Foreign Fund Flows and Asset Prices: Evidence from the Indian Stock Market*

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Abstract

We study the effect of foreign fund flows on asset prices by investigating the link between foreign institutional investor (FII) flows and stock returns in India. Stocks experiencing high innovations in order flow are associated with a permanent price increase, whereas stocks experiencing low innovations are associated with a partly-transient price decline. The differential abnormal return between high and low innovation stocks is significant, largely unrelated to firm characteristics, and increasing during periods of market stress. The findings are consistent with price "pressure" induced by FII sales, as well as information being revealed through FII purchases and FII sales.

Keywords: Foreign Institutional Investors, Foreign Ownership, Portfolio Flows, Price Impact, Volatility.

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"*Over time, we have to figure out how much we want to sort of expose ourselves to those relatively short-term flows* ..."

- Raghuram Rajan, Governor, Reserve Bank of India, February 3, 2014.[1]

"*The principal risk facing India remains the inward spillover from global financial market volatility, involving a reversal of capital flows*."

- IMF Country Report, February 2014.[2]

As suggested in these two quotes, policymakers are concerned about the *real* effects of cross-border capital flows on emerging markets and economies. Recent evidence seems to validate this concern. For instance, in 1997, the currency and stock markets of several East Asian countries (e.g., Indonesia, Thailand, Malaysia, Philippines, and South Korea) suffered a major decline due to the flight of capital to safety. However, during the interim period (1997-1999), this "Asian Financial Crisis" spread from East Asia to Latin America and drove many developing countries into recession.

There is a paucity of research on the precise channel, the magnitude, or the longevity of the impact of capital flows on financial markets. In this study, we examine the case of an emerging market (India) to see how foreign fund flows affect asset prices. We evaluate the domestic equity market performance in India both in terms of the magnitude of the immediate impact of foreign fund flows, as well as the permanence of this impact. We document that while foreign fund outflows are associated with a temporary price "pressure" on affected stocks, both inflows and outflows are also associated with permanent price movement. Our study thus sheds

[1] See "Volatility may force a rethink on short-term inflows into government bonds, Shaji Vikraman, Economic Times Bureau, February 3, 2014, 07.02AM IST.

[2] International Monetary Fund Country Report No. 14/57, February 2014 (Item No. 46, p. 20). Available at: http://www.imf.org/external/pubs/ft/scr/2014/cr1457.pdf.

light on the tradeoff between informational effects and the transient volatility effects that arise in the context of global capital flows.

Foreign fund flows in and out of Indian stock markets are now a sizeable portion of the market activity. Cumulative net investment flows from foreign institutional investors (FIIs) have exceeded USD 150 billion during 2001-2013. FII gross flows also account for a significant portion of the daily traded share value on Indian exchanges. During the same period, FII ownership averaged around 10%. The number of FIIs registered with the Securities and Exchange Board of India (SEBI) increased from 882 in March 2006 to 1,757 in March 2013; FIIs, on average, accounted for 20% to 30% of the total trades executed at the National Stock Exchange of India during the 2006-2013 period.

While FII participation in Indian equity markets has been steadily increasing, there is a widespread perception (as echoed in Governor Rajan's quote above) that foreign fund flows may be creating substantial volatility in markets, especially during periods of market stress. This concern extends more generally to emerging markets given the illiquidity of their equity markets (relative to those of developed markets) for absorbing sudden inflows and outflows of foreign funds. Figure 1 shows the relation between annual FII net inflows for India and the annualized standard deviation of the daily returns on the benchmark index for Indian equity markets, the CNX NIFTY index, for each fiscal year during the 2001-2013 period. FII net inflows were positive in all years except 2008-2009. Figure 1 shows that during the global financial crisis (2007-2009), FII inflows turned negative (net outflows of approx. USD 10 billion), consistent with the overall flight-to-quality of global capital flows. The volatility of the NIFTY is also much higher during this period in comparison to other years, lending casual support for the hypothesis that FII flows may have induced volatility in emerging markets.

If FII flows induce volatility in emerging markets, a natural follow-up question is: What are the key drivers of these FII flows? Figure 2 shows a ground-level perspective of the relation between FII flows and macro events in developed countries. We plot the average FII net flows and the Chicago Board Options Exchange (CBOE) Market Volatility Index (henceforth, CBOE VIX) indicator on a weekly basis. A broad trend of a negative relation between FII net flows and CBOE VIX levels emerges during the 2008-2010 period. Several events also illustrate the impact of global uncertainty on FII flows over short horizon intervals. For instance, the Indian capital market suffered its biggest decline on May 22, 2006, exactly at a time when the CBOE VIX was exhibiting a sharp increase, as can be seen in the bottom left corner of the figure. This behavior is consistent with a flight-to-safety. Further, the immediate recovery in FII flows around the same date mirrors a sharp reduction in the CBOE VIX, suggesting not only that global risks are an important factor in Indian capital markets but also that the FII flows are a critical channel of contagion across international markets. In a similar vein, the flash crash in Indian capital markets on May 6, 2010 happened shortly after a critical credit rating downgrade of Greece on April 27, 2010. Interestingly, the variation in FII flows is also driven by local India related events, as seen in the spikes in FII flows on November 26, 2008, when the Mumbai terrorist attacks occurred.

How do these FII flows affect asset prices and through which channels? Recent research has shed some light on the possible impact of net capital flows on domestic markets by foreign investors. In particular, researchers have examined the extent of the transmission of economic shocks from one region of the world to another. They have also examined whether the associated price pressure effects are permanent or temporary. Coval and Stafford (2007) show that sudden increases (decreases) in fund flows cause mutual fund managers in the United States to significantly adjust their holdings, resulting in price pressure effects, which are transient but may take several weeks to reverse. More closely related to our paper, Jotikasthira, Lundblad, and Ramdorai (2012) find that asset fire sales in the developed world affect fund flows to emerging markets.[3] They argue that in emerging markets, the equity markets are influenced by this "push" factor and fund flows provide an additional channel of contagion.[4,5]

Given the lack of flow data at the individual stock level by foreign investors, studies have focused on aggregate flows in and out of the emerging stock markets. Researchers have circumvented this data problem by identifying foreign flows that can be considered reasonably "exogenous" to the stock market fundamentals of the emerging market. An alternative approach would be to examine the *cross-sectional* return performance of firms within an emerging stock market that are affected differentially by foreign fund flows. We adopt the latter approach to assess how stock returns differ between stocks experiencing foreign fund inflows versus foreign fund outflows on a given day, controlling thereby for any aggregate or common information affecting all stocks on that day. We are able to accomplish this by accessing an exclusive dataset that provides information about *daily* FII flows at the individual stock level for the most actively traded stocks in the Indian stock market during the 2006-2013 period.

Lou (2012) also examines the impact of flows at the individual stock level. However, his study differs from our study on two significant counts. First, Lou (2012) aggregates *quarterly* flow-induced trading by mutual funds. In contrast, our study examines the price impact of *daily* flow-induced demand shocks. Thus our work analyzes the *short*-rum immediate impact of flows

[3] Several others have examined the impact of aggregate institutional trades on asset returns (e.g., Warther 1995; Edelen and Warner 2001; Goetzmann and Massa 2003;, Teo and Woo 2004). The main conclusion from these studies is that aggregate mutual fund flows affect contemporaneous stock returns.

[4] Jotikasthira, Lundblad, and Ramdorai (2013) also examine the relation between global fund flows and domestic real economic activity. They find that shocks in fund flows affect the investment policy of Chinese and Indian firms.

[5] Anshuman, Chakrabarti, and Kumar (2012) find that during the recent financial crisis, the influence of (aggregate) FII flows on Indian equity markets increased during periods when the U.S. markets experienced abnormal returns.

whereas his study analyzes the *long*-run impact of flows. Furthermore, the focus of his study is on the impact of *expected* flows on fund performance, whereas our focus is on the immediate price impact of *unexpected* fund flows (innovations in order flow).

Exploiting the dataset containing stock-level daily trading data for FII purchases and sales, we separate stocks into those experiencing abnormally high and low FII flow innovations. We employ a "panel regression" approach in which we run a first-pass estimation procedure for predicting FII flows at the stock level based on lagged firm characteristics, FII flows, and market-wide factors. The residuals from this estimation exercise can be considered as the abnormal or unpredictable component of FII flows and are used to rank stocks each week to form high and low FII *flow innovation portfolios*.[6] We then analyze the returns of these portfolios in the pre-formation window (five days), on the portfolio formation day, and in the post-formation window (five days).

We find that stocks with high innovations in FII flows are associated with a coincident (portfolio formation day) price increase that is permanent, whereas stocks with low innovations in FII flows are associated with a coincident price decline that is in part transient and reverses within one week (Figure 3). We also find that the transient effect accounts for nearly 16% of the annualized volatility of a typical stock. The differential cumulative abnormal return between high and low innovation stocks over a five-day period starting with the formation day is significant, both statistically and economically (relative to stock return volatility).

Our findings are similar to the findings of Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012), who study the impact of mutual fund flows on asset pricing

[6] Hasbrouck (1988) and Bessembinder and Seguin (1993) point out that the information content of trades can only be weeded out by examining the unexpected component of trading rather than the total amount of trading.

over longer horizons. They conclude that price pressure due to fund flows can cause temporary deviations of stock prices from fundamental values followed by reversals over time. The asymmetric response for the high and low innovation portfolios is similar to the findings in the empirical studies of block transactions (e.g., Holthausen et al. 1987; Chan and Lakonishok 1993; Keim and Madhavan 1996; and Saar 2001). The prevalent rationalization is that block *purchases* are motivated by information whereas block *sales* are motivated by portfolio rebalancing concerns. Our findings are consistent with this rational.

Importantly, we find that there is no pre-formation differential abnormal return between the high and low innovation portfolios. Furthermore, the abnormal return differential between the portfolios does not arise due to a difference in their pre-formation firm characteristics (such as volatility, beta or systematic risk, idiosyncratic risk, size, price impact or trading volume). We examine whether these return differentials can be explained in the time series by market-wide factors. To this end, we relate the differential abnormal return between high and low FII flow innovation portfolios to time series changes in portfolio characteristics, as well as in market-wide shocks. We find that the differential abnormal return is increasing in both global market volatility (CBOE VIX) and local stock market volatility; however, the abnormal return differential is unrelated to correlated trading by FIIs (commonality in order flow).

We also ask whether these effects are secular across stocks that vary in market capitalization. One can expect that larger stocks, being more liquid, would be more suitable for portfolio rebalancing whereas smaller stocks, being less liquid, would be more suitable for buy-and-hold strategies. To answer this question, we partition the sample into three sub-samples: large-cap, mid-cap, and small-cap stocks. We find that the magnitude of abnormal return on the high and low innovation portfolios is related to firm size (i.e., it is greater in the case of large-cap stocks, lower for mid-cap stocks, and least for small-cap stocks).

Next, we examine the post formation window for both the high innovation portfolio and low innovation portfolio for each size category to see whether the abnormal returns are permanent or transient (i.e., reversed). In large-cap and mid-cap stocks, there is no price reversal for the high innovation portfolio, but there is partial price reversal for the low innovation portfolio. This finding suggests that, in large-cap and mid-cap stocks, abnormal FII purchases are information-based trades whereas abnormal FII sales are partly driven by information and partly driven by portfolio rebalancing motives. For small-cap stocks, however, there is no price reversals for both the high and low innovation portfolios. The absence of price reversal in small-cap stock suggests that FII traders may be wary of portfolio rebalancing in small-cap stocks because of illiqudity concerns [as discussed in Amihud and Mendelson (1986), illiquidity is inversely related to firm size]. In other words, both FII purchases and sales in small-cap stock are likely to be information-based trades. These findings are consistent with the view that FII trading (purchases as well as sales) in smaller stocks is driven by the buy-and-hold motives of FII traders.

We also examine the impact of FII flows during periods of market stress. First, we compare the price impact of FII flows during the crisis period in India (January to December 2008) and during the non-crisis period. During the crisis period, excess FII sales have a greater adverse impact and during the non-crisis period, excess FII purchases have a greater impact. This finding is consistent with portfolio rebalancing being the more dominant channel during the crisis period and information-based trading being the driver of FII flows during the non-crisis period. Second, we segregate the sample into days associated with high CBOE VIX levels and days associated with low CBOE VIX levels relative to the median CBOE VIX level in the sample. The impact of FII flows is, in general, higher on days with high CBOE VIX levels as compared to days associated with low CBOE VIX levels. This finding also suggests that there is volatility spillover from the developed markets into emerging markets via the portfolio rebalancing channel.

Overall, our results are consistent with (i) price "pressure" on stock returns induced by FII sales, given the partial reversal of formation day negative returns for stocks experiencing abnormally high FII outflows; and (ii) information being revealed through FII purchases and FII sales, given the permanent nature of formation day returns for stocks experiencing abnormal FII flows. In summary, we conclude that while FII outflows contribute to transient volatility for stocks experiencing the outflows, trading by FIIs also generates new information. As suggested in Shleifer and Vishny (1997) and Gromb and Vayanos (2010), the first result suggests "limits to arbitrage" at work when the aggregate risk appetite of global financial firms is low (i.e., in periods associated with high CBOE VIX levels), with liquidity providers (in our setting, the domestic investors in Indian stock markets who purchase stocks being sold by the FIIs) generating excess returns in such states. The second result suggests that as in developed markets [see, for instance, the seminal work of French and Roll (1986)], in emerging markets too, trading, and in particular, FII trading contributes to the generation of information. These relative effects of foreign fund flows must be balanced against each other while evaluating their desirability for emerging markets.

An exception to our main finding is during the period of the "taper tantrum," which arose when the U. S. Federal Reserve hinted at a tighter monetary policy in the summer of 2013 (May 22nd 2013, to be precise). Sahay et al (2015) document a significant capital outflow accompanied by sharp revisions in asset prices across the world, especially in emerging markets.[7] To study the effects of the taper tantrum on the Indian equity markets, we employ the panel regression model built with our historical data (until April 15th 2013) on the out-of-sample data in the period around the taper tantrum (April 15th 2013 to June 30th 2013). As in the in-sample analysis, we create two portfolios based on extreme values of unanticipated FII buy order flow and FII sell order flow.

We find that, as compared to the in-sample period, the return differential between the high innovation and the low innovation portfolios is more significantly different in the post-taper period (May 23rd 2013 to June 30 2013) than in the pre-taper period (April 15th 2013 to May 22nd 20-13). The key source of the difference is that the portion of the return differential between the high and low innovation portfolios that is temporary is more exaggerated in the post-taper period as compared to the pre-taper period. The reversal in the return differential in the post-formation window reflects this temporary price effect. However, there continues to be a permanent return differential even after a 5-day window, as found in the in-sample analysis. This finding suggests that, the taper tantrum primarily induced a greater degree of non-information (e.g., portfolio-rebalancing) based FII flows, resulting in temporary asset-price impacts that were reversed subsequently, but information-based FII flows during the taper-period continued to have a permanent price impact, as experienced during normal times.

The rest of the paper is organized as follows. In Section 1, we describe the data and methodology. In Section 2, we discuss the key empirical results. In Section 3, we provide robustness checks. In Section 4, we examine the taper tantrum period. We conclude in Section 5.

[7] Emerging markets received approximately half the global capital flows during 2008-2013 in comparison to the 20 percent share that they received during 2002-2008. Sahay et al (2015) estimate a capital "overflow" of $500 billion in the post-crisis period; 80 percent of this overflow was directed at six of the largest emerging markets (China, Brazil, Mexico, Turkey, Indonesia and India).

1. Data and Methodology

Our sample period is from January 1, 2006 to June 30, 2013. We use data from January 1, 2006 to December 31, 2011 for an in-sample analysis and the data from January 1, 2012 to June 30, 2013 for out-of-sample tests. The dataset contains daily purchases and sales of FIIs, as well as daily adjusted closing prices on the most actively traded stocks preferred by FIIs in the Indian economy. The data come from three sources. The first source is a proprietary data set of daily stock-wise FII trading obtained from the National Stock Exchange (NSE); the second source is the Prowess database created by the Centre for Monitoring Indian Economy (CMIE) for daily adjusted closing prices of NSE listed stocks; and the third source is www.finance.yahoo.com for data on the S&P 500 Index and the CBOE VIX Index of the U.S. market.

