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.[16] From the perspective of a policymaker worried about FII outflows in response to very bad days in the Indian stock

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[16] 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.

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. However, the effects observed are small: the point estimate on a two-day horizon from the event dates is 0.92 times the standard deviation of the daily time-series of the FII investment series, with a 95% confidence band from 0.04 to 1.79 standard deviations.

Figure 5 shows the reverse relationship to the previous figure. How do Nifty returns respond to extreme values of FII flows? Here, the y axis of the event study is the same as the conventional event study: It pertains to cumulative returns. This permits the same interpretation as with conventional event studies. An efficient markets response is a step response on the event date, and a flat profile thereafter. Rejections of the null of efficiency could take the form of under-reaction (a slow response towards the long-run outcome, spread over many days after the event) or over-reaction (an extreme response around event date that is reversed in following days).

In the case of Figure 5, the pattern for positive extremes is similar to what was observed for the obverse case. Nifty returns are positive *before* the very good day for FII flows. This is likely to reflect both foreign investor 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 null hypothesis of a flat profile cannot be rejected, which is consistent with an efficient response to the extreme event. There is no evidence of overshooting or undershooting.

The right pane of Figure 5 analyses very bad days for FII flows, i.e., large outflows. These do not seem to be preceded by 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.

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, however, 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.

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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, at least on average over the period[17]. 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. If the central bank has an exchange rate target, when FIIs sell, the central bank buys dollars and injects rupees into the economy. If sterilization is less than complete, as is generally the case, there would be a direct impact upon the call money rate. These effects would thus vary based on the exchange

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[17] The discussion in footnote 1 is relevant here as well.

rate regime (i.e. the extent to which the central bank targets the exchange rate) and the extent of sterilization. The results of the event study reflect overall averages across the substantial changes that have taken place, within the sample period, in the exchange rate regime and the extent of sterilization.

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. In the case of outflows ("very bad" days for FII flows), the depreciation appears to precede the extreme 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 0.85 and 2.26 times the standard deviation for appreciation and depreciation respectively.

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. The results for uncontaminated events (on a single day where an extreme event is observed, but no other day in the event window is an extreme event) are present in all the figures as well and largely agree with the main results.

5. Robustness checks

In the main results of the paper, global shocks were measured by returns on the S&P 500 index. As a robustness check, Figure 10 shows the analysis conducted using VIX, the implied volatility index computed using S&P 500 option prices traded on the CBOE, which has been

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demonstrated to have strong links to investments in emerging markets. The patterns seen in Figure 10 are qualitatively similar to those seen in Figure 6 for the S&P 500. Extreme events with a decline of VIX are associated with increases in foreign investment into India. The reverse (response to an increase in VIX) does not have a statistically significant response.

6. Reproducible research[18]

An R package named `eventstudies'[19] has been released into the public domain, with an open source implementation of the methods of this paper. An example shown in this package replicates all the calculations of this paper for two series: S&P 500 and Nifty.

7. 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, where the term `destabilising' is interpreted as meaning `taking prices away from fundamental value'. 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 fundamental 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, none the less, be concerned about the financial stability implications of such

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[18] Dataset and package for replicating results can be found at
http://macrofinance.nipfp.org.in/releases/PatnaikShahSingh2013_Foreign_Investors.html
[19] This package can be found on CRAN at http://cran.r-project.org/web/packages/eventstudies/

behavior.

In this paper, we have adapted the event study methodology to directly address these questions. 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 equity investment by foreign investors in India. Our results are relatively benign. One element of the concern expressed by skeptics about financial globalisation, about the instability associated with financial globalisation, are not supported in this setting, at least in the sense of "average" tail or extreme events[20].

Further research can usefully proceed in four 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

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[20] Thus, the "100 year flood" nature of the global financial meltdown of 2008-09 as it affected domestic markets everywhere is not dismissed as irrelevant, merely recognized as exceptional even in the category of extreme events. We are grateful to Rakesh Mohan for urging us to clarify the interpretation of our methodology and results.

information and illiquid markets. In particular, small developing countries which are not members of the `BRIC' club may face greater difficulties owing to greater illiquidity of 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. *Fourth*, while this paper is about the equity market, the most important concerns about financial globalisation in the literature are about short term debt flows, particularly when borrowing is done in foreign currencies. These methods could usefully be applied to a dataset with daily activities of foreign investors in each debt security. If the results are significantly different with debt securities, they would support the hypothesis that there is a hierarchy of capital flows, where liberalization of capital controls for equity flows is safer when compared with short-term debt, both local-currency and foreign currency.

References

Acharya, Viral V., Lasse H. Pedersen, Thomas Philippon, and Matthew Richardson (2010), Measuring Systemic Risk, Stern School of Business, NYU, Working Paper

Angrist, J. D., and J. S. Pischke (2010), The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics, *Journal of Economic Perspectives* 24 (2), 3-30.

Anshuman, V. Ravi, Rajesh Chakrabarti and Kiran Kumar (2010), Trading Activity of Foreign Institutional Investors and Volatility. Paper presented at 7th meeting of NIPFP-DEA research program, New Delhi, September 1.

Broner, Fernando, Tatiana Didier, Aitor Erce, Sergio L. Schmukler (2010). Financial Crises and International Portfolio Dynamics, Working Paper, June 28.

Brown, Stephen J. & Jerold B. Warner (1980), Measuring security price performance, *Journal of Financial Economics* 8:3, 205—258.

