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Foreign Fund Flows and Equity Prices During COVID-19: Evidence from India

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ABSTRACT

We study the period of the COVID-19 outbreak to assess the impact of foreign institutional investor (FII) flows on asset prices in an emerging market. In a dataset of stock-level foreign fund flows on 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 outbreak, the 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 the relation of foreign fund flows and equity prices in the immediate aftermath of the COVID-19 outbreak.

KEYWORDS

Foreign Institutional Investors (FII); foreign ownership; portfolio flows; price impact; VIX; volatility

JEL

F21; G11; G14; G15

1. Introduction

A wide body of literature demonstrates that foreign fund flows affect domestic asset prices.[1] For instance, Froot and Ramadorai (2008) show that lagged (weekly) foreign fund flows predict future local market returns; more importantly, they find that this relation is driven by an information effect rather than a price pressure effect. Jotikasthira, Lundblad, and Ramadorai (2012) report 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 argue that in emerging markets, the equity markets are influenced by this "push" factor and fund flows provide an additional channel of contagion.[2] Hence, policymakers fear that "hot money," i.e., portfolio flows that are extremely fickle and unpredictable, may exacerbate a moderate economic shock into a financial market meltdown, which could eventually spread across 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 recessions.[3]

We examine this important concern regarding the fund flow-return relation during the outbreak of the COVID-19 pandemic in the first half of the year 2020 for the equity market in an emerging market, viz., India.[4] These crisis periods have posed significant challenges to policymakers, but they have also provided them an opportunity to sharpen their toolkits in dealing with sudden swings in capital flows. In particular, the COVID-19 outbreak was followed in its immediate aftermath 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, providing researchers also an opportunity to assess how the fund flow-return relation during crisis periods is affected by such policy stabilization measures.

Our study contributes to the literature in two significant ways. First, it benchmarks the fund flow-return relation during normal non-crisis periods. We find that abnormally high FII inflows are

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associated with a permanent price effect, but abnormally high FII outflows are associated with both a permanent price effect as well as a transient effect that is subsequently reversed. Second, using this as the benchmark, we analyze how the fund flow-return relation evolved during (i) the onset of the crisis, (ii) the period when the Federal Reserve initiated policy stabilization measures, and (iii) the post-stabilization period. We find that the overall COVID-19 period (January 1st 2020 to June 30th 2020) relation between foreign fund flows and equity returns resemble that of the non-crisis period but price impacts and then reversals are highly exaggerated, with the stabilization measures deployed during the COVID-19 crisis period effective in dampening the overall relation between foreign fund flows and asset prices. Our important finding is that the stabilization policy period of March 24th 2020 to April 15th 2020 shows a significant reversal of the immediate effect of COVID-19 induced foreign fund flows on emerging market stock returns, as evidenced in India.

To elaborate, we examine data on foreign fund flows to (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*.[5] We then analyze the immediate short-run returns of these portfolios on the portfolio formation day (Day 0) - where the return is measured from Day −1 close to Day 0 close. We also observe the returns in the four-day pre-formation window (Day −5 to Day −1) and the five-day post-formation window (Day 0 to 5).

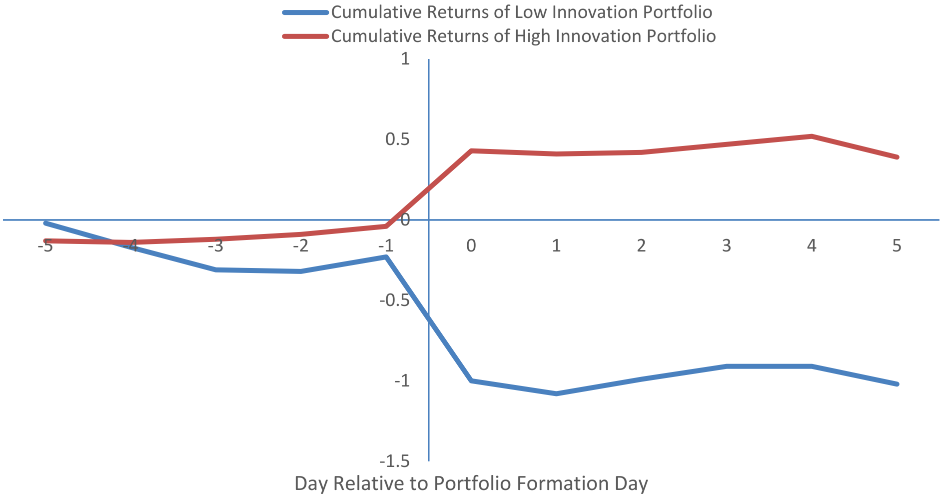
We first analyze the pre-COVID-19 period between January 1, 2019 and December 31, 2019 . Figure 1 (Panel A) presents the cumulative abnormal returns (CARs) on stocks experiencing abnormally high/low innovations in FII flows. The high and low innovation stocks exhibited similar behavior in the pre-formation 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 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 shows that the difference between the CARs of high and low innovation stocks exhibits a permanent increase that sustains over the (0, 5) window. 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 overreaction on Day 0 due to price pressure.[6]

