# Trading Activity of Foreign Institutional Investors and Volatility[+]

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**Abstract**

We investigate whether the trading activity of foreign institutional investors (FIIs) adversely affects volatility in the Indian stock markets. Aggregate trading activity of FIIs dampens market volatility whereas aggregate trading activity of domestic investors exacerbates market volatility. Positive shocks in aggregate trading activity have a greater impact than negative shocks; this asymmetry is stronger for aggregate domestic trades. We also relate individual stock volatility to tick-by-tick transaction volume, conditional on trader type and transaction type. Trading among FIIs does not increase stock volatility, but when FIIs sell to domestic clients or when domestic clients trade amongst themselves, volatility increases.

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**Trading Activity of Foreign Institutional Investors and Volatility**

"*…With each decade, the role of speculative capital has magnified. For speculative capital, nimbleness is the essential attribute. Rushing in when it sees an opportunity and heading for the exit at the first sign of trouble, speculative capital has too often turned upswings into bubbles and downward cycles into crises…*"

- Henry Kissinger, May 29, 2008 (International Herald Tribune)

Portfolio flows into emerging markets are often viewed as a double-edged sword. On the one hand, investments by foreigners in emerging economies (especially, in those countries that are undergoing liberalization) are believed to improve market efficiency and lower the cost of capital.[1] On the other hand, there is a counter view, widely held by policy makers, that foreign institutional investor (FII) trades exacerbate volatility in markets. This is well illustrated by the above quotation from Henry Kissinger. Policy makers in several emerging economies concur with Henry Kissinger's views and have deliberated the introduction of curbs on FII trading in fear of their adverse influence on volatility.[2] An equally popular remedy that has found favor with policy makers is the introduction of some kind of "tax" on FII trading.[3] The purpose of such a tax is to reign in the tendencies of FII's sudden decisions to either move in or move out funds from the markets.[4]

The essence of the Kissinger's argument is that: (a) foreign capital flows are highly variable (b) this variability in foreign flows results in high asset price volatility and (c) volatility in markets causes adverse effects in the real economy. Each of these sub-arguments merits a separate study. However, our focus in this study is only on the second issue, namely, the

[1] See Stultz (1999), De Santis and Imrohoroglu (1997), Bekaert and Harvey (1997, 1998, 2000), Errunza (1999), Henry (2000), and Kim and Singal (2000) for literature discussing how liberalization has had a positive effect on emerging economies.

[2] Consider the Reserve Bank of India Chairman, Y. V. Reddy's statement in 2005: "While quotas and ceilings may not be desirable at this stage, there is merit in our keeping such an option open and exercising it selectively if needed, after due notice to the FIIs." Quite often, such statements have been followed by panic reactions in the stock market, eventually leading up to clarifications by policy makers - as in this particular case, Mr. Reddy explained immediately after wards: "So we are not in favor of any ceiling, but at some stage if it is required, we should have the option."

[3] Most recently, an economic survey found that participants favored a Pigouvian tax. Seee, "Tax private capital flows to guard against volatility: Survey, Press Trust of India / New Delhi July 2, 2009, 16:02 IST."

[4] It is interesting to note that whenever such taxes have been proposed, they are often followed by immediate clarifications! On one such instance, the then finance minister added: ""I am quite clear in my mind that there is no question of taxing FII inflows, (there is) no such proposal under examination."

relationship between trading activity of foreign investors and volatility. We are assuming that anecdotal evidence supports (a)[5] and economic theory sheds light on (c). The critical question, therefore, is the relationship between trading activity and volatility.

Much of the perception about the *adverse effects* of trading by foreign institutional investors (FII) and volatility is based on hearsay and plausible conjectures, but there have been very few systematic studies of the relationship between FII trading and volatility.[6] Most commentators seem to confuse between the level of the stock market and the volatility of the stock market. There is little doubt that in the long-run the level of the stock market is related to the FII inflows. Capital flows in the long run depend on the relative attractiveness of India as an investment destination. This phenomenon is essentially a macroeconomic story and there is little that regulators can do "manage" it. Paradoxically, this empirical evidence of a relationship between FII inflows and stock market levels is widely cited (supposedly, as sufficient proof) to conclude that FII trading causes volatility in stock markets. However, the level of the stock market and the volatility of the stock market are two distinct statistics, and such conclusions are unwarranted. While the stock market level may change over time, volatility refers to the short-run fluctuations of the stock market around the trend that captures the level of the stock market.

If the market index exhibits wild fluctuations within a short span of time, the research question is: What is the role of FII trading in causing this short term volatility? Indeed, the NIFTY Index seems to be quite volatile in the short run. For instance, during the April 2007 to August 2009 period, the NIFTY increased by more than 2% (3%) on a single day on 49 (92) occasions. During the same period, the NIFTY declined by more than 2% (3%) on a single day on 95 (56) occasions. Not surprisingly, regulators are concerned about such abnormal short run movements in the stock market.

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[5] Froot, O'Connell and Sesholes (2001)) find that flows are stationary but more persistent than returns. Portfolio flows are related to past returns, consistent with positive feedback trading strategies by international investors. Local stock prices are significantly positively related to inflows. Brennan and Cao (1997) has also examined the issue of international portfolio flows.

[6] Another perspective on the ill-effects of a liberal stance on FII trading is provided by Bhagwati (1998) , who argues that free trade in capital cannot be justified in the same way as free trade in real goods because capital mobility is crisis-prone and imposes a negative externality on emerging economies. Capital mobility has been linked to the Asian financial crisis (1997-98), the Mexican peso crisis (1994) and the South American debt crisis (1980s).

Very few studies have addressed the relationship between volatility and FII trading activity in the context of emerging markets.[7] An exception is the study of the Jakarta Stock Exchange (Indonesia) by Wang (2000), who finds that FII sales to domestic investors significantly affects market volatility, but, in contrast, transactions among FII traders has little impact on market volatility. More importantly, the Wang (2000) study establishes that aggregate foreign flows may not capture volatility effects and conditioning the relationship on transaction type can help us understand the subtleties of the volatility volume relationship.

In this paper, we examine the effects of trading activity of FIIs on the volatility in the Indian Capital Markets. More importantly, if FII trading does affect volatility, follow-up questions of interest are: What is the mechanism by which FII trades affect return volatility? Do positive shocks have the same effect as negative shocks?[8] Answers to these questions will help policy makers address the problems of FII flows much better.

Our study differs from earlier studies in two significant ways. First, empirical studies on foreign institutional trading have relied on longer horizon data, either on a daily or a monthly horizon. However, global trading flows are extremely dynamic these days, and our research questions can be meaningfully answered only if one examines tick-by-tick market microstructure data. Since FII inflows and outflows occur within minutes these days, our analysis, which also examines intraday data provides meaningful conclusions for policy makers.

Policy makers often express concern about market volatility. However, a large amount of foreign trading is directed at individual stock and not necessarily at the market index.[9] In order to address this dichotomy, we perform our study as a two-part experiment. First, using daily data over the period 2007-2009, we examine how aggregate trading activity of FIIs, domestic

[7] Most studies on foreign trading in emerging markets have largely focused on trading performance, for example, Dvorak (2005) and Agarwal et al (2009) studied the Indonesian markets and Cho, Kho, and Stulz (2005) studied the Korean markets.

[8] Black (1976) argues that negative shocks have a much stronger effect on volatility than positive shocks.

[9] FII trading in stocks is widely prevalent, as suggested by Mr. Jitendra Panda, senior vice-president, Motilal Oswal Financial Services: "…a lot of action in the market has "moved away from the Nifty" to "momentum stocks, …you look at the last four-five months, markets have behaved in a range-bound manner and action on the Nifty has not been significant…On the other hand, sectors like cement and pharma saw a lot of stock-specific action, with many momentum stocks outperforming the index. So, funds also moved away from the Nifty to stocks." (See "FIIs shift focus from index to stocks," by Ashish Rukhaiyar, Business Standard, May 21st, 2010)".

institutions investors (DII) and other investors affects market-wide volatility. We decompose aggregate trading activity into expected and unexpected components and show that trading activity of FIIs dampens market volatility, whereas trading activity of DIIs and others exacerbates market volatility. We also find that positive shocks in trading activity have a greater impact than negative shocks. This asymmetric response is much stronger for domestic trades than for FII trades.

