Center for Analytical Finance
University of California, Santa Cruz

Working Paper No. 13

How Do Extreme Global Shocks Affect Foreign Portfolio Investment? An Event Study for India[#]

April 13, 2015

Anick Yaha[*]
Nirvikar Singh[*]
Jean Paul Rabanal[+]

Abstract

Foreign portfolio flows in and out of India are relevant for policymakers, and are often portrayed in the media as having a destabilizing effect on the domestic market. We use an event study approach to examine whether extreme global shocks trigger abnormal responses in foreign equity flows in and out of India, or abnormal responses in the Indian stock market. We do not find strong evidence of abnormal responses, even for the case of the global crisis of 2008.

[#] We are grateful to the International Growth Centre for financial support. Neither institution is responsible for the views expressed here. We are also grateful to Suman Bery, Tarun Ramadorai, Subir Gokarn and seminar participants at IGC, UCSC and Stanford for comments on related work. We especially wish to acknowledge the contributions of Vimal Balasubramaniam, who did significant initial data analysis, and Ila Patnaik and Ajay Shah, who provided intellectual guidance at many points. However, the authors are solely responsible for all errors and omissions.

[*] University of California, Santa Cruz, California
[+] Ball State University, Muncie, Indiana

Introduction

The global financial crisis and its aftermath have brought renewed concerns about the impact of international capital flows on emerging markets. While academic economists focus more on the manner in which global financial markets work overall (e.g., are they efficient in some sense?[1]), policy makers have more basic concerns about stability of their domestic financial markets in the presence of waves of global capital that may drown them or leave them high and dry. There is renewed debate on the merits and appropriate forms of capital controls in this context, and continued efforts to understand the impact of foreign capital on emerging markets and the effects of capital controls (e.g., Ostry et al., 2011, Forbes et al., 2013, Ahmed and Zlate, 2014).

Our paper seeks to address a basic empirical concern of policy makers in emerging markets: how do extreme global shocks affect foreign investment into such markets, and the markets themselves? By focusing on extreme shocks, we recognize that policy makers are typically not worried about "normal" fluctuations, but do not want to be overly exposed to large global forces that might destabilize their economies through no fault of their own. Our empirical implementation uses data on foreign portfolio investment in India to examine the question just posed. India is an important emerging market, with a liquid stock market and no restrictions on foreign portfolio investment, beyond qualifying conditions for who can participate. The popular perception of this regime has often been that foreign portfolio investors are "hot money" that creates wild swings in the domestic stock market.

Our analysis complements that of Patnaik, Shah and Singh (2013), who introduced the idea of focusing on extreme events in studying the behavior of foreign investors in the Indian stock market, and the impacts of that behavior. Their paper did not find uniform evidence that foreign investors "destabilize" the Indian market, or act as a vector of crisis transmission, though there was some indication that they amplified domestic booms. However, their statistical methodology required pooling instances of extreme events, which could have the effect of masking the impact of truly exceptional events such as the recent global financial crisis. Accordingly, the analysis of this paper uses an alternative approach, which imposes additional parametric and distributional assumptions, but allows us to examine extreme events one by one.

The next section describes our methodological approach in more detail, including a description of the data and some institutional background. We explain exactly how we differ from Patnaik et al. (2013), and also provide some brief references to the literature. A more detailed discussion of the literature and its relation to our event study approach may be found in Patnaik et al. (2013). The section following that sets out our results and discusses them. Essentially, even when we use the alternative approach here, which allows us to isolate the effect of individual extreme events,

[1] See, for example, Choe et al. (2001), and Froot and Ramadorai (2001, 2008).

our results suggest that foreign portfolio flows into India are not a vector of crisis transmission. The final section provides a summary conclusion and discussion of further research directions.

Data and Methodology

Data

India has a complex system of capital controls (Patnaik and Shah, 2012; Hutchison, Pasricha and Singh, 2012), but the restrictions on foreign portfolio investment are relatively clear. There are no quantitative restrictions or taxes on such flows, except that only qualified financial institutions can undertake equity investment.[2] These institutions include banks, asset management firms, hedge funds, trusts and foundations, and they must register with the Indian securities regulator. They are commonly described as "foreign institutional investors," or FIIs. There is a nominal legal restriction on the proportion of shares of any listed company that can be held by foreigners, but this ceiling can be raised up to 98% by a resolution of the shareholders, making the ceiling somewhat irrelevant in practice. In essence, once an institution is qualified and registered, its actions in the Indian market are unconstrained by regulations specific to FIIs.

