Price Impact of Unexpected Foreign Fund Flows: Information and Price Pressure Effects

ONLINE APPENDIX

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In this section, we investigate the robustness of the results reported in the primary text. First, we test the robustness of our findings to an alternative specification of the FII flow measure. Next, we examine whether our results differ for stocks associated with derivative contracts and stocks for which derivative trading is not allowed. We then employ a parametric approach to identify the impact of FII flow innovations and attempt to uncover any asymmetry (buy side vs. sell side), as well as any nonlinear effects associated with FII flow innovations. We also recognize that FII order flow may be persistent and therefore we redefine our portfolio formation criterion in terms of cumulative innovations in FII flows over the previous 5-day period rather than in terms of the concurrent FII innovation. Finally, we validate the panel regression model using out-of-sample data during the period January 2012 to June 2013.

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A1. An Alternative measure for *FII_NET*

One concern with our measure of *FII_NET* is that the variation in this measure may be driven by the variation in the scaling variable in the denominator: daily trading value (rupee volume). To avoid spurious results due to the scaling variable, we use a time-neutral scaling variable (shares outstanding). The new measure for FII flows is defined as *Net FII Flows* (in Rupees)/outstanding number of shares. The mean of this new measure is close to the mean of our existing measure. However the new measure is a volatile series that is highly skewed (-40.9 as against 0.25 for the existing measure) and highly leptokurtic (35426 as against 6 for the existing measure). Despite this issue, we replicated Figure 5 for this new measure. We find that there is a permanent impact associated with the high innovation portfolio, and both permanent and temporary impacts are associated with the low innovation portfolio. The abnormal return differential between the high innovation portfolio and the low innovation portfolio on the portfolio formation day is a statistically significant 1.75%. Overall, the qualitative nature of the return differential pattern for this alternative measure is similar to what has been reported for the FII flow measure used in the paper, as can be seen in Figure A1.

A2. Impact of Derivative Trading

Next, we consider whether the presence of derivative contracts affects information flows to the spot market, and consequently FII flows in the spot market. In the Indian financial markets, derivative trading is allowed only for a select set of stocks. In our sample, 141 stocks have no derivative contracts and remaining 82 have derivative contracts. We find that the results for the two subsamples are similar to what we find in the overall sample. For instance, the differential abnormal returns for the “derivative” (“no derivative”) sub-samples are as follows: (i) in the pre-formation window, a statistically significant return of -0.17% (-0.06%), (ii) on Day 0, a statistically significant return of 1.98% (1.39%), and (iii) in the post formation window, a statistically significant return of -0.34% (-0.05%). There is little difference in the qualitative nature of the results across the two sub-samples, other than the fact that the differential abnormal return on Day 0 for the derivatives sub-sample is slightly higher.

We also considered the possibility that stocks associated with American Depository Receipts (ADRs) may behave differently. However, we ruled out this exercise after discovering that only 6 stocks out of the entire sample have their ADRs listed on US bourses.

A3. Asymmetric and Non Linear effects of FII Flows

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

The results are shown in Table A1. The dummy variable is significant for the overall sample, but this result is largely driven by high *VIX* level days. Thus the impact of negative innovations in FII flows differs from that of positive innovations in FII flows. The nonlinear effect of FII flows is pervasive and independent of market stress levels. The asymmetric and nonlinear effects can be more readily observed in Figure A2. In Panel A, the nonlinear effects are obvious from the curvilinear nature of the plot for both positive and negative FII innovations. The asymmetric effect is highlighted by the dotted line, which mirrors the curvilinear part for positive FII innovations on the negative side. A comparison of Panel B and Panel C shows that the abnormal returns for positive FII innovations are similar on low VIX days and high VIX days. However, for negative FII innovations, the magnitude of abnormal returns on high VIX days is higher than on low VIX days (the plot for high VIX days is closer to the -1.5% line on the bottom left of the figures). These findings suggest that FII sales trigger more adverse reactions than corresponding FII purchases and confirm our findings from the non-parametric approach discussed in Section 2.