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

(Panel A)
Cumulative abnormal returns of high innovation and low innovation portfolios



(Panel B)

Cumulative abnormal differential returns of high innovation and low innovation portfolios

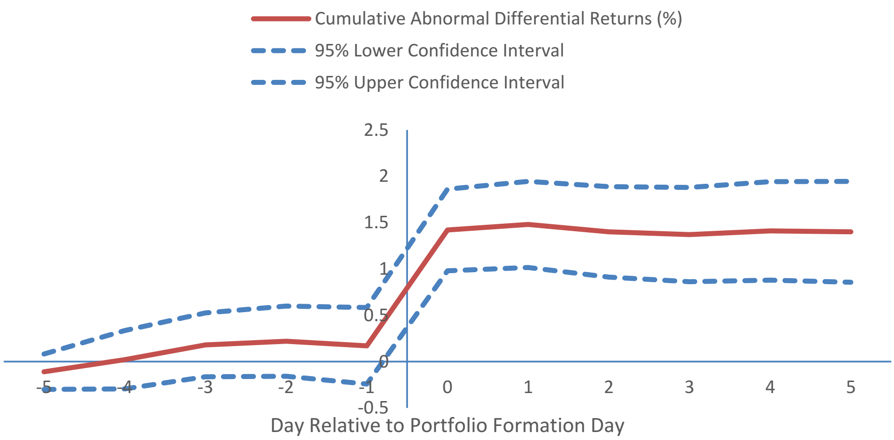


Figure 1. (Panel A) Cumulative abnormal returns of high innovation and low innovation portfolios. (Panel B) Cumulative abnormal differential returns of high innovation and low innovation portfolios. Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows ($FII\_NET_{i,t}$), 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 Jan 2019 to Dec 2019 period, firms are ranked according to innovations in *FII_NET* at the beginning of every week (typically, every Monday) and sorted into five quintiles.

economy overwhelmed the normal-time magnitude of flow-pice relation seen during the pre-COVID -19 period. Overall, the results demonstrate 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 seem to have indeed been a timely response. Once policy stabilization measures were 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 outbreak. Finally, during the post-stabilization period, the price patterns reverted to the same behavior as in the pre-COVID-19 normal times.

To summarize, we exploit the richness in 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 – are both more exaggerated during the COVID-19 period but dampened in part by stabilization policy measures. Our analysis and methodology provide a template for policymakers in the future to assess the effectiveness of their measures in dampening shocks from foreign fund flows on asset prices during crisis periods.[7]

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 relation is likely to be significantly different than during normal periods. We exploit this richness in our dataset to provide nuances of the information and price pressure effects that can help policy-making in assessing the benefits and costs of capital controls. Our findings explain the nature of the tradeoff 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 in 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 relation and stabilization policies adopted by the Federal Reserve Bank around the COVID-19 crisis. Section 3 describes the data and empirical methodology. Section 5 presents the key empirical findings related to the impact of FII flows on asset price formation during the COVID-19 crisis. Section 6 concludes the study.

