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**Working Paper**

## Foreign fund flows and equity prices during the Covid-19 pandemic: Evidence from India

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**ADB Working Paper Series**

**FOREIGN FUND FLOWS  
AND EQUITY PRICES DURING  
THE COVID-19 PANDEMIC:  
EVIDENCE FROM INDIA**

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Viral V. Acharya, V. Ravi Anshuman,  
and K. Kiran Kumar

No. 1333  
July 2022

**Asian Development Bank Institute**

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**Abstract**

We study the period of the COVID-19 pandemic to assess the impact of foreign institutional investor (FII) flows on asset prices in an emerging market. Using a dataset of stock-level foreign fund flows of Indian equities, we show that 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. During the COVID-19 pandemic, immediate price effects were exaggerated and followed by higher transient volatility. Our methodology shows the efficacy of stabilization policies, initiated notably by the Federal Reserve, in dampening this relationship of foreign fund flows and equity prices in the immediate aftermath of the COVID-19 pandemic. We find the price effects of the FII flows in the pre-stabilization phase to be similar to those during the earlier crisis periods of the taper tantrum and the global financial crisis.

**Keywords:** foreign institutional investors (FIIs), foreign ownership, portfolio flows, price impact, taper tantrum, VIX, volatility

**JEL Classification:** F21, G11, G14, G15

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## 1. INTRODUCTION

A wide body of literature has demonstrated that foreign fund flows affect domestic asset prices.<sup>1</sup> For instance, Froot and Ramadorai (2008) showed that lagged (weekly) foreign fund flows predict future local market returns; more importantly, they found that this relationship is largely driven by an information effect rather than a price pressure effect. Jotikasthira, Lundblad, and Ramadorai (2012) reported that asset fire sales in the developed world affect fund flows to emerging markets, suggesting that price pressure feeds into itself during fire sales. They argued that, in emerging markets, equity markets are influenced by this “push” factor and fund flows provide an additional channel of contagion.<sup>2</sup> Hence, policymakers fear that “hot money”, i.e., portfolio flows that are extremely fickle and unpredictable, may exacerbate a moderate economic shock, causing a financial market meltdown, which could eventually spread to the real economy; e.g., during the Asian crisis of 1997–1999, many East Asian countries faced abnormally high capital outflows and subsequently experienced a recession.<sup>3</sup>

We examine this important concern regarding the fund flow–return relationship during the COVID-19 pandemic in the first half of the year 2020 for the equity market<sup>4</sup> in an emerging market, viz., India, and compare this with the relationship observed during significant crises of the last two decades, namely the taper tantrum and the global financial crisis. These crisis periods have posed significant challenges for policymakers, but they have also provided them with an opportunity to sharpen their toolkits for dealing with sudden swings in capital flows. In particular, the COVID-19 pandemic was immediately followed by a period in which policymakers—notably from the standpoint of global capital flows, the Federal Reserve—deployed a wide array of stabilization measures to contain the global market collapse, also providing researchers with an opportunity to assess how the fund flow–return relationship during crisis periods is affected by such policy stabilization measures.

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<sup>1</sup> See Bohn and Tesar (1996), Brennan and Cao (1997), Froot, O’Connell, and Seasholes (2001), and Hau (2001) for initial studies on this topic.

<sup>2</sup> Mutual fund flows within a country can also affect asset prices; however, such domestic fund flow effects are not the focus of our study. Coval and Stafford (2007) showed that sudden increases (decreases) in quarterly fund flows cause mutual fund managers in the United States to adjust their holdings significantly, resulting in price pressure effects that are transient but may take several weeks to reverse. Price pressure due to fund flows can cause temporary deviations of stock prices from fundamental values, followed by reversals over time. Frazzini and Lamont (2008) found that mutual fund flows reflect retail investor sentiment and higher inflows are associated with lower future returns.

<sup>3</sup> Cross-border capital flows can also cause significant real effects. For instance, during the early 1990s, several East Asian countries experienced significant amounts of capital flows into their markets but subsequently faced a sudden reversal of capital flows in 1997. The currency and stock markets of Indonesia, Thailand, Malaysia, the Philippines, and the Republic of Korea suffered a major decline due to the flight of capital to safety. Although capital flows reverted to their original levels by 1999, during the interim period (1997–1999), the crisis spread from East Asia to Latin America, leaving many developing countries in a state of recession.

<sup>4</sup> We focused on foreign equity flows rather than foreign bond flows data because the bond market in India is highly illiquid and the data are sparse. Only the government bond market has sufficient depth to make it amenable to analysis. However, flight to safety often drives flows in these treasury securities and the overall bond market is less sensitive to fundamental information. Conversely, equity markets are more liquid and capture the information effect better. Bond market flows may be considered in a future study that explicitly accounts for the price effects due to flight to safety.

Our study contributes to the literature in two significant ways. First, it benchmarks the fund flow–return relationship during normal non-crisis periods. We find that abnormally high FII inflows are associated with a permanent price effect but that abnormally high FII outflows are associated with both a permanent price effect and a transient effect that is subsequently reversed. Second, using this as the benchmark, we analyze the evolution of the fund flow–return relationship during (i) the onset of the COVID-19 crisis; (ii) the period when the Federal Reserve initiated policy stabilization measures; and (iii) the post-stabilization period. We find that the relationship between foreign fund flows and equity returns during the overall COVID-19 period (1 January 2020 to 30 June 2020) resembles that of the non-crisis period but that the price impacts and then reversals are highly exaggerated, with the stabilization measures deployed during the COVID-19 crisis period effectively dampening the overall relationship between foreign fund flows and asset prices. Our important finding is that the stabilization policy period of 24 March 2020 to 15 April 2020 shows a significant reversal of the immediate effect of COVID-19-induced foreign fund flows on emerging market stock returns, as evidenced for India.

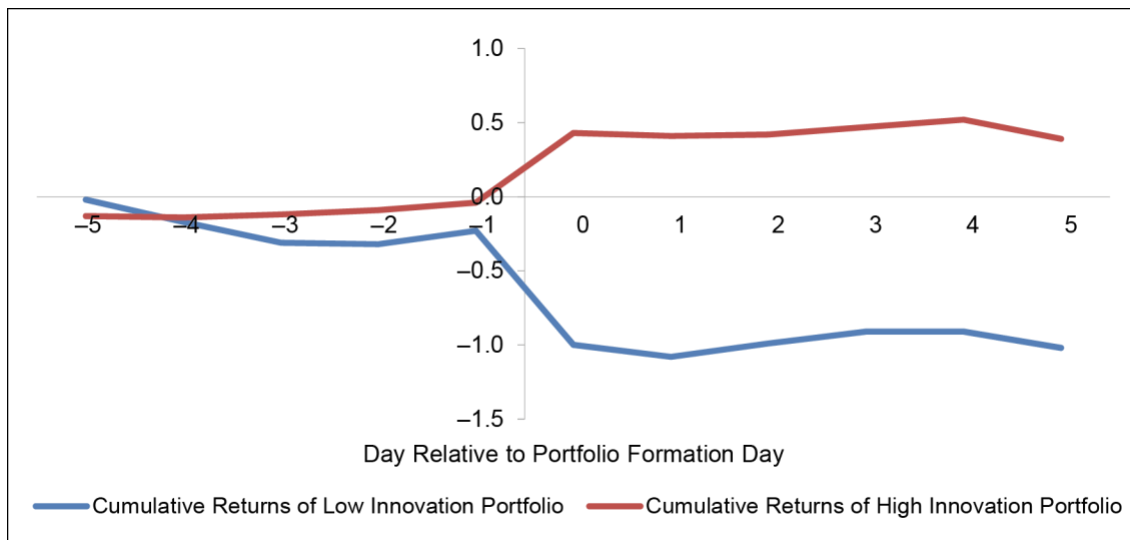
To elaborate, we examine data on foreign fund flows into (and out of) India using an exclusive dataset that provides information about *daily* FII flows at the *individual* stock level for the most actively traded stocks in the Indian stock market during the 2019–2020 period. We employ a novel “panel regression” approach in which we estimate the predicted (expected) FII flows at the stock level based on lagged firm characteristics, lagged FII flows, and market-wide factors. The residuals from this estimation exercise capture the abnormal or unpredictable component of FII flows. These residuals or innovations are used to rank stocks each week, thereby forming high- and low-FII flow *innovation portfolios*.<sup>5</sup> We then analyze the immediate short-run returns of these portfolios on the portfolio formation day (Day 0), measuring the return from the Day –1 close to the Day 0 close. We also observe the returns in the 4-day pre-formation window (Day –5 to Day –1) and the 5-day post-formation window (Day 0 to Day +5).

To obtain the benchmark case of the fund flow–return relationship during normal (non-crisis) periods, we first analyze the pre-COVID-19 period between 1 January 2019 and 31 December 2019. Figure 1 (Panel A) presents the cumulative abnormal returns (CARs) on stocks experiencing abnormally high/low innovations in FII flows during this period. Panel A shows that the high-innovation stocks and the low-innovation stocks exhibited similar behavior in the pre-formation window (–5, –1). However, on Day 0, the high-innovation stocks experienced a permanent price effect, whereas the low-innovation stocks experienced a partially permanent price effect. In the post-formation window (0, 5), the CAR plot for the low-innovation stocks showed a delayed reaction over the interval (0, 1) and then an equal amount of reversal over the interval (1, 4). Figure 1 (Panel B) confirms that the difference between the CARs of high- and low-innovation stocks exhibits a permanent increase that sustains over the (0, 5) window.

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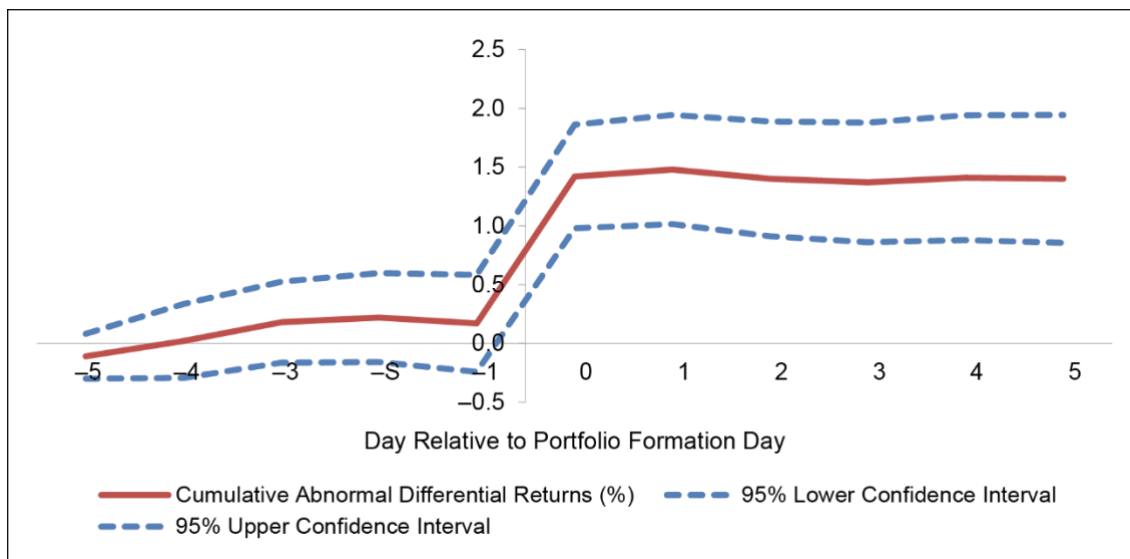
<sup>5</sup> Hasbrouck (1988) and Bessembinder and Seguin (1993) pointed out that the information content of trades can be weeded out by examining the unexpected component of trading rather than the total amount of trading.