Chakrabarti, Rajesh (2001), FII Flows to India: Nature and Causes, *Money and Finance*, October-December.

Chakrabarti, Rajesh (2006), Foreign Institutional Investment, in Basu, Kaushik, and Annemie Maertens, eds. (2010). *The Concise Oxford Companion to Economics in India.* New Delhi: Oxford University Press.

Choe, Hyuk, Bong-Chan Kho and Rene Stulz (1998), Do Foreign Investors Destabilize Stock Market? The Korean Experience in 1997, NBER Working Paper 6661, July

Choe, Hyuk, Bong-Chan Kho and Rene Stulz (2001), Do Domestic Investors Have More Valuable Information about Individual Stocks than Foreign Investors? NBER Working Paper 8073

Clark, John and Elizabeth Berko (1996), Foreign Investment Fluctuations and Emerging Market Stock Returns: The Case of Mexico, Federal Reserve Bank of New York, Research Paper 9635.

Cumperayot, Phornchanok and Tjeert Keijzer and Roy Kouwenberg (2006), Linkages between extreme stock market and currency returns, Journal of International Money and Finance, 25, 528—550.

Davison, A. C., D. V. Hinkley, and E. Schechtman (1986): "Efficient bootstrap simulation," *Biometrika*, 73(3), 555–566.

Dolley, James Clay (1933), Characteristics and procedure of common stock split-ups. *Harvard Business Review*, 316—326.

Engle, Robert and Matthew Richardson (2012), Capital Shortfall: A New Approach to

Ranking and Regulating Systemic Risks. *Forthcoming*, *American Economic Review Papers and Proceedings,* May 2012.

Fama, Eugene F., Lawrence Fisher, Michael C. Jensen & Richard Roll (1969), The adjustment of stock prices to new information, *International Economic Review*, 10, 1—21.

Froot, Kenneth and Tarun Ramadorai (2001), The Information Content of International Portfolio Flows, NBER Working Paper 8472, September

Froot, Kenneth and Tarun Ramadorai (2008), Institutional Portfolio Flows and International Investments, *Review of Financial Studies*, 21(2), 937-971

Gordon, James and Poonam Gupta (2003), Portfolio Flows into India: Do Domestic Fundamentals Matter? IMF Working Paper 03/20, Washington DC

GoI (Government of India), Ministry of Finance (2005), Report of the Expert Group on Encouraging FII Flows and Checking the Vulnerability of Capital Markets to Speculative Flows, New Delhi, November.

Hartmann, P, S. Stractmans and C.G. De Vries (2004), Asset Market Linkages in Crisis Periods. *The Review of Economics and Statistics,* Vol. 86, No. 1, pp. 313-326, Feb 2004.

Jotikasthira Chotibhak, Lundblad, Christian and Tarun Ramadorai (2011), Asset Fire Sales and Purchases and the International Transmission of Financial Shocks, Oxford University Said School of Business, Working Paper, January

Kothari, S. P., and Jerold B. Warner, 2007, Econometrics of event studies, in B. Espen Eckbo, ed., *Handbook of Corporate Finance, vol. 1: Empirical Corporate Finance* (Elsevier: North-Holland).

Lasfer, M. Ameziane and Arie Melnik and Dylan C. Thomas (2003), Short-term reaction of stock markets in stressful circumstances, *Journal of Banking and Finance*, 27, 1959—1977.

Lasfer, M., Lin, Sharon X. and Gulnur Muradoglu (2012), Optimism in foreign investors, Review of Behavioural Finance, Vol. 4, No. 1, pp 8—27.

Lefebvre, Jeremie (2007), The Bootstrap in Event Study Methodology, MSc Thesis, Département de Sciences économiques, Faculté des Arts et des Sciences, Université de Montréal

Manova, Kalina (2008), Credit Constraints, Equity Market Liberalizations and International Trade, Stanford University Working Paper

Mukherjee, Paramita, Suchismita Bose and Dipankar Coondoo (2002), Foreign Institutional Investment in the Indian Equity Market, *Money and Finance,* April-September.

Myers, John H. & Archie J. Bakay (1948), Influence of stock split-ups on market price. *Harvard Business Review* 26:2, 251—265.

Pynnonen, Seppo (2005), On regression based event study, in *Contributions to Accounting, Finance, and Management Science: Essays in Honor of Professor Timo Salmi.* Acta Wasaensia No. 143, 327—354. Eds Erkki K. Laitinen and Teija Laitinen

Patnaik, Ila and Ajay Shah (2012), Did the Indian capital controls work as a tool of macroeconomic policy? *IMF Economic Review,* 60, 439—464.

Rakshit, Mihir (2006), On Liberalising Foreign Institutional Investments. *Economic and Political Weekly*, 18 March, 991-998.

Shah, Ajay and Ila Patnaik (2007), India's experience with Capital Flows: The Elusive Quest for a Sustainable Current Account Deficit, in *Capital Controls and capital flows in emerging economies: Policies, practices, and consequences"* NBER and University of Chicago Press. Ed. Sebastian Edwards.

Shah, Ajay and Ila Patnaik (2011), India's financial globalization, in *Encyclopedia of Financial Globalization*, Ed. Jerry Capiro, chapter 67, Elsevier, 2011.