As opposed to the above experiment where we examine the effects of *aggregate* trading volume on *market-wide* volatility, our second experiment focuses exclusively on stock specific transactions using a dataset of intraday trades during the 3-month period in 2006. For this unique dataset, we have information about the type of trader behind *each* transaction. Thus, this experiment allows us to use information not only about trader type but also transaction type. For purposes of tractability, we categorize the trades into three types: FII and domestic trades, which are further classified into broker-initiated proprietary trades and broker initiated non proprietary trades for clients. As before, we decompose trading volume of each trader type and each transaction type into expected and unexpected components and examine how the volatility volume relationship manifests itself at a stock-by stock transaction level. We find evidence consistent with our first experiment. Trading activity amongst FIIs doesn't have an adverse impact on stock volatility. However, FII sales to domestic clients (expected as well as surprises) increases stock volatility. Overall, volatility increases mainly because of trades amongst domestic clients and to some extent due to trades amongst domestic proprietary trades.

These results are similar in spirit to Wang's (2000) findings for the Indonesian stock market. Specifically, he concludes that trading among FIIs investors does not exacerbate market volatility, possibly because FIIs share homogenous beliefs. However, Wang (2000) also reports that Indonesian market is very sensitive to selling activities of foreign investors.

Section 2 presents related literature. Section discusses the first experiment addressing the impact of aggregate trading activity conditional on trader type on market wide volatility. Section 4 presents the findings of the impact of individual stock level trading activity conditional on trader type and transaction type on stock volatility. Section 5 summarizes with a conclusion.

## 2 Related Literature

The relationship between volume and volatility has been a topic of interest for academic researchers during the past few decades. Karpoff (1987) is a seminal work that set the tone for exploring this relationship. Much of the literature on the relationship between volume and volatility has been conducted in the context of futures markets. The general conclusion is that there is a positive relationship between volume and volatility.

Over time, more sophisticated econometric methodologies have been employed to examine this relationship. First, the observed persistence in volatility is accounted for in the conditional volatility specification formulated by Schwert (1990), which continues to form the basis of most recent studies. However, Anderson and Bollerslev (1998) point out that the intra-day volatility proxies are more reliable for calculating ex-post volatility as compared to daily return-based volatility proxies, because these turn out to be more noisy estimates.

Second, Bessembinder and Seguin (1993) decomposed trading volume into an expected component (to capture the effects of trends) and an unexpected component (to estimate the impact of both positive and negative shocks). Daigler and Wiley (1999) examined the role of trader type in the context of futures markets and Wang (2001) examined the role of trader type in the context of FII traders and DII traders in the Indonesian stock markets. We extend this line of research by examining the volume-volatility relationship conditional on who is trading (in the first experiment) and also the type of transaction (in the second experiment, we distinguish between an FII sale to a domestic trader and a domestic trader sale to an FII).

Several hypothesis/models have provided an explanation of this positive relationship: (i) mixture of distributions hypothesis (Clark, 1993, Epps And Epps, 1976), which suggests that price changes arise from a mixture of normal distributions where the number of information arrivals (or volume per transaction) is the mixing variable – an outcome of this model is that there is a positive relationship between volume and volatility, (ii) sequential arrival of information models, where trading helps "discover" new information and this results in contemporaneous increase in volume and price movements, and thereby a positive correlation between volume and volatility, (iii) asymmetric information models, e.g., Admati and Pfleiderer (1988), where informed trades pool their trades - thus trading volume is positively related to price volatility, (iv) differences in opinions models (Varian, 1985, 1989, Harris and Raviv, 1993, Shalen, 1993), where divergence of beliefs cause trading volume and the associated positive relationship between volume and volatility, (v) positive feedback trading models, where strategic trading by informed trader exacerbates volatility (Cutler et al. 1990, De Long et al. 1990)[10] and (vi) noise trading hypothesis, where uninformed traders destabilize prices and their trading volume drives volatility (Friedman 1953).

## 3. **Impact of aggregate trading activity on market volatility**

### 3.1 Data and Summary Statistics

We obtained daily NSE NIFTY Index data from Apr 16, 2007 to Aug 31, 2009 from the National Stock Exchange of India Ltd. (www.nseindia.com). For trading volume, we accessed data from the Securities Exchange Board of India (SEBI, www.sebi.gov.in), which posts daily *aggregated* buy and sell value (in Rs. crores) of FIIs and DIIs across the two major exchanges of India, the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). DII net trading value (buy-sell) includes aggregate net trading value of banks, domestic financial institutions, insurance companies, mutual funds and the new pension system funds.

We also separately obtain the total turnover on the BSE (www.bseindia.com) and the NSE (www.nseindia.com) from these exchanges and use this data to deduce the net trading value of the remaining traders, who we classify as "Others" – these trades are made by non FII and non DII traders, presumably retail traders. Thus, Others buy = Total BSE turnover + total NSE turnover – total FII and DII buy value.  Similarly, Others sell = Total BSE turnover + total NSE turnover – total FII and DII sell value.

**Table 1A** gives descriptive statistics of trades of FIIs, DIIs, and Others in terms of the daily summary (average, standard deviation, maximum and minimum) trading volume (buy as well as sell)  in Rs crores. On average, FIIs sell more than they buy and DIIs buy more than they sell. The Others sell buy more than they buy.

**Table 1 B** gives pair-wise correlation between trader-type buy and sell volumes. We can see that the correlation between FII buys (sells) and DII sells (buys) is more compared to the

[10] In contrast, Froot et al (1992) and Bikhchandani et al. (1992) argue that herding or positive-feedback behavior by informed traders can actually move prices toward than away from fundamental values.

correlation between FII buys (sells) and DII buys (sells). Table 1 C reports pair-wise correlation between aggregate net trading volumes of FII, DII and Others with NIFTY index daily returns. It is interesting to observe that Nifty returns have a strong positive correlation with aggregate FII net trading volume but a negative correlation with that of DII and Others. **Table 2** provides the descriptive statistics of Nifty daily returns. The summary statistics show that the NIFTY index returns series exhibits strong autocorrelation in returns as well as in squared returns. Further, all aggregate net trading volume series by trader type and total trading volume series are stationary as the ADF test statistics are higher than the critical values. .

### 3.2 Methodology

Bessembinder and Seguin (1993) suggest that one can decompose trading volume into expected and unexpected components to allow us to examine the extent to which surprises versus trend activity variables affect the volatility-volume relation. As in Chan and Fong (2001), we use net traded volumes (total buy – total sell) of FII, DII and Others, as well overall trading volume.

To obtain expected and unexpected components of net volume, we fit an appropriate ARMA model after accounting for day of week effects. The fitted net volume is the expected part and the residual volume is the unexpected part. **Table 3** shows the pair-wise correlations between the expected and unexpected net traded volumes by trader type. There exists strong negative correlation between FII expected (unexpected) net volume and expected (unexpected) components of DII as well as Other. However, the correlation is very positive between DII and Other both expected and unexpected components. It appears that, on average, aggregate FII trading activities go in opposite directions to that of DII and Other trading activities. The trading beliefs of FII are opposite to that of remaining traders in Indian market.

#### 3.2.1 Choice of Volatility Proxy

An accurate measure of daily volatility is crucial in determining the volatility-volume relation and how different types of traders affect the volatility-volume relation. Most literature on empirical examination of volume-volatility relation employs Schwert volatility or GARCH framework. Anderson and Bollerslev (1998) points out that the intra-day volatility proxies are more reliable for calculating ex-post volatility as compared to daily return-based volatility proxies, because these turn out to be more noisy estimates. Further, Wiggins (1992) shows that the volatility estimators obtained from extreme values are efficient than the estimators obtained from closing values. Taking cue from these and since high-frequency data is available, this study employs volatility proxies based on intra-day data namely: Parkinson volatility (uses day's high and low); Garman Klass Volatility (uses days's open, high, low and close) and intra-day volatility (5-minute return standard deviation).

