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

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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.

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1. 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 our analysis on extreme shocks (to be defined precisely later in the paper), 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 from India on "foreign institutional investors," or FIIs, which include banks, asset management firms, hedge funds, trusts and foundations during the period 1999-2011. The global shocks we study are defined as extreme fluctuations in two of the most significant stock market indexes, i.e. those of the USA and Japan. We also analyze how the FIIs respond to, and how they influence, the local fluctuations of the Indian stock market (National Stock Exchange or NSE). During our period of analysis, India has experienced one of the fastest expansions of the stock market among emerging economies. Its market is relatively liquid and there are no restrictions on foreign portfolio investment, beyond qualifying conditions for who can participate. Indeed, the popular perception in India has often been that FIIs represent "hot money" that creates wild swings in the domestic stock market, but this has mostly not been subject to rigorous and detailed empirical analysis.

The techniques we apply are event study methods that are well-known in the traditional finance literature, but less used in international contexts. We estimate a linear model that captures the "normal" relationship between the variables of interest (FIIs flows and stock market returns) and compare the predicted model against the outcome observed right after an extreme event. This procedure allows us to analyze independently each extreme event. In this regard, our paper differs from the previous work of Patnaik, et al. (2013); they use the same data and also focus on extreme events, but pool all extreme events in order to obtain non-parametric estimates. They find that FII outflows in cases of "average" extreme events do not negatively affect the Indian stock market, but the impact of truly exceptional events such as the recent global financial crisis

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

may be masked in this approach. The main contribution of our work is therefore that we are able to clarify the impact of each individual event, such as the recent global financial crisis.[2]

The next section expands on the above introduction, relating our work to the existing literature and motivating our approach. Section 3 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 provide references to the literature. Section 4 sets out our results and discusses them. Essentially, our results confirm that foreign portfolio flows into India were not a vector of crisis transmission during the period 1999-2011. This holds even during the period of extreme instability that heralded the Great Recession, something which our technique is able to demonstrate more precisely than previous work. The final section provides a summary conclusion and discussion of possible future research directions.

2. Literature and Motivation

Unsurprisingly, attention to the volatility of global capital flows, already of concern in the 1990s (e.g., Bacchetta and van Wincoop, 1998; Obstfeld, 1998; Bosworth et al., 1999), increased greatly in the aftermath of the global financial crisis and Great Recession. A large number of recent studies have tried to understand the behavior and impacts of these movements of capital. For example, Fratzscher (2011) uses a factor model to show how equity and bond flows responded to country-specific and common factors during and after the global financial crisis. Similarly, Lo Duca (2012) uses a time-varying regression model to study portfolio flows to emerging markets, and finds evidence of "panicky" behavior in crisis periods. Jotikasthira et al. (2012) identify forced asset "fire sales" as a factor in this behavior.

Agosin and Huaita (2012) specifically consider aggregate capital flows to emerging markets, and show that surges in such flows (booms) are predictors of subsequent contractions in flows – this is interpreted as an overreaction phenomenon. Broto et al. (2011) argue that global factors have become increasingly important in determining the volatility of three kinds of capital flows in emerging markets: equity, FDI and bank flows. Forbes and Warnock (2012) also find that global factors and contagion are associated with extreme capital flow episodes. Similarly, Broner et al. (2013) find evidence that gross capital flows are pro-cyclical, and more volatile than net flows. By contrast to some of the other studies, Bekaert et al. (2014) examine equity flows and find that country-specific factors were more important than global effects in the crisis period, leading to domestic contagion across industries.

Several other studies have focused on the special challenges of emerging markets. For example, Bekaert and Harvey (2014) conclude that emerging economy stock markets have different risk

[2] In either case, however, when there are large observed impacts, one cannot distinguish whether FII outflows are a source or just a vector of crisis transmission, without a full structural model.

characteristics than developed countries, being much more volatile. Tillmann (2013) finds that emerging Asian markets are more sensitive to foreign capital flows than are developed markets. McCauley (2012) analyzes how policy responses in emerging markets contribute to these differential phenomena. Bae et al. (2012) find evidence that the degree of accessibility of foreign investors to emerging economy stock markets improves information transmission and stock market efficiency.