FIIs are required to settle their trades through custodian banks, who in turn must supply data to the regulator and the government. This provides us with detailed transaction data for individual FII transactions. For the current analysis, the data is aggregated across all transactions in a day, giving us the net change in FII investment on a daily basis. The time span of our data is January 6, 1999 to July 29, 2011. This time period was one of rapid expansion of the Indian stock market, therefore, it is appropriate to divide the FII volumes by the market capitalization (CMIE Cospi Index). The stock market data we use is daily and is computed as closing prices for three stock market indices: the 'Nifty' stock market index for India (Shah and Thomas, 1998), the S&P 500 index for United States, and the Nikkei index for Japan. In our analysis, the last two indices represent global conditions, and changes in these indices capture the idea of global shocks.[3] In fact, we use daily rates of return as the relevant series, rather than the indices themselves. Hence, for example, a large negative daily return on an index will be an extreme (bad) event, in the left tail of the returns distribution.

[2] To harmonize the different routes for foreign portfolio investment in India, in 2014 the Securities Exchange Board of India (SEBI), which is the Indian securities market regulator, created a new category, Foreign Portfolio Investors (FPIs). This was formed by merging the existing classes of investors through which portfolio investments were previously made in India: FIIs, Qualified Foreign Investors (QFIs) and sub-accounts of FIIs. The QFI category had been introduced in 2011-12, as part of a partial liberalization of eligibility for foreign investors in Indian equities. Our data predates all these changes, so avoids any issues related to changing regulations.

[3] In the case of holidays, we assume that the index remains the same for the holiday, implying a zero return for such days. This allows us to avoid problems which arise from the fact that there are different holidays in the two markets. Furthermore, in lining up Indian and US data, while for a particular calendar date, the Indian market is open before the US market, and closes before the US market opens, the likely chain of causality runs from the US market to the Indian market. Therefore we line up the previous calendar day of US data with the Indian data.

Table 1 presents descriptive statistics for Net FII flow, S&P 500, Nikkei and Nifty indices. Flows are the most volatile of all four variables with a standard deviation of 1.71, although the units are different from the other three variables. Nifty returns are the most volatile of the three returns indices, although the differences are not big. For all three returns variables, the 2.5th and 97.5th percentiles are about four standard deviations apart.

General methodology

In a traditional event study, the event is an identifiable action at a specific point in time, such as an announcement of a merger or stock split (e.g., Dolley, 1933; Myers and Bakay, 1948; Fama et al., 1969; and Brown and Warner, 1980). In more recent applications, events may also be more spread out, such as trade liberalization (e.g., Manova, 2008), financial crises (e.g., Broner et al.) or introduction of capital controls (e.g., Ostry et al., 2011). In this paper, we define event dates as those on which extreme values of returns or flows are observed. As an example, we examine the distribution of daily returns on the S&P 500, and identify the dates on which the returns were in the tails.

Patnaik et al. (2013) use the same definition of events as in this paper, namely, observations in the tail of the relevant distribution. However, that paper pools and averages tail events and constructs confidence intervals for statistical inference through a bootstrap procedure. This bootstrap approach has the advantages of avoiding imposing distributional assumptions such as normality and being robust against serial correlation. However, these benefits come at a cost of pooling all extreme events, so that responses are measured as average responses to the "average" extreme shock.

Here, we follow the more traditional event study approach. Briefly, we use regressions for computing abnormal returns. For each extreme event, an estimation window that precedes the event is used to estimate a linear relationship between the response variable being analyzed (Nifty stock returns or FII flows), and the explanatory variable, which is daily returns on the S&P 500 or the Nikkei index. This represents the structural relationship linking the response variable to global market conditions in what may be considered "normal" times. Using the coefficients from this relationship, we obtain predicted values for the response variable in the pre-event and post-event windows. Next, we analyze whether these predicted values are statistically different from the actual realizations of the dependent variable. For example, when studying the response of Nifty returns to a given event, predicted "normal" Nifty returns are computed using coefficients from the estimated relationship between S&P 500 and Nifty returns. These pre-event and post-event predicted returns are then compared to the actual returns recorded in those windows. The same procedure is followed to calculate predicted flows that are then compared to actual flows. Statistically significant differences between predicted and actual values are considered to be "abnormal" and are the main focus of our analysis. Using t-tests, we check whether these estimated abnormal returns/flows are significantly different from zero.

