Information and Price Pressure Effects of Unexpected Foreign Fund Flows*

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Abstract

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Abstract

We study the impact of foreign fund flows on asset prices using a dataset of Indian equity market returns. Stocks experiencing abnormally high innovations in foreign fund flows face a permanent price increase (an "information" effect), whereas stocks experiencing abnormally low (negative) innovations in foreign fund flows suffer a partly-transient price decline (i.e., both an "information" effect as well as a "price pressure" effect). The information effect is positively related to stock illiquidity and higher during periods of market stress, such as on high VIX days and during the crisis period. The price pressure effect is also positively related to stock illiquidity, but, surprisingly, not higher during periods of market stress.

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"*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.[1]

Studies in the field of financial economics have focused on the differential information possessed by foreign and local investors,[2] and the relative importance of the two sets of investors in explaining the relation between foreign fund flows and contemporaneous returns. Two key insights emerge from these studies. On the one hand, trading by foreign investors may help in price discovery if foreign investors have superior information in comparison to local investors (Grinblatt and Keloharhu (2000), Seasholes (2000), Dvořák (2005), Froot and Ramdorai (2008)), i.e., an "information" effect. On the other hand, foreign investors may be responding to economic shocks in their own markets; thus, trading by foreign investors may trigger spurious price movements in local markets, resulting in volatility spillover and contagion across markets (Calvo and Reinhart 1996, Forbes and Rigobon 2002),[3] i.e., a "price pressure" effect. This latter reasoning implies that foreign investors could, in some economic states impede, rather than facilitate, price discovery.

Given the contradictory predictions of these two insights, understanding the nuances of the foreign fund flow-return relation is critical. If foreign fund flows help discover prices, it would be interesting to uncover the underlying drivers of the information effect, i.e., exactly what information is being generated by foreign investors. In contrast, if foreign fund flows trigger excessive price deviations in local markets, it would be useful to quantify the magnitude and longevity of the price pressure effects and the firm characteristics that influence price

[1] 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.

[2] See Bohn and Tesar (1996), Brennan and Cao (1997), Froot, O'Connell and Seasholes (2001), and Hau (2001) for initial studies on this topic.

[3] Studies in international finance are closely related to our work. However, we discuss these studies separately in a later section because their focus has been on the larger context of all the varieties of cross-border capital flows: portfolio flows, banking flows, and foreign direct investment, whereas our focus is only on portfolio flows, and within this segment, only on equity flows. In addition, international finance studies often perform country-level analysis whereas we are examining foreign fund flows to one specific emerging market.

pressure effects. These findings would help regulators assess the tradeoffs involved in moderating capital flows from across borders.

Our study sheds light on this debate on how foreign fund flows affect asset prices. In contrast to previous studies based on longer horizon effects, we develop a simple, yet powerful, methodology to provide evidence on both the information effect and the price pressure effect at short-horizons. More importantly, we also identify the key firm characteristics and market conditions that drive both the effects.

Overview of the Study

We employ data on foreign fund flows to (and out of) India, specifically 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. In contrast to most of the earlier studies based on aggregate fund flow data, our analysis of *stock-level* foreign fund flow data allows us to detect specific firm characteristics that can explain the relation between foreign fund flows and local asset prices. We assess how stock returns differ between stocks experiencing foreign fund inflows and stocks experiencing foreign fund outflows on a given day, thereby controlling for any aggregate or common information affecting all stocks on that day.

We employ a "panel regression" approach in which we estimate FII flows at the stock level based on lagged firm characteristics, lagged 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 used to rank stocks each week, thereby forming high and low FII flow *innovation portfolios*.[4] We then analyze the returns of these portfolios in the pre-formation window (four days prior to portfolio formation day), on the portfolio formation day (Day 0), and in the five-day post-formation window (Day 0 to Day +5).

Assuming an efficient market, the information effect should be entirely captured in the Day 0 return, and the post-formation window (0, 5) should not show any patterns in prices. On

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

the other hand, market inefficiency can cause post-formation price patterns. Two situations may arise. First, overreaction due to price pressure can cause price reversals in the post-formation window (0, 5). Alternatively, underreaction due to incomplete information assimilation can result in price continuation in the post-formation window.

Figure 1 captures some of the key findings of our paper. Stocks with high innovations in FII flows are associated with a coincident (on the 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 transient and reverses in part within one week. The extent of reversal in the post-formation window (0, 5) is approximately 22% of the Day 0 abnormal returns of -1%. Thus, we find evidence consistent with an information effect when FIIs indulge in excessive purchases. There is no continuation or reversal in the post-formation window for high innovation portfolios implying that the buy-side is associated with a pure information effect. In the case of excessive sales, there is both an immediate information effect on Day 0 and a price reversal in the post-formation window, consistent with overreaction on Day 0 due to price pressure. We also find that the differential cumulative abnormal return between high and low innovation stocks persists over the five-day post-formation day window, and is significant, both statistically and economically (relative to stock return volatility).

We also ascertain that the difference in abnormal returns on Day 0 between the high innovation portfolio and the low innovation portfolio is not driven by differences in firm characteristics immediately prior to the portfolio formation procedure. Our portfolio formation procedure is robust and well-designed to capture the relation between returns and flows.

To further analyze the information effect, we decompose the abnormal returns on the portfolio formation day into overnight returns and during-day returns. We find that abnormal return differential between the high innovation stocks and low innovations stocks on the portfolio formation day is mostly driven by during-day returns. This finding strongly suggests that abnormal FII flows cause *contemporaneous* asset price changes, consistent with the view that trading, *per se*, is integral to information assimilation, as shown in French and Roll (1986)

for U.S. markets and by Gagnon and Karolyi (2009) for cross-market listed stocks.[5]

We find that large-cap and mid-cap stocks drive the overall sample behavior. In these sub-samples, abnormal FII purchases are information-based trades whereas abnormal FII sales are partly driven by information and partly driven by portfolio rebalancing motives that cause price pressure. In contrast, small-cap stocks experience a permanent price effect for the high innovation portfolio (as in the overall sample), but there is no price reversal for the low innovation portfolio. The absence of price reversal in small-cap stocks 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. Overall, our results suggest that larger stocks, being more liquid, would be more suitable for portfolio rebalancing, i.e., buy-and-rebalance strategies, whereas smaller stocks, being less liquid, would be more suitable for buy-and-hold strategies.

We then examined the impact of FII flows during periods of market stress. First, we find that FII outflows are more (adversely) influential during the global financial crisis period (January 1st, 2008 to December 31st, 2008). More interestingly, in stark contrast to the overall sample findings, there is a reversal associated with FII purchases but no reversal associated with FII sales. This finding suggests that, during the crisis period, there was an overall negative sentiment that not only mitigated the information effect associated with FII inflows, but also completely offset the price reversals caused by price pressure of FII outflows. In addition, we observe that the impact of FII flows (on Day 0 returns) is higher on days with high CBOE VIX levels as compared to days associated with low CBOE VIX levels. This finding suggests that there is a volatility spillover from the developed markets into emerging markets via the portfolio rebalancing channel, consistent with the conclusions in Forbes and Warnock (2012) and Rey (2015).

[5] French and Roll (1986) show that during day trading variance of returns is greater than overnight return variance and conclude that trading, per se, can generate information. Using a sample of cross-listed stocks, Gagnon and Karolyi (2009) find that transmission of short-horizon returns on high trading volume days are more likely to be transmitted across markets in stocks that face greater risk of informed trading, thus linking trading volume with information generation.

Next, we analyze the drivers of the information effect and the price pressure effect by analyzing the time-series trends in the difference between the Day 0 abnormal returns of the high and low innovation portfolios. This Day 0 differential abnormal return captures the returns on a long-short portfolio, which is long on high innovation stocks and short on low innovation stocks. It captures the economic significance of the information effect associated with unanticipated FII flows.

We relate the Day 0 differential abnormal return to the differences in the underlying portfolio firm characteristics and market-wide shocks in risk perception. We find that the Day 0 differential abnormal return is significantly positively related to the time-series variation in the differences in the underlying portfolio firms' global market beta and their sensitivity to foreign exchange rate risk. The first result suggests that local firms that are more sensitive to global risk factors react more steeply to innovations in FII flows, i.e., experience a greater information effect. This finding is consistent with the arguments in Albuquerque et al (2009) and Bae et al (2012), who point out that foreign investors provide a positive role in discovering information related to global cues. The second result suggests that firms that are more sensitive to foreign exchange risk (either through its direct impact or through the indirect impact of competition) experience a greater information effect due to foreign fund flows. In addition to the above firm characteristics, we find that differential abnormal returns are negatively related to the difference in underlying firms' illiquidity, potentially because foreign investors prefer holding more liquid stocks. The information effect is also positively related to the following market characteristics: lagged local market (*NIFTY*) returns, lagged local market volatility (*NIFTY_VOL*) and lagged global volatility (*VIX*).

To understand the determinants of the price pressure effect, we regress the abnormal returns in the post-formation window (0, 5) on firm characteristics and market variables. If there is overreaction on Day 0 due to the price pressure effect, we should observe price reversals in the post-formation window (0, 5). We find that stock illiquidity and percentage of retail ownership are the key determinants of the price pressure effect. The illiquidity result is consistent with the argument that price pressure created on Day 0 due to FII outflows is exacerbated in illiquid stocks. Consequently, price reversals, as measured by the differential

abnormal return over the post-formation window, are greater in illiquid stocks. More interestingly, we also find that there is a greater price pressure effect in stocks with higher retail ownership. This finding suggests that noise trading by retail traders may be driving overreaction on Day 0, resulting in price reversals in the post-formation window.

Finally, we examine the flow-return relation during the "taper tantrum" period as an out-of-sample test of the model's predictions.[6] We find that, as compared to normal periods, the returns of the high innovation and the low innovation portfolios are more significantly different in the post-taper period (May 23rd, 2013 to June 30th, 2013) than in the pre-taper period (April 15th, 2013 to May 22nd, 2013). The key source of the difference is that the transient portion of the price effects of FII flows is much more exaggerated in the post-taper period as compared to the pre-taper period, i.e., price pressure effects are greater in the post-taper period. In other words, the taper tantrum appears to have primarily induced a *greater amount* of non-information based FII flows, resulting in sharp temporary asset-price changes (overreactions) that were reversed subsequently, consistent with the country-level findings reported in Karolyi and McLaren (2017).[7]

In summary, we conclude that while FII outflows contribute to transient volatility (price pressure effect) for stocks experiencing the outflows, trading by FIIs also generates new information for both outflows and inflows (information effect). The information effect is positively related to stock illiquidity and higher during periods of market stress, such as on high VIX days and during the crisis period. The price pressure effect is also positively related to stock illiquidity, but, surprisingly, not higher during periods of market stress. Our study also shows that exposure to global risk factors (global market risk and foreign exchange rate risk) drive the information effect and retail ownership exacerbates the price pressure effect.

As suggested in Shleifer and Vishny (1997) and Gromb and Vayanos (2010), these results also imply "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); consequently,

[6] Sahay et al (2014) document a significant capital outflow in response to the taper announcement, accompanied by sharp revisions in asset prices across the world, especially in emerging markets.

[7] In related work, Karolyi and MacLaren (2017) find that unexpected flows into emerging markets in the post-tantrum period are positively related to the magnitude of the local market returns.

liquidity providers (in our setting, the local investors in Indian stock markets who purchase stocks being sold by the FIIs) earn excess returns in such states by taking advantage of subsequent price reversals. The profits from such strategies are contingent on retail ownership at the firm level. Furthermore, as in developed markets, in emerging markets too, trading, and FII trading, per se, contributes to the generation of information, especially information related to global cues and the forex rates. These relative effects of foreign fund flows must be balanced against each other while evaluating their desirability for emerging markets, and any consequent implications on the attractiveness of capital controls on both FII flows into and out of equity markets.

The rest of the paper is organized as follows. Section 1 stylized evidence of the flow-return relation at a descriptive level; we also review related literature to provide context to our work but place this discussion toward the end of document in Section 6. Section 2 describes the data, empirical methodology and testable hypotheses. Section 3 presents the key empirical findings. Section 4 presents robustness checks. In Section 5, we examine the price effects of FII flows during the taper tantrum period of 2013. Finally, after the related literature section, we conclude in Section 7.

1. Stylized Evidence on Flow-Return Relation

We also present some market-based evidence on foreign fund flows and the associated volatility (both short-horizon and long-horizon) in Indian equity markets. This evidence helps us uncover interesting stylized facts about the flow-return relation. Figure 2 highlights this issue in the context of long horizon price movements. It shows the relation between annual FII net inflows in 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[8] during the 2001-2013 period. FII net inflows were positive in all years except 2008-2009. However, 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

[8] The financial year in India runs from April 1 to March 31.

of the NIFTY is also much higher during this period in comparison to other years, lending support to the hypothesis that FII outflows induce volatility in emerging markets.

Next, we examine the relation between FII flows and price movements in the short-run. Figure 3 explores this issue by depicting the relation between FII flows and macro events in developed countries. We plot the average FII net flows and the CBOE VIX indicator on a *weekly* basis. A broader trend of a negative relation between FII net flows and CBOE VIX levels emerges during the 2008-2010 period.

Several events (shown in Figure 3) 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. 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 a key driver of FII flows, but also that FII flows are a critical channel of contagion between the U.S. markets and the Indian equity markets. In a similar vein, the flash crash in Indian capital markets on May 6, 2010 occurred shortly after a critical credit rating downgrade of Greece on April 27, 2010. Variation in FII flows is also driven by risk factors in the local Indian markets, as seen in the spikes in FII flows on November 26, 2008, when the Mumbai terrorist attacks occurred.

2. Data and Methodology

Foreign fund flows in and out of Indian stock markets are now a sizeable portion of market activity. Table 1 shows the annual FII net flows in dollars, FII ownership and FII gross flows as a percentage of total traded value during the 2006-2013 period. Cumulative net investment flows from foreign institutional investors (FIIs) exceeded USD 113 billion. FII gross flows accounted for about 20% of the daily traded share value. 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.

The data for analysis come from three sources. The first source is a proprietary data set of daily stock-wise FII trading (purchases and sales) 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. The 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.

Our sample consists of 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. This filter allows us to exclude stocks that are infrequently traded. The resulting sample consists of 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 (we require beta for abnormal returns calculations) 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 CNX NIFTY Index data series is used to measure broader 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 are used to capture the broad global market performance and the “risk appetite” of the global financial sector, respectively.

2.1 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:

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

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:

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

We define net FII flows 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*).

$$FII\_Net_{it} = \frac{FII\_BUYS_{it} - FII\_SELLS_{it}}{RUPEE\_VOLUME_{it}}, \quad (3)$$

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.[9]

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 return on the NIFTY Index is 0.0333%, and on the S&P 500 Index, is 0.0014%. 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. Finally, the mean FII ownership level was 24.55% in the sample.

[9] Some studies have used an alternative definition in which net FII trading is normalized by the sum of FII purchases and sales. However, since FII trading can vary significantly with size, normalization by overall trading volume, as used in our measure, better captures the economic significance of FII trading in that stock.