3.2.2 Examining Volatility-Volume relation with trader type activities

Following Bessembinder and Seguin (1993); Wang (2002) among others, we examine the volatility–volume relation by regressing volatility estimate on lagged volatility estimates, expected and unexpected components of market-wide trading volume and expected and unexpected components of net trading volumes of FII, DIIs and Others.

$$\sigma_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i \sigma_{t-i} + \beta_1 Tot\_ExpV_t + \beta_2 Tot\_Un\exp V_t + \gamma_1 ExpNVol_{jt} + \gamma_2 Un\exp NVol_{jt} + \gamma_3 Dum * Un\exp NVol_{jt} + \varepsilon_t \qquad (1)$$

*j*=FII, DII and Other

The regression is estimated separately for FII, DII and Others. *Dum* takes a value of 1 if *UnexpNVol* (unexpected net volume) is positive and takes a value of zero otherwise. The estimate $\gamma_2$ gives the impact of negative shocks of net trading volume on volatility and $\gamma_3$ gives incremental impact of positive shocks of net trading volume over and above that of negative shocks on volatility.[11]

3.3 Empirical results

Table 1 summarizes the basic statistical features of Nifty index return series as well as trading volume of FII, DII and Others. The average daily returns are positive and very small compared

[11] Bessembinder and Seguin (JFQA, 1993) suggest that positive and negative shocks in net traded volume give rise to asymmetric effects on financial market volatility. In their study, positive volume shocks have a larger effect on volatility than negative shocks.

with the return standard deviation. The Nifty return series is slightly positively skewed and displays significant excess kurtosis. This implies that the Nifty index return series is characterized by a distribution with tails that are significantly heavier than in a normal distribution. Additionally, the Ljung-Box Q (10) and $Q^2(10)$ statistics for returns and squared returns indicate linear dependence and volatility clustering in Nifty return series.

### 3.3.1 Volatility and Overall trading activity

The analysis starts by examining the relationship between overall trading activity (volume in Rs crores) and market-wide volatility for the study period. Results are reported in **Table 4.** The impact of unexpected volume (coefficient $\beta_2$) on volatility is much higher than that of expected volume (coefficient $\beta_1$). Unexpected volume (coefficient$\beta_2$) has a positive (and significantly) contemporaneous impact on market volatility whereas expected volume has no significant effect. This result holds qualitatively with all proxies of volatility, namely, GKV, Parkinson as well as intra-day volatility proxy. This is consistent with the findings of Bessembinder and Seguin, 1993, Wang 2002 and others.

### 3.3.2 Volatility and Net trading activity by trader type

**Table 5** presents the results of the regression of market volatility on expected and unexpected net trading volume by trader type, as shown in Equation (1). The coefficient estimates on trader type net volumes ($\gamma_1$, $\gamma_2$ and $\gamma_3$) give the impact of trader-type trading volume on market volatility after taking into account the effect of aggregate overall trading volume. The table shows the results for the GKV estimator, the Parkinson estimator and the intraday volatility measure in different panels. The results discussed below are for GKV estimator and qualitatitively similar results are obtained for other proxies of estimators, viz. Parkinson and Intra-day volatility estimators.[12]

Market volatility is negatively related to FII trading activity, both expected ($\gamma_1$) and unexpected ($\gamma_2+\gamma_3$). Positive shocks in unexpected volume ($\gamma_3$) of FIIs impacts volatility much more than negative shocks ($\gamma_2$), but the overall impact of unexpected volume of FIIs is a

[12] For robustness, we performed the same analysis for the CNX S&P 500 Index, a much broader market proxy than the NIFTY Index (which is based on 50 stocks). The results are qualitatively similar, and are available upon request for the GKV and Parkinson volatility proxies. Intraday data for the CNX S&P 500 Index is not readily available and we were unable to generate results for the intraday volatility measure.

reduction in market volatility. The incremental explanatory power of the regression improves by 15% (adjusted $R^2$ increases from 0.399 to 0.458 implying 14.78% increase) after including FIIs trading activity over and above the overall trading activity variables.

DII trading activity, expected ($\gamma_1$) as well as unexpected ($\gamma_2+\gamma_3$), increases market-wide volatility. Negative shocks of DII ($\gamma_2$) do not co-vary with market-wide volatility. However, Positive shocks of DII ($\gamma_3$) cause a significant increase in market volatility. The impact of DII on volatility is similar across other volatility proxies. Market volatility increases significantly with the trading activities of Others (both expected and unexpected net trading volumes). This result appears to be robust across other volatility estimators.

Irrespective of the trader type, shocks in net trading volume have asymmetric impact on volatility depending on whether the shock is positive or negative. The magnitudes and statistical significance of estimated coefficients imply that the impacts of positive unexpected net trading volumes are higher than that of negative shocks for DII as well as Others. The magnitude of asymmetry of positive and negative shocks is the ratio of coefficient estimate of positive shock to negative shock. The asymmetry is minimal for FIIs (approximately 0.003) whereas for DIIs it is 10.54 and for Others it is 119.05.

## 4 Impact of trading activity on volatility at individual stock level

### 4. 1 Data

For this experiment, we rely on a proprietary dataset that provides us with tick-by-tick data for 50 stocks (NIFTY stocks?) during a 3 month period (April-Jun 2006). This dataset is unique in the sense that it contains an indicator of trader type (e.g., FII, DII and several different types of trader types).[13]

[13] Institutional investors can also participate in the stock market by taking up positions in the derivatives markets (stock options and stock futures). While it is difficult to get precise amount of this type of trading activity by FIIs, it is abundantly clear that such trading is relatively minor. From NSE Factbooks, we could gather data on the extent of institutional investors (both FII and domestic institutional investors) in Indian derivatives markets. Their share of trading in the derivatives segment (Index Futures and Options, Stock Futures and Options) was 1% in 2003-04 and gradually increased to 13.37% by 2008-09. Given the total trading value of 13.37%, it is safe to conclude that the share of FII trading in stock options and futures is relatively minor.

The larger question is whether volatility is driven by FII trades or by trades of domestic investors. Underlying this question is the unsubstantiated belief that FIIs are sophisticated traders and domestic investors are naïve traders who are "fooled" by FIIs. We are able to address such issues because our dataset allows us to classify domestic trades into proprietary (trades initiated by a broker on his own account) and non-proprietary or client orders (orders placed by broker on behalf of clients). The clients could be domestic institutional investors or individual investors. It is likely that broker initiated proprietary trades reflect a degree of sophistication in comparison to client trades, which may be closer to naïve noise trading. Thus our classification allows us to decompose domestic trades into sophisticated and noisy trades. In short, we classify transactions into three types according to the trader type – initially, we split trades into FII trades and non-FII trades; we further split the non-FII trades into broker initiated proprietary trades (PROP) and broker initiated client trades (CLIENT). Further, the trading activities are classified depending up on the counter party of the trade and transaction type (buy/sell) of trading activity.

| **Buyer** | **Seller** | **Code** |
|---|---|---|
| FII | FII | FF |
| FII | PROP | FP |
| FII | CLIENT | FC |
| PROP | FII | PF |
| PROP | PROP | PP |
| PROP | CLIENT | PC |
| CLIENT | FII | CF |
| CLIENT | PROP | CP |
| CLIENT | CLIENT | CC |

The total value of trades under each of the above nine trading activities on daily basis are calculated.[14] **Figures 1a, 1b, and 1c** provide stock-wise average trading activity (number of trades) of different transaction types for the study period: April-June 2006. It can be seen that across most stocks, domestic clients (FII) show a higher level as well as a greater variation in trading activity. **Table 6** gives the summary statistics of the trading activity by trader type and transaction type. In terms of number of transactions, domestic clients account for 61 percent, domestic proprietary traders account for about 31 percent, and FIIs account for only about 8 percent of the transactions. However, in terms of traded value, domestic clients account for 49

[14] FIIs have little (no) interest in following stocks during study period: ICICI Bank, PNB Orient Bank, SBIN, Bharti, Hindpetro, SCI, and Tatasteel.

percent, domestic proprietary traders account for about 28 percent, and FIIs account for about 23 percent.