We check for the presence of cumulative abnormal returns/flows as well because we are also interested in assessing the cumulative effects of global shocks over given time windows, and in comparing daily responses to cumulative responses. Cumulative abnormal returns/flows over a given time period are obtained by adding up all daily returns from the relevant time window. We further test whether those cumulative returns/flows are statistically different from zero.

In instances where tests do not reject the null hypothesis of zero abnormal returns/flows, we conclude that the extreme event at study did not produce any abnormal behavior. When tests reveal that we can reject the null hypothesis of zero abnormal returns, we conclude that the event at study caused some disruption on domestic Indian markets. When the null hypothesis of zero abnormal flows can be rejected, we conclude that the event caused foreign institutional investors to behave in an unusual manner.

Statistical Tests

More specifically, we define an event as a daily return on the S&P 500 or the Nikkei index that is in one of the 2.5% tails of the relevant distribution. In other words, an event window is just a single day. This differs from the treatment in Patnaik et al. (2013), where in some cases clusters of extreme daily returns or flows are treated as individual events. As explained later, we allow for this clustering in a different manner. Since there are 3,298 observations, we have 83 extreme events in each 2.5% tail of each distribution that we consider.

Next, we define the estimation window, pre-event window and post-event window as follows; with the event day defined as t_0, the estimation window is the time span between day t_{-30} and day t_{-11}. In other words, we use the first 20 days of the 30 preceding the event as the estimation window. The pre-event window is made up of the days preceding the extreme event (t_{-10} to t_{-1}), while the ten days after the event make up the post-event window (t_1 to t_{10}).

Using data for the estimation window, we fit the following linear model to the data,

$$y_t = b_0 + b_1 x_t + \epsilon_t$$

where y_t is the daily return on the Nifty index or the daily net FII flow, x_t is the daily return on the S&P 500 and ϵ_t is the error term.

We choose to estimate this model in the simplest form possible, but other relevant explanatory variables (exchange rates, transactions costs, etc.) could be added to capture the relationship between Nifty returns/FII flows and global markets. We do not see this as being a problem as long as no significant change in those other variables is recorded across time windows for a given event.

Since returns are highly correlated over time, we cannot assume the error term ϵ_t to have all the desirable properties of the classical linear regression model – residuals are correlated over time.

An ordinary least squares (OLS) estimation, in this setting, would produce unbiased coefficients but faulty standard errors. We circumvent this issue by using a Newey-West procedure that produces the same coefficients as OLS, but yields standard errors that are robust to autocorrelation and heteroskedasticity.

For each day in the pre-event and post-event windows, abnormal quantities are calculated as follows:

$$y_{ab_t} = y_t - \hat{y}_t$$

where

$$\hat{y}_t = (b_0 + b_1 x_t)$$

The variance of each daily abnormal quantity is computed as:

$$\sigma^2(y_{ab_t}) = \sigma^2(y_t) + \sigma^2(b_0 + b_1 x_t)$$

because y_t and $\hat{y}_t$ are assumed to be uncorrelated. After rearranging, we obtain:

$$\sigma^2(y_{ab_t}) = \sigma^2(y_t) + \sigma^2(b_0) + x_t^2 \sigma^2(b_1) + 2\sigma(b_0, b_1)]$$

The test statistic used for the t-test is then calculated as:

$$tstat_t = \frac{y_{ab_t}}{\sigma(y_{ab_t})}$$

Cumulative abnormal quantities are obtained by summing up the daily returns in a given window. So, for a window of length *m* starting at time T, the cumulative abnormal quantity is:

$$y_{cu} = \sum_{t=T}^{t=T-m} y_{ab_t}$$

Following Coutts (1995), the variance associated with this cumulative quantity is computed:

$$\sigma^2(y_{cu}) = \sum_{t=T}^{t=T+m} \sigma^2 y_{ab_t} + CX'VX''C' / L$$

where:

- C' is a vector of ones of dimension

- $X^{-'} = \begin{bmatrix} 1 & \cdots & 1 \\ x_{\tau} & \dots & x_{\tau+m} \end{bmatrix}$

- V is the variance-covariance matrix produced by the Newey-West procedure

- L is the length of the estimation window

The test statistic is then calculated as:

$$ts_{cu} = \frac{y_{cu}}{\sigma(y_{cu})}$$

As noted earlier, it may be the case that there is another tail event that falls in one of the two periods (estimation window and pre-event window) that precedes any single event. Rather than cluster such events, as in Patnaik et al. (2013), where the time domain is not central to the analysis, here we preserve the time series structure, and merely categorize each set of extreme events further by the nature of incidence of other extreme events in the preceding periods. We term the presence of such other events as "contamination." Hence, there are four cases: no contamination, only the estimation window contaminated, only the pre-event window contaminated; and both windows contaminated. We report results for each of the four cases, and can compare patterns of significant abnormal returns across the four different types of cases.

Results

Responses to global shocks

Table 2A summarizes results for the impact of those global shocks on daily returns in the Indian stock market, as measured by the Nifty index. In this case, the global shocks are proxied by events in the 2.5% tails of the distribution of daily returns on the S&P 500 index. Results for positive and negative shocks are presented separately in the table. In each case, there are 83 observations in the tail, and these constitute the extreme events. These 83 events are further broken down by the pattern of other tail events that precede the shock in question. Thus, for positive shocks, in 21 of the cases, there was no extreme shock in the preceding pre-event or estimation periods. In 19 cases, there was at least one positive shock in the estimation window only; in 10 cases, in the pre-event window only; and in 33 cases, there were other positive extreme events in both preceding windows. For each of the 83 positive tail cases, we estimate a linear model of returns, using the predefined estimation window for that event. Abnormal domestic returns in the pre-event and post-event windows are then determined relative to this estimated relationship.

Columns 3 and 4 of Table 2A report the average number of days of abnormal returns in the pre-event and post-event windows respectively. This figure is obtained as follows: First, all the days with significant abnormal returns are added up for each tail event over the concerned window to obtain a first count. The figure reported in the table is an average of this first count over all the events of the category being considered. For example, the figure in the third column of the second line of the table is obtained by averaging the first count over all the 83 positive tail events while the figure right below it is an average that includes only 21 events. Responses of returns to tail events are very low across the board. All 83 positive tail events produced less than two days of significant abnormal returns on average in the pre-event window as well as in the post-event window (1.35 and 1.25 days, respectively, on average). On the cumulative level, only 23% of the shocks created significant cumulative abnormal returns both in the pre- and post-event windows.

Responses to negative extreme shocks on global markets seem stronger but are still very low. Average of significant abnormal returns closer to two are recorded: 1.49 and 1.77 in the pre-event and post-event windows respectively. Looking at the cumulative abnormal returns, 29% and 24% of the 83 events produced significant returns in the pre-event and post-event windows respectively.

Contamination patterns do not seem to make much of a difference at the cumulative level, but they seem to matter at the daily level. In fact, for both positive and negative shocks, events with no contamination recorded the highest numbers of days with significant abnormal returns.

Similarly Table 2B presents results for the impact of extreme global shocks on FII flows into or out of India. Recall that global shocks are proxied by observations in the 2.5% tails of the distribution of daily returns on the S&P 500 index, with 83 observations in each tail. The breakdown of cases is the same as in Table 2A. For each of the 166 cases, we estimate a linear model, this time with FII flows as the dependent variable using the predefined estimation window for that event. Abnormal flows in the pre-event and post-event windows are then determined relative to this estimated relationship. Compared to the response of domestic stock market returns, FII flows are definitely more sensitive to global shocks in terms of cumulative results. In fact, there are fewer days of significant abnormal flows than days of abnormal returns, but higher percentages of events producing significant cumulative abnormal flows.