A4. Cumulative Innovations Analysis

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

Table A2 (Panel A) shows that the results are qualitatively similar to earlier findings because FII order flow is known to exhibit strong persistence. However, the differential abnormal return on Day 0 is 0.82%, somewhat lower than the 1.83% when we use the daily measure of FII flow innovations to construct portfolios. Again, this difference is not altogether surprising, because persistence in orderflow implies that prices start moving upward (for the high innovation portfolio) or downward (for the low innovation portfolio) from Day -5, thereby mitigating the effect on Day 0. We can see this by noting the values of *AB_RET* (-5,-1), the CARs over the (-5, -1) window, which is significantly negative (positive) for the low (high) innovation portfolio.

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

A5. Out of Sample Analysis

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

Table A2 (Panel B) shows that there are significant differences in abnormal returns for the high innovation and the low innovation portfolios. The Day 0 abnormal return for the high innovation portfolio is 0.73% and the Day 0 abnormal return for the low innovation portfolio is -0.77%, implying a differential abnormal returns of 1.50%. The reversal pattern is similar, but weaker than what we found in the in-sample data. As before, only the low innovation portfolio experiences a reversal in price. As found in the in-sample analysis, the pre-formation window abnormal return differential is statistically insignificant.

A6. Commonality in Order Flow

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

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

One potential proxy for commonality in order flow is the aggregated trading volume of FIIs. This measure (*AGGR_FFLOW*) was considered in our earlier analysis, reported in Table 6, which examined the relation between abnormal returns and firm characteristics and market variables. We found that aggregate net order flow (*AGGR_FFLOW*), is unrelated to explain the abnormal returns associated with the low innovation (Q1) and high innovation (Q5) portfolios. However, aggregate net flow (*AGGR_FFLOW*) may not be a good measure of correlated trading activity because netting masks the extent of correlated trading activity on the buy and sell sides of the market. Correlated trading activity can be better measured by examining the buy and sell sides of the market separately.

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

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

The R-square value (*FII_TRDS_RSQ*) obtained from the above regression is our proxy for the degree of commonality in FII trades. It captures the extent to which the total FII trading volume explains the FII trades in a particular stock. Next, we relate abnormal returns to firm characteristics and market variables, with this additional independent variable. The analysis here is constrained to be on a monthly portfolio formation basis because we require a sufficient number of observations for the first pass regression described above to estimate commonality in order flow. The average of the R-squared values in these stock-wise regressions was 61% (60%) for FII buy (sell) trades across all 15,168 stock-month observations, confirming our expectation that there is commonality in FII trades.[1]

Table A3 shows the results for Day 0 abnormal returns of the low (Q1), high (Q5), and abnormal return differential (Q5 – Q1) innovation portfolios. For the low innovation portfolio, we employ the R-square measure of commonality in *sell* side orders as an independent variable. Likewise, for the high innovation portfolio, we employ the R-square measure of commonality in *buy* side orders as an independent variable. For the high-low innovation portfolio, all the independent variables are computed as the difference in corresponding values for the low and high portfolios.

We can see in Table A3 that abnormal returns are unrelated to the R-square measure (*FII_TRDS_RSQ*). Further, none of the firm characteristics affect abnormal returns. Among market variables, only past *NIFTY* returns are related to abnormal returns. Overall, the results indicate that while there is commonality in order flow of FIIs, it has no material impact on abnormal returns. This finding reinforces our earlier conclusion that abnormal returns reflect

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

information being revealed through FII buying and selling activities rather than other exogenous factors.

Figure A1

Differential (cumulative) abnormal return plots for an alternative measure of FII flows.

An alternative measure of FII flows, defined as the difference between the *FII_BUYS* and *FII_SELLS* scaled by the total number of outstanding shares, is used to examine the robustness of the differential abnormal return patterns. Residuals are obtained from a similar panel regression model (see Equation (5)) with the alternative FII flow measure as the dependent variable. The residuals (innovations) in FII flows are used to form high innovation and low innovation portfolio during the 2006-2011 period. Firms are ranked according to innovations at the beginning of every week (typically on every Monday) and sorted into five quintiles. This figure presents the cumulative daily abnormal stock returns for stocks that experience extremely high or low innovations in FII flows.