## 4.2 Methodology

As in Bessembinder and Seguin (1993), we decompose trading volume into expected and unexpected components using the same procedure as in the first experiment. As opposed to the earlier experiment, in this stock based experiment, we deal with trading volume rather than net traded value. This allows us to find the marginal impact of different types of transactions. For instance, we can find out the impact of FII sales where the counter party is a broker who trades on his own account (domestic proprietary trades). This impact can be compared with the impact of domestic proprietary sales to FIIs. Our second experiment, therefore, allows us to examine the impact of trading activity condition on trader type as well as transaction type on volatility.

To extract the expected and unexpected components of different activity volumes, we regress log(volume) against day dummies, trend, lagged volatility, lagged returns, past (5 lags) volume, where volume refers to volume conditional on trader type (FII, PROP, or CLIENT) and transaction type (BUY/SELL). The fitted series is the expected component and the residual component is unexpected component.  This decomposition allows us to examine the extent to which surprises versus trend activity variables affect the volatility-volume relation. **Table 7** shows the pair-wise correlations between the expected and unexpected net traded volumes by trader type. We can see that the expected and unexpected components are negatively related across trader type and transaction type.

We employ two proxies for volatility: (i) hourly standard deviation of returns based on five-minute frequency and (ii) Parkinson measure, the latter being range based estimators, which is computed on a daily basis.

## 4. 3 Empirical Results

We run appropriate fixed effects (cross sectional dummies) panel regression models to examine volatility-volume relation. Essentially, log (volatility) is regressed against past volatility (to capture volatility clustering 5 lagged values are used) and different expected and unexpected components of trading activity by trader type and transaction type.

$$\sigma proxy_{i,t} = FixedEffects + \sum_{p=1}^{3}\sum_{q=1}^{3} \alpha_{0,pq} Exp\_Volume_{pq,it} + \sum_{p=1}^{3}\sum_{q=1}^{3} \beta_{0,pq} Un\exp\_Volume_{pq,it} + e_{it}$$

$i$=stock ; $t$=day; $p$ =1 for FII purchases; 2 for domestic proprietary purchases & 3 for domestic client purchases; $q$=1 for FII sales; 2 for domestic proprietary sales & 3 for domestic client sales.

**Table 8** shows the results of the regression. First, we can see that the coefficient on the variable reflecting FII trades amongst themselves is insignificant. Also, in most cases where FII trades are involved either as buyer or seller, the coefficients are insignificant. Second, FII sales to domestic clients (expected as well as surprises) seem to increase stock volatility. Finally, we can see that volatility increases mainly because of trades of domestic clients and to some extent due to domestic proprietary trades. Thus it appears that FII investors add to Indian market liquidity (market depth) because they account for as much as 23% of the total traded volume; at the same time their trades are not a major driver of excess volatility.

## 5 Conclusion

This study was motivated by the well publicized adverse effects of foreign institutional investors on the volatility in Indian markets. This issue has been a much debated topic among policy makers in the Ministry of Finance as well as several economists and politicians. Our study presents a comprehensive examination of this issue based on unique datasets that have been designed to address these questions. We conduct two separate tests. In the first test, we examine the impact of aggregate trading activity conditional on trader type (FII, DII, or other traders) on market wide volatility. In the second test, we examine the impact of stock-level trading activity conditional on trader type (FII, domestic proprietary trades, and domestic client trades) and transaction type (buy of one trader type with sell of one trader type) on stock-volatility.

Both our tests provide similar insights. In the first test, we show that trading activity of FIIs dampens market volatility, whereas trading activity of DIIs and others exacerbates market volatility. We also find that positive shocks in trading activity have a greater impact than negative shocks. This asymmetric response is much stronger for domestic trades than for FII trades. In the second test, we show that trading activity amongst FIIs doesn't have an adverse impact on stock volatility. However, FII sales to domestic clients, trade amongst domestic clients, and to some extent trade amongst domestic proprietary trades, increases stock volatility.

Overall, these results suggest that trading activity among non FII investors is the key driver of volatility, but FII sales also play an important role. We have used different specification for measuring volatility, but all these estimates are contemporary measures of volatility. It might be worth examining a forward-looking measure of volatility – for instance, the market traded volatility index, VIX. Another extension of this study could be the examination of market microstructure effects around FII trades – for instance, one could examine the price impact of trades conditional on trader type, or one could examine the degree of price reversal conditional on trader type. Such explorations would shed light on the impact of FII trades on the overall market environment.

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Figures 1a-1c plot stock-wise average trading activity (number of trades) of different transaction types for the study period: April-June 2006. Figure 1a displays FIIs as buyers in a trade where the counter party is either a FII or a proprietary trades (placed by brokers on his behalf) or a client trade (placed by brokers on others behalf). Figure 1b presents similar plot when Proprietary traders are acting as buyers and Figure 1c presents that of clients as buyers.