2. Stylized Evidence on the COVID-19 Crisis

Figure 2 shows the relation between monthly FII net inflows and the annualized standard deviation of the daily returns on the CNX NIFTY index from January 1, 2019 to June 30, 2020 . This period

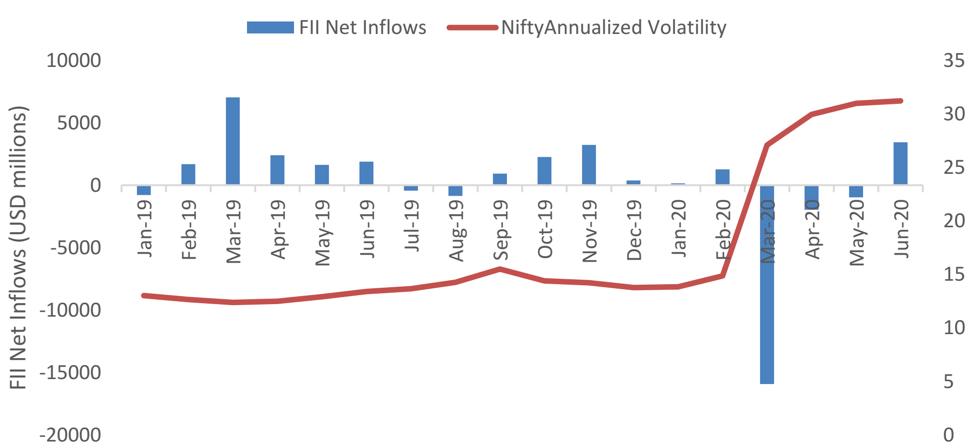


Figure 2. FII monthly net flows into and NIFTY volatility around COVID-19 period (2019–20). This chart shows the relation between monthly FII net inflows and the annualized standard deviation of the daily returns on the CNX NIFTY index for each fiscal year over the period, 2019-20

captures about one year of data before the COVID-19 crisis (the pre-COVID-19 period) and an additional six months of data during which COVID-19 set in and policymakers initiated stabilization measures, and also 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 attained levels only slightly below zero, before finally turning positive in June. By this time, 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.

To gauge the impact of fund flows immediately around the onset of COVID-19, we undertook a more granular exercise by examining how *daily* net FII portfolio flows (both in debt and equity markets) and *daily* market volatility varied during the period from January 1, 2020 to June 30, 2020 . Figure 3 shows some preliminary insights on the daily fund flows and volatility during this period. Net FII flows into debt and equity markets entered negative territory in mid-February and continued to stay negative till mid-April. It was only after April 15th that FII inflows surpassed FII outflows and net FII flows turned positive. At the same time, forward-looking volatility (*IVIX*) sharply increased around mid-February and continued to rise until mid-March before beginning to drop after that.

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

In the wake of these extreme developments, the Federal Reserve Bank initiated several policy measures to mitigate the adverse impact in financial markets as it was worried about the impact on the real economy. First, on March 17th, 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 March 18th, the Fed opened up the money market mutual fund liquidity facility, again with no specified limits. Furthermore, on March 23rd, an 850 billion dollar corporate credit facility was established, followed by the municipal liquidity facility ($500b limit), the main street facility ($600b limit), and the payment protection program lending facility, on April 9th. In addition, the Fed also

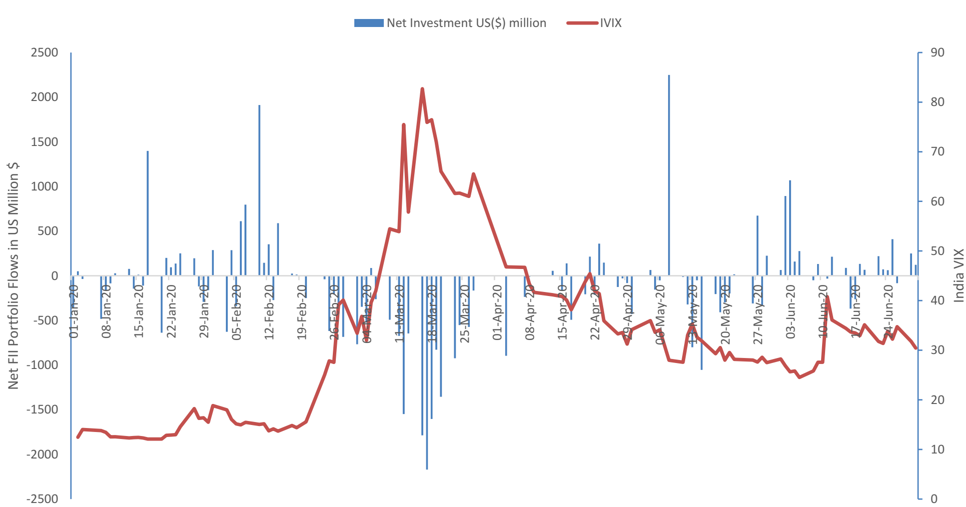


Figure 3. Net FII portfolio flows (equity and debt) vs India VIX during the COVID-19 period (January 1st 2020 – June 30th 2020).

opened up currency swap agreements with foreign central banks to ensure liquidity in the market for dollars.