The above literature uses cross-country data, typically at annual or quarterly frequencies. Our analysis focuses on India as a major emerging market, with daily data. In addition to Patnaik et al. (2013), which we discuss further in the next section, several other papers examine the impact of foreign investors on Indian stock markets, as well as the reverse direction of causality, typically using vector autoregressions. These studies include Chakrabarti (2001), Mukherjee et al. (2002), Gordon and Gupta (2003), Anshuman et al. (2010), Stigler et al. (2010) and Acharya et al. (2015). With the exception of the last three, none of these papers use high frequency (daily) data, and none of them focus on extreme events.

3. Data and Specification

3.1. Data

India has a complex and somewhat nontransparent system of capital controls,[3] but the restrictions on foreign portfolio investment have been relatively clear. For the period under analysis there were no quantitative restrictions or taxes on such flows, except that only qualified financial institutions could undertake equity investment.[4] These institutions included banks, asset management firms, hedge funds, trusts and foundations, and they had to register with the Indian securities regulator. They are commonly described as "foreign institutional investors," or FIIs.

The actions of FIIs registered according to law are fairly unconstrained. One possible restriction on the portfolios of FIIs is that there is a limit on the proportion of shares of any single listed company that they can hold. However, this ceiling can be raised up to 98 percent by a resolution of the shareholders, making the ceiling somewhat irrelevant in practice.

In terms of their daily operations, 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. The data we work with is aggregated across all

[3] For a discussion of India's institutional framework on international capital flows, see Patnaik and Shah (2012) and Hutchison, et al. (2012).

[4] 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.

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, resulting in a total of 3298 daily observations. 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 (using the Cospi Index of the Centre for Monitoring the Indian Economy), to normalize for this increase.

Regarding the stock market data relevant to our study, we use daily closing prices for three stock market indices: (i) 'Nifty', the stock market index for India's National Stock Exchange (NSE) (Shah and Thomas, 1998), (ii) the S&P 500 index for United States, and (iii) the Nikkei index for Japan. For the purposes of our analysis, the last two indices represent global economic conditions, and changes in these two indices capture the idea of global or regional shocks respectively.[5] In fact, we work with daily rates of return as the appropriate variables used in our regression analysis, rather than the indices themselves. Hence, for example, a large negative daily return on an index will be a negative extreme event, lying in the left tail of the returns distribution. Similarly, a large positive daily return will be an extreme positive event, lying in the right tail of the distribution.

Table 1: Summary Statistics of Net FII flow, S&P 500, Nikkei and Nifty Returns

	Net FII inflow	S&P 500 (%)	Nikkei (%)	Nifty (%)
Mean	0.36	0	-0.01	0.05
2.5th percentile	-2.4	-2.67	-3.09	-3.59
97.5th percentile	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

Note: Net FII inflow is divided by the market capitalization. All returns are computed as daily returns (in percentage). The data frame is 6/01/99 to 07/29/2011.
* The dates for the minimum values are 9/17/08, 10/16/08, 10/16/08 and 5/17/04, respectively.
**The dates for the maximum values are 11/5/10, 10/14/08, 10/14/08 and 5/18/09, respectively.

Table 1 presents descriptive statistics for Net FII flows, as well as S&P 500, Nikkei and Nifty daily returns. On average, the net FII flows are positive, meaning that during the time period 6/01/99 to 07/29/2011 there were net inflows into India. The average daily returns of the stock

[5] There are a few intricacies in lining up dates of the indices across time zones. In particular, 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 that 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.

markets in the three countries over this period were quite small. In Japan, we even observe a negative average daily return. For all three returns variables, the 2.5^{th} and 97.5^{th} percentiles are about four standard deviations apart. Nifty returns are the most volatile of the three returns indices, although the differences are not large. Also notice that minimum and maximum values of daily returns for the S&P500 and Nikkei occurred at the same date, while the dates of the minimum and maximum values of daily returns of the Nifty differ from the other two markets.