Shah, Ajay and Susan Thomas (1998), Market microstructure considerations in index construction", CBOT Research Symposium Proceedings, Summer 1998.
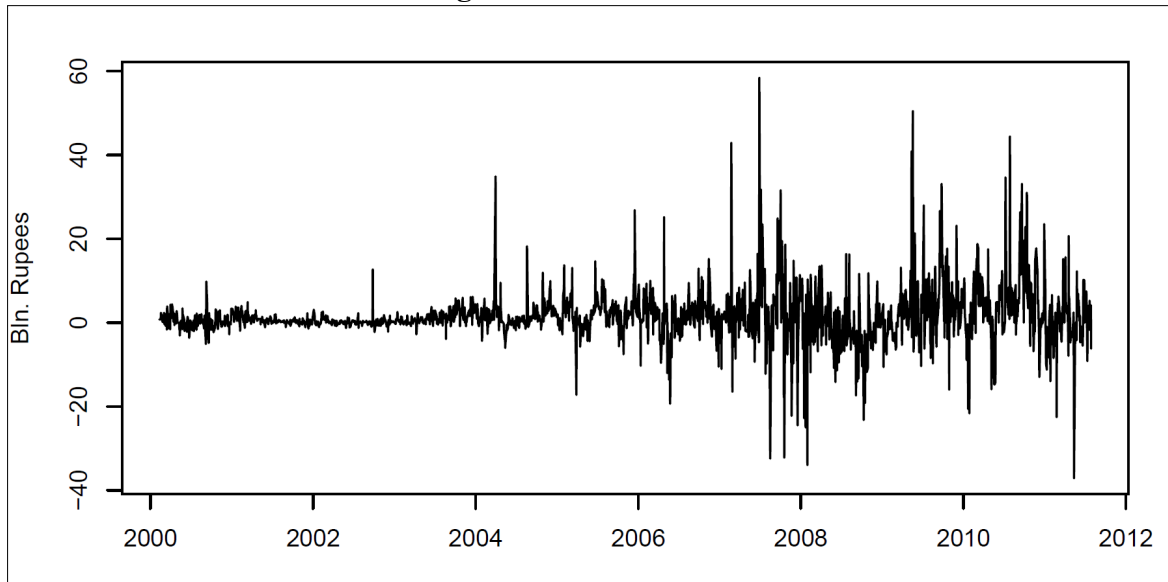
Stigler, Matthieu, Ajay Shah, and Ila Patnaik (2010), Understanding the ADR Premium under Market Segmentation, NIPFP Working Paper 71, July 2010.

Zeileis, Achim, Ajay Shah and Ila Patnaik (2010), Testing, monitoring and dating structural changes in exchange rate regimes, *Computational Statistics and Data Analysis*, 54(6), page 1696-1706, June 2010.
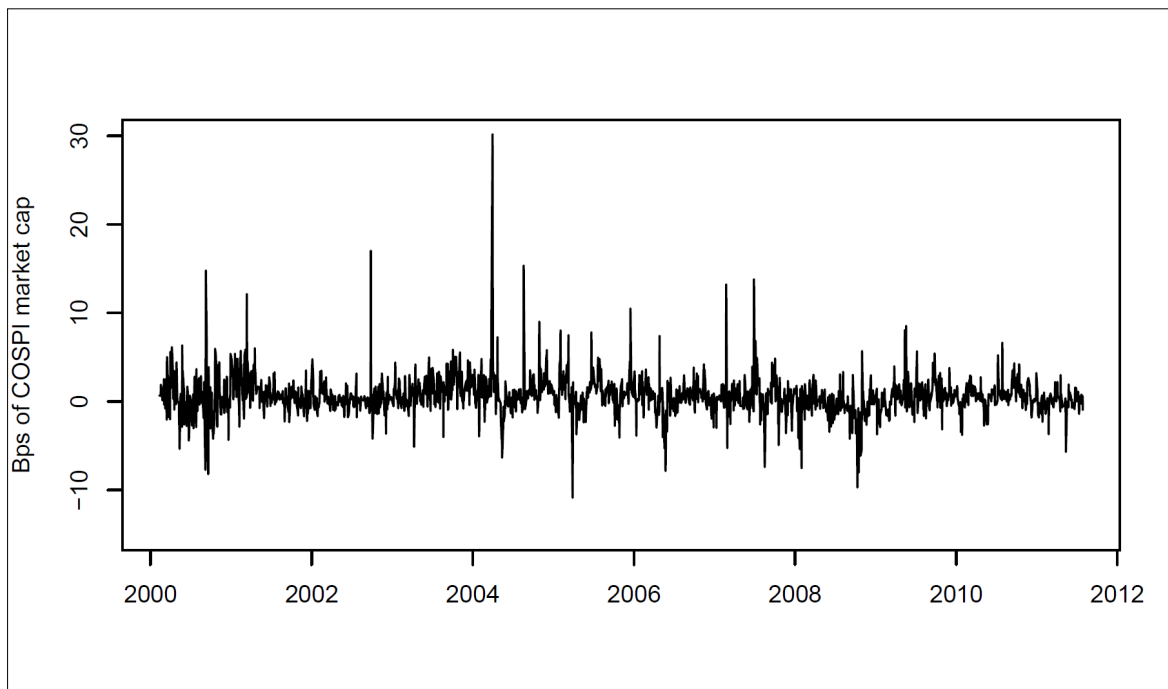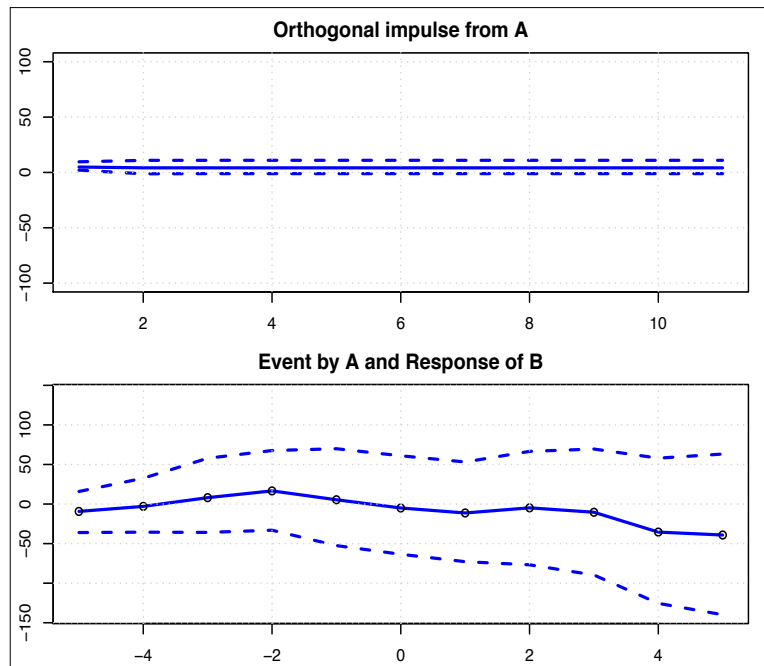
Tables and Figures