2.2 Empirical Design

2.2.1 Exchange Timings

A key source of information generation regarding global cues is the U.S. It is likely that the *information that triggers FII flows* is originating from the U.S., e.g., the Federal Reserve's policy announcements. We therefore consider the linkages between the U.S. financial markets and the Indian financial markets as a good representation for understanding how the flow of information is reflected in FII orders. Figure 4 shows the opening and closing time of NYSE/NASDAQ in the U.S. and the NSE in India, and the potential flow of information across the two exchanges. Given the time difference between India and the U.S., there is no time-overlap between the operations of the stock exchanges in these two countries. Moreover, there is a time gap of around 8 hours between the closing time on the NYSE and the opening time on the NSE the following day. This non-overlapping disjoint nature of operational times allows for cleaner identification of the information impact of an event in one country on the returns in the other country. After the close of trading in U. S. exchanges, there is sufficient time for assimilation of information before the markets open in India on the next day. FIIs, based in the U.S., would find it easy to react to events in the U.S. by altering the flow of funds to India on the next trading day. For immediate action, they would place their orders at the opening of trading on the next day. They could also use the entire trading session on the next day to strategically spread their orders over time.

2.2.2 Experimental Design

In this paper, we rely on a simple econometric procedure to infer the information content of FII flows. First, we estimate residuals (we refer to them as "innovations") from a panel regression model, which capture the average daily trading behavior of FIIs over the entire sample period (2006-2011). We then construct portfolios at the beginning of each week based on the innovation in FII flows. Finally, we examine the short-run performance of these portfolios and how it is related to innovations in FII flows.

This approach is described in Figure 5. The residuals from a panel regression model

define (daily) innovations in FII flows. The residuals, which measure *unexpected* FII flows, are used to form 5 quintile-portfolios every Monday (or the first trading day of the week).[10] The extreme tail portfolios are tracked over a 10-day window around the portfolio formation day, as depicted in Figure 5. We examine the abnormal return on these portfolios over a 10-day trading window centered on the day of portfolio formation (Day 0). The 10-day window also includes a pre-formation period over the (-5, -1) window and a post-formation period over the (0, 5) window. We estimate the cumulative abnormal returns of the extreme portfolios, i.e., the cumulative abnormal returns of the *HIGH innovation* and *LOW innovation* portfolios over the pre-formation (-5, -1) window, the portfolio formation day (-1, 0), and the post-formation (0, 5) window. These return measures are used to infer the impact of unexpected FII flows on stock prices.

2.3 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 model includes firm fixed effects. The control variables are related to firm characteristics and market factors. Firm characteristics include firm size (*SIZE*), stock illiquidity (AMIHUD) turnover (*TOVER*), and percentage of retail (*RETAIL_OSHP*) and institutional ownership (*INSTITUTIONAL_OSHP*) in the firm. To capture time-varying effects, we also include the following lagged market variables: aggregate FII flows (*AGGR_FFLOW*), volatility index (*VIX*), differences in the volatility index (*ΔVIX*), NIFTY Volatility (*NIFTY_VOLATILITY*) S&P 500 returns (*S&P500_RET*), and NIFTY returns (*NIFTY_RET*). The volatility index (*VIX*) and the market return variables capture the role of funding constraints. Aggregate FII flows (*AGGR_FFLOW*), defined as the aggregate of *FII_NET* over all stocks on a trading day, captures the commonality in FII flows. The model specification is described below:

[10] We examined other week-day choices for the portfolio formation day and find that the results of our study are qualitatively similar under these alternative choices.

$$FII\_NET_{i,t} = FirmFEff + \sum_{j=1}^{5} FII\_NET_{i,t-j} + \sum_{k=1}^{5} \mathrm{Re}t_{i,t-k} + \delta_1 SIZE_{i,t} + \delta_2 TOVER_{i,t} + \delta_3 RETAIL\_OSHP_{i,t-1} + \delta_4 INSTITUTIONAL\_OSHP_{i,t-1} + \alpha_1 AGGR\_FFLOW_{t-1} + \alpha_2 VIX_{t-1} + \alpha_3 \Delta VIX_{t-1} + \alpha_4 NIFTY\_RET_{t-1} + \alpha_5 S\&P500\_RET_{t-1} + \alpha_6 NIFTY\_VOLATILITY_{t-1} + e_{i,t}. \quad (4)$$

The above regression serves the purpose of a first-pass panel regression.[11] 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 FII flows.

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 portfolio rebalancing motives (rather than buy-and-hold motives) of FII traders.

The other variables with significant coefficients are market stress (*VIX*), the first difference in market stress (ΔVIX), aggregate FII flows (*AGGR_FFLOW*), and local NIFTY volatility (*NIFTY_VOLATILITY*). The coefficient on lagged S&P 500 returns is insignificant while the coefficient on lagged NIFTY returns is negative.

The residuals obtained from this panel regression (*FII_NET_INNOV*) are used as a proxy for surprises or innovations in FII flows. To ascertain the robustness of *FII_NET_INNOV*, we examine the association between concurrent returns and predicted component of flows (expected FII Flows based on the panel regression model). We find that the simple correlation is only 0.01609, which is economically insignificant (statistically

[11] We explored alternative specifications with and without firm fixed effects and time fixed effects. These variations turned out to be qualitatively similar.

significant at the 5 % level; however, given the large number of observations of approximately 240,000, a 5% significance level is quite weak). In contrast, we find that the correlation between concurrent returns and *FII_NET_INNOV* is significant (0.21). These statistics suggest that innovation in FII flows is a superior indicator of abnormal returns than predicted FII flows. We explore this relation further in the rest of our analysis.

2.4 Abnormal Returns

Abnormal returns for the i^{th} stock on day t are defined as excess returns over the expected returns obtained from a three-factor model (described below) using 52 prior weekly observations, i.e., $AB\_RET_{it} = RET_{it} - E(RET_{it})$ is defined as,

$$AB\_RET_{it} = RET_{it} - \beta_{iN} NIFTYRET_t - \beta_{iG} S\&P500RET_t - \beta_{iX} XRATE_t . \qquad (5)$$

The above specification accounts for the sensitivity of stock returns to local market risk (β_{iN}), global market risk (β_{iG}) and exchange rate returns (β_{iX}), where $XRATE_t$ is a proxy for risk exposure to foreign exchange rate fluctuations.[12] For our sample data, we find that the cross-sectional mean local beta (β_{iN}) is 1.00, the mean global beta (β_{iG}) is -0.11 and the mean exchange rate beta (β_{iX}) is -0.31.

2.5 Testable Hypotheses related to Fund Flows

If local market valuations are unaffected by cross-border fund flows, then under market efficiency, foreign fund flows should not influence local asset returns. The null hypothesis, stated below, reflects this line of reasoning. On the other hand, if foreign fund flows impact asset price formation, this effect can be captured by the abnormal returns on the portfolio formation day i.e., the Day 0 abnormal returns (information effect) and the post-formation window (0, 5) abnormal returns (price pressure effect). Thus, we propose two sets of hypotheses, one related to the information effect and the other relates to the price pressure effect.

[12] For robustness, we also define abnormal returns in terms of the usual market model, which includes only the local market factor, and we find that our results are qualitatively invariant to this alternative specification. Our results also hold for raw returns. All results reported in the paper refer to abnormal returns obtained from the three-factor model.

H1. (INFORMATION EFFECT) *Abnormal foreign fund flows reflect information-based trading; therefore, the price effects should be permanent.*

H2. (PRICE PRESSURE EFFECT) *Abnormal foreign fund flows reflect portfolio rebalancing requirements; therefore, price reversals should be transient.*

The null hypothesis is that abnormal foreign fund flows pose no systematic price effects, i.e., there should be no abnormal returns on the portfolio formation day (Day 0) and during the post-formation window (0, 5). The alternative hypotheses, as stated above, are developed further into testable empirical implications below. First, we begin with the *Information Effect Hypotheses*:

H1a. *The portfolio formation day (Day 0)* a*bnormal returns on the portfolio formation day (Day 0) abnormal returns should be significant and irreversible in the post formation window (0,5).*

H1b. *The portfolio formation day (Day 0) abnormal returns associated with foreign fund flows should be positively related to stock (il)liquidity*.

H1c. *The portfolio formation day (Day 0) abnormal returns associated with foreign fund flows should be positively related to market stress.*

H1d. *The portfolio formation day (Day 0) abnormal returns associated with foreign fund flows should be positively related to global market beta*.

H1e.*The portfolio formation day (Day 0) abnormal returns associated with foreign fund flows should be positively related to foreign exchange rate beta*.

Hypothesis H1a is the key hypothesis related to the information effect. There should be an immediate price effect on Day 0 that should not be subsequently reversed in the post formation window (0.5). Furthermore, it is likely that this effect would be exacerbated in illiquid stocks, as argued in Hypothesis H1b. We can also expect this effect to increase during periods of market stress when investors become more sensitive to fundamental information (Hypothesis 1c). For Hypotheses H1d and Hypothesis H1e, we build on the work by Albuquerque et al (2009) and Bae et al (2012), who establish that foreign investors play a

significant role in incorporating global private information. We postulate that the immediate impact of foreign investors should be more pronounced in stocks that are more sensitive to global markets conditions (hence, the global market factor). We also note that the Indian economy has over time become more integrated with the global economy and thus profitability of Indian firms should depend on the foreign exchange rate: the impact of foreign investors is likely to be greater in stocks that are more exposed to exchange rate fluctuations, directly (through exports/imports) or indirectly (through competition from firms that export/import). We, therefore, define abnormal returns based on a three-factor model: a local market index, a global market index, and the US $/INR exchange rate. Hypotheses H1c and H1d follow. Now, we turn to the *Price Pressure Hypotheses*, stated below.

H2a. *Price reversals reflecting price pressure effects, should arise during the post-formation window (0, 5).*

H2b. *Price reversals during the post-formation window (0, 5) should be positively related to stock (il)liquidity*.

H2c. *Price reversals during the post-formation window (0, 5) should be positively related to market stress.*

H2d. *Price reversals during the post-formation window (0, 5) should be positively related to percentage of retail ownership*.

H2e. *Price reversals during the post-formation window (0, 5) should be unrelated to global market beta and foreign exchange rate beta*.

First, we expect price reversal, as captured by the differential abnormal return in the post-formation window (0, 5), should be different from zero (Hypothesis 2a). To develop hypotheses related to determinants of the price pressure effect, we consider potential variables of interest. We expect price reversal to be greater in more illiquid stocks (Hypothesis H2b). If periods of market stress create more noise trading, then there would be a price reversal in the post formation window (0, 5). However, periods of market stress are given this label precisely because there is greater uncertainty about fundamental information. Therefore, we hypothesize that there will less price reversal in the post formation window during periods of market stress

(Hypothesis 2c). We also expect that a higher retail ownership may cause more noise trading leading to a greater overreaction on Day 0 and subsequent price reversal. Hypothesis H2d reflects this argument. Finally, we expect that information variables (global market beta and foreign exchange beta) should not matter in the post-formation window (0, 5) because their effects would be fully captured in the Day 0 abnormal returns. If the information effect is persistent, it should show up as a price continuation (if the market is inefficient and underreacts). However, any price reversal is purely an artefact of the overreaction on Day 0. Hypothesis H2e states this argument formally.

3. Empirical Analysis

3.1 Abnormal Returns Associated with Innovations in FII Flows

To assess the price effects of unexpected foreign find flows, we 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 shows the abnormal returns patterns for the portfolios with the lowest innovations (Q1) in *FII_NET* and the portfolio with the highest innovations (Q5) in *FII_NET*. We refer to these portfolios as the high innovation portfolio and the low innovation portfolio, respectively. *CAB_RET* (-5, -1) is the cumulative abnormal return over the (-5, -1) window, *AB_RET* (-1, 0) is the abnormal returns on the portfolio formation day (Day 0), and *CAB_RET* (0, 5) is the cumulative abnormal return over the (0, 5) window. The table also shows the difference in the abnormal returns of these two portfolios (Q5-Q1).

As can be seen in Table 5 (Panel A second row), the abnormal return over the (0, 1) window, *AB_RET* (-1,0), is economically and statistically significant. The abnormal return for the low innovation portfolio is negative (-0.99%), but for the high innovation portfolio it is positive (0.84%). The (abnormal) return difference between the high-low innovation portfolios (Q5 - Q1) is thus equal to an economically significant 1.83% that is also statistically significant (We refer to this difference as the Day 0 differential abnormal return and it serves as our proxy for the immediate Day 0 price impact). These findings indicate that FII inflows are associated

with a contemporaneous price appreciation and FII outflows are associated with a contemporaneous price decline.

It is possible that the differences in the portfolio returns arise due to differences in firm characteristics if our portfolio formation procedure is biased toward certain firms. Panel B in Table 5 presents details of the average firm characteristics of the high innovation portfolio (Q5) and the low innovation portfolio (Q1) as well as the difference between the average characteristics of the two portfolios. As one can see form the last column two, none of the pre-formation portfolio characteristics of the Q5 and Q1 portfolio are statistically significant. Only post-formation volatility and retail ownership are weakly statistically significant but economically insignificant (almost 0). These results provide confirmation that the difference in abnormal returns on Day 0 between the Q5 and Q1 portfolios is not driven by differences in firm characteristics. We can be reasonably assured that our portfolio formation procedure is robust and well-designed to capture the relation between returns and flows.

Next, we decompose the abnormal return on portfolio formation day into two components: the overnight return (based on the closing price on Day -1 and the opening price on Day 0) and the during-day return (based on the opening price of Day 0 and the closing price on Day 0). It is strikingly clear that the differential abnormal return on Day 0 is mainly driven by during-day differential abnormal returns (Table 5, third and fourth rows). The overnight returns are smaller and similar for both Q1 and Q5 portfolios and the differential abnormal *overnight* return of 0.04% is insignificant (both, statistically and economically). The *during-day* differential abnormal return of 1.81% is, however, significant.[13] The decomposition of abnormal returns into overnight returns and during-day returns thus strongly suggests that

[13] The open prices used to measure overnight returns in our sample may be stale, because they represent the first transacted price of the trading day. Give the priority given to time in executing order flow, a single trade may not be representative of a bunch of orders waiting to be executed at the open. The open price from a call auction procedure is likely to be more representative of the true price. Fortunately, in our sample period, the opening procedure was changed to a call auction procedure from 18th Oct. 2010 for a sub-sample of large cap stocks. To ascertain the impact of stale open prices, we examined overnight returns and during-day returns for this sub-sample of large cap stocks. We found that the results were virtually identical for this sub-sample, which covers the period Oct. 18th, 2010 to Dec. 31st, 2011 (the end points of the in-sample data). For instance, the overnight differential abnormal return (Q5 – Q1) was 0.0304% (t-statistic of 0.58), whereas the during-day differential abnormal return (Q5 – Q1) was 1.93% (t-statistic of 19.72). These numbers are comparable to the numbers reported in Table 7 for large-cap stocks over the entire in-sample period. We conclude that overnight returns and during-day returns are not affected by the stale price issue.

abnormal FII flows are influencing contemporaneous asset returns.[14]

In contrast to the positive differential abnormal returns (between high and low innovation stocks) on the portfolio formation day (Day 0), the differential abnormal return in the post-formation window (0, 5) is negative (-0.28%) and statistically significant.[15] The CAR in the post-formation window (0, 5) is significantly positive (0.27%) for the low innovation portfolio (Q1), but insignificantly negative (-0.01%) for the high innovation portfolio (Q5). This pattern indicates a reversal of prices in the post-formation window. However, there is significant reversal *only* for the low innovation portfolio. Thus, the statistically significant differential abnormal return of -0.28% 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 (-0.09%).