3.2 Specification

In a 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 (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. 2013) or introduction of capital controls (e.g., Ostry et al., 2011). In this paper, we define events as those dates on which extreme values of returns or flows are observed. For example, we examine the distribution of daily returns on the S&P 500, and identify the dates on which the returns were in the 2.5% lower and upper tails (see Table 1 for the values of the percentiles at 2.5^{th} and 97.5^{th}). The same criterion is used for defining extreme events for the other three distributions: net FII flows, Nikkei returns and Nifty returns. In total we have 3,298 observations, so we obtain 83 events in each tail (2.5 percent).

Patnaik et al. (2013) use the same definition of events as in the current paper, namely, observations in the tail of the relevant distribution. The confidence intervals in that paper are computed using a bootstrap procedure. The advantage of that approach is that it does not require distributional assumptions such as normality and is also robust against serial correlation in the series. However, these advantages come with the requirement that all extreme events are pooled, so that responses are measured as average responses to the “average” extreme shock. One could argue that each of these extreme shocks is different in nature, and therefore it is also useful to study them separately. This is the approach we adopt in our paper, which can be considered as complementary to the analysis of Patnaik et al. (2013).

More specifically, by analyzing each extreme event separately, we are able to single out extreme events of particular interest, and relate global shocks identified as extreme movements in stock market indices to underlying events such as significant policy changes. Hence, we are also able to tie in our analysis to the traditional event study approach that focuses on events such as policy announcements, and market responses, providing further possible insight for policymakers.

We analyze each extreme event following a relatively standard event study approach. The technique requires the estimation of a (typically linear) model during a pre-specified time window in order to capture the structural relationship of returns and FII flows during a timeframe outside of, but relatively close to, the date of the event of interest.

The linear model fitted during the estimation window is

$$y_t = b_0 + b_1 x_t + \epsilon_t \quad (1)$$

where y_t is the daily return on the Nifty index or the daily net FII flow, and x_t is the daily return on the S&P 500 or Nikkei and ϵ_t is the error term. This represents the structural relationship linking the response variable to global market conditions in what may be considered "normal" times.

In particular, we define our estimation window, with the event day defined as t_0, as 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. To analyze behavior before and after the event, we define the pre-event and post-event window as the ten days preceding the extreme event (t_{-10} to t_{-1}), and the ten days after the event (t_1 to t_{10}), respectively. In the literature, there is not a consensus about the days one should use for the different windows. The main reason to choose 20 days in our estimation window is to have enough days that mitigate the daily fluctuations observed in stock market data, while not going too far back in time.

We choose to estimate the linear model (1) in the simplest form possible since we do not expect changes in other variables (i.e. exchange rates or monetary shocks) that can explain the relationship between the returns and the FII flows. Furthermore, it is important to correct for the residual correlation present in daily data. The estimation of equation (1) uses a Newey-West procedure that produces the same coefficients as OLS and yields standard errors that are robust to autocorrelation and heteroskedasticity.

Recall that we are interested in analyzing whether the behavior predicted by the estimation of equation (1) is different around the event (pre-event and post-event windows). We defined the difference between the variable observed and predicted as "abnormal," or $y_{ab_t} = y_t - \widehat{y_t}$, where $\widehat{y_t}$ is the predicted value. The variance of each daily abnormal variable is computed as:

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

since y_t and $\widehat{y_t}$ are assumed to be uncorrelated. We formally test whether these abnormal returns are significantly different from zero using a t-test.

In addition to analyzing the daily returns, we also study the difference of behavior in terms of cumulative pre- and post-event returns. Assessing the cumulative effects of global shocks over given time windows around an event also provides relevant information on possible destabilizing effects of external shocks. Thus, we define the cumulative abnormal return for a window of length m starting at time T as $y_{cu} = \sum_{t=T}^{t=T+m} y_{ab_t}$ and perform a t-test to analyze whether the cumulative abnormal returns are different from zero. In this case, we compute the appropriate variance of the cumulative returns following the work of Coutts et al. (1995),

$$\sigma^2(y_{cu}) = \sum_{t=T}^{t=T+m} \sigma^2 y_{ab_t} + CX^*VX^{*\prime}C' /L \tag{3}$$

where C is a vector of ones, X* is the matrix of covariates, V is the variance-covariance matrix produced by Newey-West procedure and L is the length of the estimation window.