Figure 1: Net FII Flows
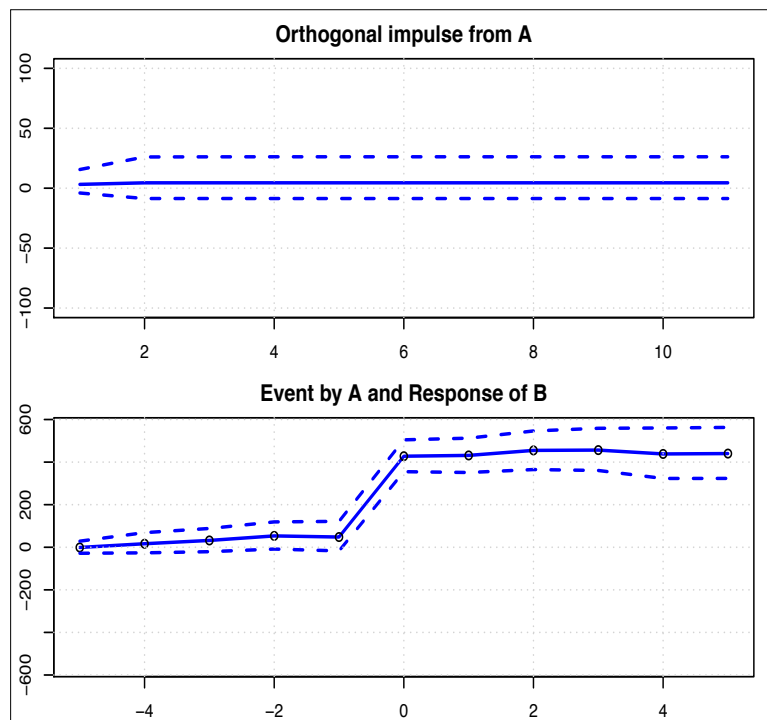

Figure 2: Normalized Net FII Flows

Figure 3: Monte Carlo experiment

Case (I)

Orthogonal impulse from A

Event by A and Response of B

Case (II)

Orthogonal impulse from A

Event by A and Response of B

Figure 4: Extreme event on Nifty and response of FII

Very good (by Nifty)

Very bad (by Nifty)
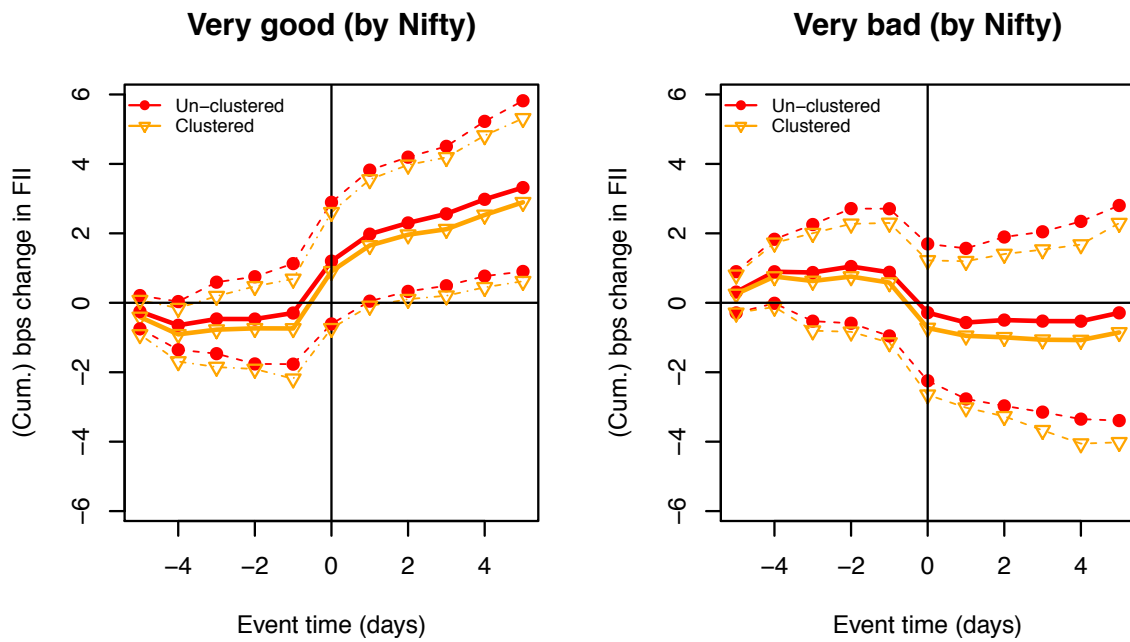
Figure 5: Extreme event on FII and response of Nifty