These results can be more easily seen in Figure 1, 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. The CARs in the post-formation period remain flat for the high innovation portfolio. However, for the low innovation portfolio, the CAR plot start rising in the post-formation 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* price pressure effects, which are reversed over the post-formation window. In other words, trade imbalances on the buy side and the sell side are associated with asymmetric effects, thereby confirming the claims in Hypotheses H1a and H2a,

[14] It is important to point out a caveat regarding this conclusion. We cannot be too sure about the direction of causality between flows and asset returns. It is possible that information contained in asset price changes induce abnormal FII flows, rather than the other way around. One requires intraday data to completely ascertain the direction of causality in this relation. It is likely that FIIs take clear views on their portfolio holdings at the close of trading in the U.S. and transmit their orders for execution in Indian stock exchanges in the immediately following trading session. Therefore, we are more inclined toward the hypothesis that abnormal flows drive asset prices.

[15] 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.

while rejecting the null hypothesis of no price effects. Note that the *differential* abnormal return on Day 0 and during the post-formation window (0, 5) are positive and significant (indicating that abnormal returns are related to the size of the innovations).

When we examine abnormal returns for the low innovation portfolio in Figure 1, we can see that slightly more than 27% of the abnormal return on Day 0 is reversed in the post-formation period.[16] Given that the volatility of a typical stock in the sample is around 47.06%, a return reversal of approximately 0.27% (over a 5-day window) indicates that the transient effect accounts for $0.27*\sqrt{(52)}/47.06$, or 4.14% of the annualized volatility of a typical stock.

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

We also replicate the portfolio formation procedure using predicted values of *FII_NET* (i.e., expected FII flows) instead of innovations in *FII_NET* derived from the panel regression model. We find that the differential abnormal returns between the high predicted FII flows portfolio and the low predicted FII flows portfolio on Day 0 is economically and statistically insignificant (-0.019% with a t-statistic of 0.51). This finding provides further credence to our empirical methodology of using FII flow innovations rather than raw FII flow to form portfolios. Filtering out the predictable component of FII flows allows us to make reasonable inferences about the marginal impact of FII flows on asset prices.[17]

[16] From Table 5, note that the Day 0 abnormal return is -0.99% and the reversal over the (0, 5) window is equal to 0.27%. Thus, approximately 27% of the Day 0 abnormal return is reversed within 5 days.

[17] We find that the pre-formation window (-5, 1) exhibits a high abnormal return differential of 3.18% (t-statistic of 45.81). This result is consistent with what we find in the panel regression model. *FII_NET* is found to be positively related to previous period returns, reflecting trend chasing behavior of FIIs. Thus, portfolios based on predicted FII flows are already skewed toward stocks that experience high past returns. By construction, the high predicted FII flow portfolio would contain securities that have performed well and the low predicted FII flow portfolio would consist of securities that have done poorly.

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 both 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.

3.2 Size Effect

FIIs have a strong preference for large cap stocks. In our sample, 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. It is likely that the price effects of FII flows depend on market capitalization.

To examine the role of market capitalization on the flow-return relation, 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 6 shows the differential abnormal returns between the high and low innovation portfolios by market capitalization. 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).

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%. In contrast, the mid-cap and small-cap stocks experience abnormal return differentials of 1.70% and 1.63%, respectively. Figure 6 presents the CAR plots across the (-5, +5) window. We can see that the

Day 0 differential abnormal returns on the high and low innovation portfolios are higher in the case of large cap-stocks, lower for mid cap-stocks, and the least for small cap stocks.

To compare with the earlier results, recall that in the overall sample, the high innovation portfolios are associated with a permanent price effect, whereas the low innovations portfolios experience both a permanent price effect as well as a partial reversal in the post-formation window. We find that, in large-cap and mid-cap stocks, the price effect for the high innovation is permanent, just as we found in the full sample. Inspecting Table 6, we can observe that the price reversal observed in the post-formation window for the low innovation portfolio is slightly greater for large-cap stocks (0.62%) than for mid-cap stocks (0.29%). 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 that result in price pressure.[18]

For small-cap stocks, there is a permanent price effect for the high innovation portfolio (as in the overall sample), but there is no price reversal for the low innovation portfolio. The absence of price reversal in small-cap stocks 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. Overall, the findings are consistent with the view 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.

Across all the panels, it is apparent that the Day 0 differential abnormal returns are mainly driven by during-day price changes rather than overnight returns. More interestingly, the importance of during-day returns is inversely related to size. Large cap stocks experience the greatest during-day differential abnormal returns on the portfolio formation day. This

[18] To compare the reversal in large cap stocks with the overall sample, we estimate the annualized reversal for large-cap low innovation stock portfolio. As can be seen in Table 6, the Day 0 abnormal return for the large-cap low innovation stock portfolio is -1.05%. The reversal of 0.62% amounts to 59.05% of the Day 0 abnormal return. In effect, the reversal upon annualization is equal to $0.5905*\sqrt{(52)}/47.06$, or 9.05% of the annualized standard deviation of a typical stock (for the overall sample, the equivalent number was 4.14%).

finding is not surprising given the fact that FIIs are more actively trading in large-cap stocks as compared to small-cap stocks. This evidence adds credence to our belief that its is FII trading that drives asset returns, rather than the other way around.

3.3 Market Stress

In this sub-section, we examine how global market stress affects the flow-return relation. One would expect that during uncertain times, global risk aversion may increase and trigger capital outflows in search of safe assets. One would expect that such capital outflows would adversely affect emerging market returns. This conjecture is borne out in the data. Figure 7 shows the time-series relation between the differential abnormal returns (between the high and low innovation portfolios) and lagged *VIX*.[19] The differential abnormal return series seems to move in unison with lagged VIX. As a preliminary check we estimate the time-series correlation between differential abnormal returns and lagged CBOE VIX. It is a statistically significant 0.3823. High CBOE VIX levels may be causing FII flows to be driven more by portfolio rebalancing than fundamental information, and therefore, leading to a greater differential abnormal return on the portfolio formation day (Day 0).

The global financial crisis provides an excellent opportunity to examine the influence of market stress on the price effects of unexpected FII flows.[20] 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 impacted the price effects of FII flows. Our conjecture is that the price effects of FII flows would be greater during the crisis.

3.3.1 Crisis Period Effect (H3a)

The financial crisis period is identified as the period from January 2008 to December 2008.[21] The remainder of the sample period is classified as the non-crisis period. We examine the

[19] 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.
[20] Fratzscher (2012) finds that the capital outflows from emerging markets to the U.S. were largely a flight-to-safety effect.
[21] 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.

abnormal return differentials between portfolios with high and low innovations in FII flows in both periods. Table 7 (Panel A) shows the results. The differential abnormal return between high and low innovation portfolios is much higher during the crisis period (2.40%) than in the non-crisis period (1.71%), i.e., there is a 40% greater impact of FII flows during the crisis period.

This evidence can be more easily seen in Figure 8. The magnitude of the Day 0 abnormal returns for the high innovation portfolio in the crisis period is comparable to that in the non-crisis period. However, the magnitude of the Day 0 (negative) abnormal return is significantly higher than in the non-crisis period. Thus FII outflows are more (adversely) influential during the crisis period. More interestingly, FII inflows are associated with price reversals but FII outflows are not associated with any price reversal – a result that is exactly the opposite to what we find in the overall sample. This finding suggests that, during the crisis period, there is an overall negative sentiment that completely offsets the price reversals associated with FII outflows and adversely affects the price effects associated with FII inflows.

3.3.2 High and Low Stress Days

Next, we divide the portfolio formation days into two groups: days associated with low CBOE VIX levels and days associated with high CBOE VIX levels. This procedure is useful in estimating the impact of the CBOE VIX on prices of high and low FII flow innovation portfolios. Table 7 (Panel B) and Figure 9 show the results, when the portfolio formation days are partitioned on the CBOE VIX. The abnormal return differential between high and low innovation portfolios is much higher during high *VIX* days than on low *VIX* days. The abnormal differential return on Day 0 is greater on days associated with a high *VIX* (2.03%), as compared to days associated with a low *VIX* (1.58%), which is more than a 28% difference.

To extend our analysis further beyond the univariate relations discussed in this sub-section, we now turn to a multi-variate analysis of the time series variation in differential abnormal returns.

3.4 Role of Firm Characteristics and Market Conditions

Having established that there are both permanent information effects and transient price pressure effects associated with innovation in FII flows, we now examine the role of differences in firm characteristics and market conditions in explaining the time-series variation in these effects.

To examine this issue further, we first compute the cross-sectional average of the differential returns (Y_t) between high and low innovation stocks on each portfolio formation day (Day 0), as in Table 8, and during the post-formation window (0, 5), as shown in Table 9. In these tables, we show the results of regressing Y_t 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, as shown below:

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

3.4.1 *Information Effect Hypotheses* (H2a/H2b/H2c)

Consider the analysis of the information effect as captured by the portfolio formation day (Day 0) abnormal returns reported in Table 8. From the baseline regression in Column (1), we can see that the time-series of the differential return on Day 0, (Q5 – Q1), is significantly positively related to the time-series of the Amihud illiquidity measure and lagged *NIFTY* returns as well lagged *NIFTY* volatility. These findings are along expected lines. The price effect is likely to be higher in illiquid stocks (relation with Amihud illiqudity measure); trend chasing behavior can explain the relation with lagged *NIFTY* returns; and finally, price pressure effects are larger during more volatile period (relation with laged *NIFTY* volatility).

3.4.1.1 Global Market Stress

In the second regression specification (see Column 2, Table 8), we add two variables which proxy for volatility in the foreign investor markets. We consider the lagged value of CBOE VIX Index as well as the lagged value of the first difference in CBOE VIX Index, which reflects the growth rate of VIX, i.e., the rate at which uncertainty in foreign markets is increasing (or

decreasing, as the case maybe). We find that the lagged value of CBOE VIX Index has a statistically significant coefficient, indicating that volatility from outside Indian markets affects price pressure effects in the Indian markets. This finding echoes recent literature on volatility spillover effects of cross-border capital flows (Forbes and Warnock (2012), Rey (2015)). The coeffcient on the change in VIX variable is however insignificant, indicating that only the first lag of VIX matters and higher order lags of VIX are unimportant.

3.4.1.2 Globally Determined Firm Characteristics

First, we confirm Hypothesis H2a by noting that the Amihud illiquidity measure shows a positive coefficient in all the columns. Next, we consider adding two globally determined firm characteristics, as postulated in Hypotheses H2b and H2c. In the regression specifications in Columns (3) - (4), we first add global market beta (*GLOBAL_βETA*), then exchange rate beta (*XRATE_βETA*) to the regression specification in Column (2). Each firm characteristic is considered in isolation (without including the other two firm characteristics) in these regressions. We find that, differential abnormal returns are weakly related to global market beta and more strongly related to exchange rate beta, when each firm characteristic is added in isolation.

Finally, in the regression specification in Column (5), we include all the three firm characteristics together. We find that there is a relation between differential abnormal returns and global market beta (positive, significant at the 5% significance level). With exchange rate beta, the relation is positive and significant at the 1% significance level. Furthermore, the R-sq. values in the regression specification show an increasing trend (from 25% in Column (1) to 32% in Column (5)), indicating that there is an improvement in the explanatory power when we include these firm characteristics in our regressions. The import of these findings is that price effects are stronger in firms that are more integrated with global markets and thus more exposed to global market risks and foreign exchange rate risk. The positive relation with global market beta and exchange rate risk is consistent with the narrative that differential abnormal returns increase with risk (confirming Hypotheses H2b and H2c). It is also interesting to note that the intercept is statistically significant and positive, indicating that even after controlling

for the time-series variation in these variables, going long on a high innovation portfolio and short on a low innovation portfolio provides a positive alpha.

In summary, the differential abnormal return between high and low innovation stocks is significantly related to the time-series variation of the following firm characteristics: global market beta (positive relation) and foreign exchange rate beta (positive relation), and stock illiquidity (negatively relation). These relations are exacerbated during periods of global and local market stress (positive relation). Nevertheless, being exposed to these risks is rewarded by the market in the form of an alpha, as reflected in the average value of the abnormal return differential.

3.4.2 *Price Pressure Effect Hypothesis* (H3a/H3b/H3c)

Table 9 show the results of the time series regression of the cumulative differential abnormal return in the post-formation window (0, 5). This analysis helps us identify the firm and market characteristics that determine the price pressure effect. We find that the price pressure effect is positively related to stock illiquidity and the percentage of retail ownership. The illiquidity hypothesis (H3a) follows from the argument that price pressure created on Day 0 due to FII outflows is exacerbated in illiquid stocks. Consequently, price reversals, as measured by the differential abnormal return over the post-formation window, is greater in illiquid stocks. This finding confirms Hypothesis H3a.

More interestingly, the results in Table 9 also indicate that stocks with greater retail ownership are more prone to experience greater price reversals, consistent with Hypothesis H3b. There is a greater price pressure effect in stocks with higher retail ownership. This finding suggests that retail trading may be driving overreaction on Day 0, resulting in price reversals in the post-formation window. It is also interesting to note that price reversal in the post-formation window (0, 5) is unrelated to risk factors (local/global market beta and foreign exchange beta), confirming Hypothesis H3c. This finding confirms that information effects are fully captured in differential abnormal returns on Day 0.

4. Robustness Checks

Our results are to robust to several variations in the empirical tests. More specifically, our results are qualitatively similar when we (i) use raw FII flows instead of innovations in FII flows, (ii) conduct the portfolio formation procedure on days of the week other than Monday, (iii) use a standard market model instead of the 3-factor model presented in this study, and (iv) try a different variation of the panel regression model without firm fixed effects. Besides these basic checks, we also performed more elaborate robustness checks. We summarize below the results of these robustness checks (for the sake of brevity, the discussion below is just a summary of the findings; the complete results with tables and figures appear in a separate online appendix).

4.1 Alternative Measure of FII Flows

We test the robustness of our findings to an alternative specification of the FII flow measure. In the measure used in the paper, the daily trade imbalance (FII purchases less sales) is scaled by daily trading value (rupee volume). One potential problem is that spurious results may arise purely due to variations in the scaling variable, daily trading value (rupee volume). In the alternative FII measure, we use daily shares outstanding, a time-neutral variable, as the scaling variable. Overall, the qualitative nature of the abnormal returns pattern for this alternative measure is like our earlier findings.

4.2 Impact of Derivatives Trading

Next, we consider whether the presence of derivative contracts affects information flows to the spot market, and consequently FII flows in the spot market. We find that there is no qualitative difference in the results between stocks associated with derivative contracts and stocks for which derivative trading is not allowed.