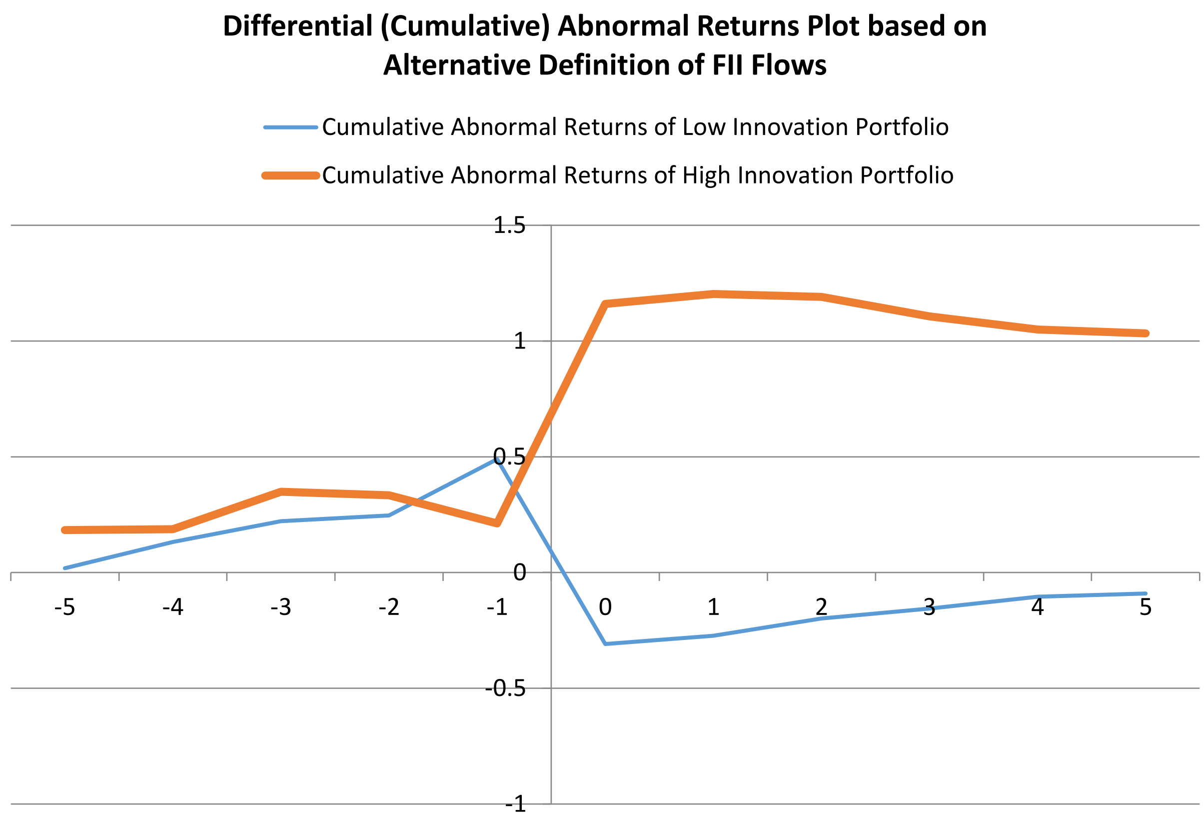

Figure A2
Asymmetric and Non Linear Effects of FII Flows

Residuals obtained from a panel regression model are used to estimate shocks (innovations) in FII flows. This figure presents the sensitivity of abnormal returns to changes in FII net innovations, depicting a possible asymmetric impact, based on the regression results reported in Table A1. Panel A shows the sensitivity of abnormal returns for all stocks. Similarly, Panels B and C shows these graphs for high CBOE VIX level days and low CBOE VIX level days, respectively.