To select the sample firms, we first consider all stocks that are part of four broad-based indices: the CNX NIFTY Index, the CNX JUNIOR Index, the CNX MIDCAP Index, and the CNX SMALLCAP Index as on June 28, 2013, in order to exclude stocks that are infrequently traded during the period January 2006 to December 2011. This filter results in 272 stocks that represent approximately 88% of the free float market capitalization of all stocks listed on the NSE. We drop 8 stocks for which data on FII flows is missing. We impose an additional filter that requires selected stocks to have at least 250 FII trading days across the entire in-sample period of 2006-2011. This filtration causes 13 stocks to be left out of the sample. Next, we truncate the sample further by imposing some restrictions on outliers; 23 stocks are dropped because they are associated with extreme outliers in beta estimates and 5 stocks are dropped because of missing data on institutional and retail ownership. Further, the FII share of trading volume on any trading day is censored at ± 95% and daily stock returns are censored at ± 20%.

Our final data set consists of an unbalanced panel of 223 unique stocks with 279,864 stock-day observations.

The data on the benchmark market index, the CNX NIFTY Index, as well as the S&P 500 Index and the CBOE VIX Index are used as follows. The CNX NIFTY Index is used to measure the broad market performance in the Indian economy. It is a well-diversified index, consisting of 50 stocks across 22 different sectors in the economy. The S&P 500 Index and the CBOE VIX Index movements capture the broad global market performance and the "risk appetite" of the global financial sector, respectively.

1.1 Variable Definitions

Stock returns are defined by continuously compounding the return on daily adjusted closing prices for the i^{th} stock on day t, as follows:

$$RET_{it} = 100 * \ln\left(\frac{P_{it}}{P_{it-1}}\right), \tag{1}$$

where P_{it} is the closing stock price adjusted for splits and dividends, etc., on day t. Similarly, the returns on the NIFTY Index are calculated as:

$$NIFTY\_RET_t = 100 * \ln\left(\frac{NIFTY_t}{NIFTY_{t-1}}\right). \tag{2}$$

Abnormal returns for the i^{th} stock on day t are defined as excess returns over the expected returns obtained from the capital asset pricing model (CAPM) model using 52 prior weekly observations.

$$AB\_RET_{it} = RET_{it} - E(RET_{it}) = RET_{it} - \alpha_i - \beta_i NIFTY\_RET_t. \tag{3}$$

We define net FII inflows as the difference between the daily rupee value of purchases (*FII_BUYS*) and the daily rupee value of sales (*FII_SELLS*) scaled by the aggregate rupee value of daily FII, as well as non-FII trading volume (*RUPEE_VOLUME*).

$$FII\_Net_{it} = \frac{FII\_BUYS_{it} - FII\_SELLS_{it}}{RUPEE\_VOLUME_{it}}, \tag{4}$$

where $RUPEE\_VOLUME_{it}$ is the aggregate rupee trading volume on day *t* for stock *i* (i.e., the denominator above includes non-FII trades). The variable *FII_NET* gives an economic measure of the daily net FII flows relative to the total daily rupee trading value.[8]

Table 2 presents the variable definitions. Table 3 presents the descriptive statistics of the variables related to firm characteristics, market characteristics, and FII trading statistics. The average firm size is 170 billion rupees (nearly $3 billion) and the average (daily) stock return is 0.0202%. During the same period, the average daily returns on the NIFTY Index is 0.0333%, and on the S&P 500 Index, 0.0014%. The mean βeta of the stocks is 1.00 and the annualized idiosyncratic volatility is 36.16%. The CBOE VIX (*VIX*) had a mean level of nearly 24 during the sample period. FII daily average purchases (*FII_BUYS*) were approximately equal to FII daily average sales (*FII_SELLS*), resulting in a daily average net FII flow (*FII_NET*) close to zero.

1.2 Empirical Design

In this paper, we rely on a simple procedure to infer the information content of FII flows. We construct portfolios on the basis of innovation in net FII flows (see Section 1.3) and then examine the short-run performance of these portfolios and how it is related to net FII flows. This approach allows us to isolate the impact of FII flows on asset returns.

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[8] We also considered an alternative definition where the net FII trading is normalized by the sum of FII purchases and sales, as has been employed in studies of stock order flow. However, in the context FII trading in emerging markets, there is considerable variation in FII trading due to differences in firm size. Our measure, as defined above, captures the economic significance of FII trading relative to overall trading volume in the stock. Thus, we are able to control for spurious correlations driven by the size effect.

We begin by sorting stocks on the basis of innovation in *FII_NET* at the beginning of every week and segregate stocks into five quintiles. We then examine the abnormal return on the portfolio of stocks over a 10-day trading window around the day of portfolio formation (Day 0). The ten-day window covers a pre-formation period over the (-5, -1) window and a post-formation period over the (0, 5) window. We examine the immediate impact of FII flows (returns on Day 0), as well as the subsequent reaction of the portfolio returns over the (0, 5) window. This allows us to determine the permanent and the transient components of the impact of FII flows on stocks returns. We also perform a time series analysis of the returns on Day 0 and the cumulative returns over the (0, 5) window to see whether these returns can be explained by differences in firm characteristics and time-varying market-wide shocks.

1.3 Innovations in FII Flows

We consider a panel regression model of *FII_NET* on lagged *FII_NET*, lagged stock returns, and other control variables; residuals from this model (*FII_NET_INNOV*) are used as a proxy for the "true" (unobserved) innovations in FII flows. The panel regression model allows for firm fixed effects. The control variables are related to firm characteristics and market factors. Firm characteristics include firm size (*SIZE*), turnover (*TOVER*), and percentage of retail (*RETAIL_OSHP*) and institutional ownership (*INSTITUTIONAL_OSHP*) in non-promoter holdings. To capture time-varying effects, we also include the following lagged market variables: aggregate FII (*AGGR_FFLOW*), volatility index (*VIX*), differences in the volatility index (*ΔVIX*), S&P 500 returns ($S\&P500\_RET_t$), and NIFTY returns ($NIFTY\_RET_t$). The volatility index (*VIX*) and the market return variables capture the role of funding constraints. Aggregate FII flows (*AGGR_FFLOW*), defined as (total *FII_BUYS* – total *FII_SELLS*) / total traded rupee value on day *t* for all stocks, captures the commonality in order flow. The model specification is as follows:

$$FII\_NET_{i,t} = FirmFEff + \sum_{j=1}^{5} FII\_NET_{i,t-j} + \sum_{k=1}^{5} \mathrm{Re}t_{i,t-k} + \delta_1 SIZE_{i,t} + \delta_2 TOVER_{i,t} + \delta_3 RETAIL\_OSHP_{i,t-1} + \delta_4 INSTITUTIONAL\_OSHP_{i,t-1}$$
$$+ \alpha_1 AGGR\_FFLOW_{t-1} + \alpha_2 VIX_{t-1} + \alpha_3 \Delta VIX_{t-1} + \alpha_4 NIFTY\_RET_{t-1} + \alpha_5 S\&P500\_RET_{t-1} + \alpha_6 NIFTY\_VOLATILITY_{t-1} + e_{i,t}. \quad (5)$$

The above regression serves the purpose of a first-pass panel regression.[9] The regression residuals define innovation (*FII_NET_INNOV*). Note that *FirmFEff* refers to firm fixed effects. Table 4 shows the results of estimating this panel regression of *FII_NET* on lagged *FII_NET*, lagged returns, firm characteristics, and market factors. The R-square value is around 19%. *FII_NET* is significantly related to the first-lagged return and up to five lagged values of *FII_NET*. The positive coefficients on lagged return are consistent with trend-chasing or positive feedback trading by FIIs. The positive coefficient on lagged *FII_NET* shows persistence in order flow. Both these findings are similar to what is reported in Anshuman, Chakrabarty, and Kumar (2012) regarding aggregate FII flows in Indian equity markets. The firm characteristics that have significant coefficients in the panel regression model are firm size, retail ownership, and institutional ownership. The positive relation between FII flows and firm size is not surprising. The negative relation with institutional ownership may reflect mean reversion arising either due to ownership constraints (there are regulatory limits on FII ownership in each stock) or the portfolio rebalancing motives (rather than buy-and-hold motives) of FII traders. The other variables with significant coefficients are market stress (*VIX*), first difference in market stress (Δ*VIX*), and aggregate FII flows (*AGGR_FFLOW*). The coefficient on lagged S&P 500 returns is insignificant while the coefficient on lagged NIFTY returns is negative. The residuals obtained

[9] We explored alternative specifications with and without firm fixed effects and time fixed effects. These variations turned out to be quite similar and the panel regression model with firm fixed effects is fairly robust.

from this panel regression (*FII_NET_INNOV*) are used as a proxy for surprises or innovations in FII flows.

2. Analysis

2.1 Hypothesis related to Fund Flows

If cross-border fund-flow is a phenomenon unrelated to domestic markets valuations, then under market efficiency, foreign fund flows should not influence domestic asset returns. Our null hypothesis, stated below, reflects this line of reasoning.

H1. Foreign fund flows have no systematic impact on market prices of domestic assets.

The alternative hypothesis is that asset returns are influenced by fund flows. Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2012) find that mutual fund flow-induced price impacts exhibit a degree of reversal. It has also been well established that information is asymmetrically incorporated on both the ask and bid sides of the market. Block purchases are associated with permanent price impact whereas block sales have been associated with transient price impact (e.g., Holthausen et al. 1987; Chan and Lakonishok 1993; Keim and Madhavan 1996; Saar 2001). One explanation for this asymmetric impact is that block purchases are motivated by information whereas block sales are motivated by portfolio rebalancing concerns. Given these possibilities, we propose alternative hypotheses as follows.

H1a. Foreign flows reflect information-based trading; therefore, they cause a permanent impact on market prices of domestic assets.

H1b. Foreign flows reflect portfolio rebalancing requirements; therefore, domestic assets experience price pressure — a transient effect that is reversed in the following periods.

An interesting way to identify price pressure effects (i.e., flow-induced price changes) is to examine the relation between the magnitude of the price effect and the magnitude of fund flows. A positive relation confirms price pressure effects, as has been demonstrated in the classic study by Scholes (1972), who studied price pressure associated with secondary distributions by firms on the New York Stock Exchange. Hypotheses H2 and H3 examine this aspect of the price pressure hypothesis.

H2. The price pressure associated with foreign flows should be positively related to the size of the shock in foreign flows.

As shown in Table 1, FII flows are related to firm size. We can, therefore, expect price pressure effects to be positively related to firm size.

H3. The price pressure associated with foreign flows should be positively related to firm size because foreign flows, as a proportion of total trading volume, increase with firm size.

Finally, if fund flows affect asset return, we should expect that uncertainty associated with fund flows should also affect asset returns. In particular, we would expect to see a greater price pressure during days associated with high global market uncertainty. We employ two proxies for global market uncertainty, namely, high CBOE VIX level days and the financial crisis period, as posited in the hypotheses below.

H4. The price pressure associated with foreign fund flows should be positively related to the uncertainty in markets (CBOE VIX).

H5. The price pressure associated with foreign fund flows should be greater during periods of financial crisis (January to December 2008) as compared to the non-crisis periods.

2.2 Abnormal Returns Associated with FII Flows

Hypotheses H1, H1a, and H1b are examined in this section. Table 5 presents results relating the innovations in FII flows to contemporaneous and subsequent stock returns. First, we rank all stocks according to daily innovations in *FII_NET* flows once every week (on Mondays) and group them into five quintiles. Over the six-year sample period, there are 315 portfolio formation days. The table presents the findings for the portfolios with the lowest innovations (Q1) in *FII_NET* and the portfolio with the highest innovations (Q5) in *FII_NET*. The table also shows the difference in the abnormal returns of these two portfolios (Q5-Q1). The returns are the cumulative abnormal returns (CARs) over the (-5, -1) window, the abnormal returns on the portfolio formation day (Day 0), and the cumulative abnormal returns over the (0, 5) window.

As can be seen in Table 5 (Panel A), the abnormal return for the low (high) innovation portfolio, Q1 (Q5), on the portfolio formation day (Day 0) is economically and statistically significant. The abnormal return over the (0, 1) window, *AB_RET* (0, 1), is -0.93% for the low innovation portfolio (Q1) but is +0.88% for the high innovation portfolio (Q5). Further, the low innovation portfolio (Q1) is associated with negative returns while the high innovation portfolio (Q5) is associated with positive returns. The (abnormal) return difference between the high-low innovation portfolios (Q5 - Q1) is also statistically significant. The differential abnormal returns between stocks with high innovation and low innovation are equal to 1.82%. These findings indicate that FII inflows are associated with price appreciation and FII outflows are associated with price declines.

In contrast to the positive differential abnormal returns (between high and low innovation stocks) on the portfolio formation day (Day 0), the differential abnormal returns in the post-formation window (0, 5) is negative.[10] The CAR in the post-formation window (0, 5) is significantly positive (0.36%) for the low innovation portfolio (Q1), but insignificantly positive (0.04%) for the high innovation portfolio (Q5). This pattern indicates reversal of prices in the post-formation window. However, there is significant reversal *only* for the low innovation portfolio. Thus, the statistically significant differential CARs (Q5 - Q1) of -0.31% in the post-formation window is largely driven by the reversal of the prices for the low innovation portfolio (Q1). In contrast to the post-formation window, the CAR differential (Q5 - Q1) over the pre-formation window, (-5, -1), is statistically insignificant (-0.08%).

These results can be more easily seen in Figure 3, which shows the CARs over the (-5, 5) window. High innovation stocks experience a significant coincident price appreciation whereas low innovation stocks experience a significant coincident price decline.[11] The CARs in the post-formation period remain flat for the high innovation portfolio. However, for the low innovation portfolio, the CARs start rising in the post-formation day period.

These findings imply that stocks with high innovations (positive residuals) in FII flows experience a coincident abnormal return that reflects a *permanent* information effect. However, stocks with low innovations (negative residuals) in FII flows experience both *permanent* information effects and *transient* effects, which are reversed over the post-formation window. In other words, order imbalances on the buy side and the sell side are associated with asymmetric effects, thereby confirming the claims in Hypotheses H1a and H1b, while rejecting the null hypothesis, H1, of no price effects. Hypothesis H2 is also confirmed in that the abnormal return

[10] This result also holds for longer windows (e.g., over (0, 10) and (0, 20)). However, given that FII trading innovations occur continuously, it would be difficult to make meaningful inferences for longer post-formation windows.
[11] This result holds for raw returns as well abnormal returns; all results reported in the paper refer to abnormal returns.

on Day 0 is positively related to the size of the innovations.

When we examine abnormal returns for the low innovation portfolio in Figure 3, we can see that approximately 40% of the abnormal returns on Day 0 are reversed in the post-formation period. Given that the volatility of a typical stock is around 36.16%, a return reversal of approximately 0.36% indicates that the transient effect accounts for $0.36*\sqrt{(252)}/36.16$, or nearly 16% of the annualized volatility of a typical stock.[12]

In summary, low innovation stocks experience both a permanent information effect as well as a transient effect on the portfolio formation day; the latter effect gets reversed during the post-formation period. On the other hand, high innovation stocks experience only a permanent information effect and there is no reversal of returns during the post-formation period. As a consequence, (negative) differential abnormal returns between high and low innovation stocks during the post-formation window are largely driven by the return reversal experienced by low innovation stocks.

We perform additional test to examine whether the differential abnormal return between high and low innovation stocks is arising because of differences in firm characteristics. We can see in Panel B of Table 5 that there are no significant differences in liquidity (as measured by the Amihud illiquidity ratio), firm size, local as well as global systematic risk exposure, volatility, and ownership structure between the high innovation portfolio and the low innovation portfolio. This finding gives us some assurance that the differences in performance of high innovation and low innovation portfolios are unlikely to be driven by differences in firm characteristics.

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[12] To obtain an idea about the magnitude of the impact of FII flow innovations on prices, we can consider the study of Hendershott and Menkveld (2013), who estimate price pressure on the NYSE. They report that a $100,000 inventory shock causes an average price pressure of 0.28% with a half-life of 0.92 days. They also report that (i) price pressure causes average transitory volatility in daily stock returns of 0.49% and (ii) price pressure effects are substantially larger for smaller stocks with longer durations.

The results are consistent with “price pressure” on stock returns induced by FII sales, given the partial reversal of formation day negative returns for stocks experiencing abnormally high FII outflows (i.e., the low innovation portfolio). The results are, however, also consistent with information being revealed through FII purchases and sales, given the permanent nature of formation day returns for stocks experiencing abnormal FII flows. While FII outflows contribute to transient volatility for stocks experiencing outflows, it appears that FII trading also generates new information.

2.3 Time Series Variation in Return Shocks

Having established that there are both permanent information effects and transient price pressure effects associated with innovation in FII flows, we now examine whether variation in the time series of these effects can due to market-wide factors. Figure 4 shows the time series relation between the differential abnormal returns (between the high and low innovation portfolios) and lagged *VIX*. The correlation between these variables 0.3913 and statistically significant. High CBOE VIX levels may be causing FII flows to be driven more by portfolio rebalancing than fundamental information, and therefore, leading to greater price pressure effects.

