The Informative Role of Trading Volume in an Expanding Spot and Futures Market.

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Abstract

This paper investigates the information content of trading volume and its relationship with range-based volatility in the Indian stock market for the period 1995-2007. We examine the dynamics of the two variables and their respective uncertainties using a bivariate dual long-memory model. We distinguish between volume traded before and after the introduction of futures and options trading. We find that in all three periods the impact of both the number of trades and the value of shares traded on volatility is negative. This result is consistent with the argument that the activity of informed traders is inversely related to volatility when the marketplace has increased liquidity, an increasing number of active investors and high consensus among investors when new information is released. We also find that (i) the introduction of futures trading leads to a decrease in spot volatility, (ii) volume decreases after the introduction of option contracts and, (iii) there are significant expiration day effects on both the value of shares traded and volatility series.

Keywords: derivatives trading; emerging markets; long-memory; range-based volatility; value of shares traded

JEL Classification: C58, G12, G15, G20

1 Introduction

The rapid growth in the market for financial derivatives has resulted in continual exploration of the impact of these financial instruments on the volatility of the spot equity (or cash) market. The ability to trade a 'derivative' security is very likely to affect the underlying security's liquidity and information flow and therefore its volume (Stein, 1987, Subrahmanyan, 1991). Trading on a new market, such as the index futures and options market, is initially very small but as more traders become aware of the market's possibilities, its trading volume is likely to increase and more information to be impounded into futures prices. The question of interest that we try to address here is how does trading in index futures/options affects the trading in individual securities. Specifically, we examine the informative role of spot volume in terms of predicting cash volatility and how this role changes after the introduction of index futures and options. Market microstructure models predict volatility-volume relationships (simultaneous and feedback) which are sensitive to the type and quality of information, the expectations formed based on this information and the trading motives of investors[1].

This study also complements the literature about the impact of derivatives trading on the volatility of cash markets in emerging market economies. The effect of derivatives trading on cash market volatility is theoretically ambiguous and depends on the specific assumptions of the model (Stein, 1987, Subrahmanyan, 1991, Mayhew 2000). The empirical evidence is also mixed. While some researchers have found that the introduction of futures and options trading has not had any impact on stock volatility, others have found evidence of a positive effect in a number of countries including, Japan, the UK and the USA. The balance of evidence suggests that introduction of derivatives trading may have increased volatility in the cash market in Japan and the USA, but it had no impact on the other markets (Gulen and Mayhew, 2000)[2].

The volatility-volume relationship and the effect of derivatives trading on the cash market are analysed

[1] A positive volatility-volume relationship is predicted by most information induced trading models while a negative one is also existent due to liquidity induced trading (Li and Wu, 2006), the extent to which new information affects the knowledge of and agreement between agents (Holthausen and Verrecchia, 1990), and the number of active traders in the market (Tauchen and Pitts, 1983). Daigler and Wiley (1999) find that the activity of informed traders is often inversely related to volatility. Moreover, Avramov et al. (2006) show that informed (or contrarian) trades lead to a reduction in volatility while non-informational (or herding) trades lead to an increase in volatility

[2] It is only recently that the development and financial literature have started exploring the impact of phenomena like market participation by foreign portfolio investors and expiration of derivatives contracts in emerging economies (see, for example, Pok and Poshakwale, 2004; Vipul, 2005, 2006; Kim et al., 2005; Wang, 2007; Bhaumik and Bose, 2009).

together in this paper by estimating a bivariate ccc AR-FI-GARCH model with lagged values of one variable included in the mean equation of the other one. The fractional integration applies to the mean and the variance specification and allows to capture the long memory characteristics of our data. Apart from using absolute values of the returns, their squares and conditional variances from a GARCH-type model as our measure of volatility, we also employ the range-based volatility estimator of Garman and Klass (1980) (hereafter GK). The GK estimator is more efficient than the traditional close-to-close estimator and exhibits very little bias, whereas the realized volatility constructed from high frequency data can possess inherent biases impounded by market microstructure factors (Alizadeh et al., 2002). Finally, we use two measures of volume, the number of trades and the value of shares traded, in order to capture differences in their information content over time and changes to it with the introduction of derivatives trading. Jones et al. (1994) find that on average the size of trades has no significant incremental information content and that any information in the trading behavior of agents is almost entirely contained in the frequency of trades during a particular interval.