**Figure 1 (Panel A): Cumulative Abnormal Returns of High-Innovation and Low-Innovation Portfolios**



Note: The residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ( $FII\_NET_{i,t}$ ), which are defined as the difference between  $FII\_BUYS$  and  $FII\_SELLS$  scaled by the total rupee value traded (across both FIIs and non-FIIs) for the  $i^{th}$  stock on the  $t^{th}$  day. During the January 2019 to December 2019 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 returns for stocks that experience extremely high or low innovations in FII flows.

**Figure 1 (Panel B): Cumulative Abnormal Differential Returns of High-Innovation and Low-Innovation Portfolios**



Note: The residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ( $FII\_NET_{i,t}$ ), which are defined as the difference between  $FII\_BUYS$  and  $FII\_SELLS$  scaled by the total rupee value traded (across both FIIs and non-FIIs) for the  $i^{th}$  stock on the  $t^{th}$  day. During the January 2019 to December 2019 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 differential returns for stocks that experience extremely high or low innovations in FII flows.



These findings imply that stocks with high innovations (positive residuals) in FII flows experienced a coincident abnormal return that reflects a *permanent* information effect. However, stocks with low innovations (negative residuals) in FII flows experienced both a *permanent* information effect and a *transient* price pressure effect, which was reversed over the latter part of the post-formation window. Thus, our evidence is consistent with an information effect when FIIs indulge in excessive purchases. In the case of excessive sales, there is both an immediate information effect on Day 0 and a partial price reversal in the post-formation window, consistent with an overreaction on Day 0 due to price pressure.<sup>6</sup>

Next, we turn to the COVID-19 crisis period. We use the above approach to analyze the fund flow–return relationship in three distinct periods: (i) the *pre-stabilization period* (1 January 2020 to 23 March 2020), when market forces had already begun reflecting the potential adverse effects of COVID-19; (ii) the *policy stabilization period* (24 March to 15 April, when the Federal Reserve initiated several policy moves to stem the downward spiral in financial markets); and (iii) the *post-stabilization period* (16 April to 30 June), well after the stabilization policies had been put in place. The motivation for this analysis is to determine how the fund flow–return relationship during these three sub-periods that covered the COVID-19 crisis (1 January 2020 to 30 June 2020) differs from that during the pre-COVID-19 normal period (1 January 2019 to 31 December 2019).

We find that, during the pre-stabilization period, the price effects in the post-formation window (0, 5) exhibited exaggerated price effects with subsequent price reversals for both the high- and the low-innovation stocks. It seems that the anticipation of the adverse effects of COVID-19 on the real economy overwhelmed the normal-time magnitude of the flow–price relationship seen during the pre-COVID-19 period. Overall, the results indicate that the market experienced a higher degree of transient volatility over the (0, 5) window in the pre-stabilization period.

Importantly, the subsequent policy interventions taken up by the Federal Reserve indeed seem to have been a timely response. Once policy stabilization measures had been put in place, there was a significant change in price patterns over the entire (–5, 5) window. First, the performance of both the high- and the low-innovation stocks was in the negative territory in the pre-formation window. However, the stabilization measures were effective in the sense that, over the (0, 5) window, they revived the performance of those stocks that were the most severely affected over the (–5, –1) window due to the onset of the COVID-19 crisis, dampening the overall impact of foreign fund flows on asset prices during the COVID-19 pandemic. Finally, during the post-stabilization period, the price patterns reverted to the same behavior as in pre-COVID-19 normal times.

We examine the data around the taper tantrum and the global financial crisis to see whether the flow–return relationship during these periods was different from that in the COVID-19 crisis period. We find that the taper tantrum of May 2013<sup>7</sup> primarily produced non-information-based FII flows for Indian equity markets, resulting in temporary price effects that were followed by significant price reversals. These findings are similar to

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<sup>6</sup> The price effects associated with the high- and low-innovation portfolios in our study mirror 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; 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.

<sup>7</sup> Sahay et al. (2014) documented a significant capital outflow in response to the taper announcement accompanied by sharp revisions in asset prices across the world, especially in emerging markets.

those for the COVID-19 crisis. One significant difference between the taper period and the COVID-19 crisis is that the taper announcement was an unanticipated shock for the market whereas the adverse impact of COVID-19 was anticipated during the weeks preceding the formal declaration of the pandemic. Thus, the immediate period before the declaration of the COVID-19 pandemic, i.e., the period that we refer to as the pre-stabilization period, is the period that is comparable to the post-taper period in this analysis. Consistent with this observation, we find that the price patterns in the post-taper period are like those in the pre-stabilization period of the COVID-19 crisis.

Finally, we examine the data from the period around the global financial crisis. We segregate the data from 2006 to 2011 into two groups—the crisis period data (2008) and the non-crisis period data (2006–2011 minus the 2008 data). We find that the impact of FII flows varies with global market stress. Both the high- and the low-innovation stocks experienced a greater price effect during the crisis period than during the non-crisis period. Furthermore, the negative sentiment in the crisis period resulted in a greater degree of transient volatility experienced by these stocks in the post-formation window. In short, our findings for the taper tantrum as well as the global financial crisis echo the price patterns in the pre-stabilization period of the COVID-19 crisis.

To summarize, we exploit the richness of our dataset on individual stock-level foreign fund flows in and out of Indian stocks to estimate the information and price pressure effects during the COVID-19 crisis period. The relative effects of foreign fund flows—transient volatility and price discovery—were both more exaggerated during the COVID-19 period but dampened in part by stabilization policy measures. Our analysis and methodology provide a template for future policymakers to assess the effectiveness of their measures in dampening shocks from foreign fund flows on asset prices during crisis periods.<sup>8</sup>

While earlier studies have also discussed the presence of an information effect and a price pressure effect due to fund flows, our study offers scope for determining the drivers of these effects because we employ stock-level flow data; furthermore, our sample covers a period spanning the financial crisis period during which the flow–return relationship is likely to be significantly different from that during normal periods. We exploit this richness in our dataset to provide nuances of the information and price pressure effects that can help policymaking in assessing the benefits and costs of capital controls. Our findings explain the nature of the trade-off between transient volatility induced by price pressure effects and price discovery induced by the information effect. In the following section, we present an overview of these key findings, which capture the contribution of our study to enhancing the understanding of the role of foreign fund flows in asset price formation.

The rest of the paper is organized as follows. Section 2 provides stylized evidence of the flow–return relationship and stabilization policies adopted by the Federal Reserve Bank around the COVID-19 crisis. Section 3 describes the data and empirical methodology. Section 4 presents the key empirical findings related to the impact of FII flows on asset price formation during the COVID-19 crisis. Section 5 presents an

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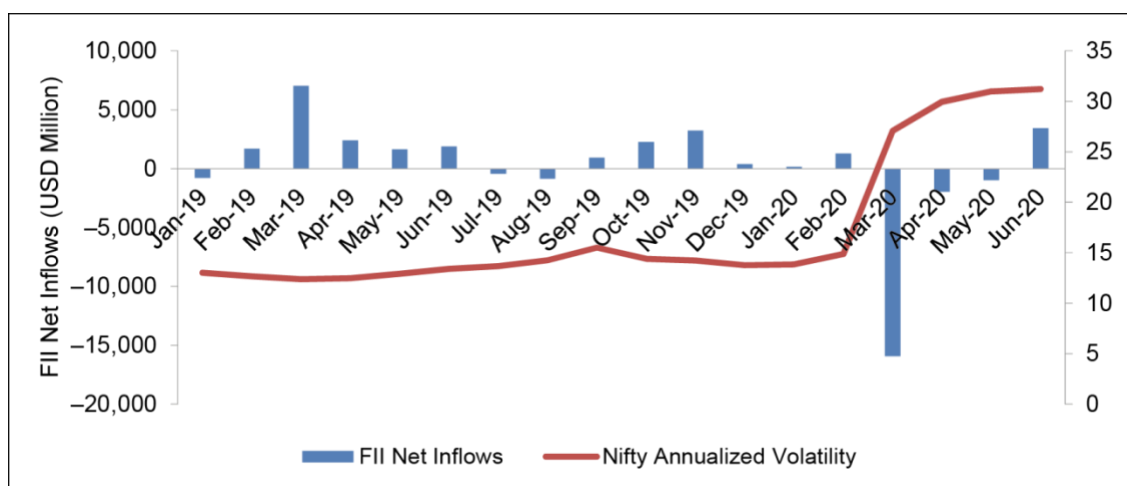
<sup>8</sup> Our study's findings are closely related to the literature on the determinants of cross-border capital flows in the field of international finance. Researchers have classified cross-border flows into three categories: (i) portfolio flows; (ii) foreign direct investment; and (iii) banking flows. A widely used framework to identify the drivers of cross-border flows is the push/pull framework suggested by Calvo, Leiderman, and Reinhart (1993) and Fernandez-Arias (1996). This framework highlights the relative importance of the local economy's "pull" factors in comparison with external "push" factors in explaining capital flows (and thereby asset price formation in the local economy). For a comprehensive review of the literature in this field, see Koepke (2019).

analysis of the taper tantrum and the global financial crisis period to provide additional information regarding the nuances of the flow–return relationship. Section 6 concludes the study.

## 2. STYLIZED EVIDENCE ON FUND FLOWS, VOLATILITY SPILLOVERS, AND STABILIZATION POLICIES DURING THE COVID-19 CRISIS

Figure 2 shows the relationship between the monthly FII net inflows and the annualized standard deviation of the daily returns on the CNX NIFTY Index from 1 January 2019 to 30 June 2020. This period captures about 1 year of data before the COVID-19 crisis (the *pre-COVID* period) and an additional 6 months of data during the period when COVID-19 set in and policymakers initiated stabilization measures as well as the post-stabilization period. It is apparent from Figure 2 that there was a sharp drop in FII net inflows in the weeks leading into March; this period was also characterized by a sharp increase in market volatility. The FII net flow recovered after March, and, by April–May, the net inflows had attained levels only slightly below zero before finally turning positive in June. By this time, the market volatility had begun to plateau (but was still much higher than in the pre-crisis period). Overall, the plot in Figure 2 suggests that there is a strong correlation between FII net inflows and volatility, thereby implying that fund flows may have an abnormal impact on asset prices during crisis periods.