Very good (by FII)

Very bad (by FII)
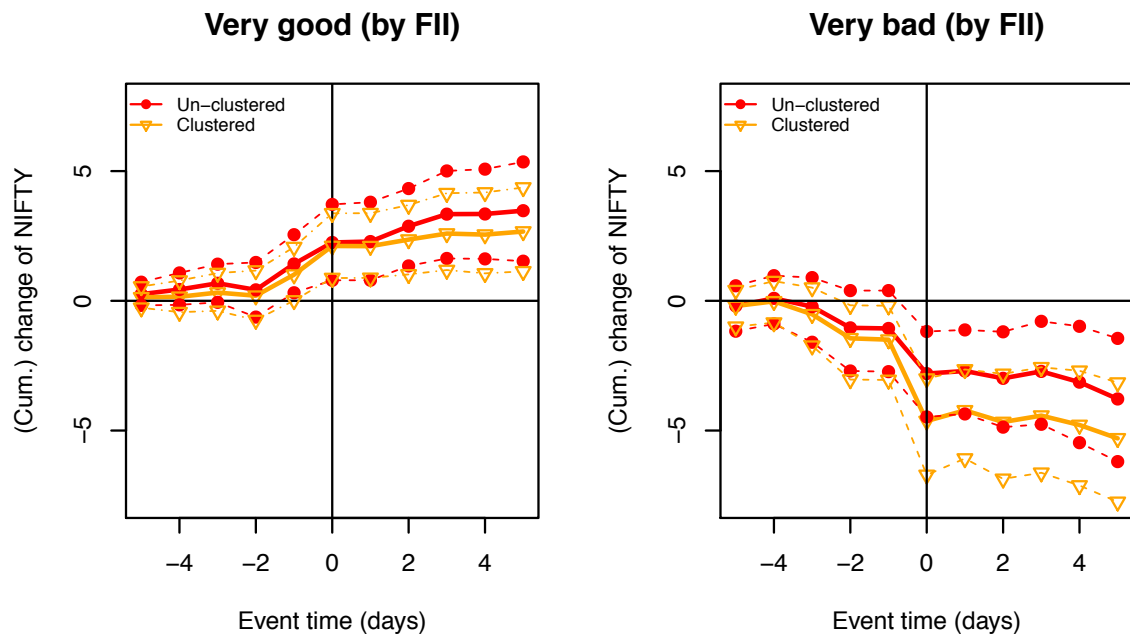
Figure 6: Extreme event on S&P 500 and response of FII
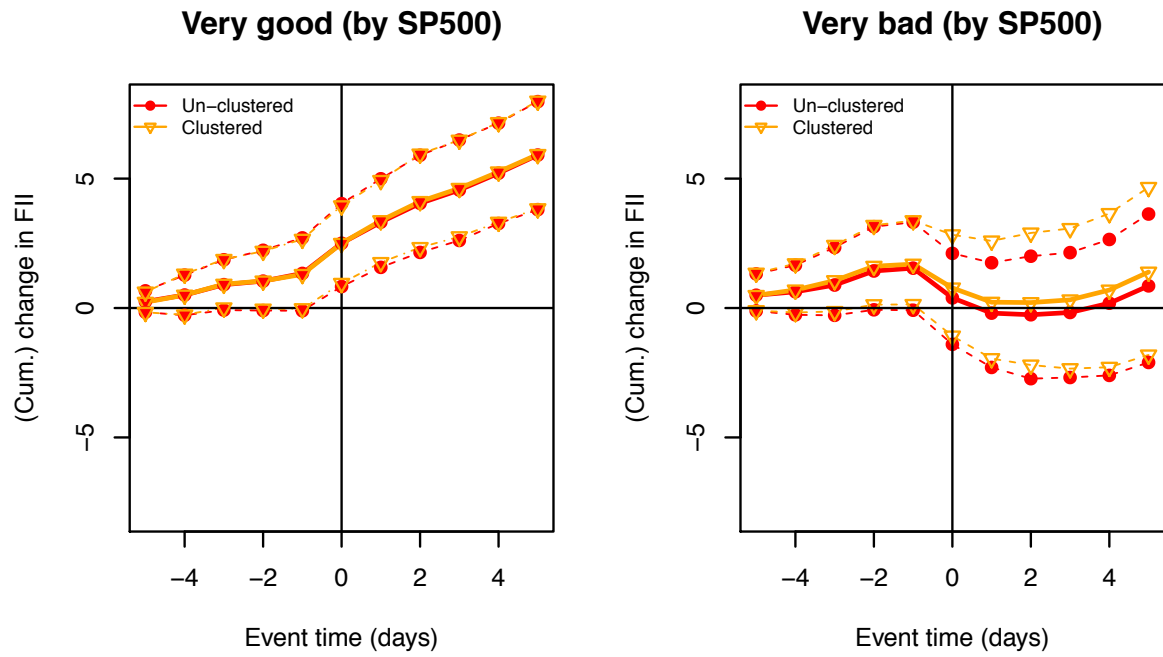
Figure 7: Extreme event on S&P 500 and response of Nifty
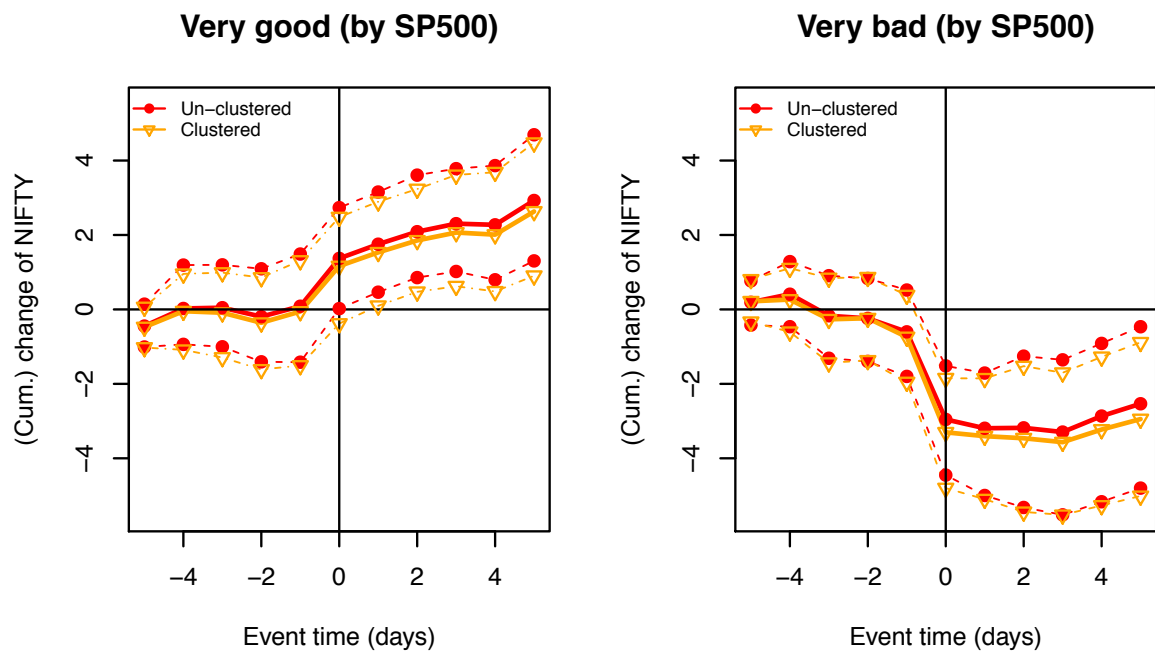
Figure 8: Extreme event on FII and response of call money rate