Notice that it is possible that another tail event falls in one of the two periods (estimation window and pre-event window) that precedes any single event. Rather than clustering 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 possible cases: (i) no contamination, (ii) only the estimation window contaminated, (iii) only the pre-event window contaminated; and (iv) both windows contaminated. In the next section, we report results for each of the four cases, and can compare patterns of significant abnormal returns across them. The goal of this classification is to investigate whether the pattern of other tail events preceding a given extreme shock affect market returns and FII flows responses.

4. Results

4.1. Average Responses to Global Shocks

The S&P 500 returns distribution has 83 observations in each of its left and right 2.5% tails. These represent the extreme events used as proxies for global economic shocks. We present the results for positive shocks in the top half of Table 2 while negative shocks are presented in the bottom half of the table.

As explained above, each event is categorized according to the pattern of other tail events that precede it. The second column of the table presents the classification of the 83 tail events according to their pattern of contamination. 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. Negative shocks present similar patterns except for a higher count of pre-event-window-contaminated events complemented by a lower count of estimation-window contamination.

Columns 3 and 4 of Table 2 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 Table 2 is an average of this first count over all the events of the category being considered. For example, the number 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.

Abnormal responses of returns to positive tail events are very low across the board. Overall, the 83 positive tail events were, on average, associated with fewer than two days of significant abnormal returns 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.

Table 2: Average responses to global shocks - Nifty returns

	Number of shocks	Average number of days of abnormal pre-event returns	Average number of days of abnormal post-event returns	Cases of cumulative abnormal pre-event returns		Cases of cumulative abnormal post-event returns	
				Negative cases	Positive cases	Negative cases	Positive cases
All positive shocks	83	1.35	1.25	8	11	7	12
No contamination	21	1.52	1.57	4	2	2	5
Estimation window only contaminated	19	1.16	0.84	0	1	2	1
Pre-event window only contaminated	10	0.90	1.5	1	1	2	1
Both contaminated	33	1.48	1.21	3	7	1	5
All negative Shocks	83	1.49	1.77	21	3	12	8
No contamination	21	2.48	2.9	7	1	4	1
Estimation window contaminated	17	0.71	1.11	0	0	0	3
Pre-event window contaminated	12	1.83	1.83	6	0	2	1
Both contaminated	33	1.15	1.36	8	2	6	3

Responses to negative global extreme shocks seem stronger but are still very low. Averages of significant abnormal returns somewhat closer to two days 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 abnormal returns in the pre-event and post-event windows respectively.

Contamination patterns do not make much of a difference at the level of cumulative returns, 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, both pre- and post-event. This could be an indication of greater surprise with more isolated extreme events. Overall, however, we can interpret that the small number of days with abnormal returns is associated with the efficiency of markets. Financial markets tend to respond quickly to the arrival of new information, which causes the normal structural relationship to hold again after a few days.

Corresponding to the results for impacts of global shocks on Indian stock market returns, Table 3 presents results for the impact of extreme global shocks on FII flows to 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 organized in the same way as in Table 2.

Table 3: Average Responses to Global Shocks - Net FII flows

	Number of shocks	Average number of days of abnormal pre-event flows	Average number of days of abnormal post-event flows	Number of cases of cumulative abnormal pre-event flows		Number of cases of cumulative abnormal post-event flows	
				Negative cases	Positive cases	Negative cases	Positive cases
All Positive Shocks	83	1.02	1.15	8	13	10	22
No contamination	21	1.24	1.29	4	5	4	5
Estimation window only contaminated	19	1.21	1.32	2	4	3	5
Pre-event window only contaminated	10	0.80	0.80	1	0	1	2
Both contaminated	33	0.85	1.09	1	4	2	10
Negative Shocks	83	1.39	1.30	16	14	14	24
No contamination	21	1.81	1.52	6	2	6	4
Estimation window contaminated	17	1.41	2.00	3	5	2	9
Pre-event window contaminated	12	1.83	1.75	3	0	3	4
Both contaminated	33	0.94	0.63	4	7	3	7

Compared to the response of domestic stock market returns, net FII flows are somewhat more sensitive to global shocks in terms of cumulative impacts. In fact, while there are fewer days of significant abnormal flows than days of abnormal returns, there are higher percentages of events producing significant cumulative abnormal flows.