We compute the cross-sectional average of the differential returns (Y_t) between high and low innovation stocks on each portfolio formation day. Y_t is then regressed on firm characteristics (X_t) and lagged market-wide factors (Z_{t-1}) (e.g., market returns and volatility in the U.S. and India), ownership structure in terms of retail and institutional ownership, and aggregate FII flows:

$$Y_t = \alpha_0 + \beta\, X_t + \gamma\, Z_{t-1} + \varepsilon_t. \tag{6}$$

The results are reported in Table 6. We can see that the time series of the differential return on Day 0, (Q5 – Q1), is positively related to the time series of the Amihud illiquidity measure and lagged *VIX*. These findings indicate that the return differential on the portfolio formation day (Day 0) is greater during times of illiquidity and a rise in the global stock market volatility (*VIX*), consistent with what we posit in Hypothesis H4. NIFTY lagged returns and volatility are also positively related to differential returns.

More importantly, the intercept is statistically significant and positive, indicating that even after controlling for firm characteristics and market-wide factors, going long on a high innovation portfolio and short on a low innovation portfolio provides a positive alpha. In summary, the time series variation in the abnornmal returns differential due to innovations in FII flows is driven by the time series variation in firm-specific illiquidity, as well as in global risk perceptions and local market risk. Nevertheless, being exposed to these risks is rewarded by the market in the form of an alpha.

2.4 Size Effect

Next, we examine the impact of firm size on how FII trading affects stock returns. Typically, larger stocks, being more liquid, would be more suitable for portfolio rebalancing whereas smaller stocks, being less liquid, would be more suitable for buy-and-hold strategies. We partition the sample into three sub-samples: large-cap, mid-cap, and small cap-stocks based on whether the stock appears on the CNX NIFTY, CNX MIDCAP, or the CNX SMALLCAP indices, respectively, of the National Stock Exchange (NSE). Table 7 shows the differential abnormal returns between the high and low innovation portfiolios by market size. Abnormal returns on Day 0 are directly related to firm size. Large-cap stocks (as in the NIFTY Index) experience a Day 0 abnormal return differential of 2.14%, which is the highest between the abnormal returns on the high and low innovation portfolios. In contrast, the mid-cap and small-cap stocks experience abnormal return differentials of 1.71% and 1.62%, respectively. Figure 5 presents the across the (-5, +5) window. We can see that the abnormal return on the high and low innovation portfolios is higher in the case of large cap-stocks, lower for mid cap-stocks, and the least for small cap stocks. This finding is consistent with what we posit in Hypothesis H3.

Note in Table 7 that large-cap stocks, on average, experience daily FII purchases of Rs 268.78 million whereas mid-cap and small-cap stocks experience daily FII purchases of Rs 36.95 million and Rs 12.23 million, respectively. Likewise, large-cap, mid-cap, and small-cap stocks experience, on average, daily FII sales of Rs 282.12, 35.92, and 12.15 million, respectively. These numbers suggest that total FII flows (FII purchases plus FII sales) are directly related to firm size and that FIIs trade less frequently in small-cap stocks than in mid-cap and large-cap stocks. We can see that Day 0 abnormal return differentials between high and low innovation portfolios exhibit the same monotonic relation with both firm size and total FII order flows.[13]

To compare with the earlier results, recall that in the overall sample, the high innovation portfolios are associated with a permanent price impact whereas nearly 40% of the price impact is reversed in the case of the low innovation portfolios. This pattern is followed in the case of large-cap and mid-cap stocks. The price reversal observed in the post-formation window is largely driven by the price reversal in the low innovation portfolio. It is slightly greater for large-cap stocks than for mid-cap stocks.

In the case of small cap stocks, there is no price reversal for both the low innovation (Q1) as well as the high innovation (Q5) portfolios. Given the low extent of FII trading in small-cap

[13] We also examine the time series average of the difference in innovations on the high and low innovation portfolios in each of the three sub-samples. The differential innovation is 0.50, 0.57, and 0.41 for large-cap, mid-cap, and small-cap stocks, respectively. These differential innovations are not monotonic in firm size. Also, *FII_NET*, which is a normalized measure of net FII flows, has a value of 0.0023 for large-cap stocks and values of 0.0198 and 0.0091 for mid-cap and small-cap stocks, respectively. Again, these measure of FII flows are non-monotonic in firm size. Essentially, as compared to both these measures, total FII order flow is better correlated with Day 0 return differentials between the high and low innovation portfolios.

stocks, it seems that when FIIs buy and sell, their order flow is perceived by the market as informed order flow and there is no significant price reversal on either side of the market. This is consistent with the view that FII trading in smaller stocks, which are less liquid, is driven by the buy-and-hold motives of FII traders. In contrast, for large-cap and mid-cap stocks, the abnormal returns associated with excess FII sales exhibit some degree of price reversal. This finding suggests that FII trading in larger stocks is driven by information and portfolio rebalancing motives.

2.5 Impact of Global Market Stress

The global financial crisis provides an excellent opportunity to examine the role of capital flows in driving asset returns. Fratzscher (2011) finds that the capital outflows from emerging markets to the U.S. were largely a flight-to-safety effect. Thus, the recent financial crisis period provides a unique opportunity to examine the impact of foreign fund flows on emerging markets during times of market stress.

To examine this effect, we identify portfolio formation days that are associated with high global market stress across all markets that fund foreign flows into Indian markets. We use the CBOE VIX Index as a measure of global market stress. We therefore examine the role of high and low CBOE VIX level periods in explaining the differential Day 0 returns. As shown in the previous section, the time series of the CBOE VIX influences the abnormal return differential associated with high and low FII flow innovations.

First, we split the sample into a crisis period sub-sample and a non-crisis period sub-sample. This segregation allows us to examine how the financial crisis affected the price impact of FII flows. Our conjecture is that the impact of FII flows would be greater during the crisis. Second, we divide the portfolio formation days into two groups: one associated with low CBOE

VIX levels and the other associated with high CBOE VIX levels. This procedure is useful in estimating the impact of the CBOE VIX on the differential price impact of high and low FII flow innovations.

2.5.1 Crisis Period Effect

In Indian capital markets, the financial crisis period is identified as the period from January 2008 to December 2008.[14] The remainder of the sample period is classified as the non-crisis period. We examine the abnormal return differentials between portfolios with high and low innovations in FII flows in both periods. Table 8 (Panel A) shows the results. The abnormal return differential beween high and low innovation portfolios is much higher during the crisis period (2.43%) than in the non-crisis period (1.68%) (i.e., there is nearly a 45% greater impact of FII flows during the crisis period), consistent with Hypothesis H4. This can also be more easily seen in Figure 6. Further, the price reversal experienced by the low innovation stocks in the post-formation window is also greater in the crisis period as compared to the non-crisis period. This finding suggests that there is greater transient volatility induced by unexpected FII sales during the crisis. Overall, our analysis indicates that concerns about contagion effects during crisis periods are well substantiated.

2.5.2 Volatility Index Effect

As can be seen in Figure 2, there is significant time variation in the CBOE VIX. It reached a peak value around September-October 2008 when the U.S. House of Representatives rejected a $700 billion bank bailout. In contrast, the CBOE VIX was at a very low level in the first quarter of 2007. To investigate the role of time variation in global perceptions of market

[14] As reported in Anshuman, Chakrabarti, and Kumar (2012), the CNX NIFTY Index declined from 6,144 on January 1, 2008 to 3,033 on December 31, 2008 and then increased in the first quarter of 2009. The results hold for alternative specifications of the crisis period.

risk, we partition the sample into into high *VIX* days and low *VIX* days based on the median *VIX* levels. Table 8 (Panel B) shows the results when the portfolio formation days are partitioned on the CBOE VIX.

The abnormal return differential beween high and low innovation portfolios is much higher during high *VIX* days than on low *VIX* days. As seen in the case of the crisis period and the non-crisis period, the abnormal differential return on Day 0 is greater on days associated with a high *VIX* (2.02%), as compared to days asscoiated with a low *VIX* (1.55%), which is a 37% difference, consistent with Hypothesis H5. As in the crisis period case, the price reversal in the post-formation window is greater on days associated with high *VIX*. Again, these findings indicate that transient volatility is also greater during times of global market stress.

2.6 Commonality in Order Flow

If institutional investors herd, either due to behavioral biases or market frictions (e.g., short selling constraints or funding constraints that are equally binding on all market participants), their behavior may influence the price reactions we observe. Irrespective of their motives, the propensity of FIIs to trade together could determine the magnitude of the abnormal returns on Day 0. In this section, we examine whether correlated trading by institutional investors contributes to the abnormal reaction observed in the low innovation (Q1) and high innovation (Q5) portfolios.

Our investigation is related to the literature on commonality in liquidity. For instance, Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Karolyi, Lee, and Van Dijk (2012) have examined the role of correlated trading activity in determining liquidity. Karolyi, Lee, and Van Dijk (2012) find that demand-side driven factors (e.g., correlated trading activity of institutional investors) are relatively more important than supply-side factors (e.g., funding constraints) in explaining the commonality in liquidity. We explore whether correlated buy (sell) order flow can be used to explain the observed pattern of abnormal returns. In short, does commonality in order flow (driven by correlated trading activity) affect abnormal returns on the portfolio formation day?

Table 6 reports the results of a regression of stock-level abnormal returns on firm characteristics and market variables. We find that aggregate net order flow (*AGGR_FFLOW*), a proxy for commonality in order flow, *cannot* be used to explain the abnormal returns associated with the low innovation (Q1) and high innovation (Q5) portfolios. However, aggregate net flow (*AGGR_FFLOW*) may not be a good measure of correlated trading activity because netting masks the extent of correlated trading activity on the buy and sell sides of the market. Correlated trading activity can be better measured by examining these separately.

To address this issue, we follow the procedure in Karolyi, Lee, and Van Dijk (2012) and construct a monthly time series measure of commonality in order flow for each stock by extracting the R-square values from a stock-month regression: Stock-wise FII buy/sell trades ($FII\_Trades_{i,t,d}$) is regressed on *aggregate* FII trades (buy/sell, respectively), $AGGR\_FII\_Trades_{t,d+j}$, along with day-of-the-week dummies. Specifically, the regression takes the following form for observations on day *d* for the i^{th} stock in the t^{th} month (D_τ is the day-of-the-week dummy):

$$FII\_Trades_{i,t,d} = \alpha + \sum_{j=-1}^{+1} \beta_{i,t,j}\, AGGR\_FII\_Trades_{t,d+j} + \sum_{\tau=1}^{5} \delta_{i,t,\tau}\, D_\tau + \varepsilon_{i,t,d}. \quad (7)$$

The R-square value (*FII_TRDS_RSQ*) obtained from the above regression is our proxy for the degree of commonality in FII trades. Next, we relate abnormal returns to firm characteristics and market variables, with this additional independent variable. The analysis here is constrained to be on a monthly portfolio formation basis because we require a sufficient number of observations for the first pass regression described above to estimate commonality in order flow. The average of the R-squared values in these stock-wise regressions was 61% (60%) for FII buy (sell) trades across all 15,168 stock-month observations, confirming our expectation that there is commonality in FII trades.[15]

Table 9 shows the results for Day 0 abnormal returns of the low (Q1), high (Q5), and abnormal return differential (Q5 – Q1) innovation portfolios. For the low innovation portfolio, we employ the R-square measure of commonality in *sell* side orders as an independent variable. Likewise, for the high innovation portfolio, we employ the R-square measure of commonality in *buy* side orders as an independent variable. For the high-low innovation portfolio, all the independent variables are computed as the difference in corresponding values for the low and high portfolios.

We can see in Table 9 that abnormal returns are unrelated to the R-square measure (*FII_TRDS_RSQ*). Further, none of the firm characteristics affect abnormal returns. Among market variables, only past *NIFTY* returns are related to abnormal returns. Overall, the results indicate that while there is commonality in order flow of FIIs, it has no material impact on abnormal returns. This finding reinforces our earlier conclusion that abnormal returns reflect information being revealed through FII buying and selling activities rather than other exogenous factors.

[15] When the same procedure is applied on the entire sample period, the average R-squared value from regression across all stocks was only around 2.3%. We therefore employ a series of stock-month regressions to detect commonality.

3. Robustness Checks

In this section, we investigate the robustness of the results reported above. First, we examine a parametric approach to identify the impact of FII flow innovations and also attempt to uncover any asymmetry (buy side vs. sell side), as well as any nonlinear effects associated with FII flow innovations. Second, we recognize that FII order flow may be persistent and therefore we redefine our sorting procedure in terms of cumulative innovations in FII flows over the previous 5-day period rather than in terms of the concurrent FII innovation. Finally, we validate the panel regression model using out-of-sample data during the period January 2012 to June 2013.

3.1 Asymmetric and Non Linear effects of FII Flows

As compared to the non-parametric approach we have adopted in our analysis, we employ a parametric approach to exploit the information contained in the full sample. We regress abnormal returns on innovations in FII flows. To account for any nonlinear effects, we include the square of the innovation in FII flows as an independent variable. In addition, to detect asymmetric behavior, we introduce a dummy variable, which takes a value of 1 for negative innovations in FII flows.

The results are shown in Table 10. The dummy variable is significant for the overall sample, but this result is largely driven by high *VIX* level days. Thus the impact of negative innovations in FII flows differs from that of positive innovations in FII flows. The nonlinear effect of FII flows is pervasive and independent of market stress levels. The asymmetric and nonlinear effects can be more readily observed in Figure 8, which shows the fitted regression lines in pictorial form. We can see that the asymmetric effect, which can be seen by the deviation of the dotted line from the full line, is most pronounced on days with high *VIX* levels. The nonlinear effects are seen for both positive and negative innovations in FII flows. These findings suggest that FII sales trigger more adverse reactions than corresponding FII purchases and confirm our findings from the non-parametric approach discussed in Section 2.

3.2 Cumulative Innovations Analysis

Since FII trading occurs continuously and FII traders may strategically split their trades over several days, a daily measure of FII flow innovations, as we have used here, may fail to capture the true level of FII flow innovations. To account for such strategic trading behavior, we accumulate daily FII flow innovations over the (-5, 0) window and use this cumulative measure of innovations to form portfolios.

Table 11 (Panel A) shows that the results are qualitatively similar to earlier findings because FII order flow is known to exhibit strong persistence. However, differential abnormal return on Day 0 is 0.79%, somewhat lower than the 1.82% when we use the daily measure of FII flow innovations to construct portfolios. Again, this difference is not altogether surprising, because persistence in orderflow implies that prices start moving upward (for the high innovation portfolio) or downward (for the low innovation portfolio) from Day -5, thereby mitigating the effect on Day 0. We can see this by noting the values of *AB_RET* (-5,-1), the CARs over the (-5, -1) window, which is significantly negative (positive) for the low (high) innovation portfolio.

We also compute *AB_RET* (-10, -5) for the window (-10, -5), which is the relevant pre-formation window given that we are using a cumulative measure of FII flow innovations. We find that the low innovation portfiolo has a *positive* and significant return, which assures us that the *negative* abnormal returns over the window (-5, -1) and on Day 0 are not driven by pre-formation negative returns. When we consider the high innovation portfolio, the abnormal return in the (-10, -5) pre-formation window is statistically *insignificant*, again assuring us that the *positive* abnormal return over the (-5, -1) and (-1, 0) windows are not due to an effect carried over from the pre-formation window.

3.3 Out of Sample Analysis

Our measure of FII flow innovations is based on residuals obtained from a panel regression done on in-sample data. The validity of the panel regression model may therefore be questionable. In order to ascertain the impact of spurious effects associated with in-sample model construction, we employ the in-sample panel regression model on an out-of-sample dataset for the January 2012 to June 2013 period. We find that our results are robust to using out-of-sample data.

Table 11 (Panel B) shows that there are significant differences in abnormal returns for the high innovation and the low innovation portfolios. The Day 0 abnormal return for the high innovation portfolio is 0.71% and the Day 0 abnormal return for the low innovation portfolio is -0.80%, implying a differential abnormal returns of 1.51%. The reversal pattern is similar, but weaker than what we found for the in-sample data. As before, only the low innovation portfolio experiences a reversal in price. As compared to the in-sample anlaysis, the pre-formation window abnormal return differential is economically and statistically significant, but is of much lower magnitude than the Day 0 effect.