The Fed's response, in the backdrop of low inflationary expectations, was highly effective in reviving financial markets. Nonfinancial corporate debt issuance and mutual fund flow picked up significantly. By the end of March 2020, mutual fund flows attained levels that were even greater than during pre-COVID-19 times. Although the actual liquidity support initially used up in these credit facilities was small and well within the maximum limits, investors read the Fed's actions as a positive signal of its willingness to be a lender of last resort.[8] The volatility in the equity and bond market substantially reduced 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 considered as the *policy stabilization* period, during which a slew of policy measures was initiated by the Federal Reserve Bank. And the period after mid-April can be treated as the *post-stabilization* period. We aim to analyze how the impact of fund flows varied in these different sub-periods. This exercise would provide information to policymakers regarding investor behavior during various phases of the crisis period and also provide 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 Center 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 for the COVID-19 Crisis is from January 1, 2019 - June 30, 2020 .

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 January 1, 2019 to June 30, 2020 from the National Stock Exchange (NSE). Five firms were dropped due to a mismatch in symbols, three firms were dropped as ownership data was not available and another ten firms were dropped as they had extreme beta outliers. Further, the FII share of trading volume on any trading day was censored at ±95% and daily stock returns were censored at ±20%. The resulting COVID-19 sample consists of an unbalanced panel of 174 stocks with 40,228 stock-day observations.

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 ith stock on day t, as follows:

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

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

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

Table 1. 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 (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 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 was estimated using 52 weekly returns before the portfolio formation day *t*.
GLOBAL_ βETA	Slope coefficient of the *S&P500_RET* in the three-factor model is estimated using 52 weekly returns before the portfolio formation day *t*.
XRATE_ βETA	Slope coefficient of the $XRATE\_RET_t$ in the three-factor model was 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 (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 on $FII\_NET_{i,t}$.
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 daily FII, as well as non-FII, rupee trading volume (*RUPEE_VOLUME*).

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

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 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 return 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 twenty-one during the sample period. FII daily average purchases (*FII_BUYS*) were 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 28.90% in the sample.

3.3. Methodology

We rely on a simple yet powerful econometric procedure to infer the information content of FII flows. First, we estimate residuals (innovations) from a panel regression model, which captures the average daily trading behavior of FIIs. We then construct two extreme (quintile) portfolios at the beginning of each week based on innovation in FII flows (a high and a low innovation portfolio). Finally, we

Table 2. Descriptive statistics.

Variable	Mean	Median	Minimum	Maximum	Std. Dev.
Panel A: Firm characteristics					
RET (%)	−0.02	−0.02	−20.00	20.00	2.76
SIZE (INR billions)	656.11	278.00	28.51	11900.00	1154.45
RUPEE_VOLUME (INR billions)	1.66	0.70	0.00	142.63	3.07
TOVER	0.00	0.00	0.00	0.47	0.01
PROMOTER_OSHP (%)	51.79	53.57	0.00	89.07	19.21
INSTITUTIONAL_OSHP (%)	33.16	30.89	2.12	89.40	15.43
RETAIL_OSHP (%)	08.86	07.73	0.62	47.96	06.10
AMIHUD_ILLIQ	0.01	0.00	0.00	488.23	1.96
LOCAL_βETA	1.09	1.06	−0.08	2.46	0.60
GLOBAL_ βETA	−0.09	−0.09	−1.00	0.79	0.45
XRATE_ βETA	−0.04	−0.01	−2.37	2.26	1.44
VOLATILITY (annualized, %)	42.68	40.57	24.79	102.44	11.82
IDIO_RISK (daily, %)	28.21	26.27	14.43	70.61	10.50
Panel B: Market-Wide Factors					
NIFTY_RET (%)	−0.02	0.03	−13.90	8.40	1.70
S&P500_RET (%)	0.05	0.10	−12.77	8.97	1.77
XRATE_RET (%)	0.03	0.00	−1.87	2.64	0.56
VIX	20.86	15.82	11.54	82.69	12.56
ΔVIX (first difference in *VIX*)	0.02	−0.12	−17.64	24.86	2.95
NIFTY_ VOLATILITY (%)	22.31	18.54	5.34	192.43	15.87
AGGR_FFLOW	−0.01	−0.01	−0.15	0.14	0.04
Panel C: FII Flows					
FII_OSHIP (%)	28.90	20.23	0	90.81	17.45
FII_BUYS (INR billions)	0.28	0.06	0	118.32	0.94
FII_SELLS (INR billions)	0.30	0.07	0	71.76	0.89
FII_NET	−0.01	−0.00	−0.97	0.96	0.18