Our sample period from November 3, 1995 to January 25, 2007 includes the introduction of (index) futures and (index) options trading, at two different points in time. We, therefore, have three distinct sub-periods in our data, one in which financial derivatives were not traded, another during which only futures contracts were traded, and finally one in which both futures and options contracts were traded. The results suggest that the impact of the value of shares traded – one of our measures of volume – on volatility is sensitive to the introduction of derivatives trading. In all three periods, the impact is negative. However, the strength of this negative relationship was weakened after the introduction of options trading, perhaps because of a reduction in the flow of information in the cash market. Similarly, the impact of the number of trades – our second measure of volume – on volatility is negative in all three periods. Overall, increases in unexpected volume (proxy for information arrival) are related with lower range-based volatility over time. This supports the hypothesis that the activity of informed traders is inversely related to volatility when the marketplace has increased liquidity, an increasing number of active investors and high consensus among investors when new information is released. In sharp contrast, both measures of volume are not affected by past changes in volatility.

Our specification allows us to examine the direct impact of introduction of futures and options trading on volume and volatility in the cash market as well. We find that (i) the introduction of futures trading leads to a decrease in spot volatility as predicted by Stein (1987) and Hong (2000) and, (ii) volume decreases after the introduction of option contracts, offering support to the view that the migration of some speculators to options markets on the listing of options is accompanied by a decrease in trading volume in the underlying security. We also control for expiration day effects in our bivariate ccc AR-FI-GARCH model. Our results indicate that expiration of equity based derivatives has a significant positive impact on the value of shares traded on expiration days and a significant negative impact on the range-based volatility. The increased trading on expiration days can easily be explained by way of settlement of futures contracts (and exercise of options contracts) that necessitate purchase and sale of shares in the cash market.

The remainder of this article is organised as follows. In Section 2, we trace the post-reforms evolution of the secondary market for equities in India. Section 3 discusses the theory concerning the link between volume and volatility and the impact of futures trading on the latter. Section 4 outlines the data which are used in the empirical tests of this paper. In Section 5 we describe the time series model for the two variables, we report the empirical results and we discuss them within the context of the Indian market. Section 6 contains summary remarks and conclusions.

2 The Indian Equity Market

The choice of NSE as the basis for our analysis can easily be justified. The market capitalisation in March 2007, the last month of the 2006-07 financial year, was Indian rupees (INR) 33,673.5 billion, more than 10 times the market capitalisation in March 1995 (INR 2,926.4 billion), the last month of NSE's first (financial) year of operation. The number of trades executed at NSE's cash market during the corresponding months was 71 million and 0.1 million, respectively. The growth in the derivatives segment of the exchange has kept pace with the growth in the cash market. Of the 1098 listed securities, 123 act as underlying assets for futures and options contracts. In addition, three indices are used as the underlying assets for futures and options trading at the exchange. The turnover in the derivatives segment increased from INR 3.81 billion in March 2001, the last month of the first (financial) year of derivatives trading at NSE, to INR 6,937.63 billion in March 2007. The corresponding increase in the daily average turnover was from INR 0.18 billion to INR 330.36 billion. In March 2007, the daily turnover in the derivatives segment of the equity market was 413% of the average daily turnover in the cash segment of the market. The meteoric growth of the cash and derivatives segments of the NSE is graphically highlighted in Figures 1-2.

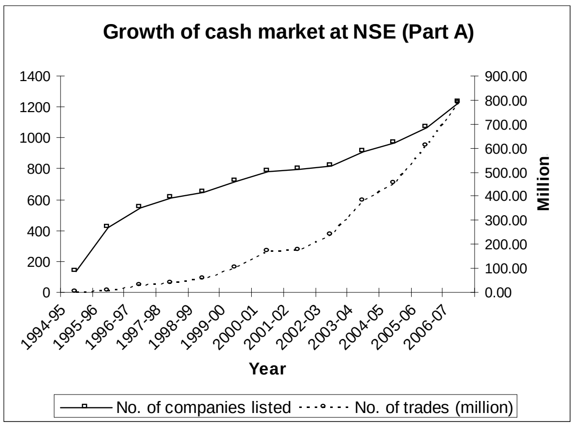

Figure 1 (Part A)