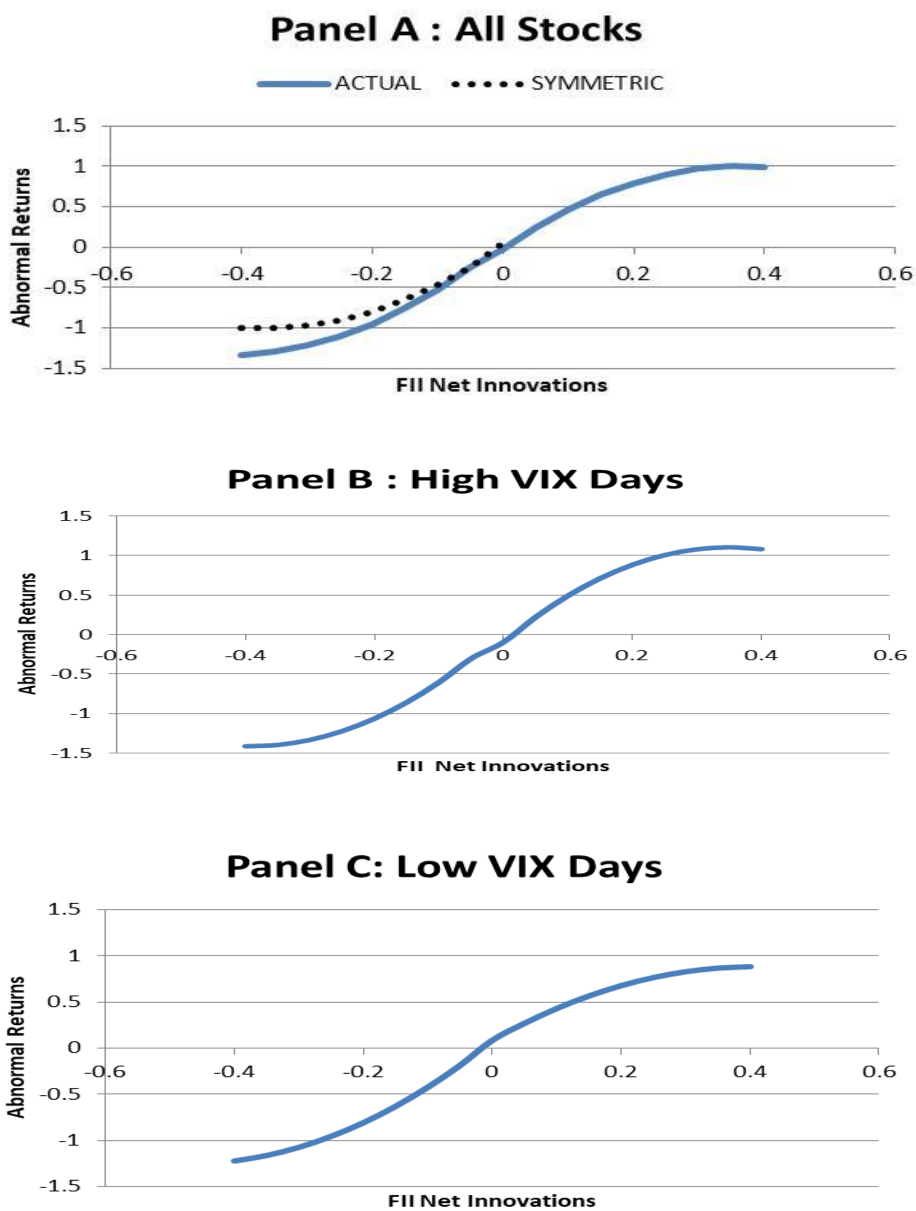

Table A1
Asymmetric and Non-linear Effects of FII Flows

This table presents the results of a cross-sectional regression between abnormal returns and FII innovations allowing for possible asymmetry and non-linearity. The following regression equation is estimated separately for all firms (column titled "ALL") and for sub-samples based on market stress (columns titled "High VIX Days" and "Low VIX Days").

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

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

Abnormal Returns (AB_RET)	**ALL firms**		**High VIX Days**		**Low VIX Days**	
	Estimate	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
Intercept	-0.02	-0.6	-0.10	-1.96**	0.09	2.00**
FII_NET_INNOV	5.62	13.08***	6.84	10.78***	3.93	7.50***
DUM	0.08	1.81*	0.14	2.08**	-0.01	0.91
*FII_NET_INNOV*DUM*	1.03	1.75*	0.58	0.67	1.68	2.30**
SQ_FII_NET_INNOV	-7.70	-7.99***	-9.75	-6.89***	-4.84	-4.05***
*SQ_FII_NET_INNOV*DUM*	15.63	11.32***	19.20	9.60***	10.74	6.31***
Adj. R^2	0.045		0.043		0.051	
Number of Observations	58033		32774		25259	