This table presents descriptive statistics of 174 sample firms listed on the National Stock Exchange of India (NSE) during the sample period from January 1, 2019 to June 30, 2020 . 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.

examine the short-run market performance of these portfolios to estimate how it 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; 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*), 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 leasing to lower information asymmetry. The variable, *AMIHUD*, 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: aggregate FII flows (*AGGR_FFLOW*), the volatility index (*VIX*), change in the volatility index (*VIX*), NIFTY Volatility (*NIFTY_VOLATILITY*) S&P 500 returns (*S&P500_RET*), and NIFTY returns (*NIFTY_RET*). 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 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*) are used to capture the role of positive feedback trading on FII flows. The model specification is described below:

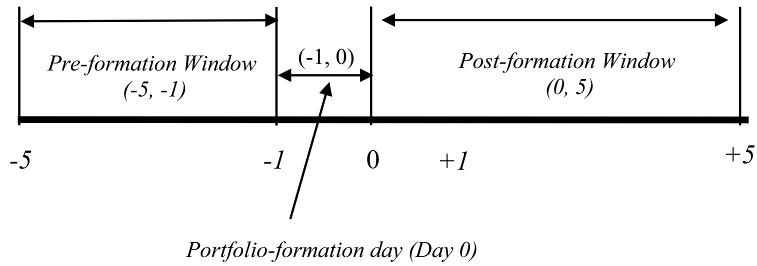


Figure 4. Portfolio formation procedure. This figure describes the portfolio formation procedure. Every Monday (Day 0), five portfolios are formed based on the innovations in FII flows. The cumulative abnormal returns on the HIGH innovation and the LOW innovation portfolios are tracked over the 10-day window surrounding the portfolio formation day (Day 0).

$$\begin{aligned} FII\_Net_{i,t} = {} & FirmFEff + \sum_{j=1}^{5} FII\_Net_{t-j} + \sum_{k=1}^{5} RET_{t-k} + \delta_1 SIZE + \delta_2 TOVER + \delta_3 RETAIL\_OSHP_{t-1} \\ & + \delta_4 INSTITUTIONAL\_OSHP_{t-1} + \alpha_1 AGGR\_FFLOW_{t-1} + \alpha_2 VIX_{t-1} \\ & + \alpha_3 \Delta VIX_{t-1} + \alpha_4 NIFTY\_RET_{t-1} + \alpha_5 S\&P500\_RET_{t-1} \\ & + \alpha_6 NIFTY\_VOLATILITY_{t-1} + e_{i,t}, \end{aligned} \tag{4}$$

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 is 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 on 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).[10] The 10-day window also includes a pre-formation window over the (−5, −1) window and a post-formation window 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), the *portfolio formation day* (Day 0) over the interval (−1, 0), and 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.

3.3.2. Abnormal Returns

Asset price effects associated with unexpected FII flows are measured by abnormal returns. AB_RET_{it} is defined as the excess return on the *i*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,

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

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. All 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 spuriously driven by 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 also 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 COVID-19

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 is divided into an in-sample period (January 1, 2019 to December 31, 2019) and an out-of-sample period (January 1, 2020 to June 30, 2020). The in-sample data is 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 are 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 difference between abnormal returns of stocks experiencing high vs. low innovations in fund flows to assess the impact of fund flows on asset prices. More importantly, we wish to see how this relation 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) January 1, 2020 to March 23rd (the pre-stabilization period), (ii) March 24, 2020 to April 15, 2020 (the policy stabilization period), and (iii) April 16, 2020 to June 30, 2020 (the post-stabilization period). The basis for 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.[11] 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 on lagged *FII_NET* shows persistence in FII flows. The positive coefficients on the lagged return are consistent with trend-chasing or positive feedback trading by FIIs.