4. Impact of FII Flows during the Taper Tantrum Period

After the financial crisis of 2008, the U. S. Federal Reserve set in motion a series of unconventional monetary policy initiatives including substantial purchases in the government bond and mortgage-backed securities markets. In 2013, starting May 22nd to be precise, the Federal Reserve announced its intention to undertake measures to tighten money supply by tapering the bond purchase program put in place post-2008. Sahay et al (2015) document a significant "taper tantrum" in the form of capital outflows accompanied by sharp revisions in asset prices across the world, especially in emerging markets. In the case of India, the immediate impact of the taper tantrum on capital flows was significant, as can be seen on Figure 9. Net portfolio flows (including both debt and equity markets) swung from a peak of $800 million to -$800 million in the post-taper period (from May 20th 2013 to June 27th 2013).

The "taper tantrum" phase provides us with an opportunity to evaluate the role of unconventional monetary policy on the relation between unanticipated FII flows and asset prices. In particular, we wish to see how FII flows affected asset prices during the taper-tantrum period; were the flows as informative as we found them to be in the pre-taper period, or were they largely driven by non-information based motives such as portfolio rebalancing by the FIIs?[16]

Since the first formal indication of the taper was announced on May 22nd 2013, we consider out-of-sample data from April 15th 2013 to June 30th 2013 and split it into two periods: April 15th 2013 to May 22nd 2013 as the pre-taper and May 23rd 2013 to June 30th as the post-taper period. We employ the in-sample panel regression model (with data until April 15th 2013) to infer the innovations in FII (daily) flows and, as before, form portfolios based on FII innovations. We examine the difference between the returns of the high innovation portfolio and the returns of the low innovation portfolio (henceforth referred to as Q5-Q1). As in the in-sample analysis, we form portfolios at the beginning of every week and track the difference in daily CAPM-beta adjusted excess returns. The CAR plots are shown in Figure 10. [17]

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[16] Our investigation is in part motivated by the concerns raised in Feroli, Kashyap, Schoenholtz, and Shin (2014): "…*we find some empirical backing for the proposition that financial market disruptions can arise without leverage…We also uncover connections between destabilizing flows and shocks to monetary policy. Less clear is whether such destabilizing effects are large enough and persistent enough to warrant policy makers to reassess in a fundamental way the tradeoff between stimulating real activity and financial stability. Further research is needed in this area*."

[17] The taper period is likely to be associated with significant shifts in risk premium, as compared to the risk premium in the in-sample data. Therefore, to focus on the marginal impact of the taper phenomenon, we

Panels A and B of Figure 10 show the plots for two periods (pre-taper and post-taper) for the entire sample of stocks, along with 95% confidence interval bands. The pre-taper plot (Panel A) indicates a slight reversal in the differential returns between the high and low innovation portfolios (Q5-Q1), but there continues to be a significant permanent effect even 5 days after the portfolio formation. The post-taper plot (Panel B) is similar, except that the reversal in the differential returns is more than in the pre-taper period; however, there continues to be a permanent, albeit lower, effect even 5 days after portfolio formation (assuming a 95% confidence level requirement). This finding suggests the transient impact of the taper is more significant in post-taper period, as compared to the pre-taper period.

Figure 11 includes plots based on sub-samples of stocks based on size (Large, Mid-cap and Small-cap) for both the pre-taper and post-taper periods (Panel A, Panel B, and Panel C, respectively). We can see that that the transient effects associated with the taper phenomenon are largely driven by the large and mid-cap stocks. In the small-cap sub-sample, there is no transient effect, both in the pre-taper and the post-taper periods. This finding is consistent with the fact that FII trading is largely concentrated on large-cap and small-cap stocks,[18] and therefore taper-induced temporary FII order flows cause price reversals only in large-cap and mid-cap stocks. We also find that independent of the size, the pre-taper period and the post-taper period reflect a permanent impact caused by FII flows, suggesting that the information-based flows have similar effects during the taper period as in normal times.

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present plots for the cumulative returns differential between the high innovation and the low innovation portfolios rather than CAR plots for the high and low innovation portfolios separately, as we did for the in-sample analysis. For completeness, we also constructed the CAR plots for the high and low innovation portfolios separately and found them to be qualitatively similar to the plots for the in-sample period.

[18] The mean FII ownership as non-promoters (i.e., ownership due to portfolio flows) for the sample of firms over the study period depends on firm size. The average FII ownership related to portfolio flows is 20.51% for the large-cap NIFTY stocks, 15.99% for the mid-cap stocks, and 12.04% for the small-cap stocks. The t-statistic for the difference between the means of large-cap NIFTY stocks and mid-cap stocks is 12.64 and that between mid-cap stocks and small-cap stocks is 12.15, both differences being significant at the 1% level.

Overall, this analysis suggests that, the taper tantrum of May 2013 primarily produced some non-information (e.g., portfolio-rebalancing) based FII flows for Indian equity markets, resulting in temporary asset-price impacts that caused subsequent price reversals. Nevertheless, the usual permanent impact of information-based FII flows continued to exist in the taper period, similar to the findings in normal times.

5. Conclusion

Employing a unique database that provides data on foreign institutional investor (FII) flows at the individual stock level in India, we are able to examine the precise impact of FII flow innovations on asset prices. We find that stocks with high innovations are associated with a coincident price increase that is permanent, whereas stocks with low innovations are associated with a coincident price decline that is in part transient, reversing itself within five days. The results are consistent with a price pressure on stock returns induced by FII sales, as well as information being revealed through FII purchases and FII sales. We show that while FII outflows contribute to transient volatility for stocks experiencing the outflows, trading by FIIs also generates new information. Interestingly, price pressure effects increase with the magnitude of innovations but are largely unrelated to firm characteristics.

Our study not only reinforces the findings in recent literature that fund flows affect stock returns (and asset prices, more generally), but also provides insights into when this relation is likely to arise. We demonstrate that price pressure is higher during periods of global market stress. These findings suggest further research possibilities for identifying the precise mechanism by which information gets transmitted through trading across global markets and also for identifying which sectors of the economy are more likely to be affected by asset price movements in response to shocks in global fund flows.

Emerging market regulators fear the adverse real effects of volatile capital flows and often employ drastic measures to curb capital flows. From a policy perspective, our findings suggest that, instead of placing restrictions on FII flows, regulators should recognize that (i) while FII outflows contribute to transient volatility for stocks experiencing the outflows, (ii) trading by FIIs also generates new information. The second result suggests that, as in developed markets, even in emerging markets, trading, and in particular, FII trading, is central to generating information. These relative effects of foreign fund flows must be balanced against each other while evaluating their desirability for emerging markets.

A caveat to our findings is the period of the taper tantrum of 2013 period after the Federal Reserve's announcement of a possible withdrawal of quantitative easing measures. We find that the differential price impact of unanticipated FII buy order flow and sell order flow consists of a greater temporary component than during normal periods, which is subsequently reversed, but there continues to be a permanent component, as during normal periods.

REFERENCES

Amihud, Y. and H. Mendelson, 1986, Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17, 223-249.

Anshuman, V. Ravi, Chakrabarti, Rajesh and Kumar, Kiran, 2012, Institutional Trading Strategies and Contagion around the Financial Crisis (September 5, 2012), http://ssrn.com/abstract=2143803

Bessembinder H, and Seguin, P.J., 1993, Price Volatility, Trading Volume and Market Depth: Evidence from Futures Markets, *Journal of Financial and Quantitative Analysis* 28, 21-39.

Chan, L. and Lakonishok, J., 1993. Institutional trades and intra-day stock price behavior. *Journal of Financial Economics* 33(2), 173-199.

Chordia, T., Roll, R., and Subrahmanyam, A., 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3–28.

Coval, J., and E. Stafford, 2007, Asset Fire Sales (and Purchases) in Equity Markets, *Journal of Financial Economics* 86, 479-512.

Edelen, R. M., and J. B. Warner, 2001, Aggregate Price Effects of Institutional Trading: A Study of Mutual Fund Flow and Market Returns, *Journal of Financial Economics* 59, 195-220.

Fama, Eugene F. and James D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy 81*(3), 607-636.

Feroli, Michael and Kashyap, Anil K. and Schoenholtz, Kermit L. and Shin, Hyun Song, Market Tantrums and Monetary Policy (February 1, 2014). Chicago Booth Research Paper No. 14-09. Available at http://dx.doi.org/10.2139/ssrn.2409092

Fratzscher, M. 2012, Capital Flows, Push versus Pull Factors and the Global Financial Crisis, *Journal of International Economics* 88, 341-356.

Frazzini, A. and O. Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

French, K. R., and Roll, 1986, Stock Returns Variances: The Arrival of Information and Reaction of Traders, *Journal of Financial Economics* 17, 5-26.

Gromb, D. and D. Vayanos, 2010, Limits of Arbitrage, *Annual Review of Financial Economics 2*, 251-275.

Goetzmann, W. N., and M. Massa, 2003, Index Funds and Stock Market Growth, *Journal of Business* 76(1), 1-28.

Hasbrouck, Joel, 1988, Trades, Quotes, Inventories and Information, *Journal of Financial Economics* 22, 229-252.

Hasbrouck, J., Seppi, D.J., 2001, Common factors in prices, order flows, and liquidity, *Journal of Financial Economics* 59, 383–411.

Hendershott, T. and Albert Menkveld, 2014, Price Pressures, *Journal of Financial Economics* 114(3), 405-423.

Holthausen, R., Leftwich, R. and D. Mayers, 1987, The Effect of Large Block Transactions on Security Prices: A Cross-Sectional Analysis, *Journal of Financial Economics* 19, 237-267.

Jotikasthira, P., Lundblad, Christian T. and Ramadorai, Tarun, 2012, Asset Fire Sales and Purchases and the International Transmission of Funding Shocks, *Journal of Finance* 67, 2015-2050.

Jotikasthira, P., Lundblad, Christian T. and Ramadorai, Tarun, 2013, How Do Foreign Investors Impact Domestic Economic Activity? Evidence from China and India, *Journal of International Money and Finance* 39, 89-110..

Karolyi, A., Kuan-Hui Lee and Mathijs Van Dijk, 2012, "Understanding Commonality in Liquidity around the World", *Journal of Financial Economics* 105(1), 82-112.

Keim, D.B. and Madhavan, A., 1996, The upstairs market for large-block transactions: Analysis and measurement of price effects, *Review of Financial Studies* 9(1), 1-36**.**

Lou Dong, 2012, A Flow-Based Explanation for Return Predictability, *Review of Financial Studies* 25(12), 3457-3489.

Saar G., 2001, Price impact asymmetry of block trades: An institutional trading explanation, *Review of Financial Studies* 14(4), 1153-1181.

Sahay, Ratna, Vivek Arora, Thanos Arvanitis, Hamid Faruqee, Papa N'Diaye, Tommaso Mancini-Griffoli, and an IMF Team, Emerging Market Volatility: Lessons from the Taper Tantrum, , IMF Staff Discussion Note.

Scholes, Myron S., 1972, The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices, *The Journal of Business* 45(2), 179-211.

Shleifer, A. and R. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance* 52(1), 35-55.

Teo, M., and S.-J. Woo, 2004, Style Effects in the Cross-Section of Stock Returns, *Journal of Financial Economics* 74(2), 367-398.

Warther, V. A., 1995, Aggregate Mutual Fund Flows and Security Returns, *Journal of Financial Economics* 39(2-3), 209-235.

Figure 1

FII Annual Net Flows into Indian Equity Markets and NIFTY Volatility during 2001-2012

The chart below shows the relation between annual FII net inflows and the annualized standard deviation of the daily returns on the CNX NIFTY index for each fiscal year over the period, 2001-2012. FII net inflows were positive in all years except 2008. The data for chart have been taken from Table 1.

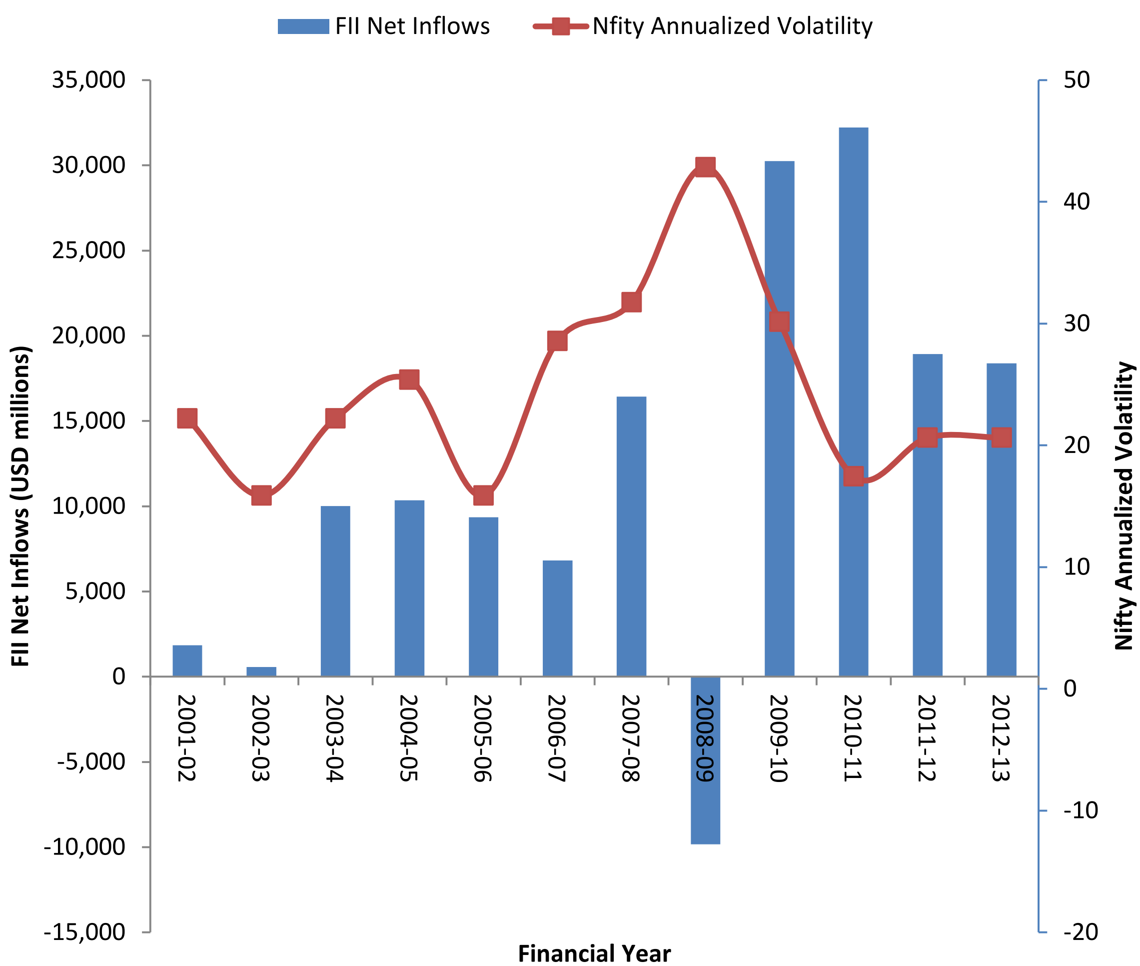


Figure 2

Average Weekly FII Net Flows vs. CBOE VIX

The chart depicts the weekly average CBOE VIX closing values and weekly average FII net flows during the 2006-2011 period. Extreme FII flows (positive or negative) are associated with specific shocks to economy (U.S. or India) and further associated with peak values of CBOE VIX.