Very good (by FII)

Very bad (by FII)

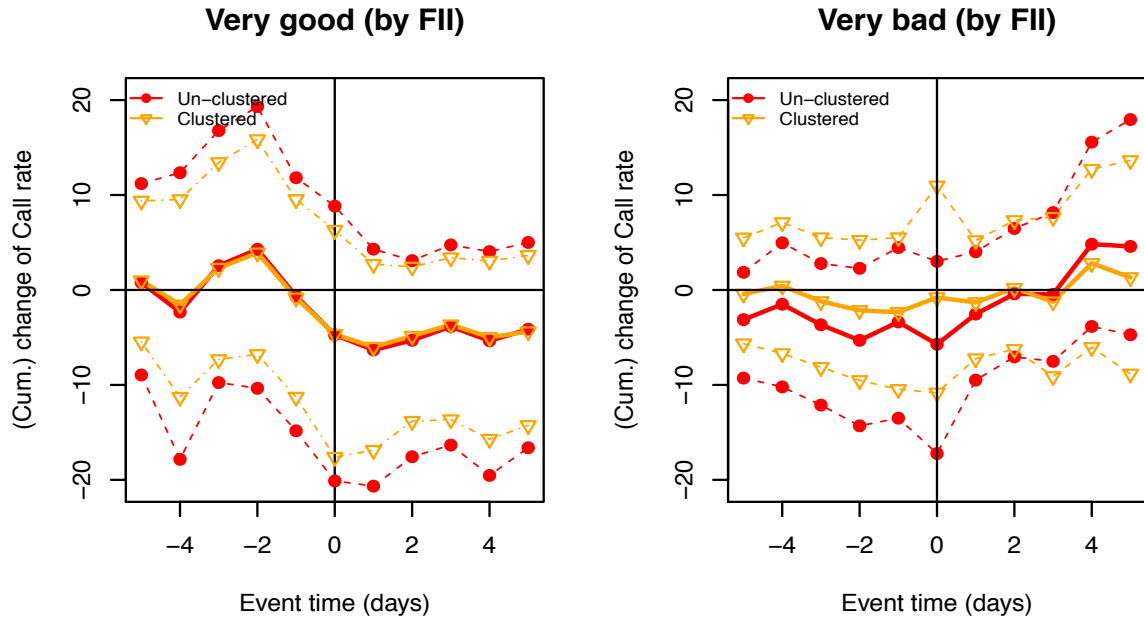# Figure 9: Extreme event on FII and response of INR