**Figure 2: FII Monthly Net Flows and NIFTY Volatility around the COVID-19 Period (2019–2020)**



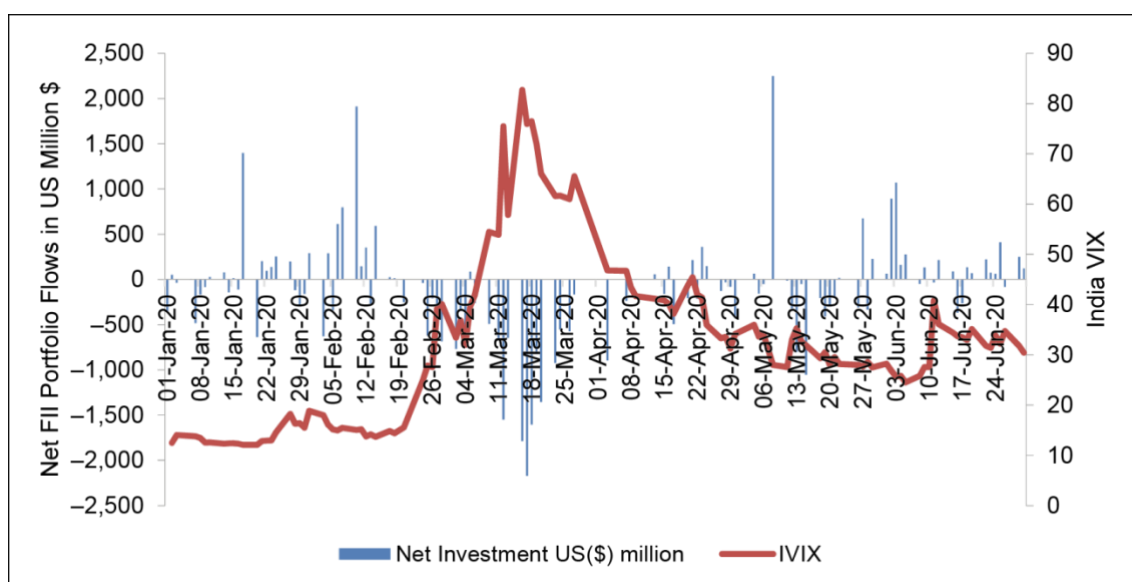
Note: The chart shows the relationship between the monthly FII net inflows and the annualized standard deviation of the daily returns on the CNX NIFTY Index for each fiscal year over the period 2019–2020.

To gauge the impact of fund flows immediately around the onset of COVID-19, we undertook a more granular exercise by investigating how *daily* net FII portfolio flows (in both debt and equity markets) and *daily* market volatility varied during the period from 1 January 2020 to 30 June 2020. Figure 3 shows some preliminary insights into the daily fund flows and volatility during this period. The net FII flows into debt and equity markets entered negative territory in mid-February and remained negative until mid-April. It was only after 15 April that the FII inflows surpassed the FII outflows and

the net FII flows turned positive. Forward-looking volatility (*IVIX*) increased sharply around mid-February and continued to rise until mid-March before beginning to drop.

The key trigger of these events was the 11 March 2020 declaration by the World Health Organization (WHO) that the COVID-19 outbreak was a pandemic. Even before this declaration, the market had become pessimistic, as can be seen in the persistent outflows in the bond and equity markets leading up to 11 March (see Figure 3). The outflows continued to increase significantly over the next 2 weeks. These outflows resulted in a “run-like” situation in the mutual fund market, and this phenomenon was witnessed not only in the US but also across all the major financial markets in the world.

**Figure 3: Net FII Portfolio Flows (Equity and Debt) vs India VIX during the COVID-19 Period (1 January 2020–30 June 2020)**



In the wake of these extreme developments, the Federal Reserve Bank initiated several policy measures to mitigate the adverse impact on financial markets as it was worried about the effect on the real economy. First, on 17 March, the Fed revived the commercial paper funding facility and the primary dealer credit facility (with no specified limits on the maximum size of the support). On 18 March, it opened up the money market mutual fund liquidity facility, again with no specified limits. Furthermore, on 23 March, an 850 billion dollar corporate credit facility was established, followed by a municipal liquidity facility (\$500b limit), a main street facility (\$600b limit), and a payment protection program lending facility on 9 April. In addition, the Fed launched currency swap agreements with foreign central banks to ensure liquidity in the market for dollars.

The Fed’s response, against the backdrop of low inflationary expectations, was highly effective in reviving financial markets. The nonfinancial corporate debt issuance and mutual fund flows picked up significantly. By the end of March 2020, mutual fund flows had attained levels that were even greater than those during pre-COVID times. Although the actual liquidity support initially used in these credit facilities was small and

well within the maximum limits,<sup>9</sup> investors read the Fed's actions as a positive signal of its willingness to be a lender of last resort. The volatility in the equity and bond markets reduced substantially after these stabilization policies were put in place. Overall, our preliminary analysis reveals that the months leading up to mid-March 2020 could be considered as the *pre-stabilization* period, during which market participants were aware of the impending bad news. The period from mid-March to mid-April can be viewed as the *policy stabilization* period, during which a slew of policy measures was initiated by the Federal Reserve Bank. Furthermore, the period after mid-April can be treated as the *post-stabilization* period. We aim to determine how the impact of fund flows varied in these different sub-periods. This exercise will provide policymakers with information about investor behavior during various phases of the crisis period as well as feedback regarding the efficacy of various policy measures.

### 3. DATA AND METHODOLOGY

#### 3.1 Data

The data for our 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](http://www.finance.yahoo.com), which provides data on the S&P 500 Index and the CBOE VIX Index of the US market. The sample period for the COVID-19 crisis is from 1 January 2019 to 30 June 2020. The sample period for the taper tantrum and the global financial crisis is from 1 January 2006 to 30 June 2013.

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. This filter allows us to exclude stocks that are infrequently traded. For the analysis of the COVID-19 crisis, we obtained stock-wise FII trade data of 192 highly liquid stocks over the period 1 January 2019 to 30 June 2020 from the National Stock Exchange (NSE). We dropped five firms due to a mismatch in symbols, three firms as ownership data were not available, and another 10 firms because they had extreme beta outliers. Further, the FII share of the trading volume on any trading day was censored at  $\pm 95\%$  and daily stock returns were censored at  $\pm 20\%$ . The resulting COVID-19 sample consists of an unbalanced panel of 174 stocks with 40,228 stock-day observations.

For the analysis of the earlier crises (the taper tantrum and the GFC), we obtained FII trade data on 251 stocks; 23 stocks were dropped because they were associated with extreme outliers in beta estimates, and five stocks were dropped due to missing data on institutional and retail ownership. Further, the FII share of the trading volume on any trading day was censored at  $\pm 95\%$  and daily stock returns were censored at  $\pm 20\%$ . Our final data set consists of 223 unique stocks with 279,864 stock-day observations. Only 99 stocks are common to both the dataset for the COVID-19 period analysis and the dataset for the taper tantrum and GFC analysis.

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<sup>9</sup> An exception was the paycheck protection program lending facility, which showed significant outlays; however, this lending was collateralized by loans with federal guarantees and was devoid of credit risk.

### 3.2 Descriptive Statistics

Table 1 presents the variable definitions. Stock returns are defined by continuously compounding the return on daily adjusted closing prices for the  $i^{\text{th}}$  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, dividends, etc. on day  $t$ . Similarly, the returns on the NIFTY Index are calculated as follows:

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

**Table 1: Variable Definitions**

$RET_{it} = \ln(P_i/P_{t-1})$	Continuously compounded return using price ( $P_i$ ) 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 (day $t$ ).
$AB\_RET_{it}$	Excess return over the three factors (domestic market, global market, and foreign exchange rate), defined in 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 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 $FII\_BUYS$ and $FII\_SELLS$ scaled by $RUPEE\_VOLUME$ across both FIIs and non-FIIs for the $i^{\text{th}}$ stock on day $t$ .
$AMIHUDD\_ILLIQ_{i,t}$	Ratio of absolute return over traded value on day $t$ for stock $i$ .
$TOVER_{i,t}$	Ratio of total traded value to market capitalization.
$LOCAL\_BETA$	Slope coefficient of $NIFTY\_RET$ in the three-factor model estimated using 52 weekly returns before the portfolio formation day $t$ .
$GLOBAL\_BETA$	Slope coefficient of $S\&P500\_RET$ in the three-factor model estimated using 52 weekly returns before the portfolio formation day $t$ .
$XRATE\_BETA$	Slope coefficient of $XRATE\_RET_t$ in the three-factor model estimated using 52 weekly returns before the 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.
$VIX(\Delta VIX)$	Change in the CBOE VIX value.
$NIFTY\_VOLATILITY$	Garman–Klass range-based daily volatility estimate of the 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-effect panel regression to $FII\_NET_{i,t}$ .
$FII\_OSHIP$	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.

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 the daily FII, as well as non-FII, rupee trading volume (*RUPEE\_VOLUME*).

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

where *RUPEE\_VOLUME<sub>it</sub>* 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.<sup>10</sup> The table provides a guide for understanding the remaining variables used in the study.

**Table 2: Descriptive Statistics**

Variable	Mean	Median	Minimum	Maximum	Std Dev.
<b>Panel A: Firm Characteristics</b>					
<i>RET</i> (%)	-0.02	-0.02	-20.00	20.00	2.76
<i>SIZE</i> (INR billion)	656.11	278.00	28.51	11,900.00	1,154.45
<i>RUPEE_VOLUME</i> (INR billion)	1.66	0.70	0.00	142.63	3.07
<i>TOVER</i>	0.00	0.00	0.00	0.47	0.01
<i>PROMOTER_OSHIP</i> (%)	51.79	53.57	0.00	89.07	19.21
<i>INSTITUTIONAL_OSHIP</i> (%)	33.16	30.89	2.12	89.40	15.43
<i>RETAIL_OSHIP</i> (%)	08.86	07.73	0.62	47.96	06.10
<i>AMIHUDDILLIQ</i>	0.01	0.00	0.00	488.23	1.96
<i>LOCAL_BETA</i>	1.09	1.06	-0.08	2.46	0.60
<i>GLOBAL_BETA</i>	-0.09	-0.09	-1.00	0.79	0.45
<i>XRATE_BETA</i>	-0.04	-0.01	-2.37	2.26	1.44
<i>VOLATILITY</i> (annualized, %)	42.68	40.57	24.79	102.44	11.82
<i>IDIO_RISK</i> (daily, %)	28.21	26.27	14.43	70.61	10.50
<b>Panel B: Market-Wide Factors</b>					
<i>NIFTY_RET</i> (%)	-0.02	0.03	-13.90	8.40	1.70
<i>S&amp;P500_RET</i> (%)	0.05	0.10	-12.77	8.97	1.77
<i>XRATE_RET</i> (%)	0.03	0.00	-1.87	2.64	0.56
<i>VIX</i>	20.86	15.82	11.54	82.69	12.56
<i>ΔVIX</i> (first difference in <i>VIX</i> )	0.02	-0.12	-17.64	24.86	2.95
<i>NIFTY_VOLATILITY</i> (%)	22.31	18.54	5.34	192.43	15.87
<i>AGGR_FFLOW</i>	-0.01	-0.01	-0.15	0.14	0.04
<b>Panel C: FII Flows</b>					
<i>FII_OSHIP</i> (%)	28.90	20.23	0	90.81	17.45
<i>FII_BUYS</i> (INR billion)	0.28	0.06	0	118.32	0.94
<i>FII_SELLS</i> (INR billion)	0.30	0.07	0	71.76	0.89
<i>FII_NET</i>	-0.01	-0.00	-0.97	0.96	0.18

Note: The table presents the descriptive statistics of 174 sample firms listed on the National Stock Exchange of India (NSE) during the sample period from 1 January 2019 to 30 June 2020. Panel A shows the firm characteristics. Panel B presents the relationship with market-wide factors. See Table 2 for variable definitions. The 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](http://www.finance.yahoo.com).