Table A2
Robustness Checks

In this table (Panel A), we re-define FII flow innovations on the basis of past cumulative innovations over the last five days. The pre-formation window relevant in this case is (-10, -5). Panel A shows the differential abnormal returns between stocks experiencing high innovation in FII flows (excess purchases) and stocks experiencing low innovations in FII flows (excess sales). Firms are ranked according to innovations in *FII* flows at the beginning of every week (typically on every Monday) and sorted into five quintiles. Q5 refers to the high innovation portfolio and Q1 refers to the low innovation portfolio. Q5-Q1 refers to the differential abnormal returns between the Q5 and Q1 portfolios. *AB_RET (t-1, t)* is the average excess returns of the given portfolio over the expected return defined from a three-factor (domestic market, global market and exchange rate) model regression. C*AB_RET* (t_1, t_2)) is the cumulative average abnormal returns for all the stocks in a portfolio accumulated over the interval (t_1, t_2). We also report the overnight return ($Close_{t-1}$ to $Open_t$), the day-time return ($Open_t$ to $Close_t$) on the portfolio formation day (Day 0). In Panel B, we examine out-of-sample (January 2012 - June 2013) behavior of the panel regression model used to define FII flow innovations. FII flow innovations in the out-of-sample period are based on the panel regression model constructed from in-sample data over the 2006-2011 period. The number of stocks in the sample is 223. The table reports mean estimates and robust Newey-West *t*-statistics, calculated with six lags.*, **, and *** indicate that the estimate value differs from zero at significance levels of 0.10, 0.05, and 0.01, respectively.

	Q1		**Q5**		**Q5-Q1**	
	Estimate	***t*-stat**	**Estimate**	***t*-stat**	**Estimate**	***t*-stat**
Panel A: Cumulative innovation in FII flows						
CAB_RET (-10, -5)%	0.02	0.30	-0.19	-3.63***	-0.21	-2.72***
AB_RET (-5, -1) %	-1.54	-32.13***	1.44	30.63***	2.98	44.39***
AB_RET (-1, 0) [Day 0 return]%	-0.47	-18.51***	0.36	14.41***	0.82	23.29***
CAB_RET (0, 5) %	0.41	7.39***	-0.07	-1.26	-0.47	-6.19***
Panel B: Out of sample data						
CAB_RET (-5, -1) %	-0.01	-0.09	0.14	1.96**	0.15	1.43
AB_RET (-1, 0) %	-0.77	-22.61***	0.73	21.83***	1.50	31.43***
CAB_RET (0, 5) %	0.23	2.58***	-0.01	-0.18	-0.24	-2.01**

Table A3
Abnormal Returns and Commonality in FII Order Flow

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

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

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

	Abnormal Return on Day 0					
	Q1		**Q5**		**Q5-Q1**	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	5.09	0.54	27.05	2.60***	1.48	5.96***
AMIHUD_ILLIQ	-0.04	-0.30	-0.32	-0.82	0.04	0.43
Log(*RUPEE_VOLUME*)	-0.13	-0.46	0.15	0.37	0.22	0.89
Log(*SIZE*)	0.04	0.11	-1.00	-1.80*	-0.54	-1.72*
LOCAL_βETA	-3.57	-2.26**	-2.53	-1.96**	-1.39	-0.93
GLOBAL_βETA	-2.13	-1.74*	-1.30	-1.57	-0.20	-0.18
VOLATILITY	-0.20	-3.19***	-0.05	-0.64	0.11	0.43
IDIO_RISK	-0.13	-0.81	0.00	-0.02	-0.40	-0.98
$NIFTY\_RET_{t-1}$	0.20	2.69***	0.09	1.36	0.02	0.21
$S\&P\ 500\_\ RET_{t-1}$	-0.15	-1.05	-0.10	-0.97	0.08	0.83
VIX_{t-1}	0.01	0.61	0.03	2.73***	0.02	1.73*
ΔVIX_{t-1}	0.02	1.12	-0.02	-1.23	-0.02	-0.92
$NIFTY\_VOL_{t-1}$	-2.29	-0.11	-28.28	-2.01**	10.93	0.69
RETAIL_OSHP	-0.05	-0.85	-0.05	-0.41	-0.05	-0.92
INSTITUTIONAL_OSHP	0.04	1.01	-0.01	-0.16	0.00	-0.06
XRATE_ βETA	-0.18	-0.57	-0.19	-0.48	-0.02	-0.10
FII_OSHIP	-0.04	-1.39	0.03	0.71	0.00	0.17
$FII\_TRDS\_RSQ_{t-1}$	-1.55	-0.48	-2.02	-0.85	-4.14	-1.28
R^2	0.46		0.41		0.40	