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

The coefficients on these variables (based on the above panel regression model trained on the in-sample pre-COVID-19 data) are then used to estimate the expected FII flows (or the predicted FII flows) in the out-of-sample period from January 1, 2020 to June 30, 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-19 Period

Using the specification in Equation (5), we estimate the sensitivity of stock returns to local market risk (β_{iN}), global market risk (β_{iG}), and exchange rate returns (β_{iX}). All results reported in the paper refer to

Table 3. Panel regression model.

Variable	Coefficient	t-statistic
Intercept	−1.7074	−9.01***
$FII\_NET_{t\text{-}1}$	0.3085	40.94***
$FII\_NET_{t\text{-}2}$	0.1046	14.73***
$FII\_NET_{t\text{-}3}$	0.0563	8.10***
$FII\_NET_{t\text{-}4}$	0.0385	5.43***
$FII\_NET_{t\text{-}5}$	0.0493	7.70***
$RET_{t\text{-}1}$	0.0033	7.03***
$RET_{t\text{-}2}$	0.0003	0.59
$RET_{t\text{-}3}$	0.0006	1.35
$RET_{t\text{-}4}$	0.0001	0.35
$RET_{t\text{-}5}$	−0.0009	−2.27**
$AGGR\_FFLOW_{t\text{-}1}$	0.0291	0.73
$SIZE$	0.0647	9.31***
$TOVER$	0.3242	3.33***
$RETAIL\_OSHP_{t\text{-}1}$	0.0033	3.44***
$INSTITUTIONAL\_OSHP_{t\text{-}1}$	−0.0015	−3.51***
$VIX_{t\text{-}1}$	0.0006	0.75
$\Delta VIX_{t\text{-}1}$	−0.0012	−0.64
$NIFTY\_VOLATILITY_{t\text{-}1}$	−0.1387	−0.27
$S\&P\ 500\_RET_{t\text{-}1}$	0.0015	0.45
$NIFTY\_RET_{t\text{-}1}$	−0.0037	−1.85*
Adj. R^2	0.23	
Durbin-Watson stat	1.99	
F-statistic	65.14***	
N	40228	
Number of Firms	174	

This table reports the results of a firm fixed effects panel regression of FII_NETi,t 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.

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

where i refers to stock i and t refers to day t; FII_NET is the difference between 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.

abnormal returns obtained from the three-factor model. For our sample data, we find that the cross-sectional mean local beta (β_{iN}) is 1.09, the mean global beta (β_{iG}) is –0.09 and the mean exchange rate beta (β_{iX}) is –0.04.

To assess the price effects of unexpected foreign fund flows, we first rank all 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 forty-six portfolio formation days. Table 5 shows the abnormal return patterns for the portfolios with the lowest innovations (Q1) in *FII_NET* and the portfolio with the highest innovations (Q5) in *FII_NET*. *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).

Figure 1 describes the pre-COVID-19 situation (January 1, 2019 to December 31, 2019). 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

Table 4. Price effects of FII flows during January 1, 2019 – December 31, 2019.

	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) %	−0.77	−14.60***	0.48	8.45***	1.25	16.15***
AB_RET (Open$_0$ to Close$_0$) %	−0.67	−13.81***	0.48	9.38***	1.15	16.31***
AB_RET (Close$_{-1}$ to Open$_0$) %	−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

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. 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 (t1, t2)) is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t1, t2). 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 significance levels of 0.10, 0.05, and 0.01, respectively).
Abnormal return behavior around the days of shocks in FII_NET.

(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 on the statistical significance of the findings displayed in Figure 1. The Day 0 abnormal returns on both Q1 and Q5 stocks are statistically significant.