**Figure 1 a:**

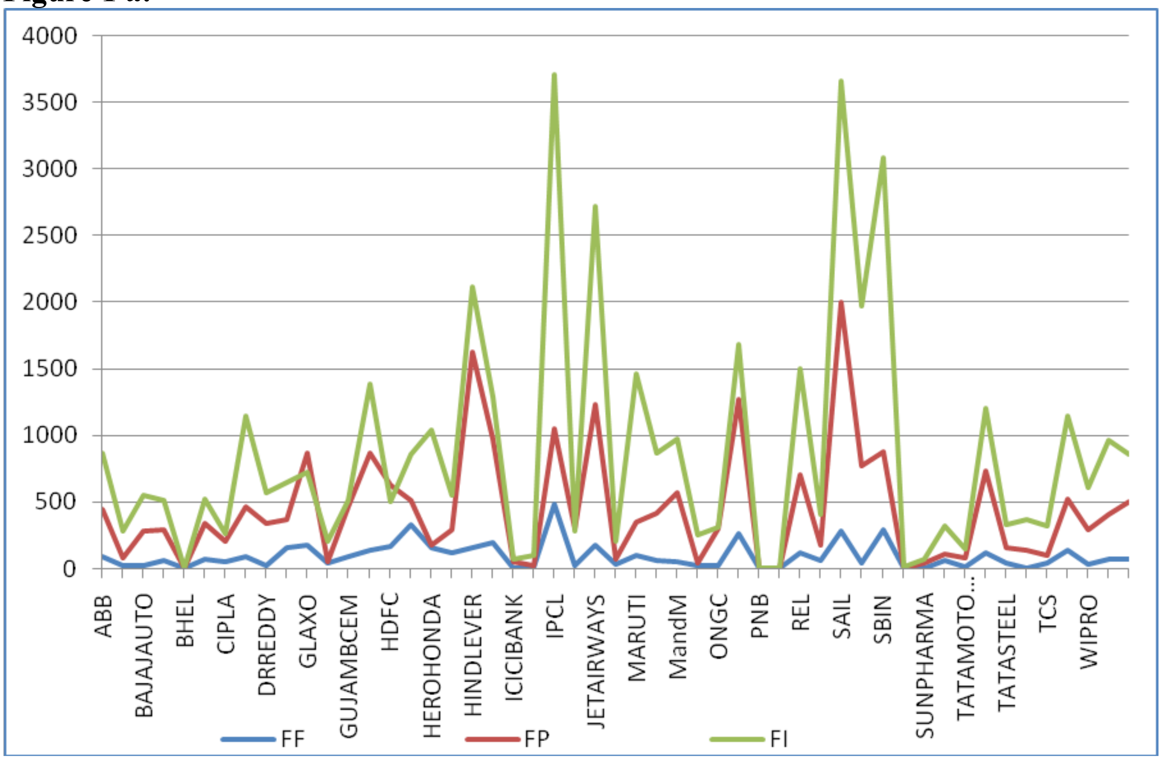


**Figure 1b:**

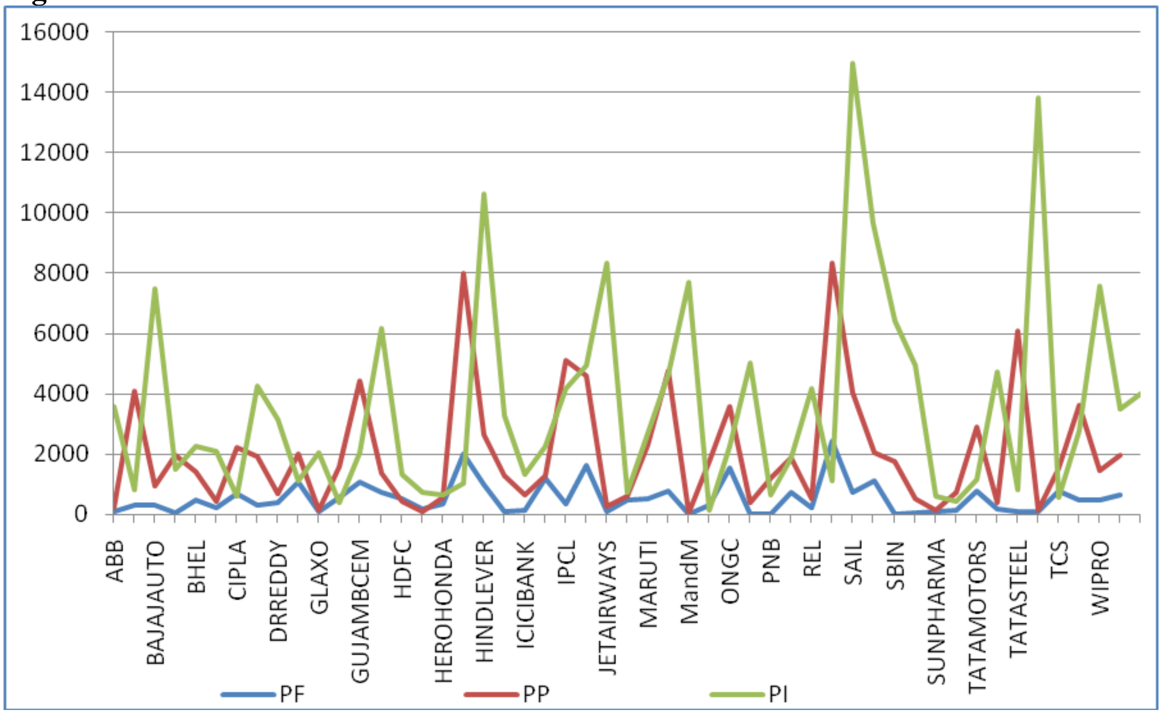
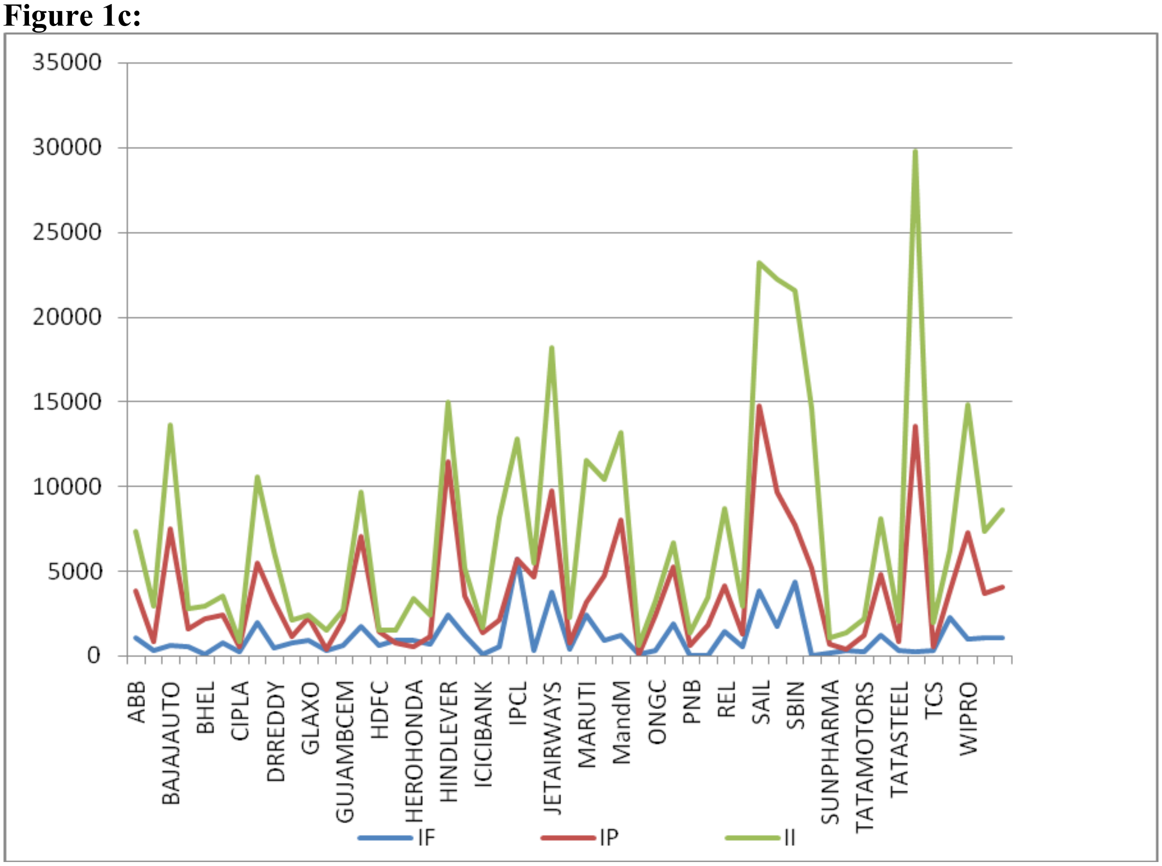



**Figure 1c:**



**Tables**

Table 1 A : Descriptive Statistics of DII and FII Trading activities

| Summary | DII | | | FII | | | Other | | |
|---|---|---|---|---|---|---|---|---|---|
| | Buy Value | Sell Value | Net Value | Buy Value | Sell Value | Net Value | Buy Value | Sell Value | Net Value |
| **Average** | 1195.34 | 990.69 | 204.61 | 2777.2 | 2941.9 | -164.64 | 15469 | 15509.3 | -40.02 |
| **Min** | 21.6 | 9.21 | -1964.2 | 56.91 | 12.27 | -4265.2 | 198.79 | 235.02 | -4213 |
| **Max** | 4430.29 | 4623.2 | 3399.2 | 12406 | 10438 | 4792.6 | 36868 | 39696.8 | 2328.6 |
| **StdDev** | 474.92 | 428.23 | 421.06 | 1356.2 | 1441.3 | 835.73 | 5330 | 5391.53 | 647.71 |

Table 1 B : Pair wise correlation matrix of DII, FII and Other trading activities

| Correlation | DII (buy) | FII (buy) | Others (buy) | DII (sell) | FII (sell) | Others (sell) |
|---|---|---|---|---|---|---|
| **DII (buy)** | 1.0000 | 0.5801 | 0.6030 | 0.5695 | 0.7133 | 0.5942 |
| **FII (buy)** | | 1.0000 | 0.6208 | 0.7094 | 0.8232 | 0.6399 |
| **Others (buy)** | | | 1.0000 | 0.7415 | 0.5469 | 0.9928 |
| **DII (sell)** | | | | 1.0000 | 0.4837 | 0.7529 |
| **FII (sell)** | | | | | 1.0000 | 0.5048 |
| **Others (sell)** | | | | | | 1.0000 |

Table1C :Pair-wise correlation matrix of Nifty Returns and DII, FII and Other net trading values

| Correlation | DII | FII | Others | NIFTY returns |
|---|---|---|---|---|
| **DII** | 1.0000 | -0.6482 | 0.1864 | -0.2080 |
| **FII** | | 1.0000 | -0.8689 | 0.4319 |
| **Others** | | | 1.0000 | -0.4221 |
| **NIFTY returns** | | | | 1.0000 |