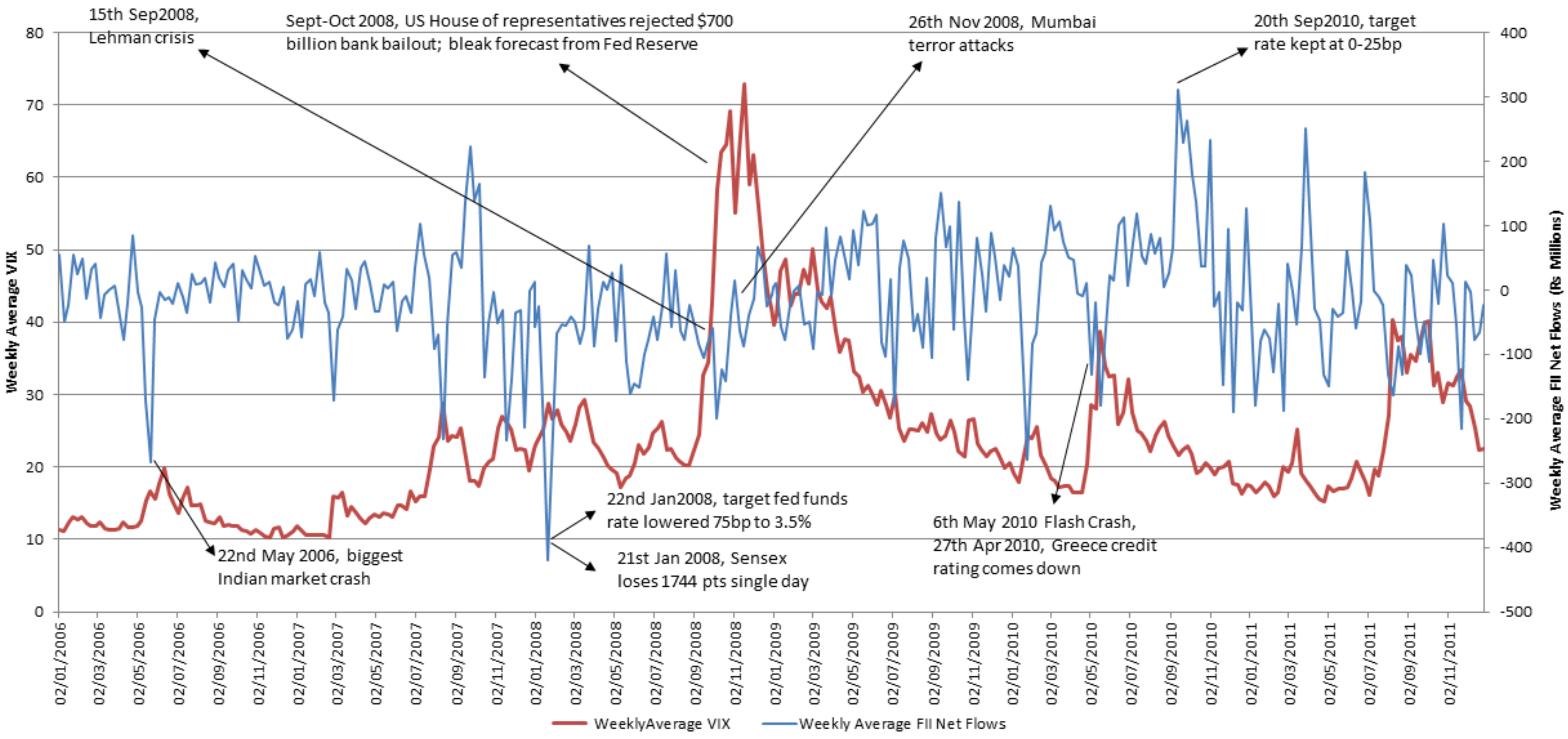


Figure 3

Cumulative abnormal returns of high innovation and low innovation portfolios

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ($FII\_NET_{i,t}$), which is defined as the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total rupee value traded (across both FII and non FIIs) for the i^{th} stock on the t^{th} day. During the 2006-2011 period, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically on every Monday) and sorted into five quintiles. This figure presents the cumulative daily abnormal stock returns for stocks that experience extremely high or low innovations in FII flows.

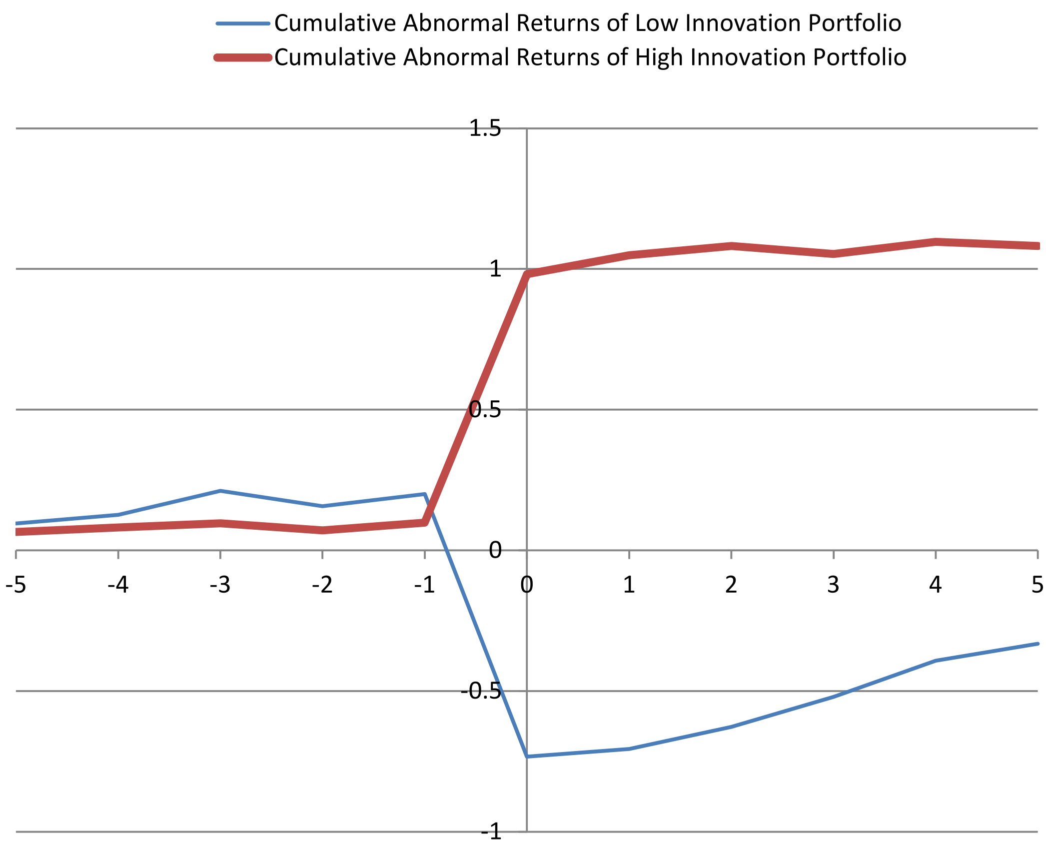


Figure 4

Time Series Variation in Abnormal Return Differential with CBOE VIX

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows (*FII_NET*$_{i,t}$), which is defined as the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total rupee value traded (across both FII and non FIIs) for the i^{th} stock on the t^{th} day. During the period 2006-2011, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically on every Monday) and sorted into five quintiles. The figure shows the time series relation between the differential abnormal returns (between high innovation and low innovation portfolios) due to innovation and lagged *VIX*.

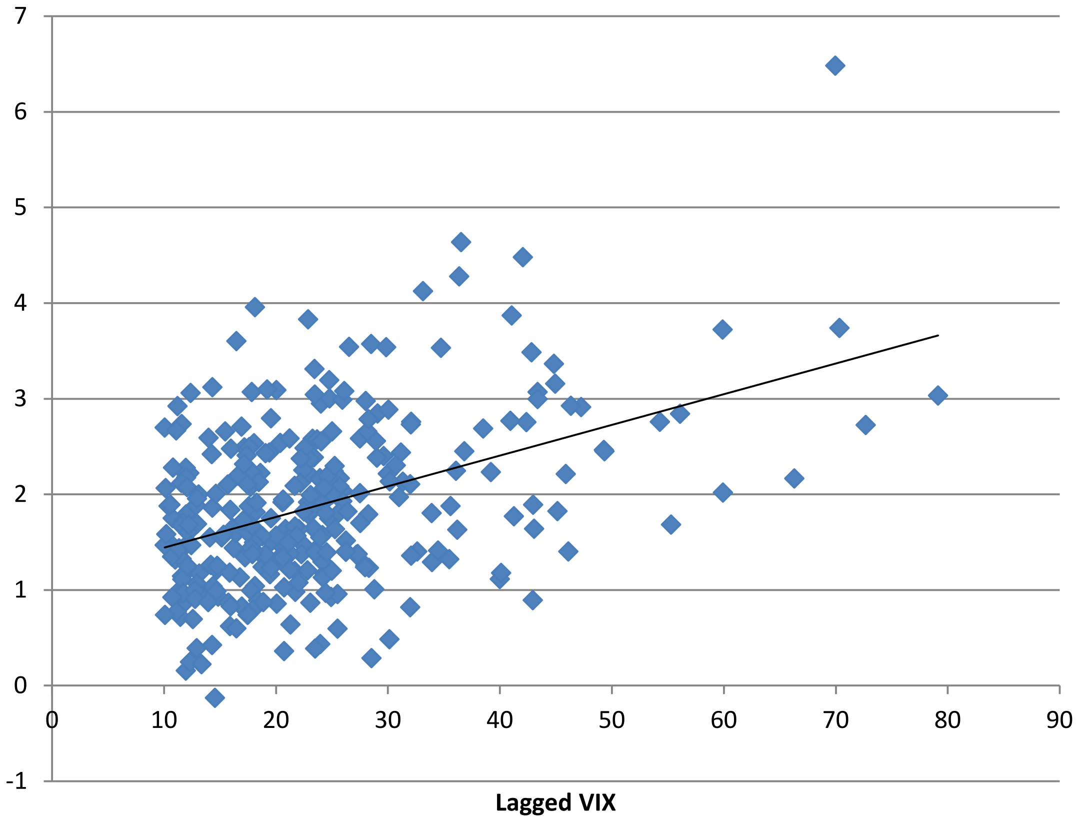
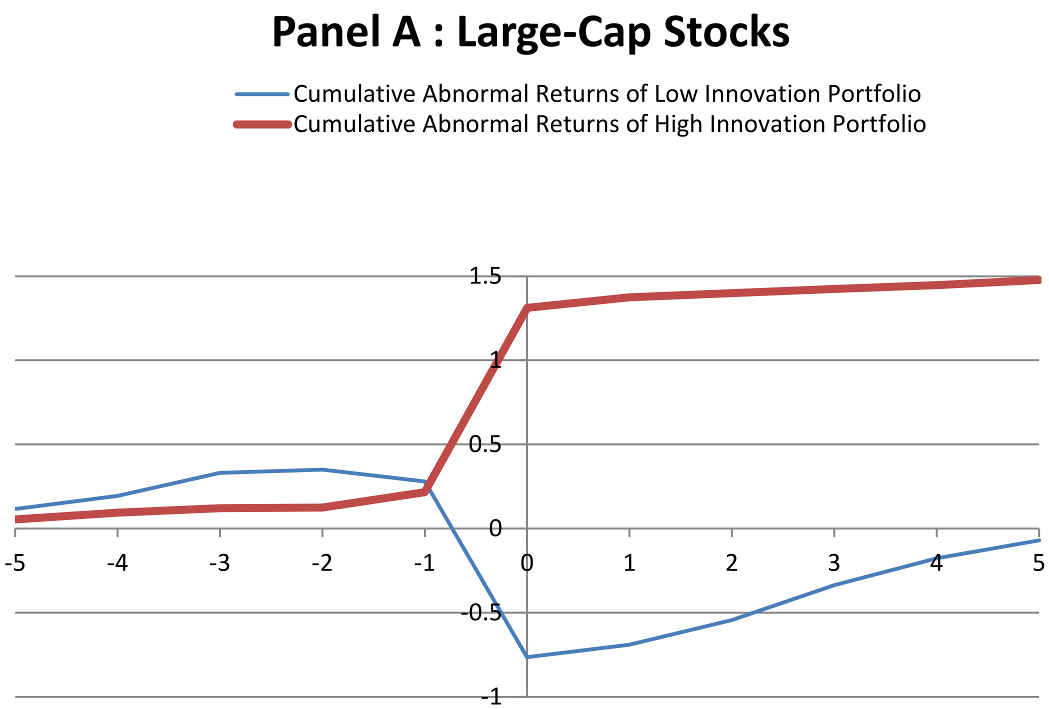
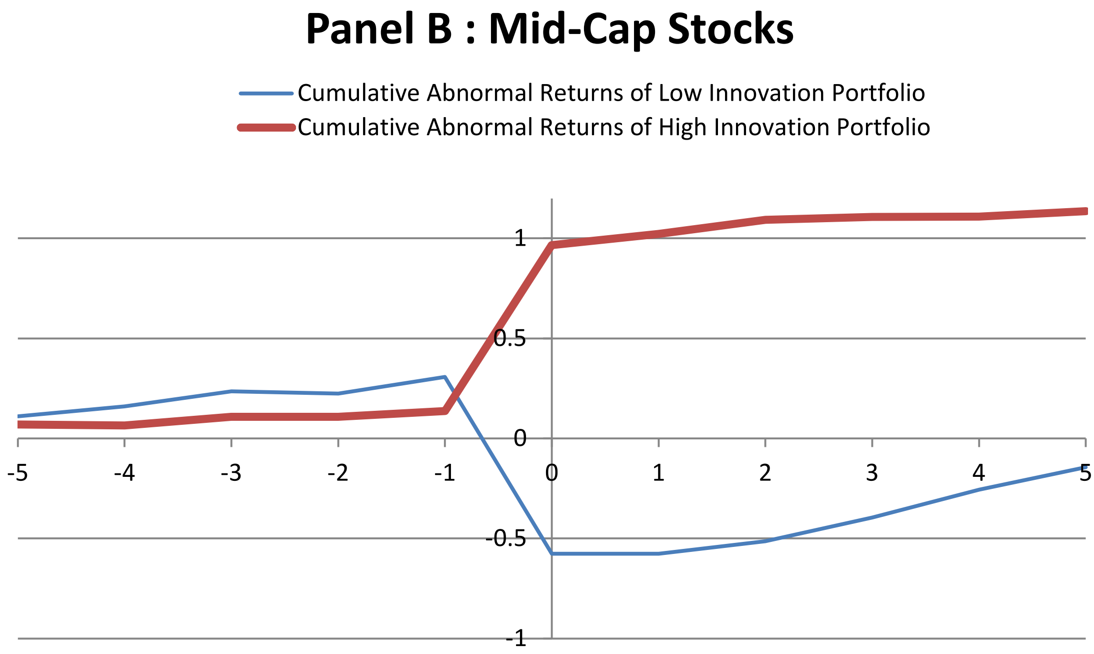


Figure 5

Cumulative Abnormal Returns around Shocks in FII Flows: Firm Size Effects

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ($FII\_NET_{i,t}$), which is defined as the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total rupee value traded (across both FII and non FIIs) for the i^{th} stock on the t^{th} day. During the 2006-2011 period, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically on every Monday) and sorted into five quintiles. Panel A shows the cumulative daily abnormal return for high and low innovation portfolios formed on the basis of innovations from panel regression model for large-cap stocks, Panel B for mid-cap stocks, and Panel C for small-cap stocks.