Furthermore, the Day 0 abnormal return differential (Q5-Q1) is also 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 on 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 of Day 0 and the closing price on Day 0). The differential abnormal return on Day 0 is driven by during-day differential abnormal returns (Table 4 Panel A, third and fourth rows). The overnight returns are smaller and similar for both Q1 and Q5 portfolios and the differential abnormal *overnight* return of 0.07% 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 returns rather than intraday, we believe that the panel regression model is more suitable for our analysis as compared to the vector autoregression approach. Moreover, our evidence on the significance of during-day returns rather than overnight returns

Table 5. Impact of FII flows during COVID-19 Period (January 1, 2020 - June 30, 2020).

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

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 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 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). CAB_RET (t1, t2)) is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t1, t2). We also report the overnight return (Closet-1 to Opent) and the during-day return (Opent to Closet) 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., Jan 2020 to Jun 2020. Panel 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 significance levels of 0.10, 0.05, and 0.01, respectively.).
Impact of FII Flows – COVID-19 period (January 1, 2020 – June 30, 2020).

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).[12]

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 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 upon the onset of COVID-19, we analyze the fund flow-return relation in three distinct periods: (i) the pre-stabilization period (Jan 1st, 2020 to Mar 23rd, 2020), when market forces were reflecting potential adverse effects of COVID-19, (ii) the policy stabilization period (Mar 24th to April 15th), when the Federal Reserve Bank initiated significant policy moves to stem the downward spiral in financial markets, and (iii) the post- stabilization period (April 16th to June 30th), when the financial markets responded to the policy initiatives taken up by the Federal Reserve. The motivation for this analysis is to assess how the COVID-19 crisis (January 1, 2020 to June 30, 2020) differs from the pre-COVID-19 normal period (January 1, 2019 to December 31, 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). Panel 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 also similar in direction but significantly larger in magnitude than 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, as well as the transient price effect over (0, 5), are more exaggerated during the pre-stabilization period as compared to 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.

Figure 5, 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 that in the pre-stabilization period as well as 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 that 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 that 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 as 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 present 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-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.

Second, the efficacy of the stabilization policies of the Federal Reserve Bank can be ascertained by the statistical significance of the coefficient on Q1, Q5, and Q5-Q1 in Panel B of Table 5. We can observe that Q5 stocks experience 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 sticks suffered a greater adverse shock during the COVID-19 crisis in comparison with Q1 stocks. However, there was a reversal of these effects in the (1, 5) window with both the Q1 and 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 most from the Federal Reserve's stabilization measures.