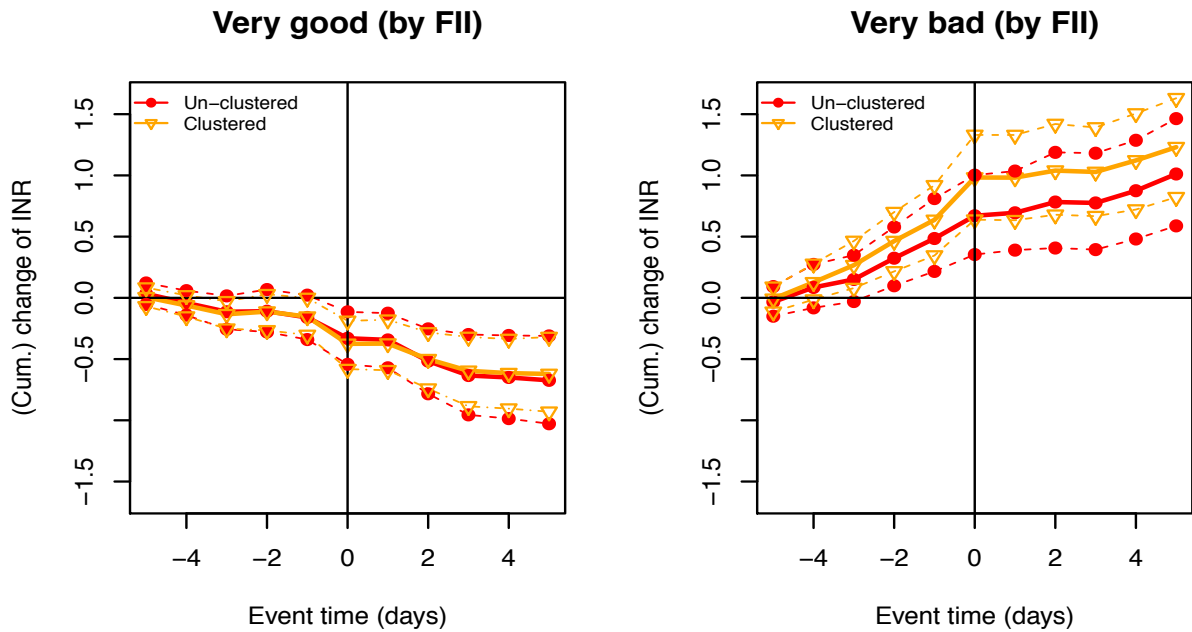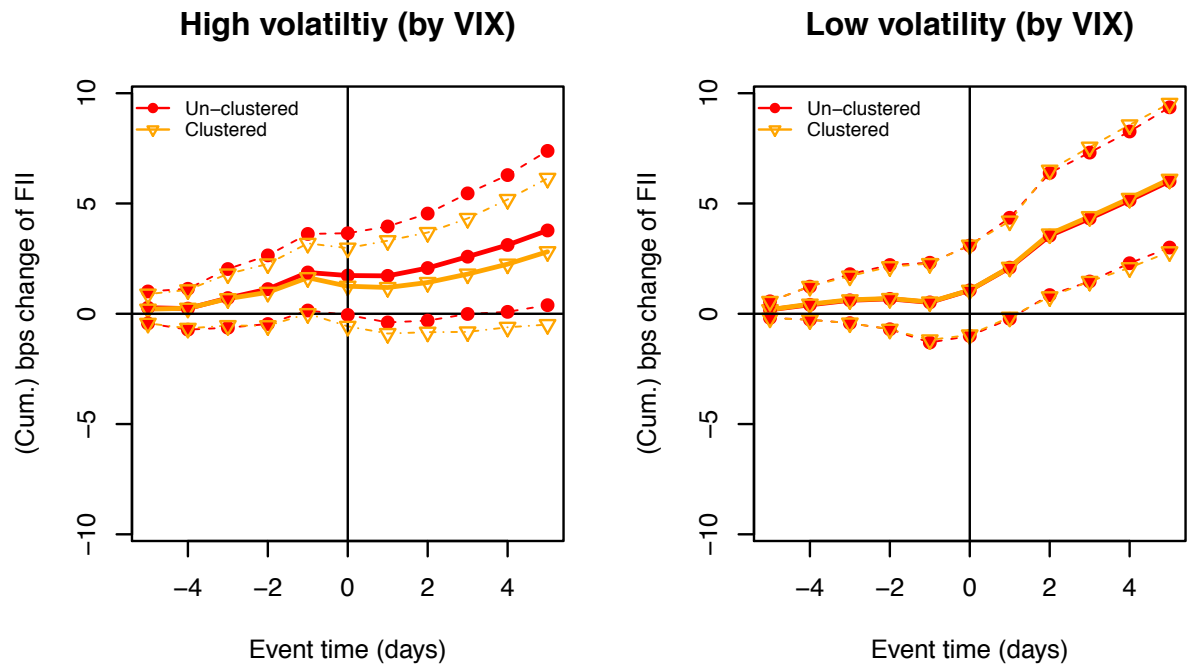**Very good (by FII)**

Very bad (by FII)

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Figure 10: Extreme event on VIX and response of FII