Panel B : Mid-Cap Stocks
Cumulative Abnormal Returns of Low Innovation Portfolio
Cumulative Abnormal Returns of High Innovation Portfolio
1
0.5
0
-0.5
-1
-5
-4
-3
-2
-1
0
1
2
3
4
5

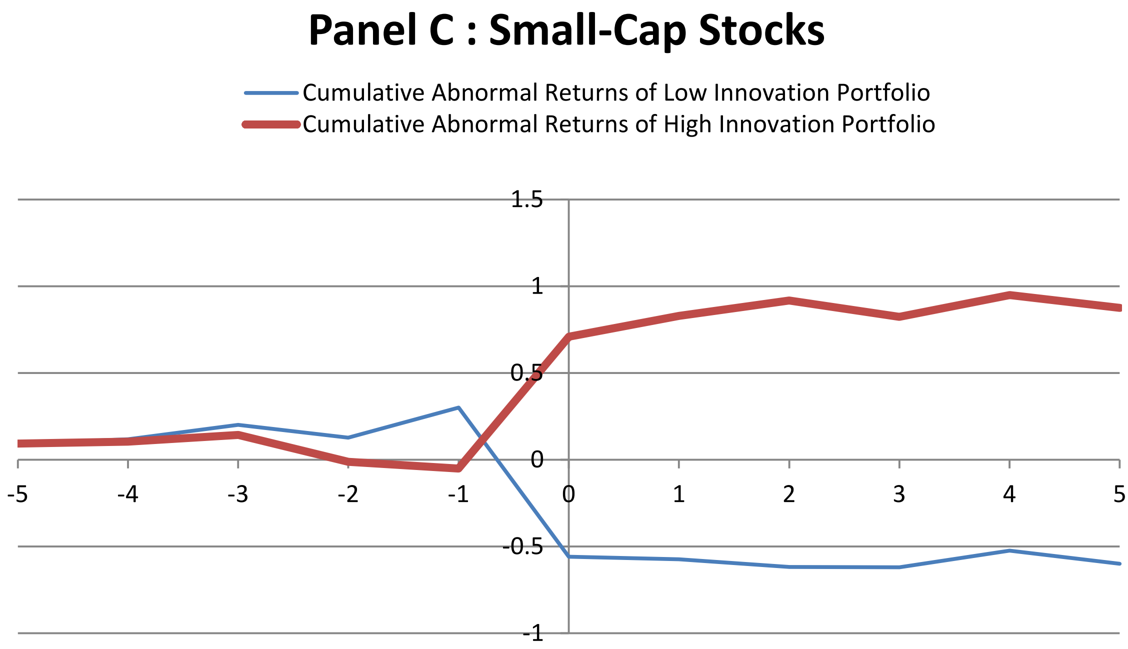
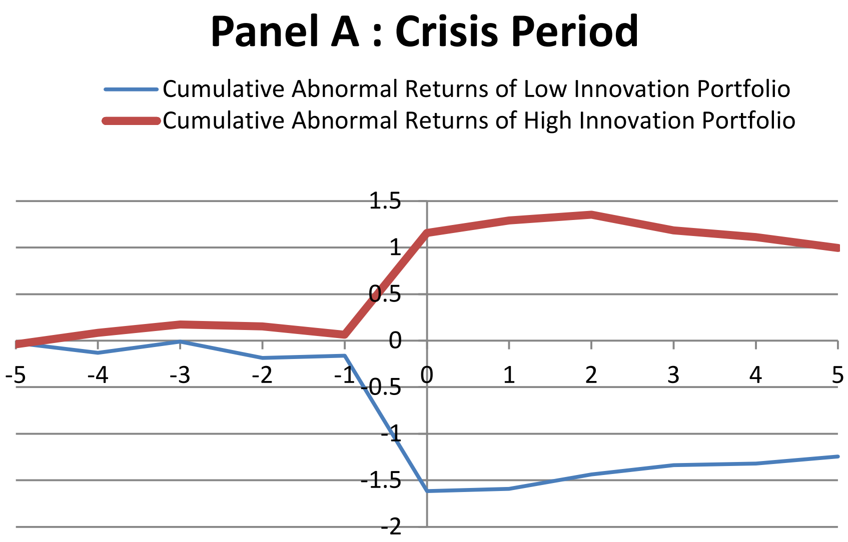

Panel C : Small-Cap Stocks
Cumulative Abnormal Returns of Low Innovation Portfolio
Cumulative Abnormal Returns of High Innovation Portfolio
1.5
1
0.5
0
-0.5
-1
-5
-4
-3
-2
-1
0
1
2
3
4
5

Figure 6

Cumulative Abnormal Returns around Shocks in FII Flows: Effects of the Recent Financial Crisis

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ($FII\_NET_{i,t}$), which is defined as the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total rupee value traded (across both FII and non FIIs) for the i^{th} stock on the t^{th} day. During the 2006-2011 period, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically on every Monday) and sorted into five quintiles. Panel A shows the cumulative abnormal stock returns for high and low innovation portfolios formed on the basis of innovations from panel regression during the crisis period (January to December 2008) and Panel B for the non-crisis period (excluding 2008: 2006-2011).



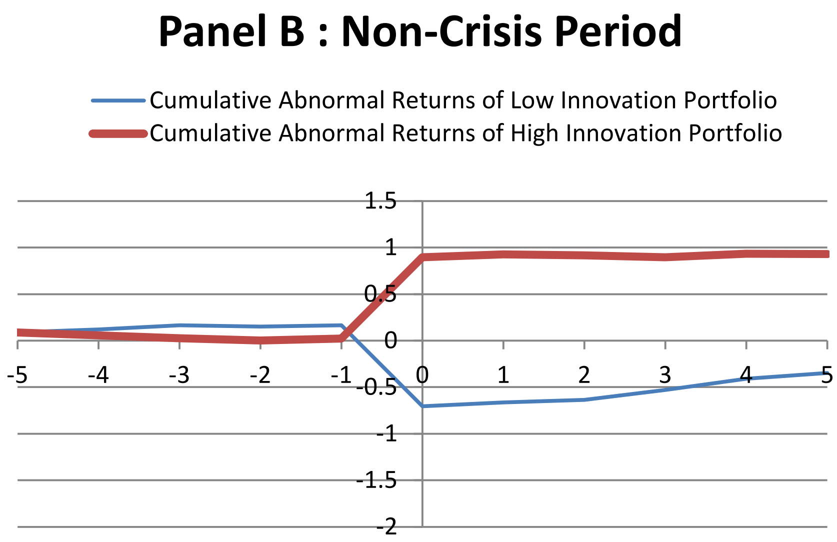


Figure 7

Cumulative Abnormal Returns around Shocks in FII Flows: High vs. Low CBOE VIX Days

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows (*FII_NET*$_{i,t}$), which is defined as the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total rupee value traded (across both FII and non FIIs) for the i^{th} stock on the t^{th} day. During the 2006-2011 period, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically on every Monday) and sorted into five quintiles. Panel A shows the cumulative daily abnormal stock returns of high and low innovation portfolios formed on the basis of innovations from panel regressions for high CBOE VIX level days and Panel B for low CBOE VIX level days.

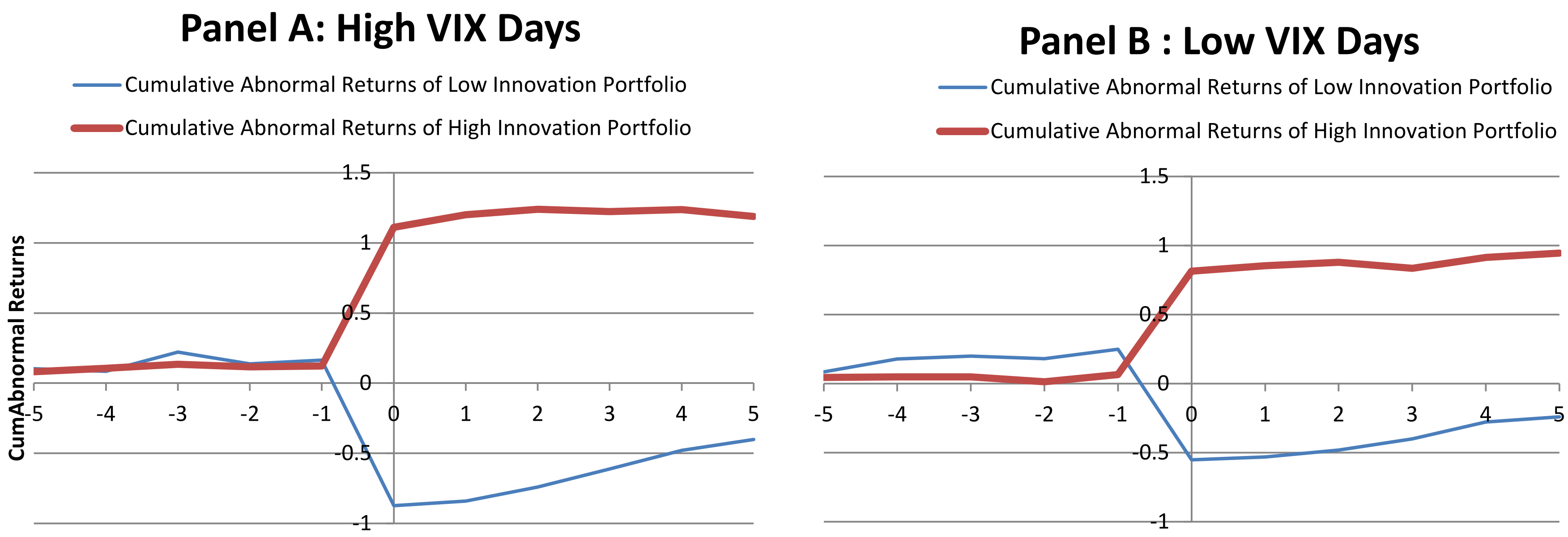
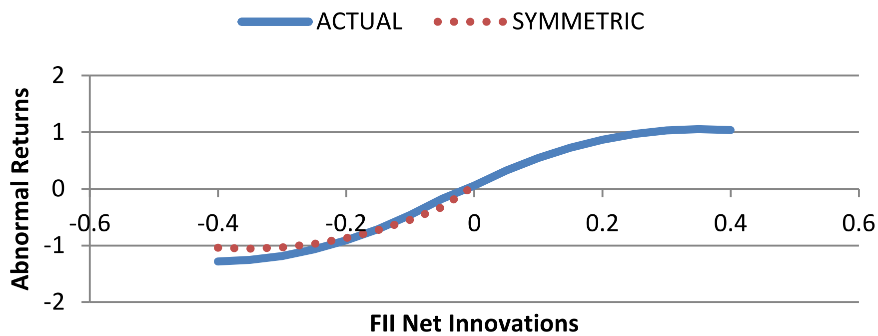


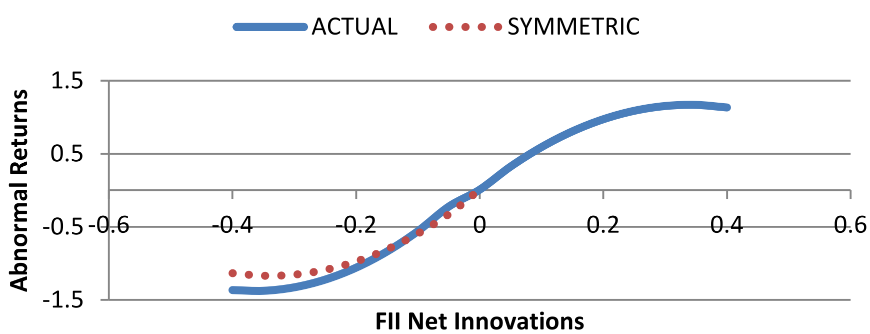
Figure 8
Asymmetric and Non Linear Effects of FII Flows

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows. This figure presents the sensitivity of abnormal returns to changes in FII net innovations, depicting a possible asymmetric impact, based on the regression results reported in Table 10. Panel A shows the sensitivity of abnormal returns for all stocks. Similarly, Panels B and C shows these graphs for high CBOE VIX level days and low CBOE VIX level days, respectively.

Panel A : All Stocks



Panel B : High VIX Days



Panel C: Low VIX Days

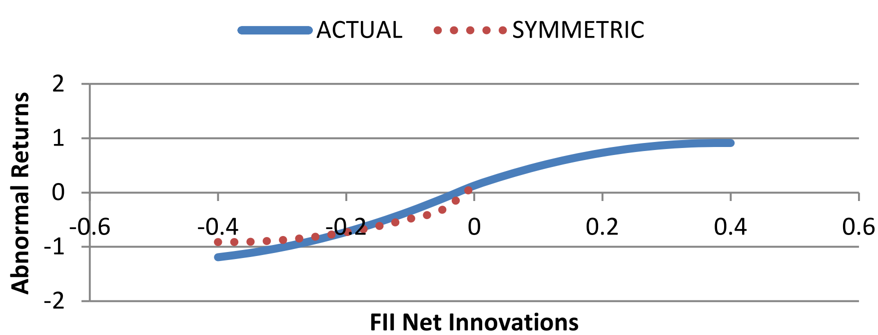


Figure 9
Net FII Portfolio Flows (Debt and Equity) during the Taper Tantrum Period (May – June 2013)

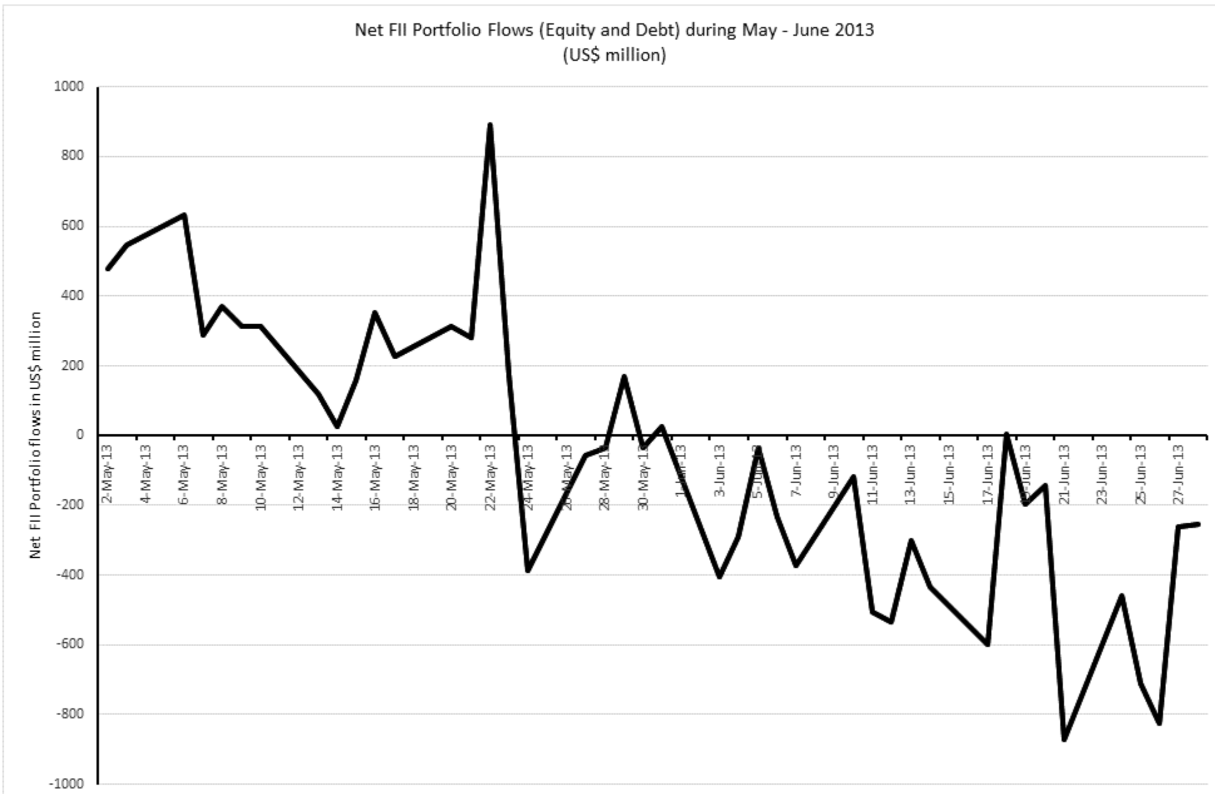
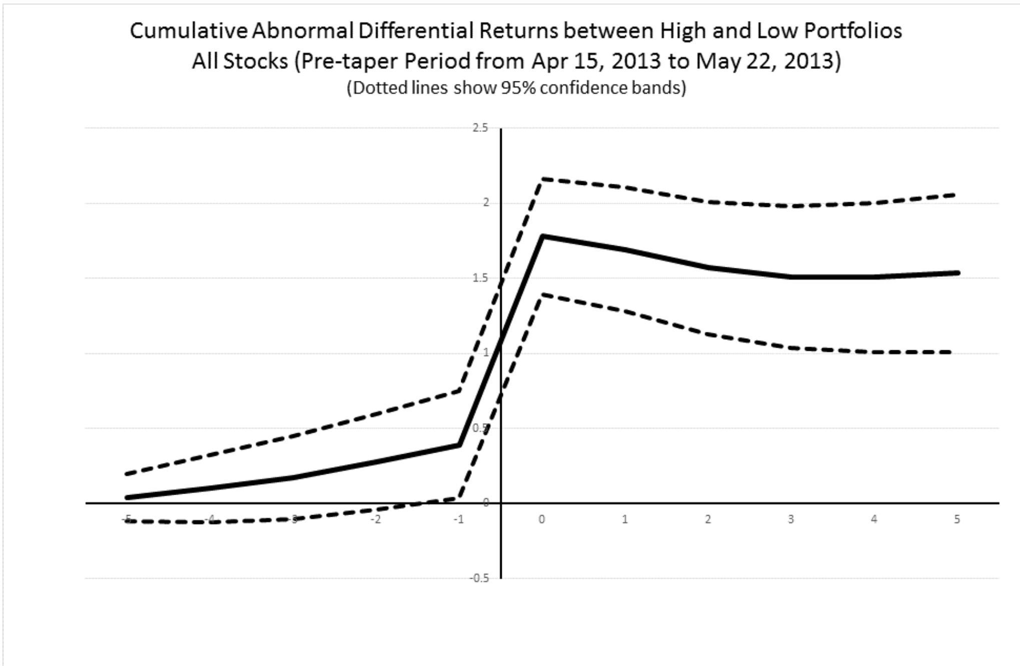


Figure 10
Impact of FII Flows during Taper Tantrum Period

Panel A: All Stocks (Pre-taper period)



Panel B: All Stocks (Post-taper Period)