4.3 Parametric Analysis

As an alternative to the non-parametric approach of using tail portfolios, we employ a parametric approach to infer the price effects of FII flows on asset returns. We estimate the

asymmetric and nonlinear price effects associated with positive and negative innovations in FII flows. Overall, these results match the findings from the non-parametric approach used in the paper.

4.4 Cumulative Innovations based Portfolio Formation

We recognize that FII flows may be persistent and therefore we redefine our portfolio formation criterion in terms of cumulative innovations in FII flows over the previous 5-day period rather than in terms of the concurrent FII innovation. The results are qualitatively similar to earlier findings because FII flow is known to exhibit strong persistence. However, the differential abnormal return on Day 0 is 0.82%, somewhat lower than the 1.83% 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.

4.5 Commonality in FII trading

Another issue is commonality in FII trading. 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. We find that while there is commonality in FII flows, 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.

4.6 Out-of-sample Analysis

We validate the panel regression model using out-of-sample data during the period from January 2012 to June 2013. We find that our results are qualitatively similar in out-of-sample data. Overall, these additional checks assure us that the key findings of this study are robust.

4.7 Foreign Ownership Restrictions

Finally, we explore whether foreign ownership restrictions play a role in determining abnormal returns. This concern may arise in situations in which the FII ownership level is close to the government-imposed limits. FII ownership in each sector of the economy is restricted to certain limits imposed by the government of India. Under the existing rules, all categories of foreign investments such as portfolio flows (FII flows), foreign direct investment (FDI) and non-resident Indian (NRI) investments are clubbed into a single category for the purposes of calculating sectoral caps ("composite cap") for different sectors in the economy. These sectoral caps are revised infrequently. Each firm has the liberty to set its preferred maximum allowable level of FII ownership, so long as it is below the government-imposed sectoral cap applicable to the firm. For this purpose, the firm's management must pass a board resolution to set the limits on FII ownerships in its stocks. The trend in the last decade has been a general increase in sectoral caps, thereby allowing for greater FII ownership.

We were unable to get reliable data on the time-series of changes in firm caps on FII ownership to help us examine the relation between differential abnormal returns and foreign ownership restrictions. However, the limited evidence (we could gather) seems to suggest that firms proactively increase these limits when they see FII demand growing but such revisions are also infrequent, suggesting that ownerships restrictions are less likely to be binding in most situations. Furthermore, the Reserve Bank of India (RBI), which monitors foreign ownership on a day-to-day basis, enforces a 2% caution cutoff – in essence, when foreign ownership reaches a level within 2% of the allowed limit, FIIs must explicitly seek permission from the RBI to trade in the firm's shares. There may be stray cases in which FII ownership limit is binding, but we believe that most of the sample data is free of these constraints, and the abnormal returns we calculate are robust to this consideration.

5. 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, on May 22nd to be precise, the Federal

Reserve announced its intention to undertake measures to tighten the money supply by tapering the bond purchase program put in place post-2008. Sahay et al (2014) document a significant "taper tantrum" in the form of capital outflows from high risk asset classes to safe asset classes. Not surprisingly, these capital outflows were 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 10. Net portfolio flows (including both debt and equity markets) swung from a peak of $800 million to -$800 million in the aftermath of the taper announcement.

The "taper tantrum" phase provides us with an opportunity to evaluate how FII flows affected asset prices during the taper-tantrum period; were the flows as informative in the post-taper period as in the pre-taper period, or were they largely driven by non-information-based motives such as portfolio rebalancing by the FIIs?[22]

We partition the taper tantrum period into two periods: a pre-taper period (April 15th to May 22nd) and a post-taper period (May 23rd to June 30th). We employ a more updated in-sample period, using the data from Jan 1, 2006 until April 15th, 2013 to build the panel regression model, which is then used to estimate the innovations in FII flows in the pre-taper and post-taper periods.[23] As was done earlier, we form portfolios based on FII innovations and examine the difference between the returns of the high innovation portfolio and the low innovation portfolio (Q5-Q1). The portfolios are constructed at the beginning of every week and we track the differential abnormal returns. We focus on differential abnormal returns rather than separately tracking the abnormal returns for high and low innovation portfolios (as we did in the in-sample analysis) because the taper period is likely to be associated with significant shifts in risk premium that may render the abnormal return estimation invalid. However, the

[22] 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."

[23] For the earlier analysis, the in-sample period was from Jan 1st, 2006 to Dec 31st, 2011, and out-of-sample data was from Jan 1st, 2012 to June 30th, 2013.

differential abnormal return is less likely to be affected by a shift in risk premium as its effect gets cancelled due to differencing.

The differential abnormal return CAR plots are shown in Figure 11.[24] Panels A and B of Figure 11 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 significantly more than in the pre-taper period. In fact, the positive Day 0 differential abnormal return is reversed quickly; the lower arm (dashed line) of the 95% confidence band hits the x-axis within 1 day.

Upon examining the abnormal return plots in the post-taper period for Q1 and Q5 separately, we find that the high innovation portfolio is associated with only a small positive return on Day 0 followed by significant negative returns over the next five days. On the other hand, the low innovation portfolio is associated with a sharp negative Day 0 followed by further negative returns over the next five days. The negative returns of the high innovation portfolio surpass the negative returns of the low innovation portfolio in the post formation window (0, 5). Thus, the differential abnormal return over the post-formation window (0,5) shows significant reversal. These findings suggest that the negative sentiment in the post-taper period swamp the abnormal return trends normally associated with FII inflows.[25]

Overall, this analysis implies that the taper tantrum of May 2013 primarily produced non-information based FII flows for Indian equity markets, resulting in temporary price effects that were followed by significant price reversals.

[24] For completeness, we also constructed the CAR plots for the high and low innovation portfolios separately and found them to be qualitatively like the plots for the in-sample period.

[25] The pre-taper plots for the high innovation portfolio show a small Day 0 positive effect, which is partially reversed. The low innovation portfolio has a high negative permanent effect and there is no reversal. These patterns are closer to the crisis period sub-sample CAR plots, suggesting that the risk perceptions were adversely trending in the weeks before the taper announcement.

6. Related Literature

6.1 Pull/Push Framework

Our study's findings are closely related to a large body of literature on the determinants of cross-border capital flows in the field of international finance. Researchers have classified cross-border flows into three categories: (i) portfolio flows, (ii) foreign direct investment, and (iii) banking flows. A widely used framework to identify the drivers of cross-border flows is the push/pull framework suggested in Calvo, Leiderman and Reinhart (1993) and Fernandez-Arias (1996). This framework highlights the relative importance of the local economy's "pull" factors in comparison to external "push" factors in explaining capital flows (and thereby, asset price formation in the local economy).

Push factors could be factors such as global risk aversion or output shocks in the foreign economy, whereas pull factors could be similar factors that are specific to the local economy. The broad conclusion from the extant literature is highly nuanced; the answer depends on the type of capital flows (portfolio flows, foreign direct investment (FDI), or banking flows) and the type of push factor (risk aversion, output shock or interest rate shock) or the type of pull factor (local country risk perception or local country output shocks). In general, both push and pull factors affect asset returns. [26,27]

In our study, we focus on one component of cross-border capital flows - portfolio flows from outside India into the Indian equity markets and analyze their impact on short-term equity returns. The price discovery (or information assimilation) and the "price pressure leading to a price reversal" channels that we unearth can also be viewed from the alternative perspective of push factors vs. pull factors, as discussed above. To elaborate, price discovery can arise either due to push factors (foreign investors impounding information into local asset prices) or pull factors (local investors playing the dominant role in information assimilation). Likewise, price

[26] For a comprehensive review of the literature in this field, see the survey by Koepke (2015).

[27] In addition to the financial channels, some studies have also tried to unravel the dynamics by which push and pull factors cause propagation of shocks, i.e., contagion or transmission of economic shocks across borders through nonfinancial channels, e.g., global trade flows and regional integration channels arising due to geographic and cultural proximity (See Calvo and Reinhart 1996, Forbes and Rigobon 2002, and Gelos (2011)).

effects can also arise both due to foreign economy-wide push factors as well as local economy-wide pull factors, such as risk aversion and output shocks.[28]

6.2 Recent Work on Fund Flows and Price Effects

Recent work that is more directly related to our research includes the studies of Coval and Stafford (2007), Frazzini and Lamont (2008), Froot and Ramdorai (2008), Jotikasthira, Lundblad, and Ramdorai (2012) and Lou (2012). These authors examine the impact of fund flows on asset pricing over longer horizons and their overall conclusion is that price pressure due to fund flows can cause temporary deviations of stock prices from fundamental values, followed by reversals over time.

Froot and Ramdorai (2008) show that lagged (weekly) foreign fund predict future local market returns; more importantly, they find that this relation is largely driven by an information effect rather than a price pressure effect. Our study explores this issue using daily measures that allow us to isolate short-run information and price pressure effects more precisely. In addition, we are interested in the cross-sectional determinants of the information and price pressure effect. Thus, our study adds to existing debate on how foreign fund flows affect asset price formation.

Coval and Stafford (2007) show that sudden increases (decreases) in quarterly 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. Frazzini and Lamont (2008) find that mutual fund flows reflect retail investor sentiment and high inflows are associated with lower future returns. Jotikasthira, Lundblad, and Ramdorai (2012) report that asset fire sales in the developed world affect fund flows to emerging markets.

[28] At the individual firm level, the tug-of-war between push and pull factors manifests itself as an information asymmetry effect between foreign investors and local investors. For instance, if a local firm's stock price is known to be affected by global risk aversion (a push factor), it is possible that foreign investors may have superior information about changes in global risk aversion, i.e., foreign investors and local investors may be differentially informed. Likewise, foreign investors and local investors could be differentially informed about the potential for output shocks in the local economy (a pull factor). In short, the information asymmetry framework we discuss in this paper is useful *at the individual firm level*, whereas the push/pull framework is more applicable at a macro *country-level* analysis.

They argue that in emerging markets, the equity markets are influenced by this "push" factor and fund flows provide an additional channel of contagion.

All the above studies examine the impact of flows aggregated over long horizons on longer horizon asset price formation. In contrast, our study examines the price effects of *daily* flow-induced demand shocks on *short-horizon* returns. Furthermore, the focus of previous studies is on the impact of *realized* flows on fund performance, whereas our focus is on the immediate price effects of *unexpected* fund flows (which we refer to as innovations in FII fund flows). The price effects associated with the high and low innovation portfolios in our study mirrors the findings in the empirical studies of block transactions in stock markets (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 a similar rationale for FII trading in emerging market stocks.

7. Conclusion

Employing a unique database that provides data on foreign institutional investor (FII) flows at the individual stock level in India, we examined the precise impact of FII flow innovations on Indian equity markets. 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 price pressure on stock returns induced by FII sales, as well as information being revealed through both FII purchases and FII sales. Thus, we show that while FII outflows contribute to transient volatility for stocks experiencing the outflows, trading by FIIs also generates new information.

These relations are exacerbated during periods of market stress, particularly during the taper tantrum period of 2013. 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 effects of unanticipated FII purchases and FII sales are largely temporary and is subsequently reversed, suggesting that the negative

sentiment in the post-taper period swamps the positive abnormal returns associated normally with the high FII inflows.

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 show that the immediate price effect (information effect) is significantly positively related to global market beta, sensitivity to foreign exchange rate risk, and illiquidity. We also find that subsequent price reversals (price pressure effect) are related to illiquidity and retail ownership.

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 FII trading, per se, is central to generating information (price discovery). These relative effects of foreign fund flows must be balanced against each other while evaluating their desirability for emerging markets.

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Figure 1

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.

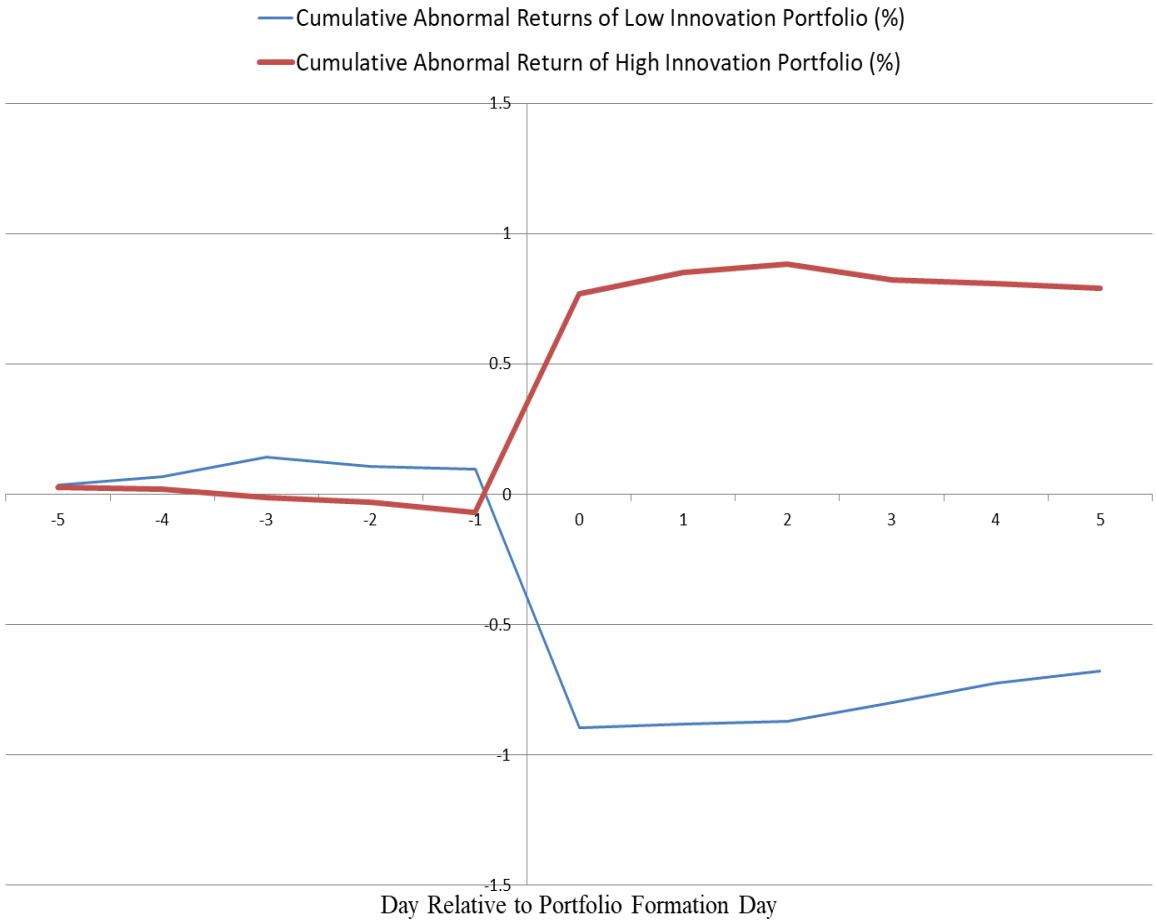


Figure 2

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

This chart 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.