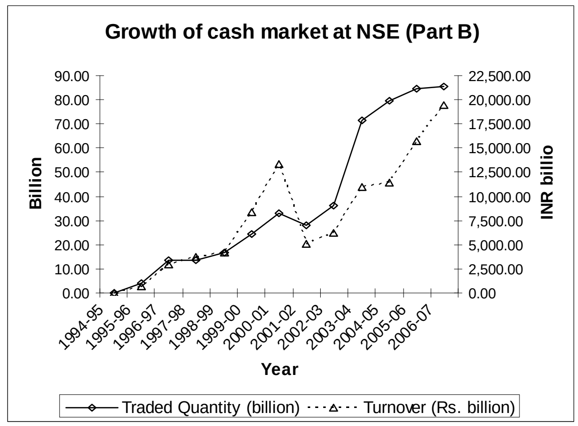

Figure 1 (Part B)

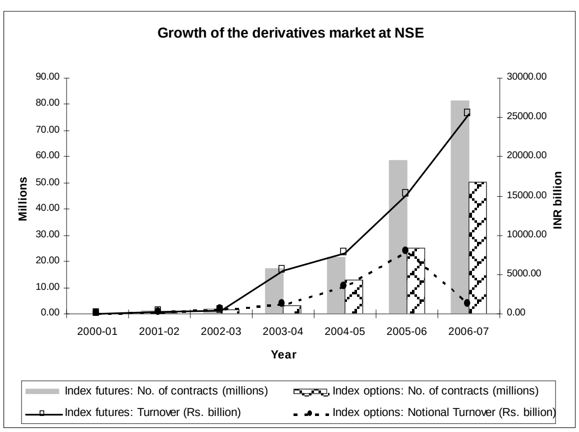

Figure 2

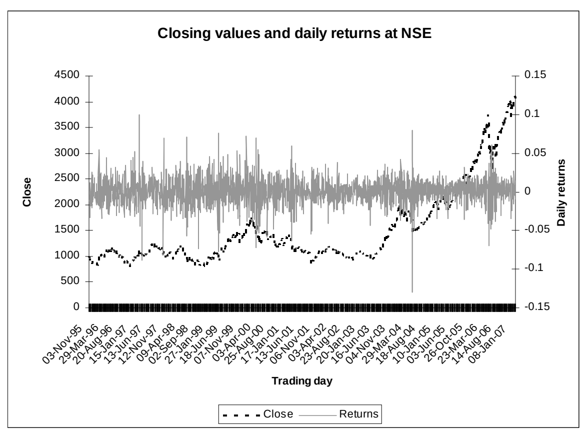

Figure 3

The reform of India's capital market was initiated in 1994, with the establishment of the NSE, which pioneered nationwide electronic trading at its inception, a neutral counterparty for all trades in the form of a clearing corporation and paperless settlement of trades at the depository (in 1996). The consequence was greater transparency, lower settlement costs and fraud mitigation, and one-way transactions costs declined by 90% from an estimated 5% to 0.5%.

However, the crisis of 1994 had initiated a policy debate that resulted in significant structural changes in the Indian equity market by the turn of the century[3]. In June 2000 the NSE (as well as its main rival, the Bombay Stock Exchange) introduced trading in stock index futures, based on its 50-stock market capitalisation weighted index, the Nifty (and, correspondingly, the 30-stock Sensex). Index options on the Nifty and individual stocks were introduced in 2001, on June 4 and July 2, respectively. Finally, on November 9, 2001, trading was initiated in futures contracts based on the prices of 41 NSE-listed companies[4]. However, in a blow to the price discovery process in the cash market, prior to the introduction of derivatives trading in India, the SEBI banned short sales of stocks listed on the exchanges.