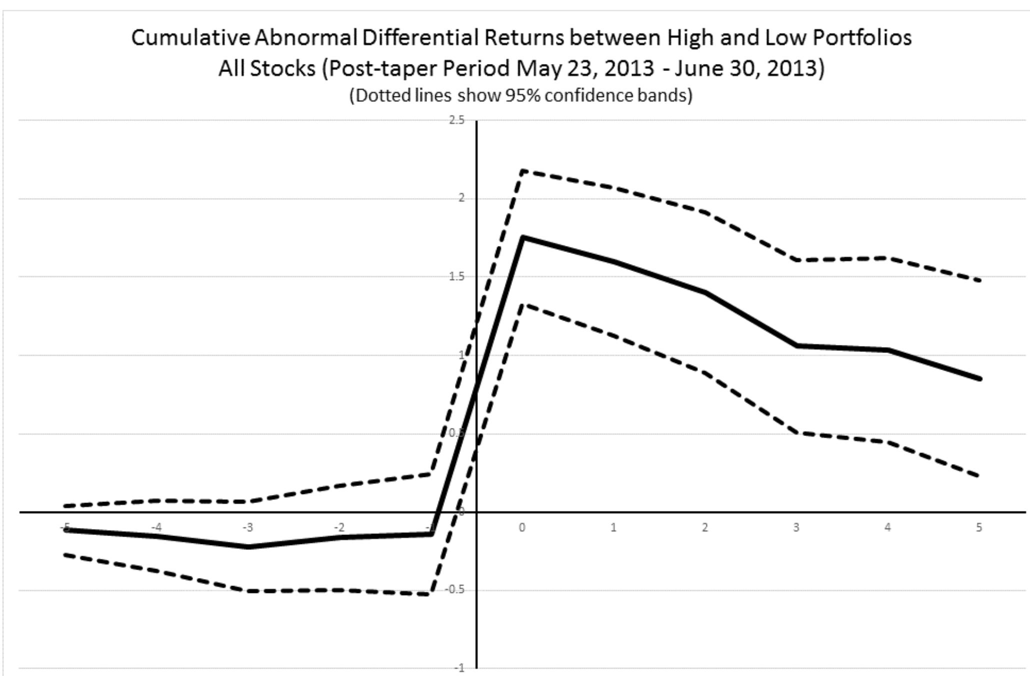
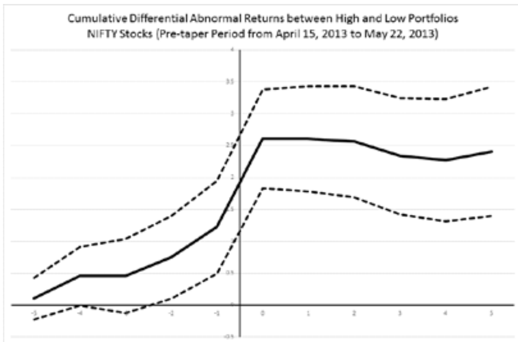
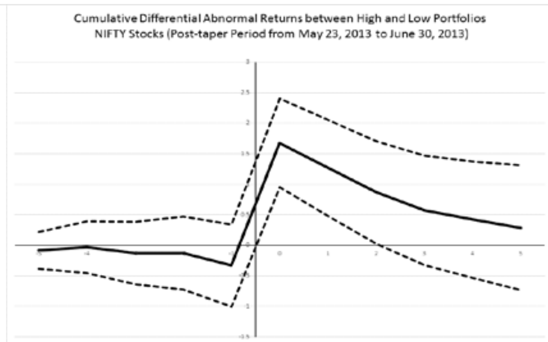


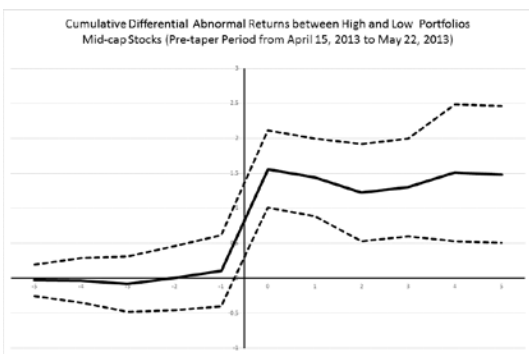
Figure 11
Impact of FII Flows during Taper Tantrum Period for Size Based Sub-samples

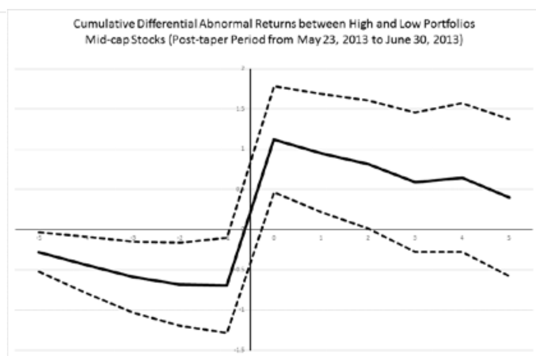
Panel A: NIFTY Stocks



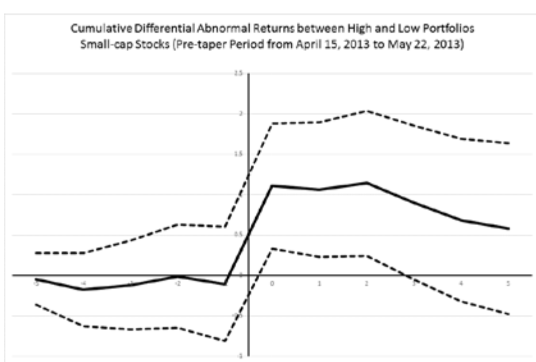


Panel B: Mid-cap Stocks





Panel C: Small-cap Stocks



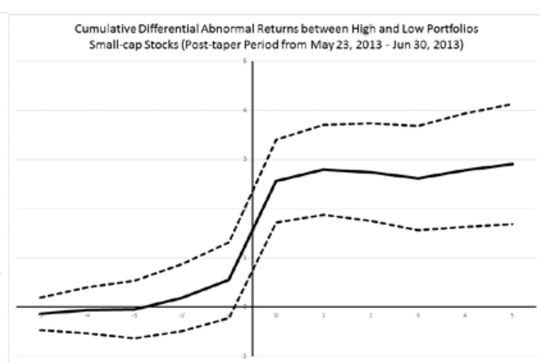


Table 1
Summary of Foreign Institutional Investor Trading Activity

This table presents a broad overview of FII trading statistics in Indian market during the study period. Column (1) reports the financial year, Column (2) shows FII net flows (buy - sell) in Indian markets in millions of dollars, while Column (3) reports the average percentage of FII ownership of firms listed on the Indian markets. Column (4) reports the daily average ratio of FII gross (buy + sell) flows to twice the total traded value for all firms in the sample, as well as separately for large-cap, mid-cap, and small-cap firms within the sample.

FIIs Flows

Financial Year	FII net flows[a] (In USD Million)	FII Ownership[a] (%)	Daily average ratio of FII gross flows to twice total traded value in sample firms			
			All	Large-cap	Mid-cap	Small-cap
(1)	(2)	(3)	(4)	(5)	(6)	(7)
2006-07	6,821	10.78	20.57	25.47	15.53	11.11
2007-08	16,442	10.62	23.18	28.18	17.99	13.80
2008-09	-9,837	8.40	19.02	21.24	15.45	8.74
2009-10	30,253	9.58	16.13	19.78	11.08	6.42
2010-11	32,226	10.32	21.32	24.99	16.85	9.99
2011-12	18,923	6.00	22.49	25.98	17.53	8.87
2012-13	18,377	6.00	22.68	27.70	15.61	7.15

[a] Source: NSE ISMR reports.

Table 2
Variable Definitions

RET_{it}	Daily continuous compounded return of the i^{th} stock, ln (P_t/P_{t-1}), where P_t is the adjusted closing price of stock *i* on day *t*.
AB_RET_{it}	Excess Return over the market return, defined from a market model regression.
$NIFTY\_RET_t$	Dailycontinuous compounded return on CNX NIFTY index on day *t*.
$S\&P500\_RET_t$	Daily continuous compounded return on S&P500 Index on day *t*.
$SIZE_{i,t}$	Market Capitalization of the stock *i* on day *t*.
$RUPEE\_VOLUME_{i,t}$	Total value traded for stock *i* on day *t.*
$FII\_BUYS_{i,t}$	Total rupee value of FII purchases for stock *i* on day *t.*
$FII\_SELLS_{i,t}$	Total rupee value of FII sales for stock *i* on day *t.*
$FII\_NET_{i,t}$	Difference between the *FII_BUYS* and *FII_SELLS* scaled by the total value traded across both FII and non-FIIs (*RUPEE_VOLUME*) for the i^{th} stock on day *t.*
$AB\_RET\ (t_1, t_2)$	Cumulative average abnormal returns for all the stocks in a portfolio on day *t* accumulated over the interval (t_1, t_2).
$AMIHUD\_ILLIQ_{i,t}$	Ratio of absolute return over traded value on day *t* for stock *i.*
$TOVER_{i,t}$	Ratio of total traded value to market capitalization.
LOCAL βETA	Slope coefficient of the *NIFTY_RET* in the market model regression estimated using 52 weekly returns prior to portfolio formation day *t.*
GLOBAL βETA	Slope coefficient of the *S&P 500_RET* in the market model regression estimated using 52 weekly returns prior to portfolio formation day *t.*
IDIO_RISK	Annualized standard deviation of residuals of the market model regression using 52 weekly returns prior to portfolio formation day *t.*
VOLATILITY	Annualized standard deviation of daily returns of the stock.
VIX (ΔVIX)	Change in CBOE VIX value.
IVIX (ΔIVIX)	India Volatility Index (Change in Indian Volatility Index).
NIFTY_VOLATILITY	Garman-Klass range based daily volatility estimate of NIFTY Index.
$AGGR\_FFLOW_t$	Aggregate FII flows, defined as the difference between total *FII_BUYS* and total *FII_SELLS* scaled by the total value traded on day *t* for all stocks.
$FII\_NET\_INNOV_{i,t}$	Residuals from fitting a firm fixed effects panel regression model to *FII_NET.*
PRE (POST)	Refers to the week before (after) portfolio formation day *t.*
PROMOTER_OSHP	Percentage of promoter shareholding.
INSTITUTIONAL_OSHP	Percentage of Institutional ownership in non-promoter shareholding.
RETAIL_OSHP	Percentage of retail ownership in non-promoter shareholding.

Table 3
Descriptive Statistics

This table presents descriptive statistics of the sample firms (223) listed on the National Stock Exchange (NSE) of India and the associated foreign institutional investor (FII) daily trading flows for January 1, 2006 to December 31, 2011. Panel A shows the firm characteristics. Panel B presents the relations with market-wide factors. See Table 2 for variable definitions Daily stock-wise FII flow data are obtained from proprietary data provided by the NSE. The other data are sourced from CMIE Prowess and www.finance.yahoo.com.

Variable	Mean	Median	Minimum	Maximum	Std. Dev.
Panel A: Firm characteristics					
RET (%)	0.02	-0.04	-20.00	20.00	3.04
SIZE (Rs. millions)	169777.89	52290.47	862.48	4681984.10	353766.20
RUPEE_VOLUME(Rs. millions)	412.66	145.23	4.77	6006.75	704.42
TOVER	0.38	0.16	0.00	70.60	0.99
PROMOTER_OSHP	51.48	52.32	0.00	90.41	19.04
INSTITUTIONAL_OSHP	36.07	34.81	4.17	93.59	16.08
RETAIL_OSHP	12.45	10.90	0.30	77.50	8.99
AMIHUD_ILLIQ	1.66	0.06	0.00	137.60	12.76
LOCALβETA	1.00	0.98	-9.61	9.63	0.48
GLOBAL_ βETA	-0.11	-0.08	-7.66	9.30	0.54
VOLATILITY (annualized)	47.06	47.08	22.56	72.14	9.43
IDIO_RISK (%)	36.16	34.13	0.00	86.18	12.42
Panel B: Market-Wide Factors					
NIFTY_RET (%)	0.0333	0.0886	-13.0142	16.3343	1.8537
S&P 500_RET (%)	0.0014	0.0669	-9.4695	10.9572	1.5712
VIX	23.37	21.18	9.89	80.86	11.20
ΔVIX (first difference in *VIX*)	0.0398	-0.3914	-35.0588	49.6008	7.3871
IVIX	26.64	24.66	15.22	56.07	8.25
ΔIVIX	-0.02	-0.05	-7.19	6.21	1.54
NIFTY_ VOLATILITY	21.11	16.99	4.29	165.57	14.60
AGGR_FFLOW	-0.0053	-0.0020	-0.2004	0.1821	0.0439
Panel C: FII Flows					
FII_BUYS (Rs. millions)	81.81	4.87	0.00	33788.04	272.99
FII_SELLS (Rs. millions)	84.28	3.83	0.00	23831.58	280.02
FII_NET	0.01	0.00	-0.95	0.95	0.22

Table 4
Panel Regression Model

This table reports the results of firm fixed effects panel regression of $FII\_NET_{i,t}$ on past *FII_NET* and past stock returns along with size and daily turnover of the firm and market-wide factors. The unbalanced sample includes 223 firms and 279,864 firm-day observations for the 2006-2011 period. The panel regression specification is as follows:

$$FII\_NET_{i,t} = FirmFEff + \sum_{j=1}^{5} FII\_NET_{t-j} + \sum_{k=1}^{5} \mathrm{Re}\,t_{t-k} + \delta_1 SIZE + \delta_2 TOVER + \delta_3 RETAIL\_OSHP_{t-1} + \delta_4 INSTITUTIONAL\_OSHP_{t-1}$$
$$+ \alpha_1 AGGR\_FFLOW_{t-1} + \alpha_2 VIX_{t-1} + \alpha_3 \Delta VIX_{t-1} + \alpha_4 NIFTY\_RET_{t-1} + \alpha_5 S\,\&\,P500\_RET_{t-1} + \alpha_6 NIFTY\_VOLATILITY_{t-1} + e_{i,t},$$

where *i* refers to stock *i* and *t* refers to day *t*; *FII_NET* is the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total value traded (across both FII and non FIIs); RET_t is the daily continuous compounded return of the stock; *SIZE* is the log of market capitalization; for other variable definitions, see Table 2. The table reports the coefficient estimates, along with time-clustered robust *t*-statistics. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

Variable	**Coefficient**	***t*-Statistic**
Intercept	-0.2601	-6.22***
FII_NET_{t-1}	0.2868	67.41***
FII_NET_{t-2}	0.1128	32.02***
FII_NET_{t-3}	0.0633	22.72***
FII_NET_{t-4}	0.0423	14.98***
FII_NET_{t-5}	0.0503	18.84***
RET_{t-1}	0.0012	6.46***
RET_{t-2}	0.0002	1.79*
RET_{t-3}	-0.0001	-0.78
RET_{t-4}	-0.0002	-1.17
RET_{t-5}	-0.0001	-0.67
$AGGR\_FFLOW_{t-1}$	0.1013	7.75***
SIZE	0.0109	6.70***
TOVER	-0.1062	-1.06
$RETAIL\_OSHP_{t-1}$	0.0017	4.22***
$INSTITUTIONAL\_OSHP_{t-1}$	-0.0005	-2.74***
VIX_{t-1}	-0.0003	-4.39***
ΔVIX_{t-1}	-0.0006	-6.59***
$NIFTY\_VOLATILITY_{t-1}$	-0.1371	-2.37**
$S\&P\ 500\_RET_{t-1}$	0.0006	1.34
$NIFTY\_RET_{t-1}$	-0.0001	-0.44
Adj. R^2	0.1929	
Durbin-Watson stat	2.0037	
F-statistic	277.4851	
N	279864	
Number of Firms	223	

Table 5
Abnormal Returns and Firm Characteristics around Portfolio Formation Day (Day 0)

This table reports the returns behavior of portfolios formed on the basis of FII flow innovations obtained from the panel regression model. During the period 2006-2011, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically on every Monday) and sorted into five quintiles. The mean estimate and *t*-statistics for the high innovation (Q5), low innovation (Q1) and the difference between the high and low (Q5-Q1) portfolios are reported.

Panel A reports the abnormal returns (*AB_RET*) – namely, excess returns over the market return defined from a (CAPM) market model regression – in the pre-formation window (-5, -1), the portfolio-formation day (Day 0), and the post-formation window (0, 5). Panel B reports the high (Q5), low (Q1) and the difference between the Q5-Q1 portfolios. See Table 2 for variable definitions. The number of stocks in the sample is 223. Newey-west standard errors are used with six lags to obtain *t*-statistics. *, **, and ***indicate that the estimate value differs from zero at significance levels of 0.10, 0.05, and 0.01, respectively.