The results, in terms of the difference between the response of domestic returns and the response of FII flows, are consistent with several possibilities, which are not mutually exclusive. First, domestic investors may have different incentives or constraints in the market compared to FIIs, which causes domestic returns to be less sensitive to global shocks than FII flows. For example, domestic investors in the Indian market may have fewer substitution possibilities, as a result of restrictions on investing abroad. Another possibility is that FII flows do not necessarily amplify global shocks in the domestic stock market, but may ameliorate them – evidenced by the large number of cases in which negative shocks are followed by larger than average flows into India. Also, foreign investors may respond to extreme events in a more gradual manner, consistent with the fact that flows are more responsive at the cumulative level than in daily terms.

4.2. Detailed responses to global shocks

The key benefit of adopting a traditional event study methodology over pooling all the extreme events (as in Patnaik et al., 2013) is that we can analyze how markets behaved after each extreme event in our sample. Taking advantage of this possibility, we can go beyond looking at average results or summaries as in Tables 2 and 3, and pay closer attention to particular events of interest.

Especially in the context of the financial crisis, the impact from the worst days of the crisis can be lost in summarizing the responses for all 83 negative tail shocks. Policy makers might be more interested in what effects specific events can have on their domestic economy: some shocks might be more destabilizing than others. To check whether this is the case, we have singled out the days of worst turmoil on markets in our sample. We have identified them as days where the S&P500 index returns reached negative values of magnitude higher than the average negative return in the overall sample of negative extreme events. In other words, we looked at days where the index returns were worse than the average of all the returns in the 2.5% tail of the distribution.

Table 4 shows the 26 events identified in this manner, and the associated market and/or policy events. They represent days of tremendous turmoil on global financial markets, including events ranging from Lehman Brothers' bankruptcy filing to announcements of various relief programs from the US government and the Federal Reserve (Fed fund rate cuts, asset buyback programs). Whereas for the statistical analysis we lined up S&P 500 performance with the next day's Nifty performance, here we report the original US market event dates. Interestingly, only four of the events identified happened outside of the timeline of the recent financial crisis, occurring much earlier in our sample period. This is in keeping with the severity of the recent financial crisis and its impact on global markets.

Table 4: Extreme Events Description

Event Date	Market Event or Policy Decision
4/14/00	Bursting of tech bubble; adverse inflation report
3/12/01	Several companies posting sub-par earnings; fears of faltering economy
9/17/01	First day of trading after 9/11
9/3/02	Day after Nikkei index fell to an 18-year low
9/15/08	Lehman Brothers' bankruptcy filing
9/17/08	Temporary emergency ban on financial companies' stocks short sales
9/29/08	Congress rejects TARP
10/2/08	Day before revised version of TARP is passed
10/7/08	The Federal Reserve Board announces the creation of the Commercial Paper Funding Facility (CPFF), which will provide a liquidity backstop to U.S. issuers of commercial paper through a special purpose vehicle
10/9/08	Day after the Federal Reserve Board authorizes the Federal Reserve Bank of New York to borrow up to $37.8 billion in investment-grade, fixed-income securities from American International Group (AIG) in return for cash collateral.
10/15/08	Day after creation of a new Temporary Liquidity Guarantee Program to guarantee the senior debt of all FDIC-insured institutions and their holding companies, as well as deposits in non-interest-bearing deposit transactions, through June 30, 2009.
10/22/08	Day after the Federal Reserve Board announces creation of the Money Market Investor Funding Facility (MMIFF).
11/5/08	The Federal Reserve Board announces that it will alter the formula used to determine the interest rate paid to depository institutions on required and excess reserve balances.
11/6/08	Day before figures show 240,000 job losses in previous month
11/12/08	U.S. Treasury Secretary Paulson formally announces that the Treasury has decided not to use TARP funds to purchase illiquid mortgage-related assets from financial institutions.
11/14/08	The U.S. Treasury Department purchases a total of $33.5 billion in preferred stock in 21 U.S. banks under the Capital Purchase Program
11/19/08	Day before Fannie Mae and Freddie Mac announce suspension of mortgage foreclosures until January 2009
11/20/08	Day before the U.S. Treasury Department purchases a total of $3 billion in preferred stock in 23 U.S. banks under the Capital Purchase Program.
12/1/08	Day before announcement of extension of three liquidity facilities, the Primary Dealer Credit Facility (PDCF), the Asset-Backed Commercial Paper Money Market Fund Liquidity Facility (AMLF), and the Term Securities Lending Facility (TSLF) through April 30, 2009
1/20/09	Inauguration of President Obama
2/10/09	The Federal Reserve Board announces that is prepared to expand the Term Asset-Backed Securities Loan Facility (TALF) to as much as $1 trillion and broaden the eligible collateral
2/17/09	President Obama signs into law the "American Recovery and Reinvestment Act of 2009"; Day before announcement of The Homeowner Affordability and Stability Plan
3/2/09	Announcement of restructuring of the government's assistance to American International Group (AIG).
3/5/09	Two days after launch of TALF
4/20/09	Day before issue of quarterly report on the operation of TARP
5/20/10	President Obama signs the Helping Families Save Their Homes Act of 2009