<sup>10</sup> 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 performed in our measure, better captures the economic significance of FII trading in that stock.

Table 2 provides summary statistics related to the COVID-19 analysis period. The average firm size is 656 billion rupees (nearly \$9 billion), and the average (daily) stock return is -0.02%. During the same period, the average daily returns on the NIFTY Index and on the S&P 500 Index are -0.02% and 0.05%, respectively. The CBOE VIX (*VIX*) had a mean level of nearly 21 during the sample period. The FII daily average purchases (*FII\_BUYS*) were approximately equal to the 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 28.90% in the sample period.

### 3.3 Methodology

We rely on a simple yet powerful 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 captures the average daily trading behavior of FIIs over the entire sample period. We then construct two extreme (quintile) portfolios at the beginning of each week based on the innovation in FII flows—more specifically, a high-innovation portfolio and a low-innovation portfolio. Finally, we estimate how the short-run market performance of these portfolios is related to innovations in FII flows.

#### 3.3.1 The Panel Regression Model

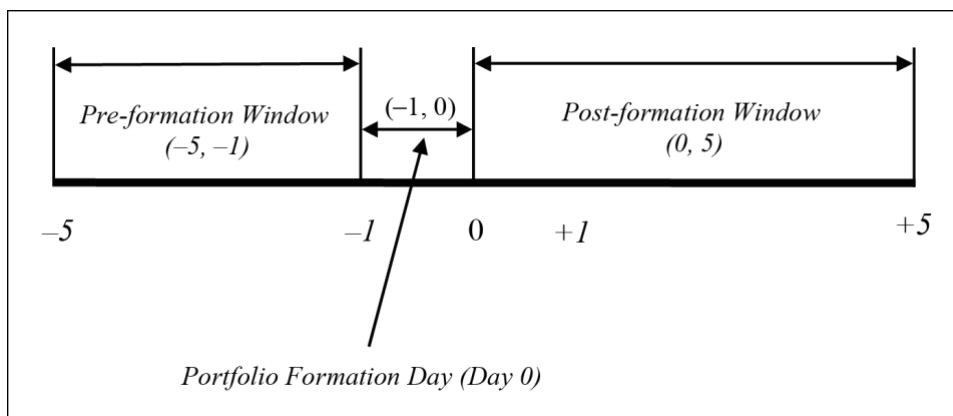
We consider a panel regression model of *FII\_NET* on lagged *FII\_NET*, lagged stock returns, and other control variables; the residuals from this model (*FII\_NET\_INNOV*) are used as a proxy for the “true” (unobserved) innovations in FII flows. The model includes firm fixed effects. The control variables are related to firm characteristics and market factors. The firm characteristics include firm size (*SIZE*), stock illiquidity (*AMIHU*), turnover (*TOVER*), percentage of retail (*RETAIL\_OSHP*), and institutional ownership (*INSTITUTIONAL\_OSHP*) in the firm. *SIZE* is included because we can expect more FII trading in bigger firms that are well known and are known to be subject to more scrutiny, leading to lower information asymmetry. The variable *AMIHU*, based on Amihud (2002), controls for the illiquidity effect, and *TOVER* controls for the average level of trading. *RETAIL\_OSHP* and *INSTITUTIONAL\_OSHP* are used to control for any ownership structure effect that may induce FII trading. To capture market effects, we also include the following lagged market variables: the aggregate FII flows (*AGGR\_FFLOW*), the volatility index (*VIX*), change in the volatility index ( $\Delta VIX$ ), NIFTY Volatility (*NIFTY\_VOLATILITY*), S&P 500 returns (*S&P500\_RET*), and NIFTY returns (*NIFTY\_RET*). The aggregate FII flows variable (*AGGR\_FFLOW*), defined as the aggregate of *FII\_NET* over all stocks on a trading day, captures the commonality in FII flows. The volatility variables (*VIX* and *NIFTY\_VOLATILITY*) are used to control for volatility-induced FII flows, and the prior market return variables (*S&P500\_RET* and *NIFTY\_RET*) capture the role of positive feedback trading on FII flows. The model specification is described below:

$$\begin{aligned}
 FII_{NET_{i,t}} = & FirmFEff + \sum_{j=1}^5 FII_{NET_{i,t-j}} + \sum_{k=1}^5 Ret_{i,t-k} + \delta_1 SIZE_{i,t} \\
 & + \delta_2 TOVER_{i,t} + \delta_3 RETAIL\_OSHP_{i,t-1} + \delta_4 INSTITUTIONAL\_OSHP_{i,t-1} \\
 & + \alpha_1 AGGR\_FFLOW_{t-1} + \alpha_2 VIX_{t-1} + \alpha_3 \Delta VIX_{t-1} + \alpha_4 NIFTY\_RET_{t-1} \\
 & + \alpha_5 SP500\_RET_{t-1} + \alpha_6 NIFTY\_VOLATILITY_{t-1} + e_{i,t}.
 \end{aligned} \tag{4}$$



The above regression serves the purpose of a first-pass panel regression in which the regression residuals define the daily innovations in FII flows (*FII\_NET\_INNOV*), which are used as a proxy for surprises or innovations in FII flows. These residuals, which measure *unexpected* FII flows, are used to form five quintile portfolios every Monday (or the first trading day of the week). The extreme tail portfolios (the low-innovation portfolio, referred to as Q1, and the high-innovation portfolio, referred to as Q5) are tracked over a 10-day window around the portfolio formation day, as depicted in Figure 4. We examine the abnormal return on these portfolios over a 10-day trading window centered on the day of *portfolio formation* (Day 0).<sup>11</sup> 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 window*  $(-5, -1)$ , on the *portfolio formation day* (Day 0) over the interval  $(-1, 0)$ , and over the *post-formation window*  $(0, 5)$ . The returns in these windows are then used to infer the impact of unexpected FII flows on stock prices, as discussed below.

**Figure 4: Portfolio Formation Procedure**



Note: The figure describes the portfolio formation procedure. Every Monday (Day 0), five portfolios are formed based on the innovations in FII flows. The cumulative abnormal returns on the high-innovation and low-innovation portfolios are tracked over the 10-day window surrounding the portfolio formation day (Day 0).

### 3.3.2 Abnormal Returns

The asset price effects associated with unexpected FII flows are measured using abnormal returns.  $AB\_RET_{it}$  is defined as the excess return on the  $i^{\text{th}}$  stock on day  $t$  over and above the expected return 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 follows:

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

<sup>11</sup> In short-run event studies, like the one conducted in our study, a 2–3-day window makes sense. However, in emerging economies, it may be advisable to use a larger 10-day window because the markets are less liquid and transient effects may contaminate returns over a window of 2–3 days, thus rendering the inference questionable. Furthermore, as Dimson (1970) pointed out, the flow of information may be delayed for smaller, less well-known firms that have a smaller analyst following. Many of the stocks in our sample are small stocks, and the use of a 10-day window ensures that all permanent and transient price effects are fully captured.

The above specification accounts for the sensitivity of stock returns to local market risk ( $\beta_{iN}$ ), global market risk ( $\beta_{iG}$ ), and exchange rate returns ( $\beta_{iX}$ ), where  $XRATE_t$  is a proxy for risk exposure to foreign exchange rate fluctuations. All the results reported in the paper refer to abnormal returns obtained from the above three-factor model.

It is important to point out that our choice of this specification reflects concerns that our results may be driven spuriously by the exposure of stocks to global market risk and foreign exchange risk because FII traders are known to factor in such risks when taking positions in domestic stocks. To control for these factors, we employ the above three-factor specification. 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. Further, our results hold for raw returns. Thus, no matter which specification is chosen, our findings are robust.

## 4. IMPACT OF UNEXPECTED FUND FLOWS ON ASSET RETURNS DURING THE COVID-19 CRISIS

Given our objective of assessing the impact of fund flows on asset returns during the COVID-19 crisis, we first discuss a panel regression model to extract the innovations in FII flows. To the extent that FII flows are predictable, the market reaction in terms of coincident price changes is more likely to be driven by the unexpected (surprise or innovations) in FII flows. The sample data are divided into an in-sample period (1 January 2019 to 31 December 2019) and an out-of-sample period (1 January 2020 to 30 June 2020). The in-sample data are used to establish the parameters of the panel regression model, which is then used to estimate the predicted FII flows in the out-of-sample period. The innovation in FII flows in the out-of-sample period is then computed as the residual, i.e., the difference between the realized FII flows and the predicted FII flows.

Next, we wish to contrast the abnormal returns of stocks experiencing high innovations with those of stocks experiencing low innovations in fund flows to assess the impact of fund flows on asset prices. More importantly, we wish to see how this relationship evolves at different points in time during the COVID-19 crisis period. For this purpose, we partition the out-of-sample period into three periods: (i) 1 January 2020 to 23 March (the pre-stabilization period), (ii) 24 March 2020 to 15 April 2020 (the policy stabilization period), and (iii) 16 April 2020 to 30 June 2020 (the post-stabilization period). This division is driven by the discussion in Section 2.

### 4.1 Innovations in FII Flows

Table 3 shows the results of estimating this panel regression of  $FII\_NET$  on lagged  $FII\_NET$ , lagged returns, firm characteristics, and market factors, as specified in Equation (4). Note that  $FirmFEff$  refers to firm fixed effects.<sup>12</sup> The adjusted R-square value is around 23%.  $FII\_NET$  is significantly related to the first lagged return and up to five lagged values of  $FII\_NET$ . The positive coefficient of lagged  $FII\_NET$  shows

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<sup>12</sup> We employ an objective Hausman test to find out whether a fixed-effect model or a random-effect model suits the data in our sample. We find that the use of a fixed-effect model is justified. For robustness, we also explore alternative specifications with and without firm fixed effects and time fixed effects. These variations turn out to be qualitatively similar. In additional tests, we conduct a sectoral analysis with three sectors (banking and financial services, manufacturing, and "others"). Our findings for the sectoral sub-samples are virtually the same as those for the overall sample.

persistence in FII flows. The positive coefficients of the lagged returns are consistent with trend chasing or positive feedback trading by FIIs.