PANEL A: Return behavior around the days of shocks in *FII_NET*

	Q1		Q5		Q5-Q1	
	Estimate	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
AB_RET (-5, -1) %	0.06	1.17	-0.00	-0.19	-0.08	-1.07
AB_RET (-1, 0) [Day 0 Returns] %	-0.93	-33.98***	0.88	31.60***	1.82	22.81***
AB_RET (0, 5) %	0.36	5.73***	0.04	0.62	-0.31	-4.76***

PANEL B: Firm characteristics	**Q1**	**Q5**	**Q5-Q1**	
Firm Characteristics	**Estimate**	**Estimate**	**Estimate**	***t*-stat**
PRE_RUPEE_VOLUME	402.18	390.25	-12.20	-0.95
POST_RUPEE_VOLUME	413.53	399.03	-14.50	-1.09
PRE_AMIHUD_ILLIQ	2.71	0.33	-2.38	-1.18
POST_AMIHUD_ILLIQ	0.34	0.26	-0.08	-1.25
PRE_SIZE	198241.00	196621.00	-1.62	-0.28
POST_SIZE	196357.00	199817.00	3.46	0.60
PRE_LOCAL_βETA	0.92	0.92	-0.00	-0.38
POST_LOCAL_βETA	0.91	0.92	0.00	0.73
PRE_GLOBAL_βETA	-0.09	-0.11	0.01	1.20
POST_GLOBAL_βETA	-0.10	-0.11	0.00	0.48
PRE_VOLATILITY (%)	2.29	2.29	0.00	0.38
POST_VOLATILITY (%)	2.37	2.33	-0.04	-1.94*
PRE_IDIO_RISK (%)	4.80	4.81	0.00	0.31
POST_IDIO_RISK (%)	4.79	4.80	0.00	0.28
PRE_ INSTITUTIONAL_OSHP	37.56	37.59	0.01	0.04
POST_ INSTITUTIONAL_OSHP	37.63	37.65	0.00	0.02
PRE_ RETAIL_OSHP	23.22	23.47	0.00	1.44
POST_ RETAIL_OSHP	22.95	23.25	0.00	1.73*

Table 6
Time Series Variation in Returns of Portfolios Based on FII Flow Innovation

This table reports the results of regressions relating the abnormal return (*AB_RET*) on day 0 for low (Q1), high (Q5), and difference between high and low (Q5-Q1) innovation portfolios (Y_t) to pre-formation firm-specific characteristics (X_t), and market-wide factors (Z_{t-1}). Firms are ranked according to innovations in *FII* flows at the beginning of every week (typically on every Monday) and sorted into five quintiles. Q5 refers to the high innovation portfolio and Q1 refers to the low innovation portfolio.

$$Y_t = \alpha_0 + \beta\, X_t + \gamma\, Z_{t-1} + \varepsilon_t.$$

The vector X_t includes mean of low and high innovation portfolio, mean difference between high and low quintile portfolio for pre-formation firm characteristics. See Table 2 for variable definitions. The sample consists of 285 weekly observations. The number of stocks in the sample is 223. The table reports coefficient estimates and time-clustered robust *t*-statistics. *, **, and ***indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	ABNORMAL RETURN on Day 0					
	Q1		Q5		Q5-Q1	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Intercept	-9.73	-2.60**	12.84	3.14***	0.97	7.77***
AMIHUD_ILLIQ	0.00	8.19***	0.06	2.39**	0.00	4.36***
Log(*RUPEE_VOLUME*)	-0.08	-0.52	0.60	3.08***	-0.20	-1.77*
Log(*SIZE*)	0.38	2.03**	-0.81	-3.90***	0.15	1.08
LOCAL_βETA	0.07	0.20	-0.72	-1.11	-0.10	-0.30
GLOBAL_βETA	0.03	0.15	-1.10	-2.29**	0.27	1.11
VOLATILITY	-0.10	-1.39	0.02	0.21	-0.09	-0.65
IDIO_RISK	0.04	0.59	-0.01	-0.26	0.18	1.13
$NIFTY\_RET_{t-1}$	0.13	4.60***	0.17	4.20***	0.06	1.99**
$S\&P\ 500\_RET_{t-1}$	-0.06	-1.56	-0.11	-1.39	-0.01	-0.14
VIX_{t-1}	-0.01	-1.15	0.00	0.02	0.02	3.41***
ΔVIX_{t-1}	-0.02	-1.90*	-0.01	-0.72	0.01	0.99
$NIFTY\_VOL_{t-1}$	-7.15	-0.71	1.32	0.14	32.70	3.95***
$AGGR\_FFLOW_{t-1}$	1.49	1.40	0.50	0.39	-0.81	-0.68
RETAIL_OSHP	0.00	-0.04	-0.06	-1.93*	-0.01	-0.29
INSTITUTIONAL_OSHP	0.02	1.20	-0.04	-2.36**	0.01	0.40
Adj. R^2	0.24		0.20		0.24	

Table 7
Size Effects

This table presents the differential abnormal returns between stocks experiencing high innovation in FII flows (excess purchases) and stocks experiencing low innovations in FII flows (excess sales). Firms are ranked according to innovations in *FII* flows at the beginning of every week (typically on every Monday) and sorted into five quintiles. Q5 refers to the high innovation portfolio and Q1 refers to the low innovation portfolio. Q5-Q1 refers to the differential abnormal returns between the Q5 and Q1 portfolios. The panels report mean value and *t*-statistics for the abnormal returns (*AB_RET*) on the high innovation (Q5), the low innovation (Q1) portfolios, and their (Q5-Q1) difference in the pre-formation window (-5, -1), the portfolio-formation day (Day 0), and the post–formation window (0, 5). The number of stocks in the sample is 223. The table reports mean estimates and robust Newey-West *t*-statistics, calculated with six lags.*, **, and *** indicate that the estimate value differs from zero at significance levels of 0.10, 0.05, and 0.01, respectively.

SIZE	**Q1**		**Q5**		**Q5-Q1**	
	Estimate	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Large-Cap						
AB_RET (-5, -1) %	0.12	1.47	0.11	1.39	-0.00	-0.08
AB_RET (-1, 0) [Day 0 Returns] %	-1.04	-23.33***	1.10	23.92***	2.14	30.43***
AB_RET (0, 5) %	0.64	6.63***	0.09	1.01	-0.53	-4.22***
Mid-Cap						
AB_RET (-5, -1) %	0.15	1.98	0.03	0.36	-0.13	-1.47
AB_RET (-1, 0) [Day 0 Returns] %	-0.88	-21.25***	0.83	20.44***	1.71	35.67***
AB_RET (0, 5) %	0.38	4.25***	0.10	1.20	-0.28	-2.95***
Small-Cap						
AB_RET (-5, -1) %	0.17	1.22	-0.17	-1.21	-0.34	-2.66***
AB_RET (-1, 0) [Day 0 Returns] %	-0.86	-13.53***	0.76	11.86***	1.62	23.47***
AB_RET (0, 5) %	-0.08	-0.53	0.13	0.82	0.21	1.33

Table 8
Impact of FII flows during Periods of Market Stress

This table presents the differential abnormal returns (*AB_RET*) between stocks experiencing high innovation in FII flows (excess purchases) and stocks experiencing low innovations in FII flows (excess sales) during periods of global market stress. Firms are ranked according to innovations in *FII* flows at the beginning of every week (typically on every Monday) and sorted into five quintiles. Q5 refers to the high innovation portfolio and Q1 refers to the low innovation portfolio. Q5-Q1 refers to the differential abnormal returns between the Q5 and Q1 portfolios. The panels report mean estimates and *t*-statistics for the abnormal returns (*AB_RET*) on the high innovation (Q5), low innovation (Q1) and the difference between high and low (Q5-Q1) portfolios in the pre-formation window (-5, -1), the portfolio formation day (Day 0), and the post–formation window (0, 5). Panel A reports the impact of the financial crisis on two sub-samples for the non-crisis and crisis periods. In Panel B, the sample is divided into days associated with high CBOE VIX levels (above its median) and low CBOE VIX levels (below its median). The number of stocks in the sample is 223. The table reports mean estimates and robust Newey-West *t*-statistics, calculated with six lags.*, **, and *** indicate that the estimate value differs from zero at significance levels of 0.10, 0.05, and 0.01, respectively.

Panel A: Impact of FII Flows - Financial Crisis

	Q1		Q5		Q5-Q1	
Non-Crisis Period	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
AB_RET (-5, -1) %	0.17	3.06***	0.02	0.49	-0.15	-2.39**
AB_RET (-1, 0) [Day 0 Returns] %	-0.82	-29.95***	0.86	32.00***	1.68	49.81***
AB_RET (0, 5) %	0.42	6.67***	0.15	2.43**	-0.28	-3.92***
Crisis Period						
AB_RET (-5, -1) %	-0.40	-2.35**	-0.16	-0.97	0.24	1.37
AB_RET (-1, 0) [Day 0 Returns] %	-1.45	-17.81***	0.97	10.34***	2.43	23.45***
AB_RET (0, 5) %	0.05	0.26	-0.46	-2.64***	-0.53	-2.65***

Panel B: Impact of FII Flows - VIX

	Q1		Q5		Q5-Q1	
High VIX days	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
AB_RET (-5, -1) %	0.00	0.04	-0.01	-0.15	-0.01	-0.14
AB_RET (-1, 0) [Day 0 Returns] %	-1.04	-25.52***	0.99	23.40***	2.02	40.59***
AB_RET (0, 5) %	0.40	4.34***	-0.01	-0.10	-0.41	-4.16***
Low VIX days						
AB_RET (-5, -1) %	0.14	2.13	-0.01	-0.11	-0.16	-2.00**
AB_RET (-1, 0) [Day 0 Returns] %	-0.80	-23.41***	0.75	22.68***	1.55	36.54***
AB_RET (0, 5) %	0.29	3.83***	0.10	1.30	-0.21	-2.30***

Table 9
Abnormal Returns and Commonality in FII Order Flow

This table reports the results of monthly regressions relating the abnormal return (Y_t) on Day 0 to pre-formation firm-specific characteristics (X_t), market-wide factors (Z_{t-1}), and the degree of commonality in FII trades (buys and sells, taken separately). *FII_TRDS_RSQ* captures the R-squared values in a stock-month regression of FII trades (*Buy/Sell*) on *aggregate* (*Buy/Sell*) FII trades across all stocks in the sample.

$$Y_t = \alpha_0 + \beta\, X_t + \gamma\, Z_{t-1} + \delta\, FII\_TRDS\_RSQ_{t-1} + \varepsilon_t.$$

The table shows results for the low (Q1) innovation portfolio, the high (Q5) innovation portfolio, and the difference between the abnormal returns of the high and low innovation (Q5-Q1) portfolios on the portfolio formation day. The vector X_t includes means of pre-formation firm characteristics. For variable definitions, see Table 2. The sample consists of 63 monthly observations for 223 stocks. The table reports coefficient estimates and time-clustered robust *t*-statistics. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

Parameter	Abnormal Return on Day 0					
	Q1		Q5		Q5-Q1	
	Estimate	*t* -stat	Estimate	*t*-stat	Estimate	*t*-stat
Intercept	1.65	0.27	22.60	1.89*	0.95	3.25***
AMIHUD_ILLIQ	-0.30	-2.34**	-0.02	-0.05	0.06	0.54
Log(*RUPEE_VOLUME*)	-0.32	-1.37	0.04	0.11	-0.01	-0.04
Log(*SIZ*E)	0.19	0.74	-0.76	-1.30	0.15	0.55
LOCAL_βETA	-0.85	-0.71	-1.46	-1.23	0.41	0.30
GLOBAL_βETA	-0.38	-0.54	-0.37	-0.30	0.10	0.11
VOLATILITY	-0.15	-0.92	-0.23	-0.76	0.09	0.23
IDIO_RISK	0.06	0.50	-0.01	-0.10	0.02	0.05
$NIFTY\_RET_{t-1}$	0.13	1.53	0.19	2.43**	0.17	2.50**
$S\&P\ 500\_\ RET_{t-1}$	-0.06	-0.61	0.14	1.15	0.10	0.76
VIX_{t-1}	-0.01	-0.54	0.01	0.85	0.02	1.51
ΔVIX_{t-1}	-0.02	-1.14	0.00	0.25	0.03	1.72*
$NIFTY\_VOL_{t-1}$	6.35	0.38	7.63	0.37	21.04	1.47
$AGGR\_FFLOW_{t-1}$	-0.97	-0.35	-0.95	-0.31	0.39	0.13
RETAIL_OSHP	-0.01	-0.13	-0.02	-0.25	0.06	1.21
INSTITUTIONAL_OSHP	0.04	1.25	0.02	0.35	0.04	1.71
$FII\_TRDS\_RSQ_{t-1}$	-2.29	-0.95	-2.82	-0.90	-4.72	-1.61
R^2	0.33		0.44		0.47	

Table 10
Asymmetric and Non-linear Effects of FII Flows

This table presents the evolution of price impact curve by regressing abnormal returns against FII innovations allowing for possible asymmetry and non-linearity. The following regression equation is estimated separately for all firms (ALL), for different size deciles (NIFTY, mid-cap, and small-cap), as well for days experiencing different levels of market stress (High VIX and Low VIX).

$$AB\_RET = \alpha_0 + \alpha_1 FII\_NET\_INNOV + \alpha_2 DUM + \alpha_3 FII\_NET\_INNOV * DUM + \alpha_4 SQ\_FII\_NET\_INNOV + \alpha_5 SQ\_FII\_NET\_INNOV * DUM + \square$$

In the above regression, *DUM*, is a dummy variable that takes value 1 for negative FII Innovations and a value of 0 for positive or zero FII innovations. See Table 2 for variable definitions. The table reports mean estimates and robust Newey-West t-statistics, calculated with six lags. *, **, and *** indicate that the estimate value differs from zero at significance levels of 0.10, 0.05, and 0.01, respectively.

	ALL firms		**High VIX Days**		**Low VIX Days**	
Abnormal Returns (AB_RET)	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
Intercept	0.06	2.01**	0.01	0.24	0.13	3.25***
FII_NET_INNOV	5.66	14.91***	6.82	12.41***	4.09	8.35***
DUM	0.10	2.48**	0.16	2.75***	0.01	0.25
*FII_NET_INNOV*DUM*	1.47	2.78***	1.64	2.15**	1.26	1.83*
SQ_FII_NET_INNOV	-8.03	-9.27***	-10.03	-7.97***	-5.32	-4.77***
*SQ_FII_NET_INNOV*DUM*	16.82	13.87***	21.58	12.44***	10.36	6.44***

Table 11
Robustness Checks

This table presents the differential abnormal returns and price impact between stocks experiencing high innovation in FII flows (excess purchases) and stocks experiencing low innovations in FII flows (excess sales). Firms are ranked according to innovations in *FII* flows at the beginning of every week (typically on every Monday) and sorted into five quintiles. Q5 refers to the high innovation portfolio and Q1 refers to the low innovation portfolio. Q5-Q1 refers to the differential abnormal returns between the Q5 and Q1 portfolios. The panels report mean value and *t*-statistics for the abnormal returns (*AB_RET*) on the high innovation (Q5), the low innovation (Q1) portfolios and their (Q5-Q1) difference in the pre-formation window (-5, -1), the portfolio-formation day (Day 0), and the post–formation window (0, 5). In Panel A, we re-define FII flow innovations on the basis of past cumulative innovations over the last five days. The pre-formation window relevant in this case is (-10, -5). In Panel B, we examine out-of-sample (January 2012 - June 2013) behavior of the panel regression model used to define FII flow innovations. FII flow innovations in the out-of-sample period are based on the panel regression model constructed from in-sample data over the 2006-2011 period. The number of stocks in the sample is 223. The table reports mean estimates and robust Newey-West *t*-statistics, calculated with six lags.*, **, and *** indicate that the estimate value differs from zero at significance levels of 0.10, 0.05, and 0.01, respectively.

	Q1		**Q5**		**Q5-Q1**	
	Estimate	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
Panel A: Cumulative innovation in FII flows						
AB_RET (-10, -5)%	0.15	2.40**	-0.08	-1.39	-0.24	-3.51***
AB_RET (-5, -1) %	-1.50	-27.26***	1.46	27.12***	2.96	45.44***
AB_RET (-1, 0) [Day 0 RET]%	-0.38	-13.02***	0.41	15.90***	0.79	23.89***
AB_RET (0, 5) %	0.48	7.80***	-0.00	-0.01	-0.49	-6.98***
Panel B: Out of sample data						
AB_RET (-5, -1) %	-0.10	-1.57*	0.14	2.26**	0.24	2.69***
AB_RET (-1, 0) [Day 0 Returns] %	-0.80	-24.68***	0.71	22.66***	1.51	33.49***
AB_RET (0, 5) %	0.30	3.62**	0.10	1.35	-0.20	-1.77*