The results are consistent with two possible hypotheses. First, the difference between the response of domestic returns and the response of FII flows fits the fact that domestic investors make decisions that are not necessarily highly correlated with those of FIIs, and this makes domestic returns less sensitive to global shocks than FII flows. Second, FII behavior does not necessarily amplify global shocks – evidenced by the large number of cases in which negative shocks are followed by larger than average flows into India.

The fact that flows are more responsive at the cumulative level is also consistent with the fact that investors do not automatically start flushing markets when extreme events occur. They respond in more of a progressive than speculative manner.

Responses to shocks on Asian markets

Table 3A and 3B present responses of the Indian stock market returns and foreign institutional investments flows to shocks on Asian markets. The shocks are proxied by events in the 2.5% tails of the distribution of daily returns on the Nikkei index. The tables summarize results for positive and negative shocks separately. In each case, there are also 83 observations in the tail and these constitute the extreme events. The 83 events are also broken down by the pattern of other tail events that precede the shock in question

Nifty returns seem more responsive to Asian markets shocks than they are to global markets shocks, but the responses are still very low. Both positive and negative Nikkei shocks result in less than two days of significant abnormal Nifty returns. This difference is however less pronounced for negative shocks where responses are more similar to those from global shocks.

Responses of flows are however quite similar across the board, with the same effects. Flows tend to be less responsive than returns at the daily level, and more responsive at the cumulative level when shocks occur.

Responses to simultaneous global and Asian shocks

Table 4A and 4B present responses to shocks occurring simultaneously on global and Asian markets. They are measured by events in the 2.5% tails of the distribution of daily returns on both the S&P500 and Nikkei indices. There are 19 observations of positive simultaneous extreme events: for 9 of them, there was no event in the pre-event and post-event windows; 2 of them had at least one other event occurring in the estimation window; 3 of them were preceded by at least one event in the pre-event window and 5 of them had at least one other extreme event in each of the estimation and pre-event window.

There are 24 observations of negative simultaneous extreme events: for 7 of them, there was no event in the pre-event and post-event windows; 5 of them had at least one other event happening in the estimation window; none of them were preceded by at least one event in the pre-event window and 12 of them had at least one other extreme event in each of the estimation and pre-event window.

Nifty returns are more responsive to simultaneous Asian and global shocks than they are to global shocks only for positive and negative events both at the daily and cumulative levels. However, their responses to simultaneous negative shocks are slightly lower than they were for negative Asian shocks at the daily levels.

At the cumulative level, Nifty returns seem more responsive to positive simultaneous shocks than they are to negative simultaneous shocks.

Flows seem to respond less than returns on the daily level, and more on the cumulative level, which is what was observed in all the cases above.

Does contamination matter?

Extreme events were classified according to the pattern of event preceding them in the estimation and the pre-event windows. The goal was to check whether responses to an event were influenced by the fact that other events had occurred in the different windows of interest preceding that event. One would assume that the response to a positive event could be amplified if other positive extreme events had occurred in the estimation and/or pre-event windows preceding that event. Since we cannot really isolate those events “contaminated” by other events occurring in their estimation and/or pre-event windows, we decided to compare their impact to those of event that were “no contaminated” (no event in both estimation and pre-event windows).

Our results indicate that contamination does not really matter here since we did not detect a systematic difference in the responses of returns and flows to “contaminated” vs. “no contaminated” events.

Conclusion

The global financial crisis and its aftermath have brought renewed concerns about the impact of international capital flows on emerging markets. For example, foreign portfolio flows in and out of India are important for policymakers, and are often portrayed in the media as having a destabilizing effect on the domestic market. In this paper, we use an event study approach to examine whether extreme global shocks triggered abnormal responses in foreign equity flows in and out of India, or abnormal responses in the Indian stock market. For the period 1999-2011, we do not find strong evidence of abnormal responses, even for the case of the global crisis of 2008. The analysis in this paper complements other work (Patnaik et al., 2013), which use a more flexible distributional assumption, but required pooling extreme events. Natural extensions of the current analysis would be to incorporate later data for India, and to examine similar issues for other emerging markets. In particular, it is possible that the degree of financial liberalization or the size of the domestic market might yield qualitatively different results.