**Table 3: Panel Regression Model**

Variable	Coefficient	t-statistic
Intercept	-1.7074	-9.01***
<i>FII_NET</i> <sub><i>t</i>-1</sub>	0.3085	40.94***
<i>FII_NET</i> <sub><i>t</i>-2</sub>	0.1046	14.73***
<i>FII_NET</i> <sub><i>t</i>-3</sub>	0.0563	8.10***
<i>FII_NET</i> <sub><i>t</i>-4</sub>	0.0385	5.43***
<i>FII_NET</i> <sub><i>t</i>-5</sub>	0.0493	7.70***
<i>RET</i> <sub><i>t</i>-1</sub>	0.0033	7.03***
<i>RET</i> <sub><i>t</i>-2</sub>	0.0003	0.59
<i>RET</i> <sub><i>t</i>-3</sub>	0.0006	1.35
<i>RET</i> <sub><i>t</i>-4</sub>	0.0001	0.35
<i>RET</i> <sub><i>t</i>-5</sub>	-0.0009	-2.27**
<i>AGGR_FFLOW</i> <sub><i>t</i>-1</sub>	0.0291	0.73
<i>SIZE</i>	0.0647	9.31***
<i>TOVER</i>	0.3242	3.33***
<i>RETAIL_OSHP</i> <sub><i>t</i>-1</sub>	0.0033	3.44***
<i>INSTITUTIONAL_OSHP</i> <sub><i>t</i>-1</sub>	-0.0015	-3.51***
<i>VIX</i> <sub><i>t</i>-1</sub>	0.0006	0.75
$\Delta$ <i>VIX</i> <sub><i>t</i>-1</sub>	-0.0012	-0.64
<i>NIFTY_VOLATILITY</i> <sub><i>t</i>-1</sub>	-0.1387	-0.27
<i>S&amp;P 500_RET</i> <sub><i>t</i>-1</sub>	0.0015	0.45
<i>NIFTY_RET</i> <sub><i>t</i>-1</sub>	-0.0037	-1.85*
Adj. <i>R</i> <sup>2</sup>	0.23	
Durbin–Watson statistic	1.99	
F-statistic	65.14***	
<i>N</i>	40,228	
Number of firms	174	

Note: The table reports the results of a firm fixed-effect panel regression of *FII\_NET*<sub>*it*</sub> on past *FII\_NET* and past stock returns along with firm characteristics and market-wide factors. The unbalanced sample includes 174 firms and 40,228 firm-day observations for the year 2019. The panel regression specification is as follows:

$$\begin{aligned}
 FII_{NET_{i,t}} = & FirmFE_{i,t} + \sum_{j=1}^5 FII_{NET_{t-j}} + \sum_{k=1}^5 Ret_{t-k} + \delta_1 SIZE + \delta_2 TOVER + \delta_3 RETAIL_{OSHP_{t-1}} \\
 & + \delta_4 INSTITUTIONAL_{OSHP_{t-1}} + \alpha_1 AGGR\_FFLOW_{t-1} + \alpha_2 VIX_{t-1} + \alpha_3 \Delta VIX_{t-1} + \alpha_4 NIFTY\_RET_{t-1} \\
 & + \alpha_5 S \& P500\_RET_{t-1} + \alpha_6 NIFTY\_VOLATILITY_{t-1} + e_{i,t}
 \end{aligned}$$

where *i* refers to stock *i* and *t* refers to day *t*, *FII\_NET* is the difference between *FII\_BUYS* and *FII\_SELLS* scaled by the total value traded (across both FIIs and non-FIIs). See Table 2 for the variable definitions. The table reports the coefficient estimates along with time-clustered robust *t*-statistics. \*, \*\*, and \*\*\* indicate the significance levels of 0.10, 0.05, and 0.01, respectively.

The firm characteristics that have significant coefficients in the panel regression model are firm size (*SIZE*), turnover (*TOVER*), retail ownership (*RETAIL\_OSHP*), and institutional ownership (*INSTITUTIONAL\_OSHP*). The positive relationship between FII flows and firm size is not surprising. The negative relationship with institutional ownership may reflect the mean reversion arising due to either the ownership constraints (there are regulatory limits on FII ownership in each stock) or the portfolio rebalancing motives (rather than buy-and-hold motives) of FII traders. The market

variables market stress ( $VIX$ ), first difference in market stress ( $\Delta VIX$ ), aggregate FII flows ( $AGGR\_FFLOW$ ), and local NIFTY volatility ( $NIFTY\_VOLATILITY$ ) all have insignificant coefficients. The coefficient of lagged S&P 500 returns is also statistically insignificant, while the coefficient of lagged NIFTY returns is negative but weakly significant.

The coefficients of these variables (based on the above panel regression model trained on the in-sample pre-COVID data) are then used to estimate the expected FII flows (or the predicted FII flows) in the out-of-sample period from 1 January 2020 to 30 June 2020. The difference between the realized FII flows and the predicted FII flows provides us with an estimate of the innovations in FII flows ( $FII\_NET\_INNOV$ ).

## 4.2 Impact of Fund Flows on Asset Prices in the Pre-COVID Period

Using the specification in Equation (5), we estimate the sensitivity of stock returns to the local market risk ( $\beta_{IN}$ ), global market risk ( $\beta_{IG}$ ), and exchange rate returns ( $\beta_{IX}$ ). All the results reported in the paper refer to abnormal returns obtained from the three-factor model. For our sample data, we find that the cross-sectional mean local beta ( $\beta_{IN}$ ) is 1.09, the mean global beta ( $\beta_{IG}$ ) is  $-0.09$ , and the mean exchange rate beta ( $\beta_{IX}$ ) is  $-0.04$ .

To assess the price effects of unexpected foreign fund flows, we first rank all the stocks according to daily innovations in  $FII\_NET$  flows once every week (on Mondays) and group them into five quintiles. Over the one-year sample period, there are 46 portfolio formation days. Table 5 shows the abnormal return patterns for the portfolios with the lowest innovations (Q1) in  $FII\_NET$  and 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 return 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).

The pre-COVID-19 situation (1 January 2019 to 31 December 2019) is described in Figure 1. Panel A shows that Q1 stocks and Q5 stocks exhibited similar behavior in the pre-formation window  $(-5, -1)$ . However, on Day 0, the high-innovation stocks experienced a permanent price effect whereas the low-innovation stocks experienced a partially permanent price effect. In the post-formation window  $(0, 5)$ , the CAR plot for low-innovation stocks shows a delayed reaction over the interval  $(0, 1)$  and then an equal amount of reversal over the interval  $(1, 4)$ . 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 a *permanent* information effect and a *transient* price pressure effect, which is reversed over the latter part of the post-formation window. Table 4 also provides details of the statistical significance of the findings displayed in Figure 1. The Day 0 abnormal returns on both Q1 and Q5 stocks are statistically significant.

**Table 4: Price Effects of FII Flows from 1 January 2019 to 31 December 2019****Abnormal Return Behavior around the Days of Shocks in *FII\_NET***

AB_RET (Close <sub>-1</sub> to Open <sub>0</sub> ) %	Q1		Q5		Q5–Q1	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
CAB_RET (–5, –1) %	–0.22	–2.23**	–0.05	–0.54	0.17	1.28
AB_RET (–1, 0) [Day 0 Returns] %	–0.77	–14.60***	0.48	8.45***	1.25	16.15***
AB_RET (Open <sub>0</sub> to Close <sub>0</sub> ) %	–0.67	–13.81***	0.48	9.38***	1.15	16.31***
AB_RET (Close <sub>-1</sub> to Open <sub>0</sub> ) %	–0.09	–3.57***	–0.02	–1.03	0.07	1.91*
CAB_RET (0, 5) %	–0.02	–0.17	0.01	0.10	0.03	0.19

Note: 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 the Q1 portfolio. Panel A presents the abnormal return patterns of Q1 and Q5 stocks.  $AB\_RET(t-1, t)$  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).  $CAB\_RET(t_1, t_2)$  is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval  $(t_1, t_2)$ . The number of stocks in the sample is 174. 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.)

Furthermore, the Day 0 abnormal return differential (Q5–Q1) is statistically significant. This can be seen in Figure 1 (Panel B), which displays the abnormal return differential between high- and low-innovation stocks. There is a significant positive difference in CARs between Q5 and Q1 stocks on Day 0 but a flat pattern in CARs in the post-formation window (0, 5), thus suggesting that the Day 0 return differential for a portfolio that is long on Q5 stocks and short on Q1 stocks is a permanent effect that does not dissipate over the (0, 5) window.

Next, we decompose the abnormal return on the 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 on Day 0 and the closing price on Day 0). The differential abnormal return on Day 0 is mainly driven by during-day differential abnormal returns (Table 4 Panel A, third and fourth rows). The overnight returns are smaller and similar for the Q1 and Q5 portfolios, and the differential abnormal *overnight* return of 0.07% is insignificant (both statistically and economically). The *during-day* differential abnormal return of 1.15% is, however, significant. The decomposition of abnormal returns into overnight returns and during-day returns thus strongly suggests that abnormal FII flows are influencing contemporaneous asset returns.

A caveat is in order. We cannot be too sure about the direction of causality between flows and asset returns. The information contained in asset price changes could also induce abnormal FII flows, rather than the other way around. While a vector autoregression (approach) provides a technique to extract more clear inferences regarding causality, we believe that such an approach may add little value when used on daily data and will work only if we employ intraday data. Given that our dataset is based on daily rather than intraday returns, we believe that the panel regression model is more suitable for our analysis than the vector autoregression approach. Moreover, our evidence on the significance of during-day returns rather than overnight returns suggests that price effects follow innovations in FII flows. We employ the panel regression approach to capture the magnitude of abnormal returns, which persist in the

post-formation window (indicating the potential for a long-short arbitrage opportunity conditional on innovations in FII flows).<sup>13</sup>

To summarize, 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 low FII outflows (i.e., the low-innovation portfolio). The results are, however, also consistent with information being revealed through both FII purchases and FII sales, given the permanent nature of Day 0 returns for stocks experiencing extreme innovations in FII flows. In contrast to FII inflows, FII outflows contribute to transient volatility; however, both FII inflows and FII outflows (i.e., FII flows in general) generate new information.