3 Theoretical Background

The volatility-volume relationship has been the subject of theoretical and empirical research for many years. The models proposed either describe the full process by which information integrates into prices or by using a less structural approach such as the Mixture of Distribution Hypothesis (MDH). According to the mixture of distributions model, the variance of daily price changes is affected by the arrival of price-relevant new information proxied by trading volume (Clark, 1973, Epps and Epps, 1976, Tauchen and Pitts, 1983). Tauchen and Pitts (1983) find that the variance of the daily price change and the mean daily trading volume depend on the average daily rate at which new information flows to the market, the extent to which traders disagree when they respond to new information and the number of active traders in the market. They predict a positive volatility-volume relationship when the number of traders is fixed

[3] An important problem was the existence of leveraged futures-type trading within the spot or cash market. This was facilitated by the existence of trading cycles and, correspondingly, the absence of rolling settlement. Given a Wednesday-Tuesday trading cycle, for example, a trader could take a position on a stock at the beginning of the cycle, reverse her position towards the end of the cycle, and net out her position during the long-drawn settlement period. In addition, the market allowed traders to carry forward trades into following trading cycles, with financiers holding the stocks in their own names until the trader was able to pay for the securities and the intermediation cost, which was linked to money market interest rates (for details, see Gupta, 1995, 1997). The use of carry forward (or badla) trades was banned in March 1994, following a major stock market crash but was reintroduced in July 1995 in response to worries about decline in market liquidity and stock prices.

[4] On January 10, 2000, rolling settlement was introduced for the first time, initially for ten stocks. By July 2, 2001, rolling settlement had expanded to include 200 stocks, and badla or carry forward trading was banned.

while a negative relation is predicted when the number of traders is growing, such as the case of T-bills futures market.

3.1 Information, liquidity and stock market volatility

Andersen (1996) suggests a modified MDH model in which informational asymmetries and liquidity needs motivate trade. The information flow is represented by a stochastic volatility process that drives the positive contemporaneous relationship between volatility and informed trading volume. Li and Wu (2006) introduce a negative effect of liquidity trading on return volatility into Andersen's (1996) model. They find that the positive volatility-volume relationship is mainly driven by informed trading and the information flow. More importantly they show that the price volatility is negatively related to the intensity of liquidity trading given the probabilities of news arrival and informed trading. This result is consistent with the contention that liquidity trading increases market depth and lowers price volatility[5].

Another class of informational asset trading models that explain the volatility-volume (and potentially causal) relationship is the Sequential Information Arrival models of Copeland (1976, 1977), and Jennings et al. (1981). A testable prediction of the above models is that there will be a positive correlation between volume and the absolute value of price changes when information arrives sequentially and traders observe the path of trades, prices, and volume. Jennings et al. (1981) predict a rather complex relationship between absolute price changes and volume sensitive to the number of investors, how current information is being interpreted by the market (i.e., the mix of optimists and pessimists) and the actual level of the expectations of each class of investors. For example, if the mix of investors is restricted to a range between 20 and 60 percent optimists, the correlation coefficient is high and positive. For an empirical study on the causal relationship of volatility and trading volume see Smirlock and Starks (1988).

A positive volatlity-volume relationship is also predicted by models of heterogeneous trader behavior arising either because informed traders have different private information (Shalen, 1993) or because they simply interpret commonly known data in a different way (Harris and Raviv 1993). In Shalen's model speculators confuse price variation caused by changes in liquidity demand (assumed random) and price

[5] A market with higher liquidity-motivated trading volume tends to have more random buy and sell orders offsetting each other and thus causing no significant changes in prices. Moreover, liquidity trading absorbs the price impact of information-based trading and in this way higher intensity of liquidity trading helps lower volatility.

variation caused by private information. This dispersion of expectations can explain both excess volume and volatility associated with market noiseness and contributes to positive correlations between trading volume and contemporaneous and future absolute price changes. Moreover, Blume, Easley and O'Hara (1994) show that sequences of volume provide information about the quality of traders' information that cannot be deduced from the price statistic alone. Even in the case where 90 percent of the traders being in the high-precision signal group, absolute value of prices changes and volume are positively related.

Harris and Raviv (1993) consider a model of trading in speculative markets assuming that traders share common prior beliefs, receive common information but differ in the way they interpret this information. They show that absolute price changes and volume are positively correlated, consecutive price changes exhibit negative serial correlation and trading volume is positively autocorrelated. However, in Holthausen and Verrecchia (1990), it is the extent to which agents become more knowledgeable (informedness) and the extent of agreement between agents (consensus), at the time of an information release, that affects unexpected price changes and trading volume. Their results imply that the variance of price changes and trading volume tend to be positively related when informedness effect dominates the consensus effect and tend to be negatively related when the consensus effect dominates the informedness effect. He and Wang (1994) find that new information, private or public, generates both high volume and large price changes, while existing private information can generate high volume with little price changes.