**Table 2**
**Panel A : Descriptive Statistics of Trading Activities in Indian Stock Market**

This table presents descriptive statistics of Nifty daily returns and overall trading volume and net trading volume by trader type for the period Apri 2007 to Aug 2009. Nifty daily return is the continuously compounded percentage return calculated using daily closing values of NSE Nifty total returns index. Total volume and Net volume (total buy – total sell) are in Rs Crores traded on BSE as well as NSE. Our data allows categorizing traders into Foreign Institutional Investors, Domestic Institutional Investors (Banks, DFIs, Insurance, MFs, NewPension system) and Other (mostly retail individual traders). LB(10) and LB2(10) are Ljung-Box test statistics for cumulative autocorrelation in a series and square of a series respectively. ADF test statistics are for the hypothesis that a series contains a unit root.

| Panel A Summary Statistic | Nifty Returns | Daily Total Volume | Daily Net Volume | | |
|---|---|---|---|---|---|
| | | | FII | DII | Other |
| **Mean** | 0.0343 | 19704.1400 | -166.6360 | 204.6566 | -40.0207 |
| **StdDeviation** | 2.4168 | 6156.6990 | 835.7319 | 421.0617 | 647.7120 |
| **Skewness** | 0.1189 | 0.6448 | -0.0198 | 1.1926 | -0.5610 |
| **Kurtosis** | 8.0138 | 3.9562 | 8.9239 | 12.7482 | 7.5438 |
| **LB(10)** | 19.2840 | 3408.6400 | 433.0700 | 325.7300 | 100.0200 |
| **LB2(10)** | 90.0560 | -- | -- | -- | -- |
| **ADF test statistic** | -22.7648 | -3.8977 | -7.2187 | -10.6006 | -18.2970 |

**Table 3: Cross-correlations between trading activities of trader categories**

This table presents cross-correlation between expected and unexpected parts of trading volume by trader categories, viz FII, DII and Other. The expected volume (suffixed by _EXP) is the fitted value of a volume series by an appropriate ARMA model. The unexpected volume (prefixed by UN) is the residual value from volume minus fitted volume.

| Correlation ( p-value) | FII_EXP | DII_EXP | OTHER_EXP | UNFII | UNDII | UNOTHER |
|---|---|---|---|---|---|---|
| **FII_EXP** | 1<br>----- | | | | | |
| **DII_EXP** | -0.699985<br>0 | 1<br>----- | | | | |
| **OTHER_EXP** | -0.841723<br>0 | 0.392307<br>0 | 1<br>----- | | | |
| **UNFII** | 0.003676<br>0.9297 | -0.076331<br>0.0664 | 0.003658<br>0.93 | 1<br>----- | | |
| **UNDII** | -0.164657<br>0.0001 | 0.00149<br>0.9715 | 0.197443<br>0 | -0.478833<br>0 | 1<br>----- | |
| **UNOTHER** | -0.088847<br>0.0326 | 0.10122<br>0.0148 | -0.000968<br>0.9815 | -0.848296<br>0 | 0.013327<br>0.749 | 1<br>----- |

**Table 4 : Volatility and Over all trading activity**

This table presents the regression results of Volatility and Overall Volume relationship. The expected component of overall trading volume is fitted value of an appropriate ARMA model with day of week dummies on overall trading value series. The unexpected component is residual value of Overall trading value minus fitted value. The volatility is proxied by three different alternate estimators, viz: Garman Klass Volatility estimate using daily Open, High, Low and Close values; Parkinson Volatility estimator using daily High and Low values and Intra-day volatility estimate is daily standard deviation of five minute return series.

$$\sigma_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i \sigma_{t-i} + \beta_1 Tot\_ExpV_t + \beta_2 Tot\_Un\exp V_t + \varepsilon_t$$

| **Variable** | **GKV estimate** | | | **Parkinson estimate** | | | **Intra-day Volatility estimate** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Coefficient** | **t-Statistic** | **Prob.** | **Coefficient** | **t-Statistic** | **Prob.** | **Coefficient** | **t-Statistic** | **Prob.** |
| **C** | 0.017146 | 4.7407 | 0.0000 | 0.022831 | 6.0441 | 0.0000 | 0.003056 | 4.9717 | 0.0000 |
| **TOTAL_EXP** | 4.99E-08 | 0.2966 | 0.7669 | -2.12E-07 | -1.2108 | 0.2265 | -3.76E-08 | -1.2501 | 0.2118 |
| **UNTOTAL** | 4.41E-07 | 4.2692 | 0.0000 | 2.32E-07 | 1.9860 | 0.0475 | -1.85E-07 | -5.7563 | 0.0000 |
| **AR(1)** | 0.497006 | 11.8523 | 0.0000 | 0.39663 | 9.2990 | 0.0000 | 0.275948 | 6.0846 | 0.0000 |
| **AR(2)** | 0.003151 | 0.0667 | 0.9468 | 0.080782 | 1.7617 | 0.0787 | 0.043077 | 0.9630 | 0.3359 |
| **AR(3)** | 0.099422 | 2.1315 | 0.0335 | 0.117018 | 2.6112 | 0.0093 | 0.069588 | 1.5860 | 0.1133 |
| **AR(4)** | 0.053978 | 1.1533 | 0.2493 | 0.112551 | 2.4977 | 0.0128 | 0.03206 | 0.7362 | 0.4619 |
| **AR(5)** | 0.10761 | 2.5705 | 0.0104 | 0.046406 | 1.1038 | 0.2701 | 0.029421 | 0.7000 | 0.4842 |
| | | | | | | | | | |
| **R-squared** | 0.406363 | AIC | - 6.6601 | 0.367751 | AIC | - 6.4798 | 0.119338 | AIC | - 9.2100 |
| **Adjusted R-square** | 0.399021 | DW Stat | 2.0276 | 0.359931 | DW Stat | 2.0104 | 0.108446 | DW Stat | 2.0018 |

**Table 5 Volatility and Net Volume by type of Trader**

This table presents the regression results of Volatility and Net volume by trader type. The net volumes for each trader category are defined as total buy value – total sell value by that trader category on a given trading day. The expected component of net trading volume is fitted value of an appropriate ARMA model with day of week dummies on net trading value series. The unexpected component is residual value of net trading value minus fitted value. The volatility is proxied by three different alternate estimators, viz: Garman Klass Volatility estimate using daily Open, High, Low and Close values; Parkinson Volatility estimator using daily High and Low values and Intra-day volatility estimate is daily standard deviation of five minute return series. The volatility proxy is regressed against expected and unexpected components of overall trading volume and expected and unexpected parts of net trading value by a trader category. Further, an interactive dummy variable (one for positive shocks and zero else) with unexpected net trading value of trader category is included to determine the asymmetric impact of unexpected shocks of net trading value of trader type on market volatility. The regressions are run for each category and each volatility proxy and Newey -West standard errors are used in calculating t-statistics. The regression results are reported in three panels, one for each volatility proxy.

$$\sigma_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i \sigma_{t-i} + \beta_1 Tot\_ExpV_t + \beta_2 Tot\_Un\exp V_t + \gamma_1 ExpNVol_{jt} + \gamma_2 Un\exp NVol_{jt} + \gamma_3 Dum * Un\exp NVol_{jt} + \varepsilon_t$$