Tables 5 and 6 report event-specific responses to the identified events in terms of numbers of cases of abnormal Nifty returns (Table 5) and FII flows (Table 6). In general, the event-specific responses present the same general pattern as their average counterparts: returns are more responsive at the daily level, while flows respond more at the cumulative level.

We noted in the previous subsection that daily responses to extreme global shocks were generally very infrequent for both Nifty returns and net FII flows. This is also the case even for specific events: daily responses are still muted across the board, with only five of 26 events for returns and one for flows being associated with five or more abnormal responses in either a 10-day pre-event or 10-day post-event window. Even after narrowing our sample to the worst events of the financial crisis, we could not find a single instance of sustained abnormal responses over any pre/post-event window. These short-lived daily abnormal responses are consistent with the muted average responses highlighted in the previous sub-section.

At the cumulative level, FII flows were generally responsive to policy announcements and economic data reports while returns were more sensitive to market events. Notable exceptions are events from September 2008 that produced cumulative abnormal responses for both FII flows and Nifty returns. This is not surprising as those September 2008 events (beginning with Lehman Brothers' bankruptcy) are widely acknowledged as crucial events that greatly affected markets around the world.

Abnormal cumulative flows occur mostly after events related to reports on the economy, or policy announcements which market participants seem to interpret as signals of worsening economic conditions (current and/or forecasted). This is consistent with a view that foreign institutional investors' behavior is driven more by economic fundamentals than by "speculative" motives. In that case, maybe policy makers should be concerned about keeping economic fundamentals sound, rather than continually worrying about the adverse effects of foreign investors leaving them "high and dry."

Table 5: Event-Specific Responses – Daily and Cumulative Nifty Returns

	Pre-event days of abnormal returns		**Post-event days of abnormal returns**		**Pre-event Cumulative abnormal returns**		**Post-event Cumulative abnormal returns**	
Event Date	Negative cases	Positive cases	Negative cases	Positive cases	Negative cases	Positive cases	Negative cases	Positive cases
14Apr00	3	2	1	1	-	-	-	-
12Mar01	5	1	-	2	-	-	-	-
17Sep01	4	1	2	4	1	-	-	-
03Sep02	-	1	-	-	-	-	-	-
15Sep08	2	-	2	1	1	-	-	-
17Sep08	1	-	1	-	1	-	-	-
29Sep08	-	1	2	1	-	-	1	-
02Oct08	-	-	2	1	-	-	1	-
07Oct08	1	-	3	1	1	-	1	-
09Oct08	2	-	3	1	1	-	1	-
15Oct08	2	1	2	3	1	-	-	-
22Oct08	2	2	-	4	-	-	-	1
05Nov08	1	3	-	2	-	-	-	-
06Nov08	-	2	-	-	-	1	-	-
12Nov08	-	1	-	-	-	1	-	-
14Nov08	-	-	-	-	-	-	-	-
19Nov08	-	-	-	-	-	-	-	-
20Nov08	-	-	-	-	-	-	-	-
01Dec08	-	-	-	-	-	-	-	-
20Jan09	-	2	-	-	-	-	-	-
10Feb09	-	-	-	-	-	-	-	-
17Feb09	-	-	-	-	-	-	-	-
02Mar09	-	-	-	-	-	-	-	-
05Mar09	-	-	-	2	-	-	-	-
20Apr09	1	-	1	1	-	-	-	-
20May10	1	1	-	-	-	1	-	-