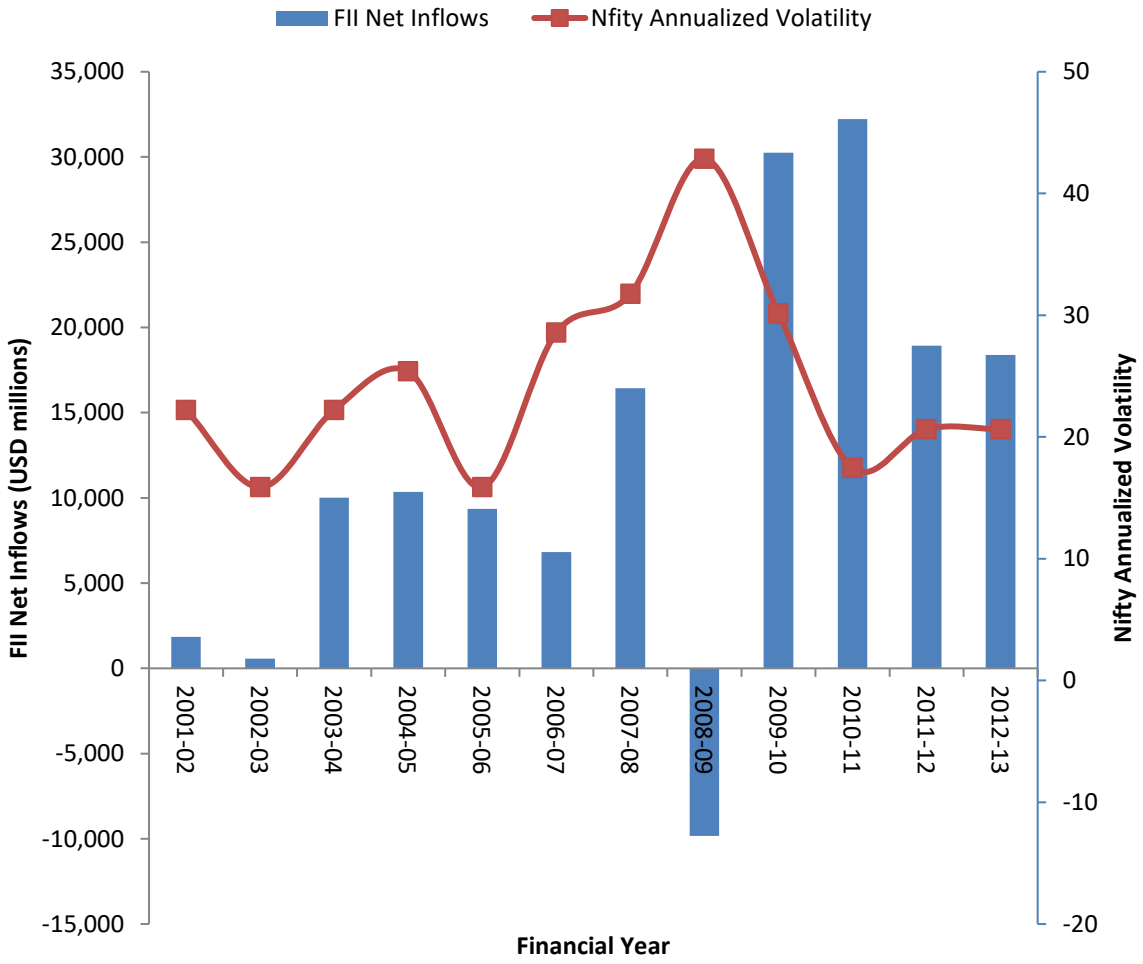


Figure 3

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 the economy (U.S. or India) and further associated with peak values of CBOE VIX.

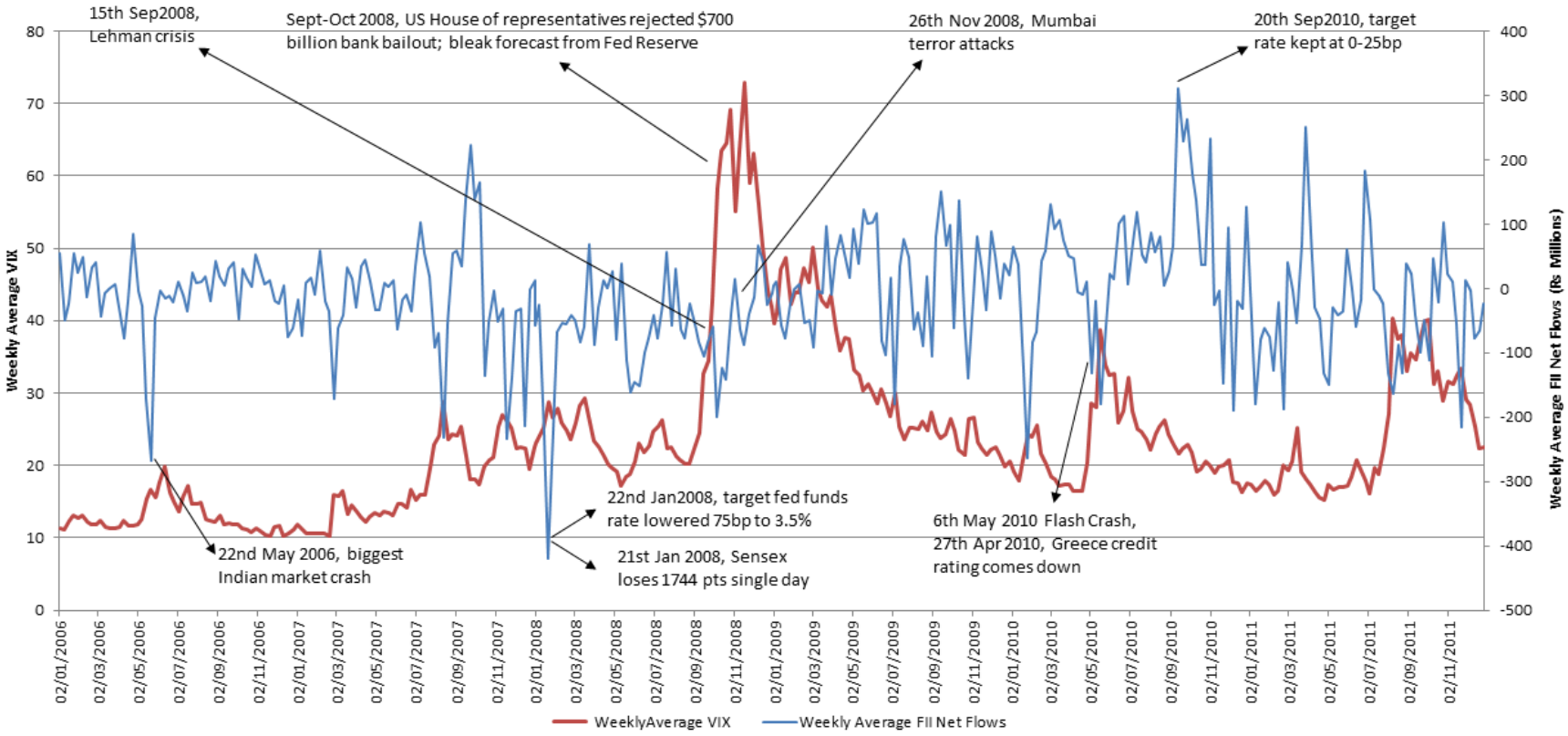
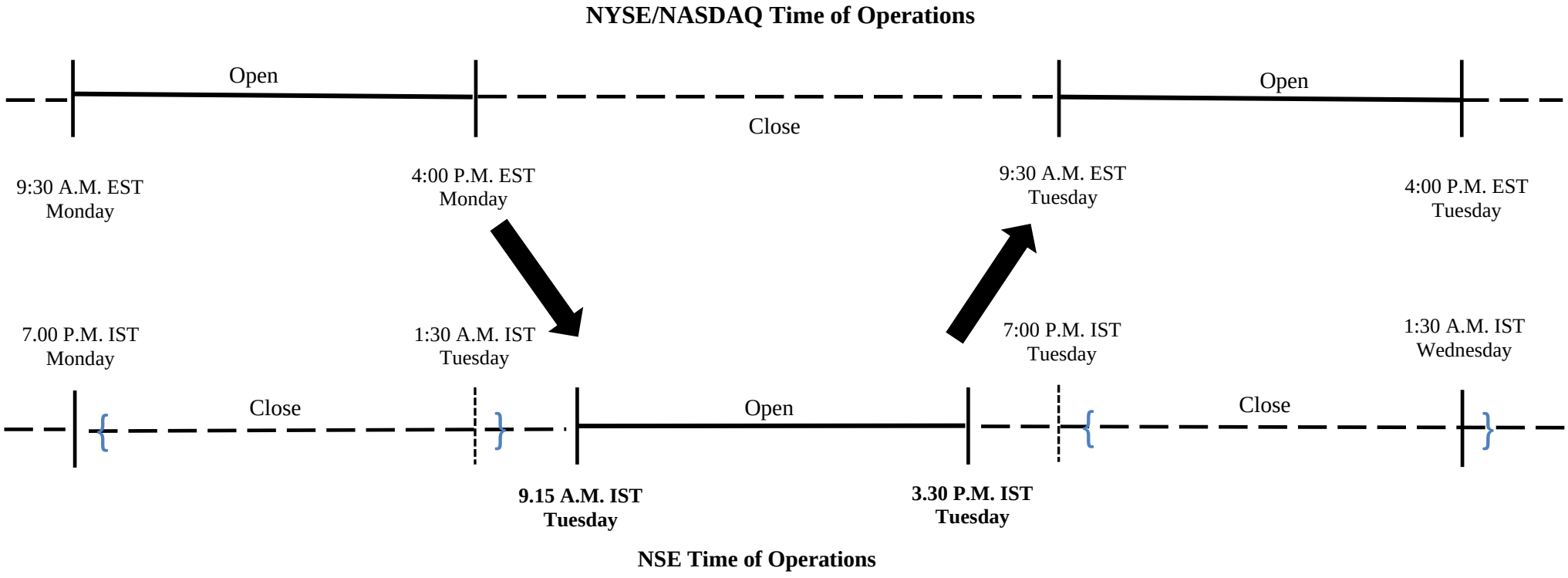


Figure 4. This figure shows the timing overlap between the NYSE/NASDAQ and the NSE.



Note:

1. Indian Standard Time (IST) is nine and half hours ahead of New York, USA during Daylight Saving (DST) and ten and a half hours during Non-DST.
2. { } shows NYSE/NASDAQ time of operation during Non-DST: 8:00 p.m. IST to 2:30 a.m. IST.

Source: https://en.wikipedia.org/wiki/List_of_stock_exchange_opening_times#cite_note-11

Figure 5. Portfolio Formation Procedure

This figure describes the portfolio formation procedure. Every Monday (Day 0), five portfolios are formed based on the innovations in FII flows (2006-2011 period). The cumulative abnormal returns on the HIGH innovation and the LOW innovation portfolios are tracked over the 10-day window surrounding the portfolio formation day (Day 0).

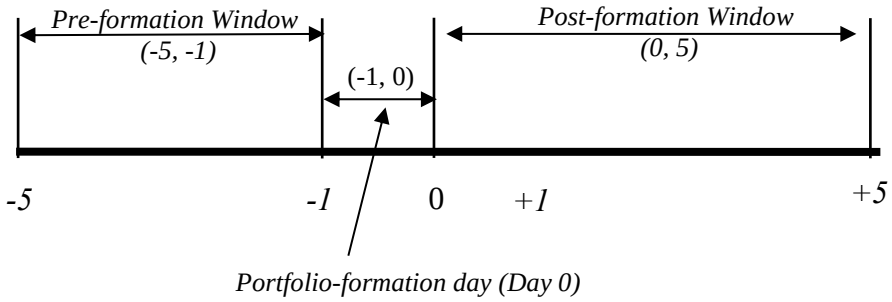
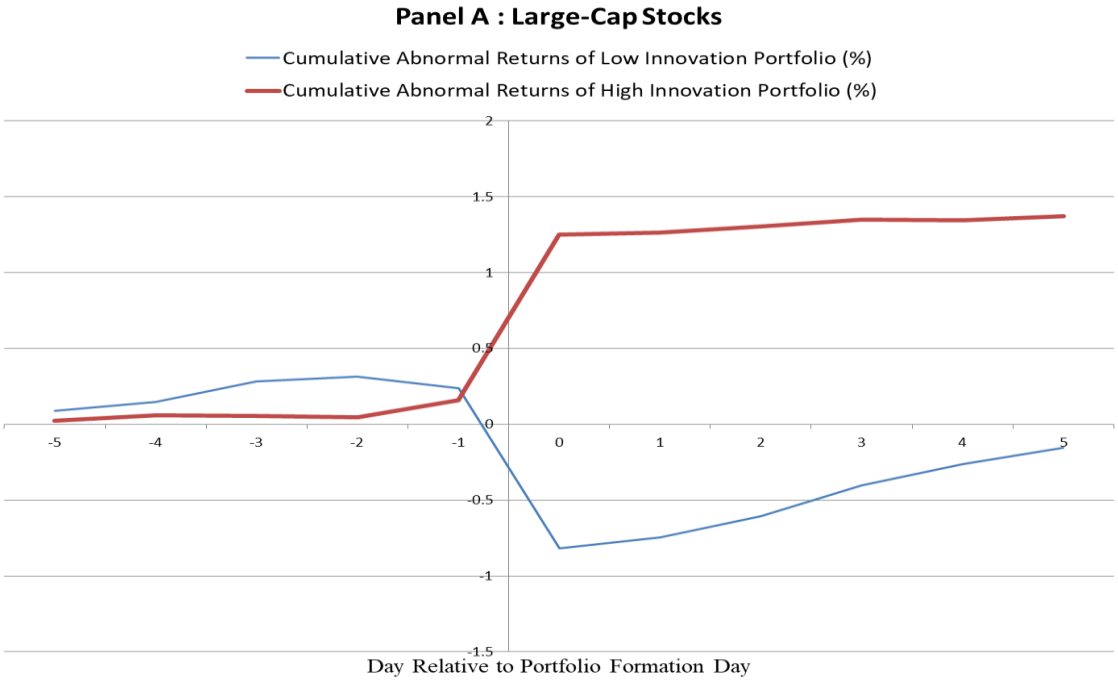
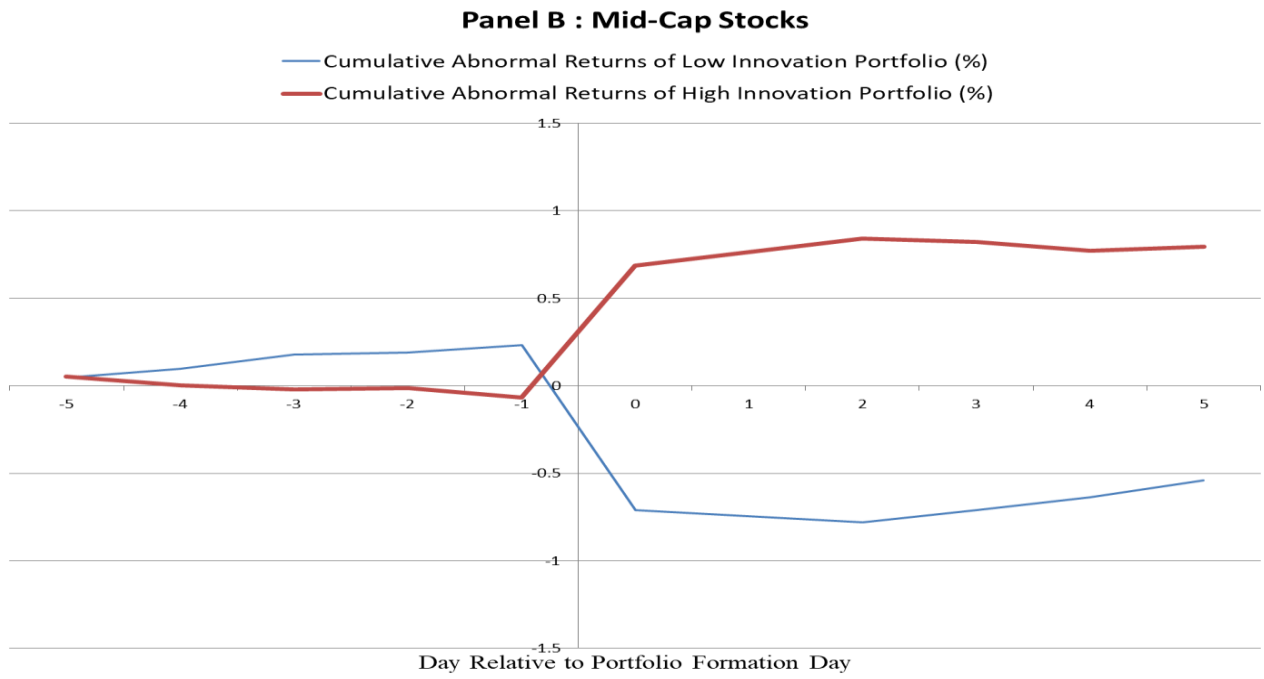