References

Ahmed, Shaghil, and Andrei Zlate (2014), Capital flows to emerging market economies: A brave new world?, *Journal of International Money and Finance*, 48, Part B, 221–248

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

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

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

Hutchison, Michael, Gurnain Pasricha and Nirvikar Singh (2012), Effectiveness of Capital Controls in India: Evidence from the Offshore NDF Market, *IMF Economic Review*, 60, 395–438

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

Forbes, Kristin, Marcel Fratzschner and Roland Straub (2013), Capitals controls and macroprudential measures: What are they good for?, Discussion Papers, DIW Berlin, No. 1343

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

Manova, Kalina (2008), Credit Constraints, Equity Market Liberalizations and International Trade, *Journal of International Economics*, 76, 33-47

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

Ostry, Jonathan D., Atish R. Ghosh, Marcos Chamon and Mahvash S Qureshi (2011), Capital Controls: When and Why?, *IMF Economic Review*, 59, 562–580

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

Patnaik, Ila, Ajay Shah and Nirvikar Singh (2013), Foreign Investors under Stress: Evidence from India, *International Finance*, 16 (2), 213-244

Tables

Table 1

	Net FII inflow	S&P 500	Nikkei	Nifty
Mean	0.36	0	-0.01	0.05
2.5%	-2.4	-2.67	-3.09	-3.59
97.5%	4.45	2.54	2.92	3.26
Minimum	-23.04	-9.47	-12.11	-13.05
Maximum	20.49	10.96	13.23	16.33
Standard deviation	1.71	1.31	1.54	1.67

Table 2A: Shocks are in 2.5% tails of S&P 500 returns, dependent variable Nifty returns

	Number of shocks	Average number of days of abnormal returns in pre-event window	Average number of days of abnormal returns in post-event window	Number of cases of cumulative abnormal returns in pre-event window			Number of cases of cumulative abnormal returns in post-event window		
				Negative Cases	Positive Cases	Total	Negative Cases	Positive Cases	Total
Positive Shocks	83	1.35	1.25	8	11	19	7	12	19
No contamination	21	1.52	1.57	4	2	6	2	5	7
Estimation window only contaminated	19	1.16	0.84	0	1	1	2	1	3
Pre-event window only contaminated	10	0.9	1.5	1	1	2	2	1	3
Both contaminated	33	1.48	1.21	3	7	10	1	5	6
Negative Shocks	83	1.49	1.77	21	3	24	12	8	20
No contamination	21	2.48	2.9	7	1	8	4	1	5
Estimation window contaminated	17	0.71	1.11	0	0	0	0	3	3
Pre-event window contaminated	12	1.83	1.83	6	0	6	2	1	3
Both contaminated	33	1.15	1.36	8	2	10	6	3	9

Table 2B: Shocks are in 2.5% tails of S&P 500 returns, dependent variable FII

	Number of shocks	Average number of days of abnormal returns in pre-event window	Average number of days of abnormal returns in post-event window	Number of cases of cumulative abnormal returns in pre-event window			Number of cases of cumulative abnormal returns in post-event window		
				Negative Cases	Positive Cases	Total	Negative Cases	Positive Cases	Total
Positive Shocks	83	1.02	1.15	8	13	21	10	22	32
No contamination	21	1.24	1.29	4	5	9	4	5	6
Estimation window only contaminated	19	1.21	1.32	2	4	6	3	5	8
Pre-event window only contaminated	10	0.8	0.8	1	0	1	1	2	3
Both contaminated	33	0.85	1.09	1	4	5	2	10	12
Negative Shocks	83	1.39	1.3	16	14	30	14	24	38
No contamination	21	1.81	1.52	6	2	8	6	4	10
Estimation window contaminated	17	1.41	2	3	5	8	2	9	11
Pre-event window contaminated	12	1.83	1.75	3	0	3	3	4	7
Both contaminated	33	0.94	0.63	4	7	11	3	7	10

Table 3A: Shocks are in 2.5% tails of Nikkei returns, dependent variable Nifty returns