Table 6: Event-Specific Responses – Daily and Cumulative Net FII flows

	Pre-event days of abnormal flows		Post-event days of abnormal flows		Pre-event Cumulative abnormal flows		Post-event Cumulative abnormal flows	
Event Date	Negative cases	Positive cases	Negative cases	Positive cases	Negative cases	Positive cases	Negative cases	Positive cases
14Apr00	-	-	-	-	-	-	-	-
12Mar01	1	1	-	-	-	-	-	-
17Sep01	3	1	-	1	-	-	-	1
03Sep02	1	-	2		1	-	1	-
15Sep08	2	1	2	-	-	-	-	-
17Sep08	3	1	3	3	1	-	-	-
29Sep08	1	-	-	-	1	-	1	-
02Oct08	-	-	-	-	-	-	-	-
07Oct08	-	-	-	-	-	-	-	-
09Oct08	-	-	-	-	-	-	-	-
15Oct08	-	-	-	-	-	-	-	-
22Oct08	-	-	-	-	-	-	-	-
05Nov08	-	1	-	3	-	-	-	1
06Nov08	-	1	-	2	-	1	-	1
12Nov08	-	4	-	-	-	1	-	1
14Nov08	-	1	-	-	-	1	-	1
19Nov08	-	1	-	-	-	1	-	1
20Nov08	-	3	1	1	-	1	-	1
01Dec08	-	-	-	-	-	-	-	-
20Jan09	1	-	1	-	1	-	-	-
10Feb09	-	-	-	-	-	-	-	-
17Feb09	-	1	1	1	-	1	-	-
02Mar09	1	-	-	-	-	-	-	-
05Mar09	2	-	-	-	1	-	-	-
20Apr09	-	1	-	3	-	1	-	1
20May10	-	-	-	1	-	-	-	-

4.3. Responses to regional shocks

An alternative possibility for capturing the impact of external shocks on the Indian stock market is to work with the Nikkei index as an independent variable. This can be interpreted as capturing regional shocks, or global shocks filtered through a regional lens. Table 7 shows that Nifty returns seem more responsive to extreme Japanese market shocks than they are to global market shocks, but the responses are still not very sizable. Both positive and negative Nikkei shocks result on average in fewer than two days of significant abnormal Nifty returns. This difference is, however, less pronounced for extreme negative shocks, where responses are more similar to those from global shocks.

Table 7: Responses to Regional Shocks - Nifty Returns

	Number of shocks	Average number of days of abnormal pre-event returns	Average number of days of abnormal post-event returns	Number of cases of cumulative abnormal pre-event returns		Number of cases of cumulative abnormal post-event returns	
				Negative cases	Positive cases	Negative cases	Positive cases
All positive Shocks	83	1.64	1.36	8	13	12	10
No contamination	28	1.68	1.25	3	5	6	3
Estimation window only contaminated	20	0.90	1.1	3	2	3	1
Pre-event window only contaminated	9	2.33	2.44	1	2	2	3
Both contaminated	26	1.92	1.31	1	4	1	3
All Negative Shocks	83	1.58	1.82	26	4	14	10
No contamination	25	1.80	1.72	8	2	5	2
Estimation window contaminated	17	0.71	1	3	0	1	1
Pre-event window contaminated	9	1.67	2	3	0	2	2
Both contaminated	32	1.84	2.28	12	2	6	5

However, responses of FII flows, presented in Table 8, are quite similar between positive and negative shocks, with similar effects in either case. FII flows tend to be less responsive than returns at the daily level and more responsive at the cumulative level when shocks occur.