### 4.3 Fund–Return Relations and Policy Response during the COVID-19 Crisis

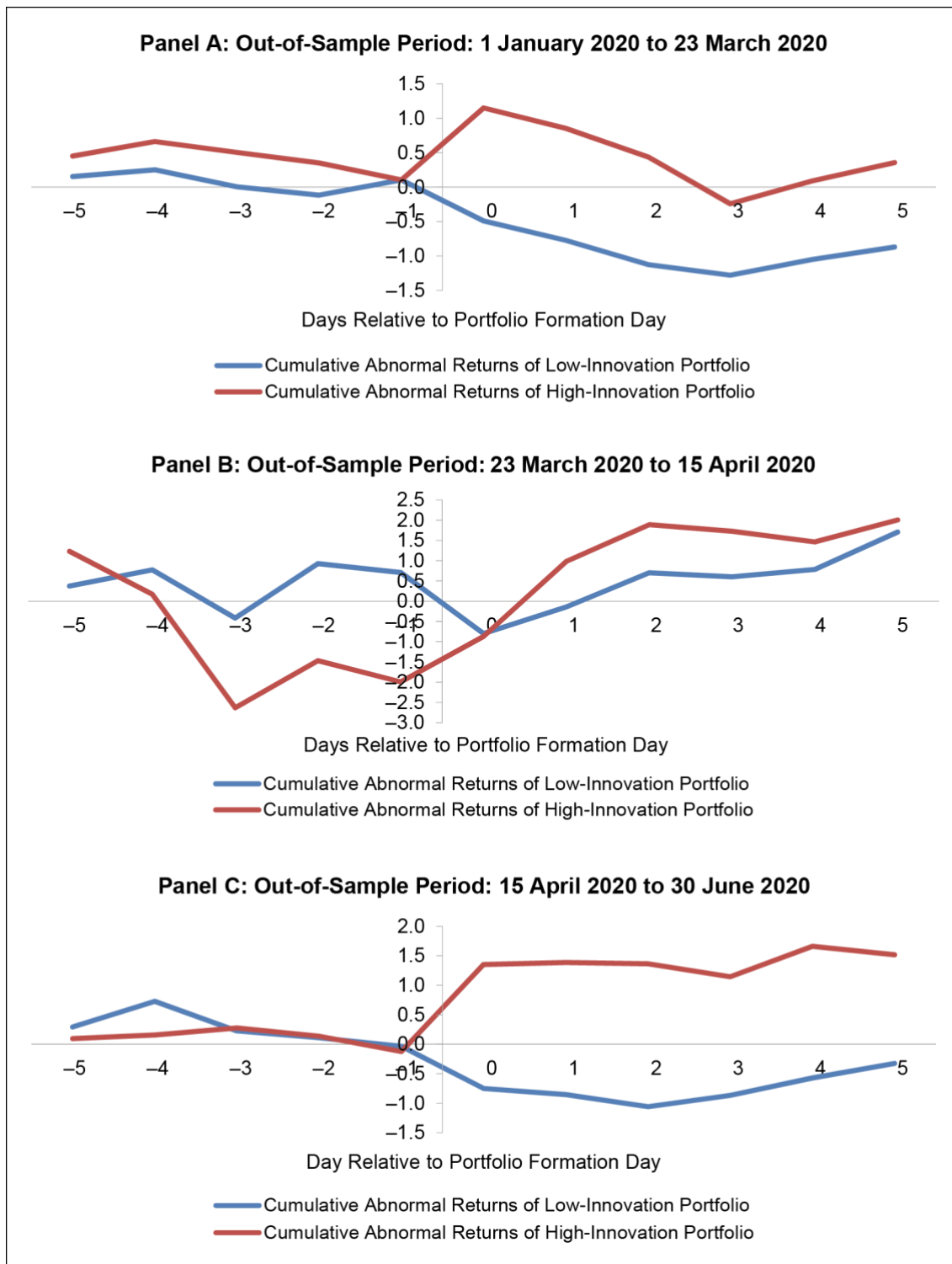
To examine the impact of the fund flows on asset prices at the onset of COVID-19, we analyze the fund flow–return relationship in three distinct periods: (i) the pre-stabilization period (1 January 2020 to 23 March 2020), when market forces reflected the potential adverse effects of COVID-19; (ii) the policy stabilization period (24 March to 15 April), when the Federal Reserve Bank initiated significant policy moves to stem the downward spiral in financial markets; and (iii) the post-stabilization period (16 April to 30 June), when the financial markets responded to the policy initiatives taken up by the Federal Reserve. The motivation for this analysis is to establish how the COVID-19 crisis (1 January 2020 to 30 June 2020) differs from the pre-COVID normal period (1 January 2019 to 31 December 2019).

Figure 5 shows the abnormal returns on both the portfolio consisting of low-innovation stocks (Q1) and the portfolio consisting of high-innovation stocks (Q5). Panels A, B, and C cover the pre-stabilization period, the policy stabilization period, and the post-stabilization period. Panel A shows that there is little difference between the CAR plots of the high-innovation stocks (Q5) and the low-innovation stocks (Q1) in the pre-formation window (−5, −1). This pattern is similar to what we observed in the pre-COVID-19 analysis (see Figure 1, Panel A). On Day 0, the CAR plot for Q5 (Q1) shows an immediate positive (negative) price impact. This price effect is similar in direction but significantly larger in magnitude than that during the pre-COVID-19 period. Furthermore, in the post-formation window (0, 5), the CAR plots show a remarkable difference in comparison with the pre-COVID-19 period. First, there is a price reversal for both Q5 and Q1 stocks, unlike the pre-COVID-19 period, during which only the low-innovation Q1 stocks experienced transient volatility. Furthermore, the transient price effects persist for a longer window (1, 3) before exhibiting a slight reversal over the window (3, 5). In short, both the initial Day 0 price reaction and the transient price effect over (0, 5) are more exaggerated during the pre-stabilization period than during the pre-COVID-19 normal period. Overall, the results in Panel A demonstrate that the market was experiencing a higher degree of transient volatility; the subsequent policy interventions taken up by the Federal Reserve Bank were indeed a timely response.

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<sup>13</sup> Given the time zone difference, it is likely that FIIs take clear views on their portfolio holdings at the close of trading in the US 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.

**Figure 5: Cumulative Abnormal Returns of High-Innovation and Low-Innovation Portfolios**



Note: The residuals obtained from a panel regression model (built on in-sample data from 1 January 2019 to 31 December 2019) are used to estimate shocks (innovations) in FII flows ( $FII\_NET_{i,t}$ ) during the out-of-sample period from 1 January 2020 to 30 June 2020. Firms are ranked according to innovations in  $FII\_NET$  at the beginning of every week (typically 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 during the out-of-sample period: from 1 January 2020 to 23 March 2020 (Panel A), from 24 March 2020 to 15 April 2020 (Panel B), and from 16 April 2020 to 30 June 2020 (Panel C).

Panel B covers the impact of fund flows during the policy stabilization period. In this case, the CAR patterns in the  $(-5, -1)$  window are remarkably different from those in the pre-stabilization period and the pre-COVID-19 normal period. Over the preformation window  $(-5, -1)$ , the high-innovation Q5 stocks were significantly (adversely) affected by the onset of the COVID-19 crisis, as can be seen in the negative returns in the  $(-5, -1)$  window. It is interesting to note that these negative returns on Q5 stocks were more negative than those on Q1 stocks. However, in the post-formation window  $(1, 5)$ , the pattern was completely reversed; the abnormal returns for Q5 stocks were significantly positive and much higher than those experienced by the Q1 stocks. In short, the stabilization measures were highly effective in that they revived the performance of the stocks that were most severely affected by the onset of the COVID-19 crisis. Finally, in Panel C, which shows the impact of fund flows in the post-stabilization period, the CAR patterns of Q1 and Q5 reverted to a similar pattern to that seen during the pre-COVID-19 period (see Figure 1, Panel A) for the  $(-5, 1)$  and  $(-1, 0)$  windows, but Q1 stocks continued to experience transient volatility in the  $(0, 5)$  window.

Table 5 presents the results shown in Figure 5 in terms of the economic and statistical significance of the coefficients associated with the abnormal returns in Q1, Q5, and Q5–Q1. First, the (abnormal) return difference between the high- and low-innovation portfolios (Q5–Q1) is equal to a statistically significant 1.64%, 2.63%, and 2.19% during the pre-stabilization period (Panel A), the policy stabilization period (Panel B), and the post-stabilization period (Panel C), respectively.

**Table 5: Impact of FII Flows during the COVID-19 Period  
(1 January 2020–30 June 2020)**

**Impact of FII Flows—COVID-19 Period (1 January 2020–30 June 2020)**

	Q1		Q5		Q5–Q1	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
<b>Panel A. 1 January to 23 March (Pre-stabilization Period)</b>						
<i>CAB_RET</i> $(-5, -1)$ %	0.15	0.47	-0.48	-1.41	-0.63	-1.34
<i>AB_RET</i> $(-1, 0)$ [Day 0 Returns] %	-0.60	-3.27***	1.05	4.11***	1.64	5.22***
<i>CAB_RET</i> $(0, 5)$ %	-0.82	-1.77*	-0.65	-1.33	0.17	0.26
<b>Panel B. 24 March to 15 April (Policy Stabilization Period)</b>						
<i>CAB_RET</i> $(-5, -1)$ %	0.12	0.12	-2.56	-2.25**	-2.68	-1.78*
<i>AB_RET</i> $(-1, 0)$ [Day 0 Returns] %	-1.51	-3.33***	1.13	1.98*	2.63	3.62***
<i>CAB_RET</i> $(0, 5)$ %	2.79	3.72***	3.30	3.45***	0.51	0.42
<b>Panel C. 16 April to 30 June (Post-stabilization Period)</b>						
<i>CAB_RET</i> $(-5, -1)$ %	-0.27	-0.83	-0.19	-0.53	0.08	0.16
<i>AB_RET</i> $(-1, 0)$ [Day 0 Returns] %	-0.71	-4.01***	1.48	9.58***	2.19	9.30***
<i>CAB_RET</i> $(0, 5)$ %	0.34	0.77	0.15	0.36	-0.19	-0.31

Note: The 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 the first phase of the COVID-19 crisis. 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 the Q1 portfolio. *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). *CAB\_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 ( $\text{Close}_{t-1}$  to  $\text{Open}_t$ ) and the during-day return ( $\text{Open}_t$  to  $\text{Close}_t$ ) experienced by the high- and low-innovation portfolios on the portfolio formation day (Day 0). Panel A reports the results for the full out-of-sample period, i.e., January 2020 to June 2020. Panels B, C, and D report the results for three sub-periods of the out-of-sample period. The number of stocks in the sample is 176. 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.)



Second, the efficacy of the Federal Reserve Bank's stabilization policies can be ascertained by the statistical significance of the coefficients of Q1, Q5, and Q5–Q1 in Panel B of Table 5. We can observe that the Q5 stocks experienced statistically significant negative returns over  $(-5, -1)$  but insignificant returns over  $(-1, 0)$ . In contrast, the Q1 stocks experienced insignificant negative returns over  $(-5, -1)$  but significant negative returns over  $(-1, 0)$ . These numbers support the contention that the high-innovation stocks suffered a greater adverse shock during the COVID-19 crisis than the Q1 stocks. However, there was a reversal of these effects in the  $(1, 5)$  window, with both the Q1 and the Q5 stocks experiencing significant positive returns. These return patterns indicate that the stocks that experienced the most negative returns in the pre-formation window benefitted the most from the Federal Reserve's stabilization measures.

Now we turn to the second part of our analysis, in which we examine two other major crisis-type events that occurred recently, i.e., the taper tantrum period in 2013 and the GFC period in 2008. The objective of our analysis is to determine whether the price effects associated with unexpected fund flows exhibited similar patterns in previous crisis periods.

## **5. EARLIER CRISIS PERIODS: THE TAPER TANTRUM (2013) AND THE GFC (2008)**

First, we present some market-based evidence on foreign fund flows and the associated volatility in Indian equity markets in the 2006–2013 period. This evidence helps to us uncover interesting, stylized facts about the flow–return relationship. Figure 6 shows the relationship between the 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<sup>14</sup> during the 2001–2013 period. The FII net inflows were positive in all the years except 2008–2009. However, during the global financial crisis (2007–2009), the FII inflows turned negative (net outflows of approx. USD 10 billion), consistent with the overall flight to quality of global capital flows. The volatility of the NIFTY Index was also much higher during this period than in other years, lending support to the hypothesis that FII outflows induce volatility in emerging markets.