	Number of shocks	Average number of days of abnormal returns in pre-event window	Average number of days of abnormal returns in post-event window	Number of cases of cumulative abnormal returns in pre-event window			Number of cases of cumulative abnormal returns in post-event window		
				Negative Cases	Positive Cases	Total	Negative Cases	Positive Cases	Total
Positive Shocks	83	1.64	1.36	8	13	21	12	10	22
No contamination	28	1.68	1.25	3	5	8	6	3	9
Estimation window only contaminated	20	0.9	1.1	3	2	5	3	1	4
Pre-event window only contaminated	9	2.33	2.44	1	2	3	2	3	5
Both contaminated	26	1.92	1.31	1	4	5	1	3	4
Negative Shocks	83	1.58	1.82	26	4	30	14	10	24
No contamination	25	1.8	1.72	8	2	10	5	2	7
Estimation window contaminated	17	0.71	1	3	0	3	1	1	2
Pre-event window contaminated	9	1.67	2	3	0	3	2	2	4
Both contaminated	32	1.84	2.28	12	2	14	6	5	11

Table 3B: Shocks are in 2.5% tails of Nikkei returns, dependent variable FII

	Number of shocks	Average number of days of abnormal returns in pre-event window	Average number of days of abnormal returns in post-event window	Number of cases of cumulative abnormal returns in pre-event window			Number of cases of cumulative abnormal returns in post-event window		
				Negative Cases	Positive Cases	Total	Negative Cases	Positive Cases	Total
Positive Shocks	83	1.443	1.57	12	20	32	10	22	32
No contamination	28	1.68	1.68	6	7	13	3	4	7
Estimation window only contaminated	20	1.15	1.35	2	6	8	2	8	10
Pre-event window only contaminated	9	2	2.56	1	2	3	4	1	5
Both contaminated	26	1.19	1.27	3	5	8	1	9	10
Negative Shocks	83	1.37	1.1	19	11	30	16	10	34
No contamination	25	1.36	1.16	4	3	7	5	2	7
Estimation window contaminated	17	1.47	1.41	6	3	9	4	2	6
Pre-event window contaminated	9	1.33	0.56	2	1	3	2	0	2
Both contaminated	32	1.34	1.03	7	4	11	5	6	11

Table 4A: Shocks are in 2.5% tails of S&P500 and Nikkei returns, dependent variable Nifty returns

	Number of shocks	Average number of days of abnormal returns in pre-event window	Average number of days of abnormal returns in post-event window	Number of cases of cumulative abnormal returns in pre-event window			Number of cases of cumulative abnormal returns in post-event window		
				Negative Cases	Positive Cases	Total	Negative Cases	Positive Cases	Total
Positive Shocks	19	1.74	1.68	3	4	7	2	5	7
No contamination	9	1.44	1.22	2	2	4	1	3	4
Estimation window only contaminated	2	1.5	3	1	0	1	1	0	1
Pre-event window only contaminated	3	1.33	2.33	0	1	1	0	1	1
Both contaminated	5	2.6	1.6	0	1	1	0	1	1
Negative Shocks	24	1.54	1.71	7	2	9	4	2	6
No contamination	7	1.71	2	2	0	2	2	0	2
Estimation window contaminated	5	0.6	0.8	0	0	0	0	1	1
Pre-event window contaminated	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Both contaminated	12	1.83	1.92	5	2	7	2	1	3

Table 4B: Shocks are in 2.5% tails of S&P500 and Nikkei returns, dependent variable FII

	Number of shocks	Average number of days of abnormal returns in pre-event window	Average number of days of abnormal returns in post-event window	Number of cases of cumulative abnormal returns in pre-event window			Number of cases of cumulative abnormal returns in post-event window		
				Negative Cases	Positive Cases	Total	Negative Cases	Positive Cases	Total
Positive Shocks	19	0.79	1.53	0	3	3	2	7	9
No contamination	9	1.11	2	0	2	2	1	3	4
Estimation window only contaminated	2	0.5	0	0	0	0	0	1	1
Pre-event window only contaminated	3	0.33	2.33	0	0	0	1	0	1
Both contaminated	5	0.6	0.8	0	1	1	0	3	3
Negative Shocks	24	1.25	0.88	4	4	8	4	6	10
No contamination	7	2	1	2	0	2	2	1	3
Estimation window contaminated	5	1.6	1.4	2	1	3	1	1	2
Pre-event window contaminated	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Both contaminated	12	0.67	0.58	0	3	3	1	4	5