Figure 6

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 the high and low innovation portfolios for large-cap stocks, Panel B shows the same 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 (%)
1.5
1
0.5
0
-0.5
-1
-1.5
-5
-4
-3
-2
-1
0
1
2
3
4
5
Day Relative to Portfolio Formation Day

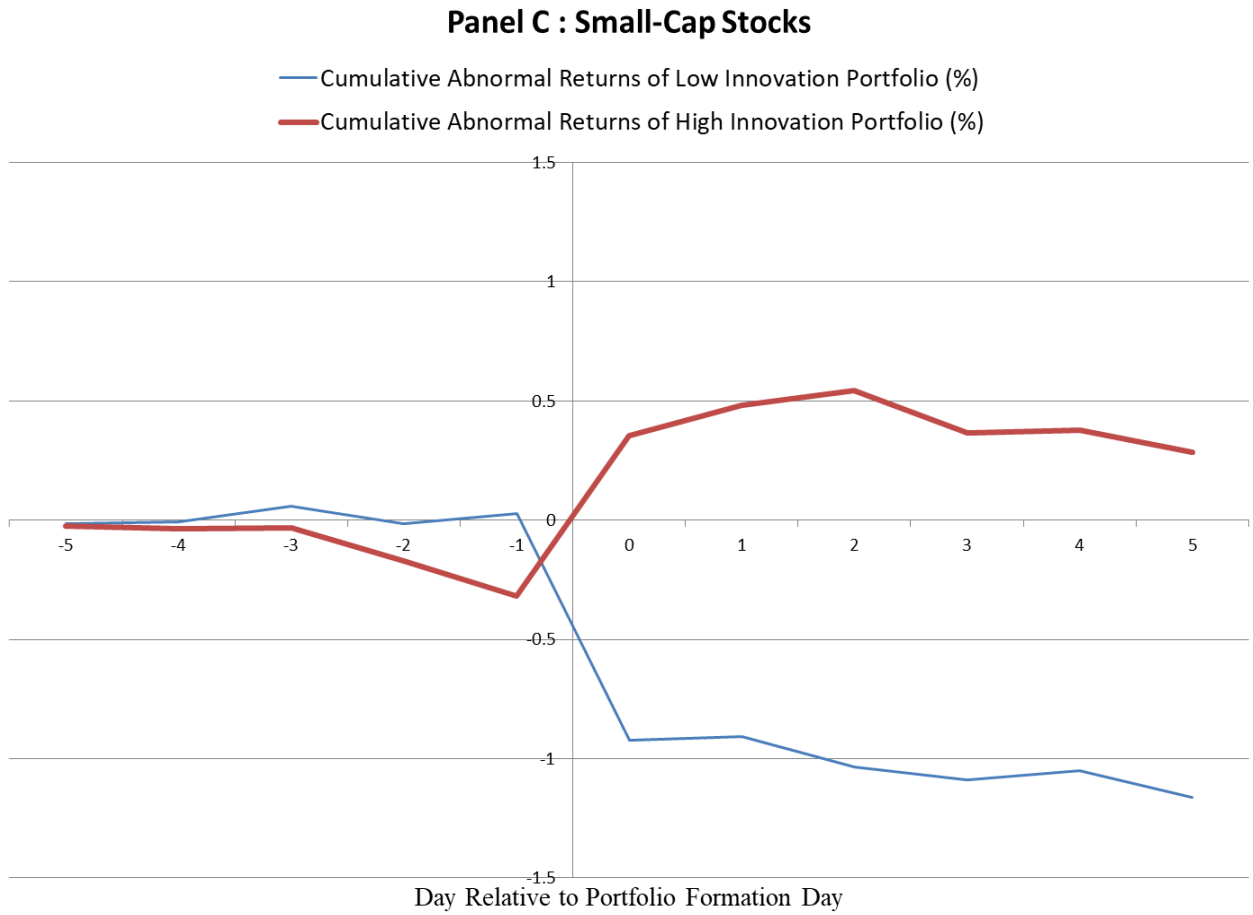

Panel C : Small-Cap Stocks
Cumulative Abnormal Returns of Low Innovation Portfolio (%)
Cumulative Abnormal Returns of High Innovation Portfolio (%)
1.5
1
0.5
0
-0.5
-1
-1.5
-5
-4
-3
-2
-1
0
1
2
3
4
5
Day Relative to Portfolio Formation Day

Figure 7

Time-Series Variation in Abnormal Return Differential and Lagged CBOE VIX (2006-2001)

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*.

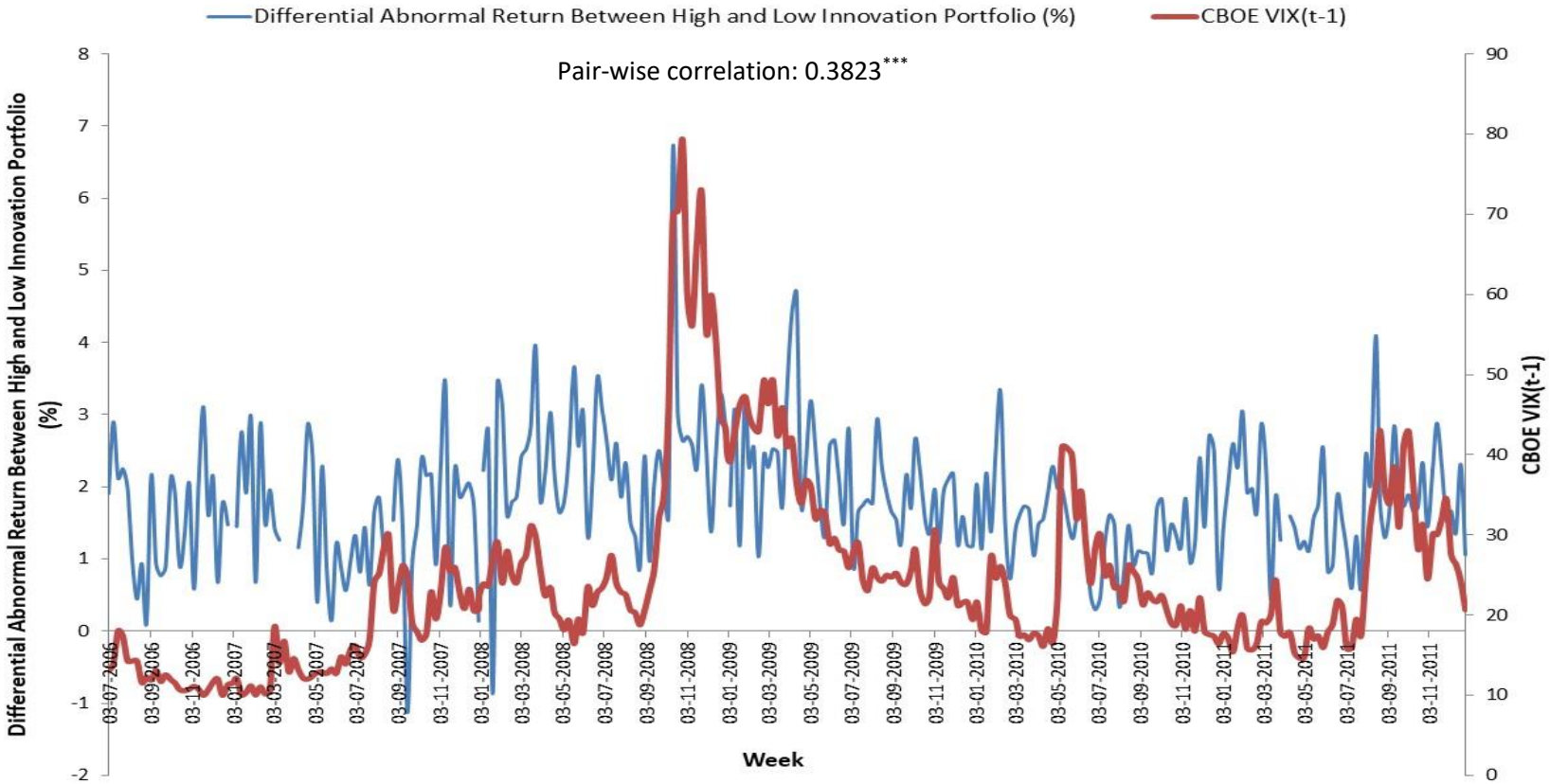


Figure 8

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 the high and low innovation portfolios during the crisis period (January to December 2008) and Panel B shows the same during the non-crisis period (excluding 2008: 2006-2011).

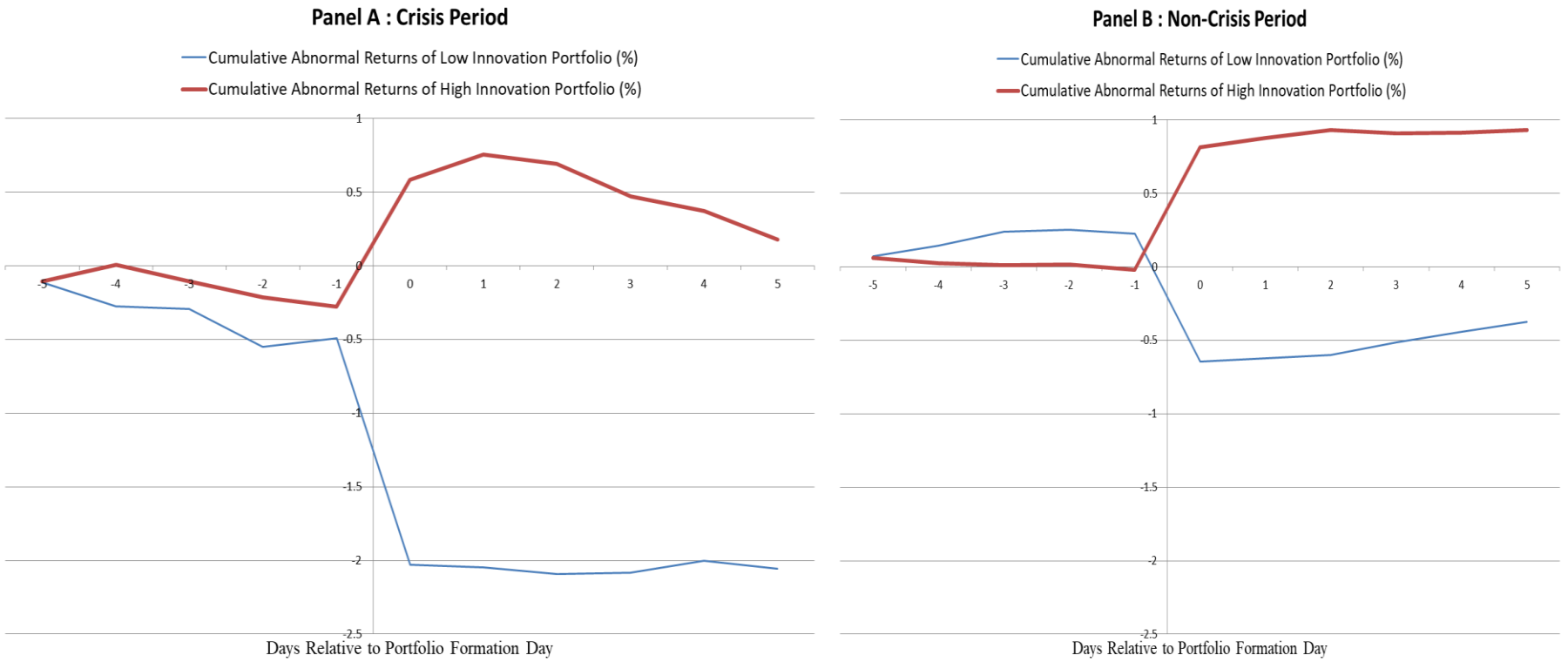
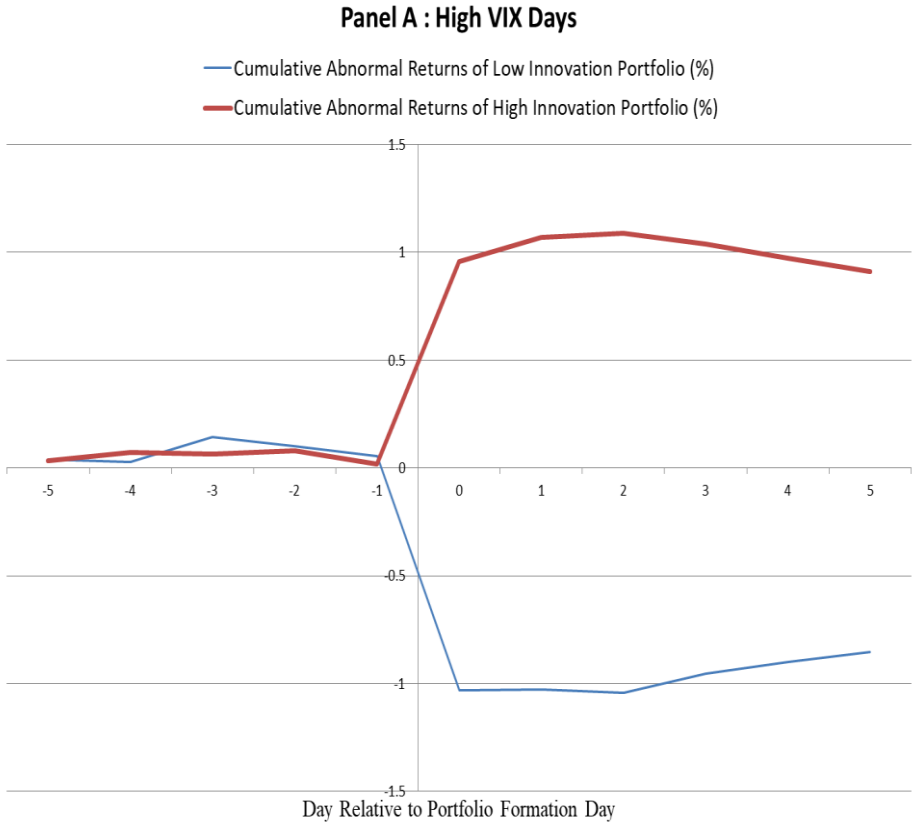


Figure 9

Price Effects of 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 the high and low innovation portfolios during high CBOE VIX level days and Panel B shows the same during low CBOE VIX level days.