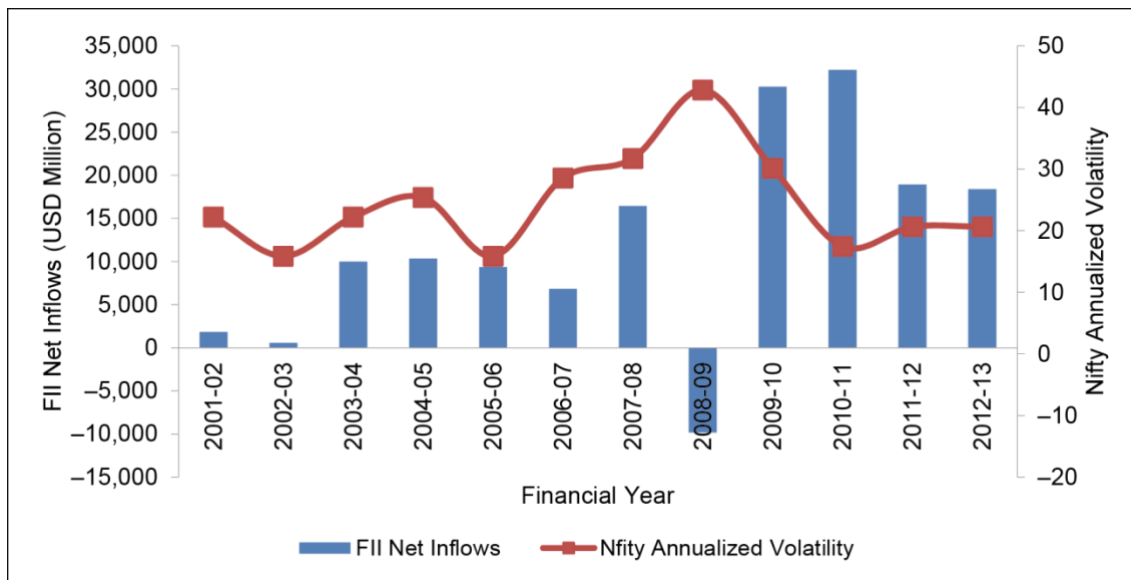
### **5.1 Impact of FII Flows during the Taper Tantrum Period**

After the financial crisis of 2008, the US 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 22 May 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) documented 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 in Figure 7. 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.

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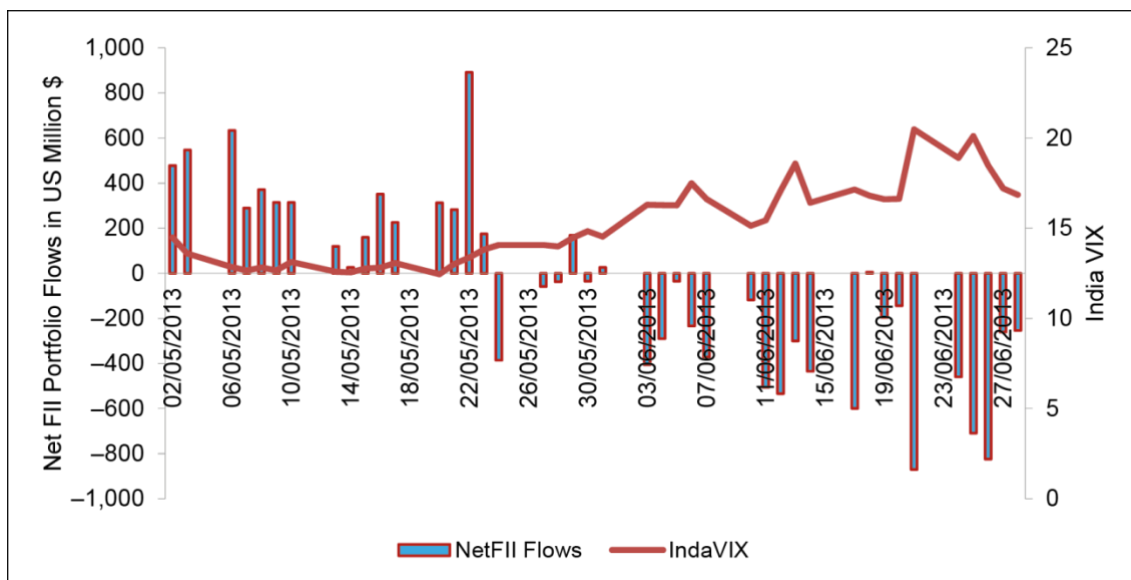
<sup>14</sup> The financial year in India runs from 1 April to 31 March.

**Figure 6: FII Annual Net Flows into Indian Equity Markets and NIFTY Volatility during the Period 2001–2012**



Note: The chart shows the relationship between the 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. The FII net inflows were positive in all the years except 2008. The data for the chart are taken from Table 1.

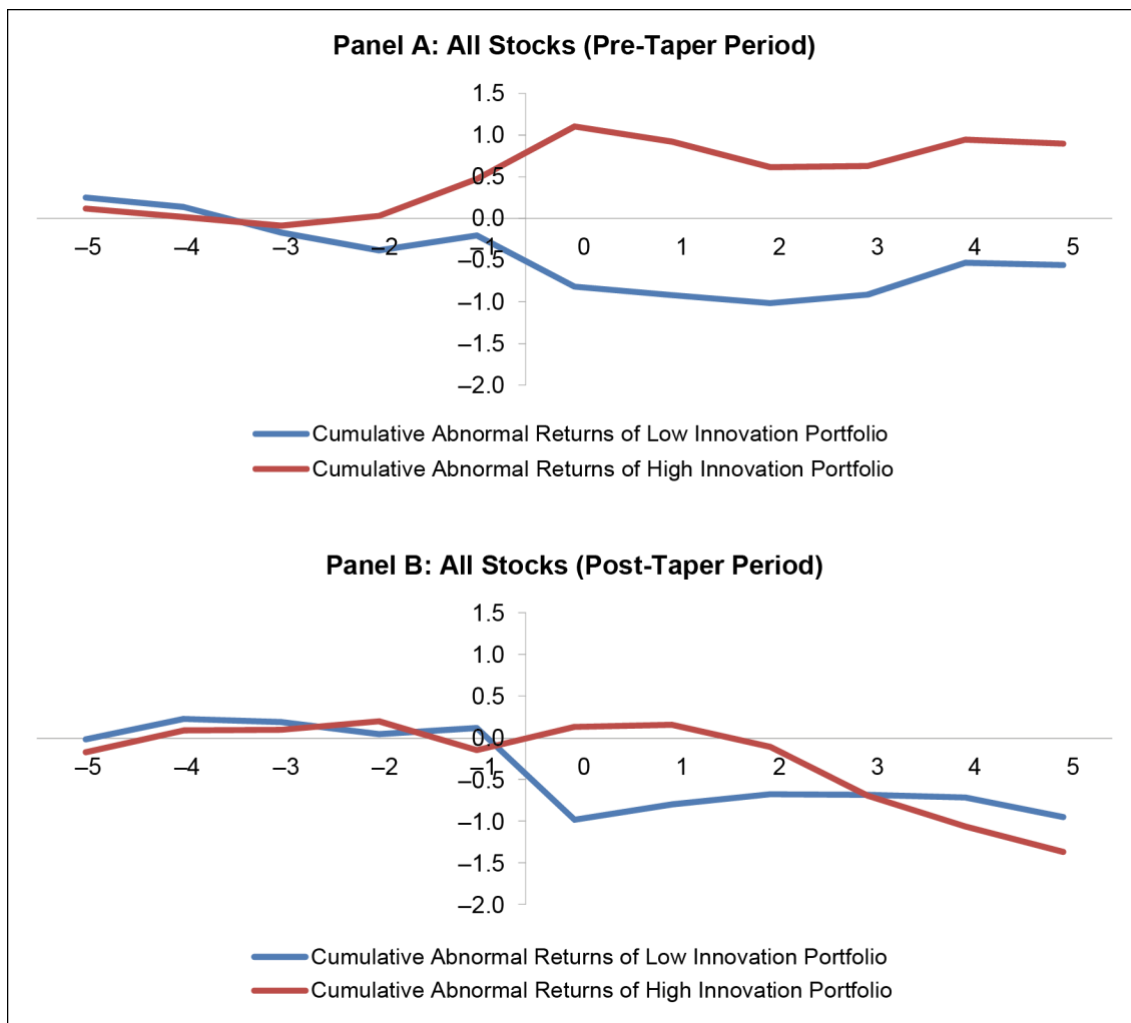
**Figure 7: Net FII Portfolio Flows (Equity and Debt) vs India VIX during the Taper Tantrum Period (May–June 2013)**



The taper tantrum period provides us with an opportunity to evaluate how FII flows affected asset prices during this crisis period. We partition the taper tantrum period into two sub-periods: a pre-taper period (15 April to 22 May) and a post-taper period (23 May to 30 June). We use the data from 1 January 2006 to 15 April 2013 to build the panel regression model, which we then use to estimate the innovations in FII flows in

the pre-taper and post-taper periods.<sup>15</sup> Like the earlier analysis, 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 daily differential abnormal returns before and after the portfolio formation day.

**Figure 8: Impact of FII Flows during the Taper Tantrum Period**



We are interested in knowing whether the fund flows in the post-taper period were as informative as those in the pre-taper period or whether they were largely driven by non-information-based motives, such as portfolio rebalancing by FIIs. The CAR plots are shown in Figure 8.<sup>16</sup> Panels A and B of Figure 8 show the plots for the two periods (pre-taper and post-taper) for the entire sample of stocks. The pre-taper plot (Panel A) indicates significant transient volatility in both Q1 and Q5 stocks in the pre-taper period,

<sup>15</sup> We include unbalanced panel data of 223 stocks. Only 99 stocks are common between the COVID-19 analysis and the analysis of the other crises examined in this study. As the economy evolves, the relevant set of firms would naturally differ across these events, and we accordingly use different sets of firms for the analysis of each crisis period. However, the sample selection of firms across the three periods is based on the same criteria.

<sup>16</sup> For completeness (although not reported here), we also construct the CAR plots for the high- and low-innovation portfolios separately and find them to be qualitatively like the plots for the in-sample period.

indicating that the markets were concerned about the Fed's policy. These transient effects are exacerbated during the post-taper plot (Panel B), which reflects the onset of the Fed's taper policy. We can see that the negative sentiment in this crisis period overwhelmed the normal price behavior of both Q1 and Q5 stocks in the (0, 5) window as compared with the pre-taper period.