**Panel A: Garman Klass Volatility Estimator as proxy of Volatility**

| Variable | FII | | | DII | | | OTHER | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Coefficient** | **t-Statistic** | **Prob.** | **Coefficient** | **t-Statistic** | **Prob.** | **Coefficient** | **t-Statistic** | **Prob.** |
| C | 0.014287 | 4.2635 | 0.0000 | 0.013649 | 4.0291 | 0.0001 | 0.016797 | 4.8793 | 0.0000 |
| TOTAL_EXP | 6.24E-08 | 0.4036 | 0.6867 | 4.99E-08 | 0.3200 | 0.7491 | 2.17E-08 | 0.1339 | 0.8935 |
| UNTOTAL | 4.08E-07 | 3.8513 | 0.0001 | 3.78E-07 | 3.5882 | 0.0004 | 4.27E-07 | 3.9892 | 0.0001 |
| Trader_EXP | -6.68E-06 | -5.4491 | 0.0000 | 1.07E-05 | 4.6941 | 0.0000 | 5.89E-06 | 2.7062 | 0.0070 |
| UNEXP | -5.96E-06 | -6.9612 | 0.0000 | -8.26E-07 | -0.4582 | 0.6470 | -4.19E-08 | -0.0448 | 0.9643 |
| DUMUNEXP | 5.94E-06 | 4.2404 | 0.0000 | 9.54E-06 | 3.3399 | 0.0009 | 5.03E-06 | 3.0102 | 0.0027 |
| AR(1) | 0.430576 | 10.2741 | 0.0000 | 0.415559 | 9.8030 | 0.0000 | 0.473258 | 11.2664 | 0.0000 |
| AR(2) | -0.02017 | -0.4395 | 0.6605 | 0.052229 | 1.1280 | 0.2598 | -0.01893 | -0.4051 | 0.6856 |
| AR(3) | 0.114751 | 2.5237 | 0.0119 | 0.080174 | 1.7634 | 0.0784 | 0.107279 | 2.3142 | 0.0210 |
| AR(4) | 0.068028 | 1.4936 | 0.1358 | 0.081197 | 1.7876 | 0.0744 | 0.049913 | 1.0750 | 0.2828 |
| AR(5) | 0.162683 | 3.8985 | 0.0001 | 0.12197 | 2.9121 | 0.0037 | 0.136258 | 3.2552 | 0.0012 |
| | | | | | | | | | |
| R-squared | 0.467993 | AIC | -6.7593 | 0.44942 | AIC | -6.7250 | 0.432113 | AIC | -6.6940 |
| Adjusted R-sq | 0.458543 | DW Stat | 2.0536 | 0.43964 | DW Stat | 2.0336 | 0.422026 | DW Stat | 2.0388 |

**Panel B : Parkinson Volatility estimator as proxy for market wide volatility**

| Variable | FII | | | DII | | | OTHER | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | t-Statistic | Prob. | Coefficient | t-Statistic | Prob. | Coefficient | t-Statistic | Prob. |
| C | 0.019091 | 5.4411 | 0.0000 | 0.019091 | 5.3925 | 0.0000 | 0.021352 | 5.9670 | 0.0000 |
| TOTAL_EXP | -1.98E-07 | -1.2178 | 0.2238 | -2.18E-07 | -1.3416 | 0.1803 | -2.31E-07 | -1.3743 | 0.1699 |
| UNTOTAL | 9.40E-08 | 0.7862 | 0.4321 | 1.60E-07 | 1.3587 | 0.1748 | 1.05E-07 | 0.8735 | 0.3828 |
| Trader_EXP | -6.84E-06 | -5.3125 | 0.0000 | 1.08E-05 | 4.5465 | 0.0000 | 7.21E-06 | 3.1368 | 0.0018 |
| UNEXP | -7.14E-06 | -7.4609 | 0.0000 | -2.11E-06 | -1.0556 | 0.2916 | -2.86E-06 | -2.7171 | 0.0068 |
| DUMUNEXP | 9.28E-06 | 5.8695 | 0.0000 | 1.23E-05 | 3.8989 | 0.0001 | 9.57E-06 | 5.0900 | 0.0000 |
| AR(1) | 0.353088 | 8.2274 | 0.0000 | 0.308382 | 7.1211 | 0.0000 | 0.394021 | 9.2092 | 0.0000 |
| AR(2) | 0.048591 | 1.0776 | 0.2817 | 0.12694 | 2.8245 | 0.0049 | 0.04855 | 1.0565 | 0.2912 |
| AR(3) | 0.110317 | 2.4950 | 0.0129 | 0.117892 | 2.6924 | 0.0073 | 0.089023 | 1.9778 | 0.0484 |
| AR(4) | 0.124702 | 2.7902 | 0.0054 | 0.121264 | 2.7576 | 0.0060 | 0.114218 | 2.5305 | 0.0117 |
| AR(5) | 0.107559 | 2.5495 | 0.0111 | 0.072071 | 1.7132 | 0.0872 | 0.089832 | 2.1314 | 0.0335 |
| | | | | | | | | | |
| R-squared | 0.439753 | AIC | -6.590 | 0.417472 | AIC | -6.551 | 0.405494 | AIC | -6.530 |
| Adjusted R-sq | 0.429802 | DW Stat | 2.0354 | 0.407125 | DW Stat | 2.0173 | 0.394934 | DW Stat | 2.0266 |

**Panel C: Intra-day Volatility estimator as proxy for market wide volatility**

| Variable | FII | | | DII | | | OTHER | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | t-Statistic | Prob. | Coefficient | t-Statistic | Prob. | Coefficient | t-Statistic | Prob. |
| C | 0.002374 | 3.1649 | 0.0016 | 0.002374 | 3.1649 | 0.0016 | 0.002585 | 5.2796 | 0.0000 |
| TOTAL_EXP | -3.72E-08 | -1.0288 | 0.3040 | -3.72E-08 | -1.0288 | 0.3040 | -3.50E-08 | -1.4154 | 0.1575 |
| UNTOTAL | -2.36E-07 | -1.4674 | 0.1428 | -2.36E-07 | -1.4674 | 0.1428 | -2.20E-07 | -6.7489 | 0.0000 |
| Trader_EXP | -5.01E-07 | -0.9961 | 0.3196 | -5.01E-07 | -0.9961 | 0.3196 | 9.06E-07 | 1.7249 | 0.0851 |
| UNEXP | -1.64E-06 | -3.5021 | 0.0005 | -1.64E-06 | -3.5021 | 0.0005 | -6.23E-07 | -2.2163 | 0.0271 |
| DUMUNEXP | 2.39E-06 | 3.1134 | 0.0019 | 2.39E-06 | 3.1134 | 0.0019 | 2.01E-06 | 4.0035 | 0.0001 |
| AR(1) | 0.267952 | 5.2257 | 0.0000 | 0.267952 | 5.2257 | 0.0000 | 0.292726 | 6.8170 | 0.0000 |
| | | | | | | | | | |
| R-squared | 0.173491 | AIC | -9.283 | 0.173491 | AIC | -9.283 | 0.140361 | AIC | -9.240 |
| Adjusted R-sq | 0.164806 | DW Stat | 1.9986 | 0.164806 | DW Stat | 1.9986 | 0.131296 | DW Stat | 2.0099 |

**Table 6 : Summary Statistics of different transaction types**
This table presents summary of trading activities of different transaction types for all NSE Nifty component stocks using proprietary data of National Stock Exchange of India for the period April-June 2006. The table reports daily stock-average number of trades and daily stock-average of trading value in Rs. lakhs for different transaction types. (F stands for FII, P for domestic proprietary, and C for domestic clients).

| | | Mean | Median | Max | stddev |
|---|---|---|---|---|---|
| Number of Trades | FF | 109 | 45 | 1699 | 161 |
| | FP | 519 | 294 | 6573 | 657 |
| | FC | 1013 | 552 | 14477 | 1409 |
| | PF | 618 | 338 | 7424 | 822 |
| | PP | 2093 | 1271 | 30471 | 2585 |
| | PC | 3618 | 2208 | 33815 | 4103 |
| | CF | 1242 | 600 | 35095 | 2023 |
| | CP | 3888 | 2432 | 40137 | 4381 |
| | CC | 7239 | 4191 | 93335 | 7812 |
| | **Total** | **20339** | **13080** | **186953** | **20934** |
| (in Rs lakhs)Trade Value | FF | 726 | 135 | 19779 | 1654 |
| | FP | 633 | 220 | 17740 | 1285 |
| | FC | 867 | 313 | 272812 | 5455 |
| | PF | 783 | 257 | 23054 | 1648 |
| | PP | 611 | 245 | 20049 | 1204 |
| | PC | 1348 | 648 | 23277 | 2200 |
| | CF | 1021 | 400 | 31918 | 2000 |
| | CP | 1502 | 742 | 27451 | 2528 |
| | CC | 2255 | 1180 | 115220 | 3765 |
| | **Total** | **9745** | **5152** | **435107** | **16717** |