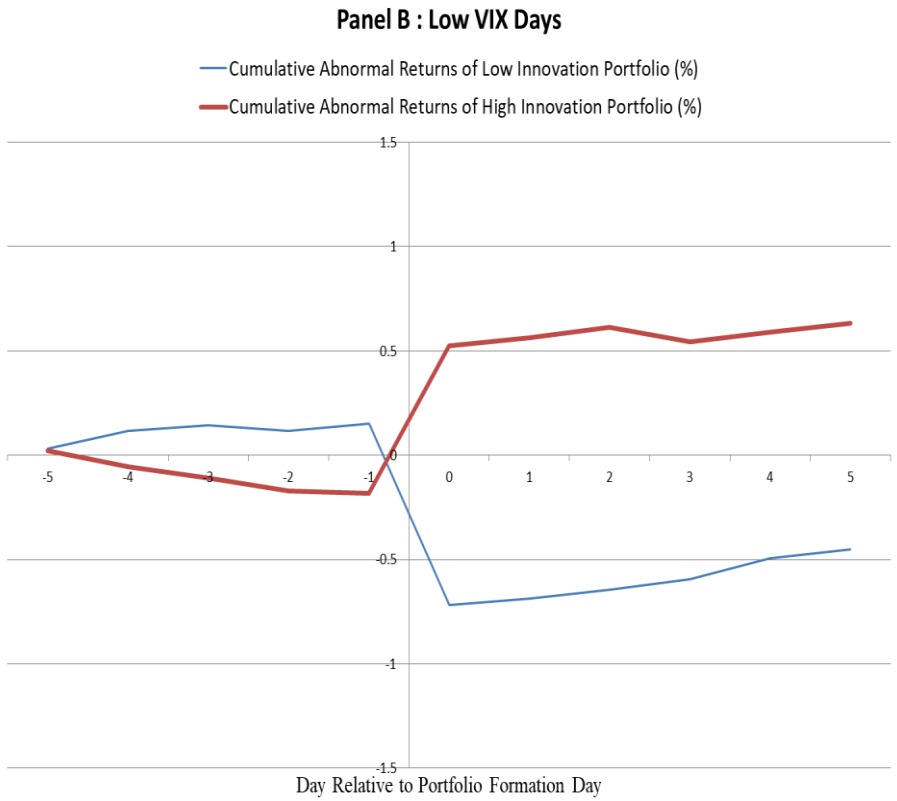


Figure 10

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

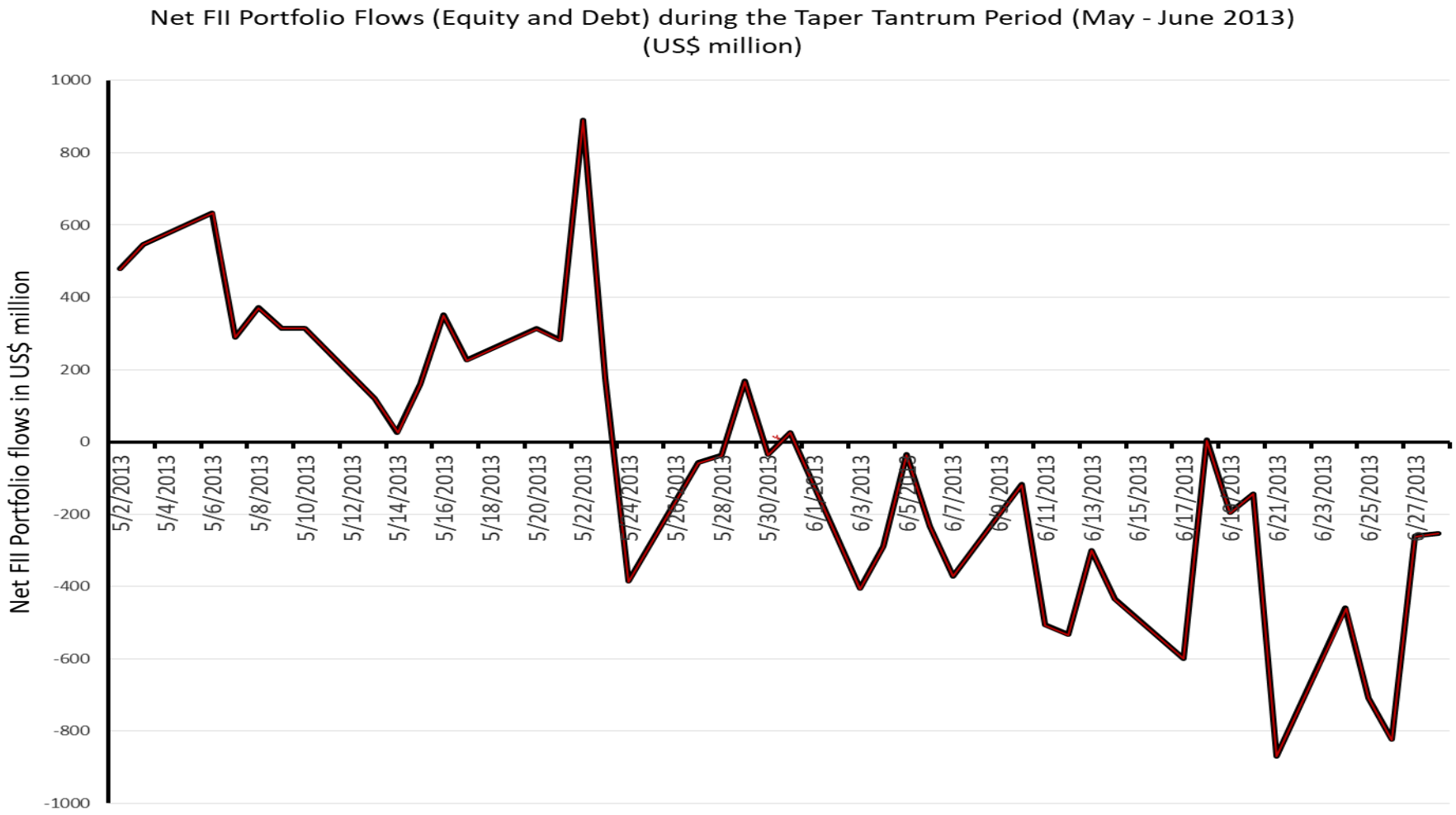
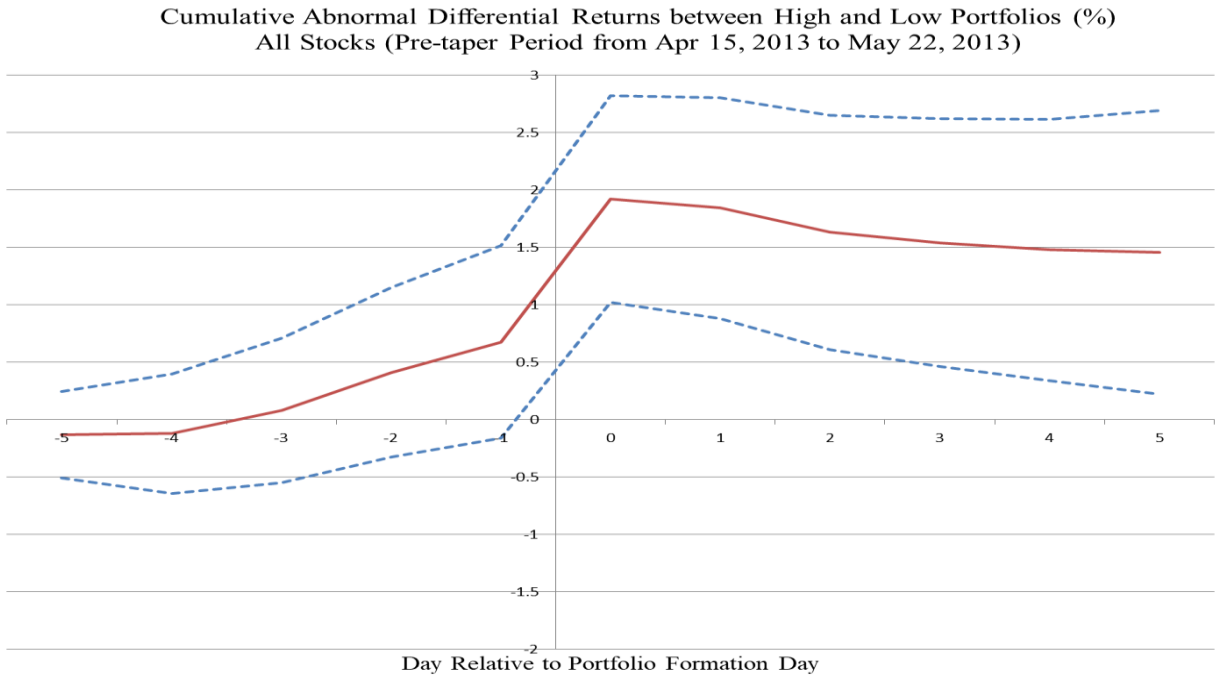


Figure 11
Impact of FII Flows during Taper Tantrum Period

Panel A: All Stocks (Pre-taper period)



Panel B: All Stocks (Post-taper Period)

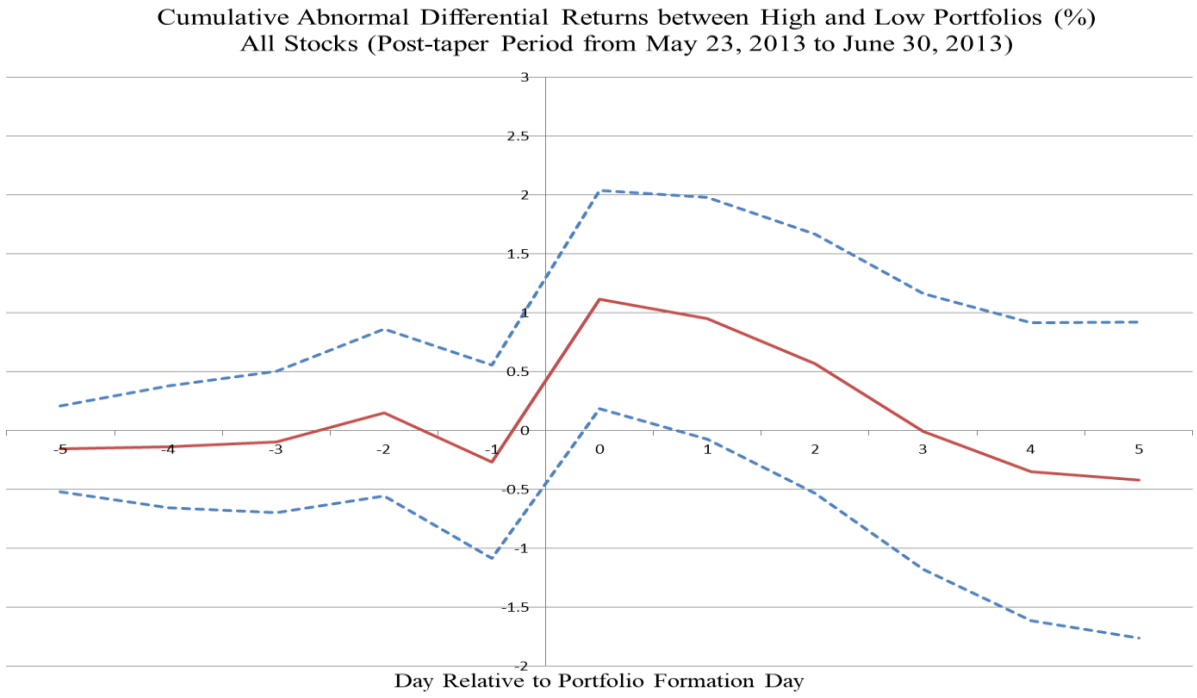


Table 1
Summary of Foreign Institutional Investor Trading Activity

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, Column (3) reports the average percentage of FII ownership of firms listed on the Indian markets, and 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; this ratio is also shown separately for large-cap, mid-cap, and small-cap firms.

FIIs Flows

Financial Year	FII net flows[a] (In USD Million)	FII Ownership[a] (%)	Daily average ratio of FII gross flows to twice the 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

$RET_{it} = \ln (P_t/P_{t-1})$	Continuously compounded return using price (P_t) for stock *i* on day *t*,
$NIFTY\_RET_t$	Continuously compounded return on the CNX NIFTY on day *t*.
$S\&P500\_RET_t$	Continuously compounded return on the S&P500 on day *t*.
$XRATE\_RET_t$	Continuously compounded return on the INR/USD Exchange Rate on day *t*.
AB_RET_{it}	Excess return over the three factors (domestic market, global market and foreign exchange rate), defined from a three-factor model regression.
AB_RET (t-1, t)	Average excess return for a portfolio of stocks on day$_t$.
CAB_RET (t_1, t_2)	Cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t_1, t_2).
$SIZE_{i,t}$	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 *RUPEE_VOLUME* across both FII and non-FII for the i^{th} stock on day t.
$AMIHUD\_ILLIQ_{i,t}$	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 three-factor model estimated using 52 weekly returns prior to portfolio formation day *t*.
GLOBAL_ βETA	Slope coefficient of the *S&P500_RET* in the three-factor model estimated using 52 weekly returns prior to portfolio formation day *t*.
XRATE_ βETA	Slope coefficient of the $XRATE\_RET_t$ in the three-factor model estimated using 52 weekly returns prior to portfolio formation day t.
VOLATILITY	Annualized standard deviation of daily returns of the stock.
IDIO_RISK	Annualized standard deviation of residuals from the three-factor model
VIX (ΔVIX)	Change in CBOE VIX value.
NIFTY_VOLATILITY	Garman-Klass range based daily volatility estimate of NIFTY Index.
$AGGR\_FFLOW_t$	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 to *FII_NET*.
FII_OSHIP	Percentage of Foreign ownership
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 223 sample firms listed on the National Stock Exchange of India (NSE) during the sample period from 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 summarized in Panel C 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 (INR billions)	169.78	52.29	0.86	4681.98	353.77
RUPEE_VOLUME (INR billions)	0.41	0.14	0.00	6.01	0.70
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
LOCAL_βETA	0.96	0.94	-0.19	2.27	0.48
GLOBAL_ βETA	-0.13	-0.11	-1.85	1.52	0.54
XRATE_ βETA	-0.31	-0.27	-4.97	3.91	2.49
VOLATILITY (annualized, %)	47.06	47.08	22.56	72.14	9.43
*IDIO_RISK (*daily, %)	34.76	32.55	16.02	90.96	12.25
Panel B: Market-Wide Factors					
NIFTY_RET (%)	0.03	0.09	-13.01	16.33	1.85
S&P500_RET (%)	0.00	0.07	-9.47	10.96	1.57
XRATE_RET (%)	0.014	0.00	-2.96	2.52	0.52
VIX	23.37	21.18	9.89	80.86	11.20
ΔVIX (first difference in *VIX*)	0.04	-0.39	-35.06	49.60	7.39
NIFTY_ VOLATILITY (%)	21.11	16.99	4.29	165.57	14.60
AGGR_FFLOW	-0.01	-0.00	-0.20	0.18	0.04
Panel C: FII Flows					
FII_OSHIP (%)	24.55	18.26	0	90.51	19.89
FII_BUYS (INR billions)	0.08	0.005	0.00	33.79	0.27
FII_SELLS (INR billions)	0.08	0.003	0.00	23.83	0.28
FII_NET	0.01	0.00	-0.95	0.95	0.22