Table 6 reports the statistical significance of the above findings. Consistent with the visual depiction in Figure 8, the Day 0 price effects during the post-taper period (Table 6, Panel B, middle row) were significantly higher for Q1 stocks (Table 6, Panel A, middle row). For Q5 stocks, the Day 0 effect on the post-taper period was insignificant. Conversely, Q5 stocks experienced significant negative returns over (0, 5) during the post-taper period. These findings echo the negative drift observed for both Q1 and Q5 stocks in Figure 8. They suggest that the negative sentiment in the post-taper period swamped the abnormal return trends normally associated with FII inflows.<sup>17</sup>

**Table 6: Impact of FII Flows during Periods of the Taper Tantrum**

**Impact of FII Flows—Taper Tantrum Period**

Panel A: Pre-Taper Tantrum Period	Q1		Q5		Q5–Q1	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
<i>CAB_RET</i> (–5,–1) %	–0.45	–1.35	0.21	0.83	0.66	1.58
<i>AB_RET</i> (–1, 0) [Day 0 Returns] %	–0.61	–5.20***	0.63	5.48***	1.25	7.55***
<i>CAB_RET</i> (0, 5) %	0.51	1.48	–0.08	–0.24	–0.59	–1.23
Panel B: Post-Taper Tantrum Period						
<i>CAB_RET</i> (–5,–1) %	0.09	0.37	0.00	0.02	–0.09	–0.26
<i>AB_RET</i> (–1, 0) [Day 0 Returns] %	–1.10	–7.32***	0.28	1.81*	1.38	6.42***
<i>CAB_RET</i> (0, 5) %	–0.03	–0.10	–0.74	–2.36**	–0.71	–1.57

Note: The table presents the abnormal return patterns of stocks experiencing high innovation in FII flows (excess purchases) and stocks experiencing low innovation in FII flows (excess sales) during periods of the taper tantrum. 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 the Q1 portfolio. *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). *CAB\_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 A reports the results for the pre-taper tantrum period, and Panel B contains the results for the post-taper tantrum period. The number of stocks in the sample is 223, the panel regression is estimated for an in-sample period from January 2006 to 15 April 2013, and innovations in FII flows are obtained for the out-of-sample period 15 April 2013 to 30 June 2013. 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.)

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. These findings resemble those that we have reported for the COVID-19 crisis. The market had already factored in the impact of COVID-19 over the months preceding the formal declaration of the pandemic. Thus, the immediate period before the declaration of the COVID-19 pandemic, i.e., the period that we refer to as the pre-stabilization period (1 January 2020 to 23 March 2020), is comparable to the post-taper period in this analysis. When we compare the CAR plots in Figure 8 (Panel B) with the CAR plot in Figure 5 (Panel A), we can see

<sup>17</sup> As a robustness check, we normalize the length of the in-sample window for the taper tantrum period to a length of one year to match the in-sample period length used in the COVID-19 crisis. We find that the abnormal returns over (–1, 0) for the Q5–Q1 portfolio remain statistically significant and follow the same pattern, as reported in Table 6.

that they are similar in that the return patterns for Q5 and Q1 stocks exhibit significant transient volatility in the (0, 5) window.

## 5.2 Impact of Fund Flows during the Global Financial Crisis (2008)

The global financial crisis also provides an excellent opportunity to examine the influence of market stress on the price effects of unexpected FII flows.<sup>18</sup> One would expect that, during uncertain times, the global risk aversion may increase and trigger capital outflows in search of safe assets. Such capital outflows would adversely affect emerging market returns. This conjecture is borne out by the data, as discussed below.

We split the sample into a crisis period sub-sample and a non-crisis period sub-sample so that we can contrast the asset price effects during the crisis period with those during normal non-crisis periods. This segregation allows us to examine the financial crisis's impact on the flow–return relationship. We conjecture that the price effects of FII flows would have exhibited more transient effects during the crisis. The financial crisis period is identified as the period from January 2008 to December 2008.<sup>19</sup> The remainder of the sample period is classified as the non-crisis period. We examine the abnormal return differentials between portfolios with high and low innovations in FII flows in both periods. Table 7 (Panel A) shows the results. The differential abnormal returns between high- and low-innovation portfolios were much higher during the crisis period (2.40%) than in the non-crisis period (1.71%); i.e., there was a 40% greater impact of FII flows during the crisis period.

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

### Impact of FII Flows—Financial Crisis

	Q1		Q5		Q5–Q1	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
<b>Panel A: Non-Crisis Period</b>						
<i>CAB_RET</i> (–5, –1) %	0.16	2.84***	0.00	0.02	–0.16	–2.17**
<i>AB_RET</i> (–1, 0) [Day 0 Returns] %	–0.87	10.23***	0.83	33.95***	1.71	47.67***
<i>CAB_RET</i> (0, 5) %	0.35	0.02	0.09	1.74*	–0.25	–3.22***
<b>Panel B: Crisis Period</b>						
<i>CAB_RET</i> (–5, –1) %	–0.46	–3.11***	–0.26	–1.88*	0.20	0.97
<i>AB_RET</i> (–1, 0) [Day 0 Returns] %	–1.54	–21.49***	0.86	10.42***	2.40	21.91***
<i>CAB_RET</i> (0, 5) %	–0.07	–0.44	–0.46	–3.02***	–0.39	–1.71*

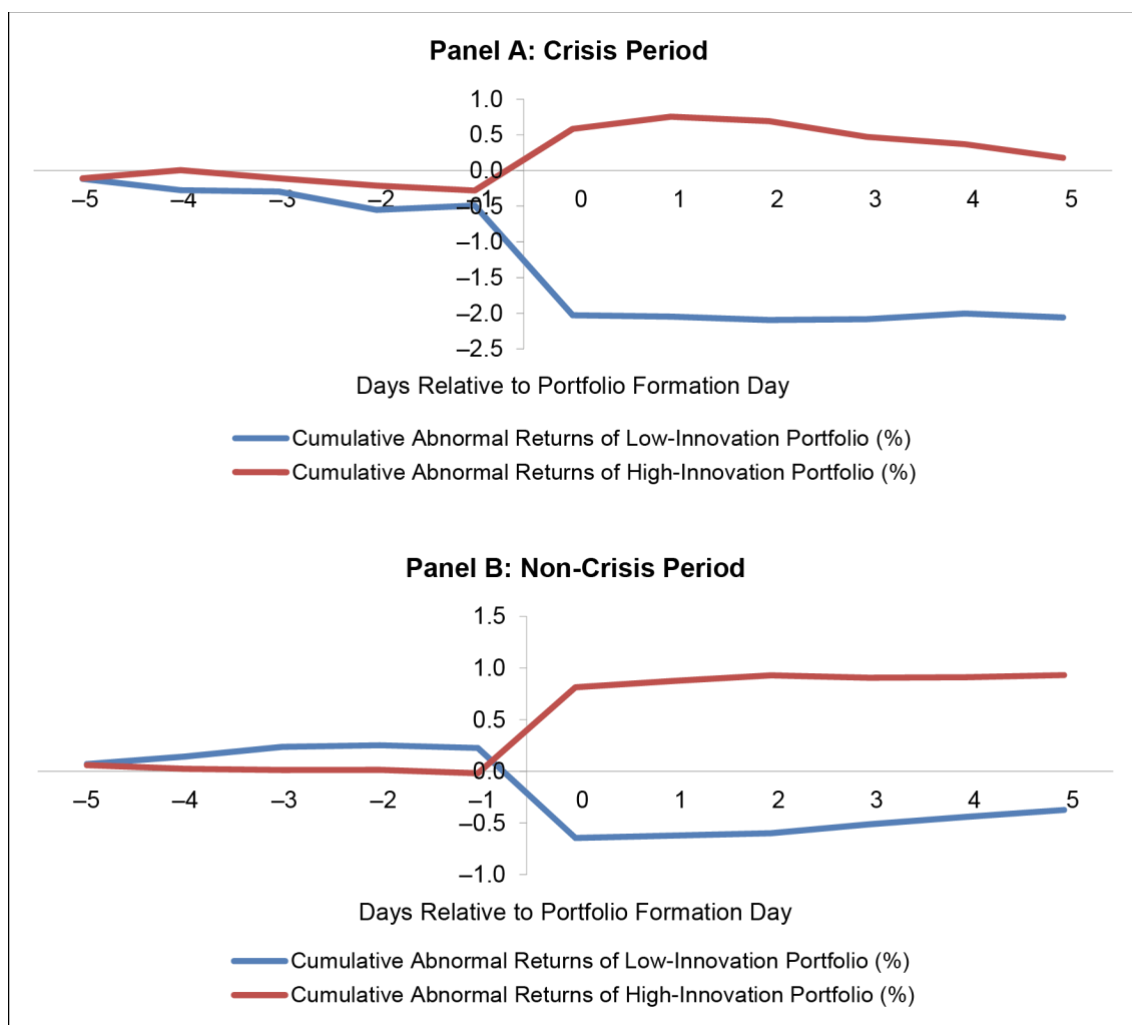
Note: The table presents the abnormal return patterns of stocks experiencing high innovation in FII flows (excess purchases) and stocks experiencing low innovations in FII flows (excess sales) during periods of global market stress. Firms are ranked according to innovations in FII flows at the beginning 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 the Q1 portfolio. *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). *CAB\_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 ( $\text{Close}_{t-1}$  to  $\text{Open}_t$ ) and the during-day return ( $\text{Open}_t$  to  $\text{Close}_t$ ) experienced by the high- and low-innovation portfolios on the portfolio formation day (Day 0). Panel A reports the impact of the FII innovation flows during the non-crisis period, and Panel B reports the impact during the crisis period. The number of stocks in the sample is 223, and the panel regression is estimated for the 2006–2011 period. 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.)

<sup>18</sup> Fratzscher (2012) found that the capital outflows from emerging markets to the US were largely a flight-to-safety effect.

<sup>19</sup> As reported by Anshuman, Chakrabarti, and Kumar (2012), the CNX NIFTY Index declined from 6,144 on 1 January 2008 to 3,033 on 31 December 2008 and then increased in the first quarter of 2009.

The transient effects can be seen more easily in Figure 9. In the post-formation window (0, 5), the crisis period CAR plot (Panel B) exhibits a greater degree of reversal than during the non-crisis period (Panel A), indicating that the Day 0 price effects were more transient during the crisis period. It turns out that FII inflows were associated with price reversals but FII outflows were not associated with any price reversal. This finding suggests that, during the crisis period, there was an overall negative sentiment that (i) completely offset the price reversals normally associated with FII outflows and (ii) adversely affected the information effect associated with FII inflows. This finding is similar to what we reported for the COVID-19 crisis (Figure 5, Panel A).

**Figure 9: Cumulative Abnormal Returns around Shocks in FII Flows during the Global Financial Crisis**



Note: The residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ( $FII\_NET_{i,t}$ ), which are defined as the difference between  $FII\_BUYS$  and  $FII\_SELLS$  scaled by the total rupee value traded (across both FIIs 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 (2008), and Panel B shows the same during the non-crisis period (excluding 2008: 2006–2011).

## 6. CONCLUSION

Employing unique 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 during the COVID-19 pandemic. Our findings 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 outflows, trading by FIIs also generates new information. More importantly, we find that the transient nature of the price effects during the COVID-19 crisis period is significantly different from that during the pre-COVID-19 period. We find that, in the weeks leading up to the declaration of COVID-19 as a pandemic, stocks experienced a high degree of transient volatility. We find that the stabilization policies initiated by the Federal Reserve helped to revive the financial markets and reduced the market volatility in India. We also examined the taper tantrum and the global financial crisis and found that the price patterns were similar to that during the pre-stabilization phase of the COVID-19 crisis.

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