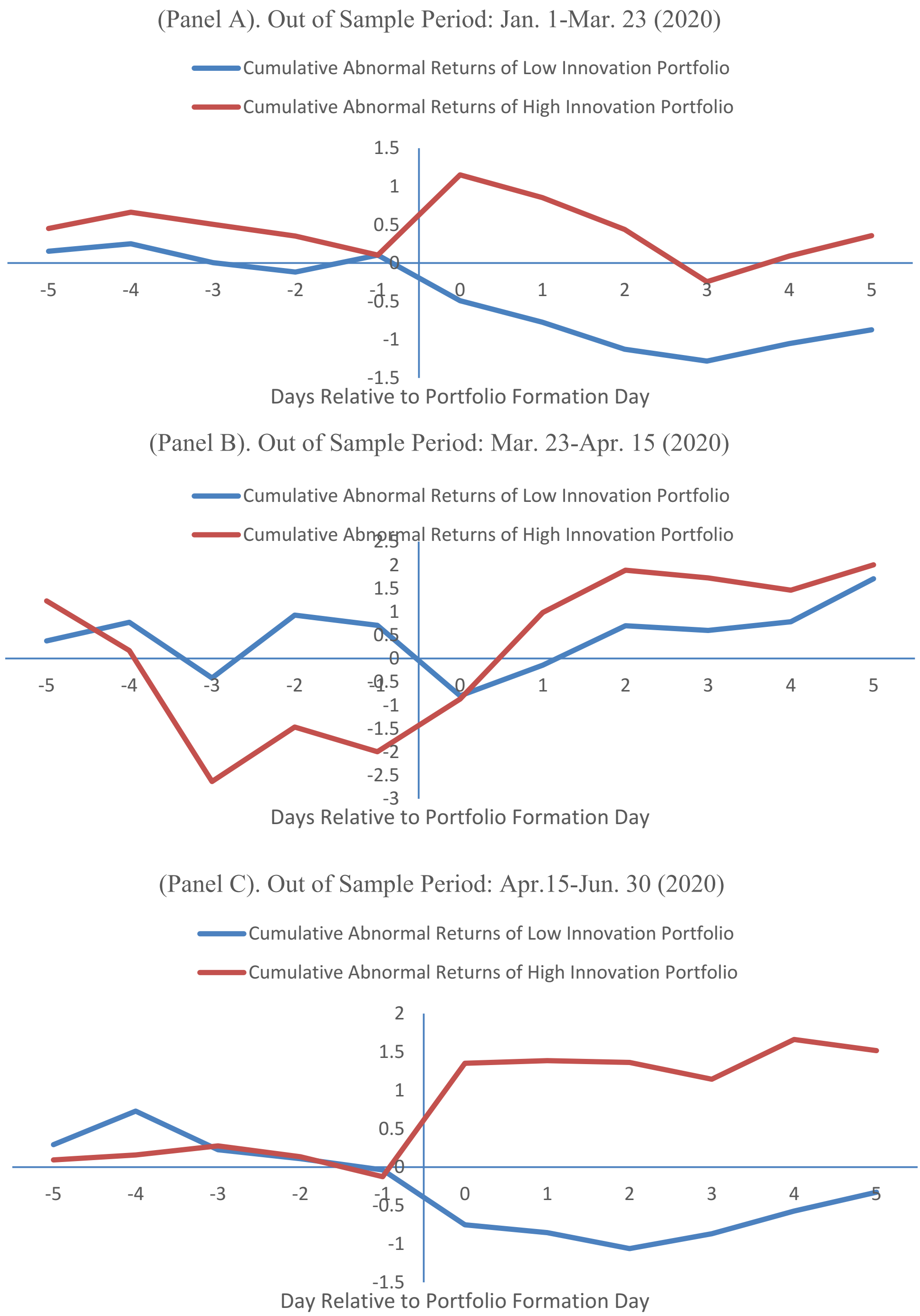


Figure 5. Cumulative abnormal returns of high innovation and low innovation portfolios. Residuals obtained from a panel regression model (built on in-sample data from January 1, 2019 to December 31, 2019) are used to estimate shocks (innovations) in FII flows (FII_NETi,t) during the out-of-sample period from January 1, 2020 to June 30, 2020. Firms are ranked according to innovations in FII_NET at the beginning of every week and sorted into five quintiles. This figure shows the cumulative daily abnormal stock returns for high and low innovation stocks during the COVOD-19 crisis period.

5. 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 outbreak. 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 the 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 stabilization policies initiated by the Federal Reserve helped revive the financial markets and reduced market volatility in India.

Notes

1. See Bohn and Tesar (1996), Brennan and Cao (1997), Froot, O'Connell, and Seasholes (2001), and Hau (2001) for initial studies on this topic.
2. 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) 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 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) find that mutual fund flows reflect retail investor sentiment and high inflows are associated with lower future returns.
3. 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, Philippines, and South 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.
4. We focused on foreign equity flows rather than foreign bond flows data because the bond market in India is highly illiquid and data is sparse. Only the government bond market has sufficient depth that makes 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. On the other hand, equity markets are more liquid and capture the information effect better. The study of bond market flows may be considered for a future study that explicitly accounts for the price effects due to flight-to-safety.
5. 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.
6. 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., Chan and Lakonishok 1993; Holthausen, Leftwich, and Mayers 1987; 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.
7. 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 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). For a comprehensive review of the literature in this field, see Koepke (2015).
8. An exception was the paycheck protection program lending facility, which showed significant outlays; however, this lending, which was collateralized by loans with federal guarantees was devoid of credit risk.
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.
10. 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 to be

questionable. Furthermore, as Dimson (1979) points out, the flow of information could be delayed for smaller less well-known firms that have lower analyst following. Several 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.

11. We employed an objective Hausman test to find out whether a fixed-effects model or a random-effects model suits the data in our sample. We find that the use of a fixed-effects model is justified. For robustness, we also explored alternative specifications with and without firm fixed effects and time fixed effects. These variations turned out to be qualitatively similar. In additional tests, we conducted 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 for the overall sample.
12. Given the time zone difference, 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.

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Disclosure statement

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