Table 4
Panel Regression Model

This table reports the results of a firm fixed effects panel regression of $FII\_NET_{i,t}$ on past *FII_NET* and past stock returns along with firm characteristics 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). See Table 2 for variable definitions. 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
Price Effects of FII Flows

Panel A presents the abnormal return patterns of 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 (obtained from the panel regression model) 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. *AB_RET (t-1, t)* is the average excess returns of the given portfolio over the expected return based on a three-factor model regression (domestic market, global market and exchange rate). C*AB_RET* (t_1, t_2)) is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t_1, t_2). Panel B reports the average firm characteristics of the high innovation portfolio (Q5) and the low innovation portfolio (Q1) and the difference between the average firm characteristics of the Q5 and 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. Abnormal return behavior around the days of shocks in *FII_NET*

	Q1		Q5		Q5-Q1	
	Estimate	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
CAB_RET (-5,-1)%	0.04	0.78	-0.05	-1.06	-0.09	-1.29
AB_RET (-1, 0) [Day 0 Returns] %	-0.99	-39.62***	0.84	33.33***	1.83	51.58***
AB_RET (Close$_{-1}$ to Open$_0$) %	0.18	6.89***	0.22	9.16***	0.04	1.26
AB_RET (Open$_0$ to Close$_0$) %	-1.25	-40.07***	0.56	17.55***	1.81	40.60***
CAB_RET (0,5) %	0.27	4.86***	-0.01	-0.15	-0.28	-3.63***

PANEL B: Firm characteristics	**Q1**	**Q5**	**Q5-Q1**	
	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

Market Capitalization and Price Effects of FII Flows

This table presents the abnormal return patterns of 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. *AB_RET (t-1, t)* is the average excess returns of the given portfolio over the expected return based on a three-factor model regression (domestic market, global market and exchange rate). C*AB_RET* (t_1, t_2)) is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t_1, t_2). We also report the overnight return ($Close_{t-1}$ to $Open_t$), the day-time return ($Open_t$ to $Close_t$) experienced by the high and low innovation portfolios on the portfolio formation day (Day 0). 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 the 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						
*CAB_RET (-5, -1) %**	0.12	1.39	0.07	0.89	-0.05	-0.40
AB_RET (-1,0) %	-1.05	-24.34***	1.09	24.07***	2.14	34.21***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.13	2.75***	0.24	5.36***	0.11	1.71*
AB_RET ($Open_0$ to $Close_0$) %	-1.20	-21.14***	0.83	14.32***	2.03	25.04***
CAB_RET (0,5) %	0.62	6.32***	0.03	0.33	-0.59	-4.30***
Mid-Cap						
CAB_RET (-5, -1) %	0.13	1.54	-0.02	-0.34	-0.15	-1.42
AB_RET (-1,0) %	-0.94	-25.05***	0.76	21.48***	1.70	32.96***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.21	6.54***	0.19	4.82***	-0.02	-0.43
AB_RET ($Open_0$ to $Close_0$) %	-1.22	-26.35***	0.48	10.82***	1.69	26.52***
CAB_RET (0,5) %	0.29	3.63***	0.09	1.22	-0.19	-1.78*
Small-Cap						
CAB_RET (-5, -1) %	0.11	0.97	-0.23	-2.11**	-0.34	-2.17**
AB_RET (-1,0) %	-0.95	-17.43***	0.67	11.48***	1.63	20.27***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.23	4.12***	0.34	7.49***	0.10	1.44
AB_RET ($Open_0$ to $Close_0$) %	-1.28	-18.79***	0.31	4.26***	1.59	15.91***
CAB_RET (0,5) %	-0.19	-1.49	-0.03	-0.20	0.16	0.90

Table 7
Impact of FII flows during Periods of Global Market Stress

This table presents the abnormal return patterns of 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. *AB_RET (t-1, t)* is the average excess returns of the given portfolio over the expected return based on a three-factor model regression (domestic market, global market and exchange rate). C*AB_RET* (t_1, t_2)) is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t_1, t_2). We also report the overnight return ($Close_{t-1}$ to $Open_t$) and the during-day return ($Open_t$ to $Close_t$) experienced by the high and low innovation portfolios on the portfolio formation day (Day 0). Panel A reports the impact of the financial crisis on two sub-samples during the non-crisis and crisis periods. In Panel B, the sample is divided into days associated with high CBOE VIX levels (above the median level) and low CBOE VIX levels (below the median level). 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 significance levels of 0.10, 0.05, and 0.01, respectively.)

Panel A: Impact of FII Flows - Financial Crisis

Non-Crisis Period	**Q1**		**Q5**		**Q5-Q1**	
	Estimate	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
CAB_RET (-5,-1)%	0.16	2.84***	0.00	0.02	-0.16	-2.17**
AB_RET (-1, 0) [Day 0 Returns] %	-0.87	10.23***	0.83	33.95***	1.71	47.67***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.22	4.78***	0.27	11.48***	0.05	1.30
AB_RET ($Open_0$ to $Close_0$) %	-1.17	-0.39	0.53	16.41***	1.70	37.09***
CAB_RET (0, 5) %	0.35	0.02	0.09	1.74*	-0.25	-3.22***
Crisis Period						
CAB_RET (-5, -1) %	-0.46	-3.11***	-0.26	-1.88*	0.20	0.97
AB_RET (-1, 0) [Day 0 Returns] %	-1.54	-21.49***	0.86	10.42***	2.40	21.91***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.00	-0.04	0.04	0.47	0.04	0.38
AB_RET ($Open_0$ to $Close_0$) %	-1.61	-18.19***	0.69	7.16***	2.29	17.58***
CAB_RET (0,5) %	-0.07	-0.44	-0.46	-3.02***	-0.39	-1.71*

Panel B: Impact of FII Flows - VIX

	Q1		**Q5**		**Q5-Q1**	
High VIX days	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
CAB_RET (-5, -1) %	-0.01	-0.08	-0.02	-0.29	-0.01	-0.12
AB_RET (-1, 0) [Day 0 Returns] %	-1.09	-29.35***	0.94	25.14***	2.03	38.51***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.19	4.98***	0.23	6.63***	0.05	0.87
AB_RET ($Open_0$ to $Close_0$) %	-1.36	-29.21***	0.65	13.43***	2.01	29.97***
CAB_RET (0,5) %	0.29	3.62***	-0.06	-0.85	-0.36	-3.23***
Low VIX days						
CAB_RET (-5, -1) %	0.10	1.63	-0.09	-1.51	-0.19	-2.23**
AB_RET (-1, 0) [Day 0 Returns] %	-0.87	-27.61***	0.71	22.66***	1.58	35.57***
AB_RET ($Close_{-1}$ to $Open_0$) %	0.16	4.92***	0.21	6.48***	0.04	0.95
AB_RET ($Open_0$ to $Close_0$) %	-1.11	-28.67***	0.44	11.67***	1.56	28.63***
CAB_RET (0,5) %	0.24	3.35***	0.07	0.95	-0.17	-1.71*

Table 8
Determinants of Time-Series Variation in Differential Abnormal Returns on Day 0

Firms are ranked according to innovations in *FII* flows at the beginning of the week (typically on every Monday) and sorted into five quintiles. The tail portfolios are referred to as the high and low innovation portfolios. This portfolio formation procedure is repeated for 258 weeks over the 2006-2011 period. This table reports the results of time-series regressions relating the differential abnormal return (Y_t) between the high and the low innovation portfolios on the portfolio formation day (Day 0) to pre-formation firm-specific characteristics (X_t), and market-wide factors (Z_{t-1}): $Y_t = \alpha_0 + \beta\, X_t + \gamma\, Z_{t-1} + \varepsilon_t$. The vector X_t includes average difference between high and low quintile portfolio for the pre-formation firm characteristics. See Table 2 for variable definitions. The sample consists 223 stocks. 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.

	Differential Abnormal Returns on Day 0									
	(1)		(2)		(3)		(4)		(5)	
	Coeff	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
Intercept	1.17	11.65***	1.01	7.74***	1.01	7.64***	0.94	7.30***	0.94	7.21***
AMIHUD_ILLIQ	0.00	4.53***	0.00	5.27***	0.00	5.03***	0.00	4.43***	0.00	4.15***
Log(*RUPEE_VOLUME*)	-0.21	-1.68*	-0.25	-1.95*	-0.23	-1.89*	-0.24	-1.99**	-0.22	-1.94*
Log(*SIZE*)	0.19	1.31	0.22	1.48	0.20	1.37	0.20	1.45	0.18	1.33
LOCAL_βETA	0.54	0.92	0.49	0.77	0.21	0.55	0.49	0.85	0.23	0.62
VOLATILITY	0.01	0.06	-0.02	-0.11	0.00	-0.02	0.02	0.11	0.03	0.20
IDIO_RISK	0.05	0.30	0.02	0.11	0.07	0.41	0.02	0.14	0.07	0.44
$NIFTY\_RET_{t-1}$	0.09	3.33***	0.09	2.98***	0.09	3.01***	0.10	3.32***	0.09	3.35***
$S\&P\ 500\_RET_{t-1}$	-0.07	-1.20	-0.02	-0.20	-0.01	-0.10	-0.02	-0.20	-0.01	-0.10
$NIFTY\_VOL_{t-1}$	47.66	6.60***	33.84	3.99***	33.05	3.87***	32.88	3.91***	32.14	3.79***
$AGGR\_FFLOW_{t-1}$	-2.43	-1.84*	-2.29	-1.73*	-1.75	-1.38	-1.84	-1.41	-1.34	-1.06
RETAIL_OSHP	-0.02	-0.59	0.00	-0.16	0.00	0.10	-0.01	-0.50	-0.01	-0.24
INSTITUTIONAL_OSHP	0.01	0.70	0.01	0.77	0.01	0.81	0.01	0.79	0.01	0.84
FII_OSHIP	-0.01	-0.76	-0.01	-0.82	-0.01	-0.90	-0.01	-0.70	-0.01	-0.78
VIX_{t-1}		--	0.01	2.70***	0.02	2.88**	0.02	3.33***	0.02	3.50***
ΔVIX_{t-1}		--	0.01	1.09	0.02	1.24	0.01	1.09	0.02	1.23
GLOBAL_βETA		--		--	0.64	1.99**		--	0.62	2.05**
XRATE_βETA		--		--		--	0.58	3.23***	0.57	3.18***
Adj. R^2	0.25		0.27		0.28		0.31		0.32	
ROOT MSE	0.78		0.77		0.76		0.75		0.74	

Table 9
Determinants of Time-Series Variation in Differential Cumulative Abnormal Returns (0,5)

Firms are ranked according to innovations in *FII* flows at the beginning of the week (typically on every Monday) and sorted into five quintiles. The tail portfolios are referred to as the high and low innovation portfolios. This portfolio formation procedure is repeated for 258 weeks over the 2006-2011 period. This table reports the results of time-series regressions relating the differential cumulative abnormal return (Y_t) between the high and the low innovation portfolios from Day 0 to Day 5 to pre-formation firm-specific characteristics (X_t), and market-wide factors (Z_{t-1}): $Y_t = \alpha_0 + \beta\, X_t + \gamma\, Z_{t-1} + \varepsilon_t$. The vector X_t includes average difference between high and low quintile portfolio for the pre-formation firm characteristics. See Table 2 for variable definitions. The sample consists 223 stocks. 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.

Differential Cumulative Abnormal Returns (0,5)

	(1)		(2)		(3)		(4)		(5)	
	Coeff	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
Intercept	-0.16	-0.84	-0.16	-0.84	-0.14	-0.73	-0.20	-1.09	-0.17	-0.93
AMIHUD_ILLIQ	0.00	9.54***	0.00	9.31***	0.00	9.18***	0.00	10.18***	0	9.60***
Log(*RUPEE_VOLUME*)	0.01	0.05	0.01	0.04	0.01	0.04	0.01	0.06	0.01	0.04
Log(*SIZE*)	0.19	0.83	0.19	0.84	0.19	0.83	0.32	1.43	0.32	1.45
LOCAL_βETA	-0.10	-0.32	-0.07	-0.16	-0.10	-0.31	-0.24	-0.81	-0.26	-0.66
VOLATILITY	0.10	0.41	0.10	0.40	0.09	0.38	0.10	0.40	0.09	0.35
IDIO_RISK	-0.02	-0.09	-0.03	-0.11	-0.02	-0.09	0.03	0.11	0.03	0.12
$NIFTY\_RET_{t-1}$	-0.04	-0.89	-0.04	-0.89	-0.05	-0.92	-0.04	-0.82	-0.04	-0.88
$S\&P\ 500\_RET_{t-1}$	-0.06	-0.82	-0.06	-0.84	-0.06	-0.82	-0.06	-0.84	-0.06	-0.84
$NIFTY\_VOL_{t-1}$	-6.68	-0.56	-6.66	-0.56	-6.23	-0.52	-10.68	-0.92	-10.18	-0.88
$AGGR\_FFLOW_{t-1}$	2.69	1.52	2.62	1.45	2.61	1.48	2.14	1.23	2.06	1.16
INSTITUTIONAL_OSHP	-0.02	-1.04	-0.02	-1.05	-0.02	-1.05	-0.02	-1.47	-0.02	-1.5
FII_OSHIP	-0.02	-1.35	-0.02	-1.34	-0.02	-1.38	-0.02	-1.44	0	0.18
VIX_{t-1}	0.00	-0.07	0.00	-0.07	0.00	-0.17	0.00	0.31	-0.02	-1.03
ΔVIX_{t-1}	-0.02	-1.16	-0.02	-1.18	-0.02	-1.17	-0.02	-1.04	-0.02	-1.48
GLOBAL_βETA		--	-0.09	-0.26		--		--	0.05	0.15
XRATE_ βETA		--		--	-0.14	-0.65		--	-0.2	-0.92
RETAIL_OSHP		--		--		--	0.11	3.03***	0.11	3.14***
Adj. R^2	0.05		0.05		0.05		0.08		0.09	
ROOT MSE	1.10		1.10		1.10		1.08		1.08	