Table 1: Summary Statistics

	Daily net FII inflow (bps to COSPI Market capitalisation)	Daily Nifty returns (per cent)	Daily returns on Nikkei 225 (per cent)	Daily returns on S&P 500 (per cent)	Daily returns on INR/USD exchange rate	Daily change in the call money rate
Minimum	-10.87	-13.97	-17.53	-9.47	-4.17	-180.40
5%	-2.24	-3.28	-2.89	-2.44	-0.62	-17.35
25%	-0.36	-0.93	-0.96	-0.68	-0.14	-1.70
Median	0.48	0.16	0.04	0.09	0.00	0.00
Mean	0.59	0.06	-0.03	0.00	0.00	0.00
75%	1.41	1.08	0.96	0.72	0.12	1.40
95%	3.55	2.95	2.60	2.25	0.69	16.71
Maximum	30.16	16.23	13.23	12.40	2.87	276.77
Standard deviation	2.12	1.98	1.85	1.57	0.44	18.99
IQR	1.77	2.01	1.92	1.40	0.26	3.10
Observations (N)	2035	2035	2035	2035	2035	2035

Table 2: Distribution of events at 5%

	Un-clustered	Clustered			Total-used	Total
Lower tail						
		Used	Not-used	Total		
Nifty	57	6	39	45	63	102
S&P 500	56	6	40	46	62	102
FII	56	41	5	46	97	102
INR	58	16	28	44	74	102
Call rate	29	3	70	73	32	102
Upper tail						
Nifty	61	12	29	41	73	102
S&P 500	65	5	32	37	70	102
FII	65	33	4	37	98	102
INR	53	15	34	49	68	102
Call rate	33	6	63	69	39	102

Table 3: Runs distribution

Run length	Two	Three	Four	Five
Lower tail				
Nifty	3	0	0	0
S&P 500	3	0	0	0
FII	7	4	0	3
INR	8	0	0	0
Call rate	0	1	0	0
Upper tail				
Nifty	4	0	1	0
S&P 500	1	1	0	0
FII	12	3	0	0
INR	6	1	0	0
Call rate	3	0	0	0

Table 4: Quantile values (per cent) for tail at 5%

	Min.	25%	Median	Mean	75%	Max.
Lower tail						
Nifty	-13.97	-5.11	-4.13	-4.69	-3.70	-3.43
S&P 500 (percent)	-7.16	-3.94	-3.05	-3.55	-2.71	-2.44
FII (bps to COSPI market capitalization)	-10.87	-3.99	-3.21	-3.76	-2.62	-2.26
INR (bps)	-4.17	-1.10	-0.86	-1.06	-0.74	-0.62
Call rate (bps)	-75.50	-27.36	-22.15	-26.62	-18.69	-17.45
Upper tail						
Nifty	2.96	3.22	3.80	4.25	4.75	16.23
S&P 500 (percent)	2.27	2.45	2.88	3.15	3.46	6.98
FII (bps to COSPI market capitalization)	3.62	4.19	4.81	5.69	5.87	17.01
INR	0.69	0.79	0.95	1.00	1.06	2.34
Call rate	16.76	18.03	22.91	32.23	26.11	131.00

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

	S&P 500 (Returns)				Nifty (Returns)				FII (bps change)			
	5% Good days		5% Bad days		5% Good days		5% Bad days		5% Good days		5% Bad days	
	No.	Median	No.	Median	No.	Median	No.	Median	No.	Median	No.	Median
2000	8	3.02	7	-2.63	3	4.04	9	-4.88	10	4.52	12	-3.37
2001	8	2.59	5	-4.41	3	2.98	5	-4.00	10	4.71	3	-2.35
2002	14	2.89	12	-3.11	4	4.17	1	-3.87	2	10.90	2	-3.93
2003	7	3.79	2	-3.80	4	3.83	2	-4.22	14	4.61	1	-4.01
2004	0		1	-2.44	3	3.04	5	-4.08	10	5.53	4	-2.56
2005	0		0		2	4.56	2	-3.47	10	4.89	6	-3.25
2006	0		0		7	3.29	3	-4.24	5	3.85	7	-3.42
2007	5	2.82	6	-2.95	8	4.25	9	-3.85	8	4.89	10	-3.16
2008	8	3.17	11	-2.98	15	4.19	16	-4.61	0		14	-3.47
2009	11	2.92	9	-3.40	13	3.50	5	-4.29	7	5.45	4	-3.04
2010	5	2.91	5	-3.16	2	3.12	2	-3.65	4	4.79	4	-2.66
2011	1	2.30	1	-2.52	2	4.40	1	-4.13	0		3	-3.70
Total	67		59		66		60		80		70	

	INR (percent change)				Call rate (percent change)							
	5% Good days		5% Bad days		5% Good days		5% Bad days					
	No.	Median	No.	Median	No.	Median	No.	Median				
2000	4	0.86	1	-0.80	5	25.92	5	-18.66				
2001	2	1.16	0		2	21.52	4	-21.62				
2002	0		0		0		2	-19.97				
2003	0		1	-0.75	1	17.09	3	-22.04				
2004	2	1.18	6	-0.86	1	18.17	1	-24.88				
2005	4	0.90	2	-0.77	0		1	-23.37				
2006	4	0.99	5	-0.80	2	30.63	1	-20.17				
2007	3	0.80	9	-0.80	4	110.36	5	-18.80				
2008	12	0.99	9	-1.09	11	23.23	5	-27.44				
2009	12	0.94	18	-0.92	3	17.99	2	-20.22				
2010	10	0.94	12	-0.88	6	19.35	1	-25.33				
2011	7	0.87	3	-0.75	1	22.57						
Total	60		66		36		30					