**Table 7 : Pairwise correlation between Expected and Unexpected Components of different Transaction types**
This table presents pairwise correlation between trading activity conditional on trader type (FII, proprietary or client) and transaction type (buy→sell), decomposed into expected and unexpected parts. The expected component of a trading volume is the fitted value in a regression of transaction volume regressed against its past five lagged values and day of the week dummies; the unexpected part is the residual value. (F stands for FII, P for domestic proprietary, and C for domestic clients).

| **Correlation** | | **Expected** | | | | | | | | | **Unexpected** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **FF** | **FP** | **FI** | **PF** | **PP** | **PC** | **CF** | **CP** | **CC** | **FF** | **FP** | **FC** | **PF** | **PP** | **PC** | **CF** | **CP** | **CC** |
| **Expected** | **FF** | 1.00 | | | | | | | | | | | | | | | | | |
| | **FP** | 0.77 | 1.00 | | | | | | | | | | | | | | | | |
| | **FC** | 0.82 | 0.91 | 1.00 | | | | | | | | | | | | | | | |
| | **PF** | 0.75 | 0.89 | 0.80 | 1.00 | | | | | | | | | | | | | | |
| | **PP** | 0.50 | 0.86 | 0.72 | 0.87 | 1.00 | | | | | | | | | | | | | |
| | **PC** | 0.51 | 0.85 | 0.78 | 0.85 | 0.97 | 1.00 | | | | | | | | | | | | |
| | **CF** | 0.79 | 0.78 | 0.81 | 0.92 | 0.73 | 0.76 | 1.00 | | | | | | | | | | | |
| | **CP** | 0.52 | 0.84 | 0.76 | 0.87 | 0.97 | 0.98 | 0.79 | 1.00 | | | | | | | | | | |
| | **CC** | 0.51 | 0.76 | 0.79 | 0.79 | 0.86 | 0.95 | 0.80 | 0.94 | 1.00 | | | | | | | | | |
| **Un Expected** | **FF** | -0.12 | -0.13 | -0.16 | -0.13 | -0.13 | -0.16 | -0.16 | -0.16 | -0.19 | 1.00 | | | | | | | | |
| | **FP** | -0.17 | -0.23 | -0.28 | -0.23 | -0.19 | -0.25 | -0.28 | -0.25 | -0.31 | 0.59 | 1.00 | | | | | | | |
| | **FC** | -0.19 | -0.24 | -0.31 | -0.25 | -0.21 | -0.26 | -0.30 | -0.27 | -0.32 | 0.57 | 0.88 | 1.00 | | | | | | |
| | **PF** | -0.17 | -0.21 | -0.27 | -0.22 | -0.19 | -0.24 | -0.26 | -0.23 | -0.29 | 0.59 | 0.45 | 0.36 | 1.00 | | | | | |
| | **PP** | -0.27 | -0.30 | -0.38 | -0.31 | -0.28 | -0.35 | -0.38 | -0.35 | -0.42 | 0.33 | 0.61 | 0.52 | 0.61 | 1.00 | | | | |
| | **PC** | -0.31 | -0.34 | -0.43 | -0.36 | -0.31 | -0.40 | -0.44 | -0.39 | -0.47 | 0.32 | 0.64 | 0.63 | 0.55 | 0.90 | 1.00 | | | |
| | **CF** | -0.18 | -0.22 | -0.28 | -0.22 | -0.19 | -0.25 | -0.27 | -0.24 | -0.29 | 0.58 | 0.36 | 0.33 | 0.88 | 0.54 | 0.51 | 1.00 | | |
| | **CP** | -0.31 | -0.34 | -0.43 | -0.35 | -0.31 | -0.39 | -0.42 | -0.39 | -0.47 | 0.33 | 0.57 | 0.53 | 0.63 | 0.90 | 0.91 | 0.63 | 1.00 | |
| | **CC** | -0.32 | -0.36 | -0.44 | -0.37 | -0.32 | -0.40 | -0.44 | -0.40 | -0.49 | 0.32 | 0.56 | 0.61 | 0.54 | 0.81 | 0.92 | 0.58 | 0.93 | 1.00 |

**Table 8:** This table presents fixed effects panel regression results of the volatility-volume relation:

$$\sigma\, proxy_{i,t} = FixedEffects + \sum_{p=1}^{3}\sum_{q=1}^{3} \alpha_{0,pq} Exp\_Volume_{pq,it} + \sum_{p=1}^{3}\sum_{q=1}^{3} \beta_{0,pq} Un\exp\_Volume_{pq,it} + e_{it}$$

*i*=stock ; *t*=day; *p* =1 for FII purchases; 2 for domestic proprietary purchases & 3 for domestic client purchases; *q*=1 for FII sales; 2 for domestic proprietary sales & 3 for domestic client sales.

| Parameter | Parkinson Volatility Estimate | | | Intraday volatility Estimate | | |
|---|---|---|---|---|---|---|
| | Coefficient | t-Statistic | Prob. | Coefficient | t-Statistic | Prob. |
| FF_EXP | -0.0168 | -0.9543 | 0.3401 | -0.0043 | -0.2789 | 0.7804 |
| FP_EXP | 0.0115 | 0.3531 | 0.7240 | -0.0383 | -1.3589 | 0.1743 |
| FC_EXP | 0.0140 | 0.3968 | 0.6916 | 0.0402 | 1.3182 | 0.1876 |
| PF_EXP | 0.0321 | 0.9002 | 0.3682 | 0.0414 | 1.3327 | 0.1828 |
| PP_EXP | 0.0011 | 0.0229 | 0.9818 | 0.0175 | 0.4110 | 0.6811 |
| PC_EXP | -0.0051 | -0.0794 | 0.9367 | -0.0943 | -1.6896 | 0.0913 |
| **CF_EXP** | **0.1073** | **2.9697** | **0.0030** | **0.0625** | **1.9932** | **0.0464** |
| CP_EXP | -0.0266 | -0.3925 | 0.6948 | 0.0685 | 1.1519 | 0.2495 |
| **CC_EXP** | **0.2267** | **3.4576** | **0.0006** | 0.0623 | 1.0921 | 0.2749 |
| FF_UNEXP | -0.0143 | -1.3199 | 0.1870 | 0.0006 | 0.0696 | 0.9445 |
| FP_UNEXP | 0.0222 | 1.0023 | 0.3163 | 0.0063 | 0.3320 | 0.7399 |
| FC_UNEXP | 0.0192 | 0.8322 | 0.4054 | 0.0171 | 0.8583 | 0.3908 |
| PF_UNEXP | 0.0119 | 0.5638 | 0.5729 | 0.0058 | 0.3190 | 0.7498 |
| PP_UNEXP | 0.0078 | 0.2367 | 0.8129 | **0.0490** | **1.7325** | **0.0833** |
| PC_UNEXP | -0.0030 | -0.0666 | 0.9469 | -0.0052 | -0.1337 | 0.8936 |
| **CF_UNEXP** | **0.0574** | **2.5648** | **0.0104** | 0.0162 | 0.8382 | 0.4020 |
| CP_UNEXP | 0.0416 | 0.8777 | 0.3802 | -0.0302 | -0.7362 | 0.4617 |
| **CC_UNEXP** | **0.2068** | **4.2821** | **0.0000** | **0.0931** | **2.2249** | **0.0262** |
| AR(1) | 0.3646 | 15.7630 | 0.0000 | 0.4524 | 19.4454 | 0.0000 |
| AR(2) | 0.1497 | 6.6907 | 0.0000 | 0.1100 | 4.8920 | 0.0000 |
| **Cross section fixed (dummy variable) effects specification** | | | | | | |
| R-squared | 0.3540 | AIC 1.3256 | | R-Square 0.3873 | AIC | 1.08 |
| Adj R-sq | 0.3334 | DW Stat 1.9978 | | Adj R-Sq 0.3677 | DW Stat | 1.99 |