Table 8: Average Responses to Regional Shocks - Net FII flows

	Number of shocks	Average number of days of abnormal pre-event flows	Average number of days of abnormal post-event flows	Number of cases of cumulative abnormal pre-event flows		Number of cases of cumulative abnormal post-event flows	
				Negative cases	Positive cases	Negative cases	Positive cases
All positive Shocks	83	1.44	1.57	12	20	10	22
No contamination	28	1.68	1.68	6	7	3	4
Estimation window only contaminated	20	1.15	1.35	2	6	2	8
Pre-event window only contaminated	9	2.00	2.56	1	2	4	1
Both contaminated	26	1.19	1.27	3	5	1	9
All negative Shocks	83	1.37	1.1	19	11	16	10
No contamination	25	1.36	1.16	4	3	5	2
Estimation window contaminated	17	1.47	1.41	6	3	4	2
Pre-event window contaminated	9	1.33	0.56	2	1	2	0
Both contaminated	32	1.34	1.03	7	4	5	6

4.4. Responses to both global and regional shocks

A further possibility is to examine the impact of extreme global shocks that simultaneously affect the Japanese and American markets. Table 9 presents the analysis when the dependent variable is Nifty returns, while Table 10 provides the analysis when the variable of interest is Net FII flows.

Table 9: Average Responses to Global and Regional Shocks - Nifty Returns

	Number of shocks	Average number of days of abnormal pre-event returns	Average number of days of abnormal post-event returns	Number of cases of cumulative abnormal pre-event returns		Number of cases of cumulative abnormal post-event returns	
				Negative cases	Positive cases	Negative cases	Positive cases
All positive Shocks	19	1.74	1.68	3	4	2	5
No contamination	9	1.44	1.22	2	2	1	3
Estimation window only contaminated	2	1.50	3.00	1	0	1	0
Pre-event window only contaminated	3	1.33	2.33	0	1	0	1
Both contaminated	5	2.60	1.60	0	1	0	1
All negative Shocks	24	1.54	1.71	7	2	4	2
No contamination	7	1.71	2.00	2	0	2	0
Estimation window contaminated	5	0.60	0.80	0	0	0	1
Pre-event window contaminated	0	N/A	N/A	N/A	N/A	N/A	N/A
Both contaminated	12	1.83	1.92	5	2	2	1

Nifty returns are more responsive to extreme shocks that occur simultaneously in both markets than they are to just extreme shocks in the S&P 500. This is what one might expect, since days when both markets move dramatically are likely to represent more significant global shocks. Surprisingly, however, the responses of Nifty returns to simultaneous negative shocks are slightly less frequent than they were for Nikkei shocks at the daily levels. This suggests the possible importance of regional factors in the dynamics of Asian markets.

Table 10 shows that Net FII 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. There is not any remarkable difference between the reactions of Net FII flows and Nifty returns. Our approach allows us to study the impacts of situations where among the worst returns were observed simultaneously in both the US and Japanese stock markets, but even on such days, there was not a significant impact on the behavior of Net FII flows in the Indian stock market, in contrast to fears of destabilizing impacts.

Table 10: Average Responses to Global and Regional Shocks - Net FII flows

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

Before we conclude, it is important to highlight that the presence of other events in the estimation or pre-event windows does not significantly alter our results. We did not detect a systematic difference of responses of either returns or flows to the extreme events categorized as "contaminated" vs. "not contaminated."

5. 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 have been a concern for policymakers, and are often portrayed in the nation's 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 in the case of the global financial crisis of 2008.[6]

In particular, we find that, when examining the impact on foreign portfolio flows into India, and on the Indian stock market, even days on which extreme low returns are observed in both Nikkei and S&P 500 indices, there is not a significant impact. This suggests that the transmission of shocks from developed countries to a large emerging market like India has been limited in the short-term., and Indian policymakers need not have acute concerns about hot money and destabilizing portfolio flows in this context.

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, investigate the impacts of specific monetary policy shocks (see footnote 6) and to examine similar issues for other emerging markets. In particular, it is possible that differences in the degree of financial liberalization or the size of the domestic market might yield qualitatively different results.

[6] A referee has suggested that the impact of specific developed country monetary policy shocks on the Indian stock market could be analyzed in our context. While there is a large event-study literature on the impacts of Quantitative Easing on interest rates and exchange rates (e.g., Thornton, 2014 and the references therein), this particular question appears not to have tackled, and is an interesting one for future research.

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