Daigler and Wiley (1999) find empirical evidence indicating that the positive volume-volatility relation is driven by the (uninformed) general public whereas the activity of informed traders such as clearing members and floor traders is often inversely related to volatility. Black (1986) argues that noise trading increases liquidity in the markets and also puts noise into the prices as they reflect both information and noise induced trading. DeLong et al. (1990a) show that the unpredictability of noise traders' beliefs creates excess risk and significantly reduces the attractiveness of arbitrage. In cases where arbitrageurs have short horizons noise trading can lead to a large divergence between market prices and fundamental values. DeLong et al. (1990b) argue, despite the fact that ra- tional speculation stabilizes prices, that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders.

The theoretical models above find volatility-volume relationships (simultaneous and feedback) which are sensitive to the type and quality of information, the expectations formed based on this information and the trading motives of investors. A positive volatility-volume relationship is predicted by most information induced trading models while a negative one is also existent due to liquidity induced trading (Li and Wu, 2006), the extent to which new information affects the knowledge of and agreement between agents (Holthausen and Verrecchia, 1990), and the number of active traders in the market (Tauchen and Pitts, 1983).

3.2 Derivatives trading and their impact on the spot/cash market

The volatility-volume relationship and the effect of derivatives trading on the cash market are analysed together as we are interested in investigating how the information content of trading volume has changed after the introduction of index futures/options trading. Trading on a new market, such as the index futures and options market, is initially very thin but as more traders become aware of the market's possibilities, its trading volume is likely to increase and more information to be impounded into futures prices. One question of interest is how does trading in index futures/options affects the trading in individual securities[6].

Several studies have examined the level of the stock market volatility before and after the introduction of futures contracts. Theoretical studies on the impact of the futures trading on the spot market have produced interesting results. Stein (1987) demonstrates that introducing more speculators into the market, through the introduction of futures, leads to improved risk sharing but can also change the informational content of prices. In some cases the entry of new speculators lowers the informativeness (ability to make inferences based on current prices) of the price to existing traders. The net result can be one of price destabilization and welfare reduction if this "misinformation" effect is strong enough relative to the need for additional risk sharing.

Subrahmanyam (1991) presents a theory of trading in markets for stock index futures or, more gen-

[6] The impact of the opening of futures markets on the spot price volatility has received considerable attention in the finance literature. Researchers and practitioners have investigated the role that the introduction of futures trading played in the stock market crash of 1987 in the USA (Gammill and Marsh, 1988) and in the Asian financial crisis (Ghysels and Seon, 2005).

erally, for baskets of securities. His model incorporates trading by strategic liquidity traders who realize their trades either in the individual securities or in a basket of these securities, depending on where their losses to informed traders are minimized. Markets in baskets are shown to be advantageous for such traders because the security-specific component of adverse selection tends to get diversified away in such markets. Moreover,when the factor sensitivities differ in sign across securities, the diversification of systematic information in the basket further reduces the adverse selection in the basket relative to that in the securities. This "diversification" benefit reduces the transaction costs of the discretionary liquidity traders when they trade in the basket. Hence, the movement of discretionary traders to the basket, results in less liquidity and greater risk of informed trading of the individual securities.

A secondary effect, if the number of informed traders is endogenous, is to affect the number of factor informed and security specific informed traders. Subrahmanayam demonstrates that in general this change is expected, first, to increase the overall informativeness of the price of the underlying portfolio and make this price more responsive to new systematic information and, second, to make individual security prices (and the price of the portfolio) less informative in the security-specific component and more informative in the systematic component. The above result implies that the introduction of a basket has no effect on the variance of price changes in component securities[7].

Although it has been suggested that the opening of a futures market may destabilize prices by encouraging irrational speculation (noise trading), Subrahmanyam argues that this need not necessarily be the case[8]. In his model an increase in noise trading actually makes price more informative by increasing the returns on being informed and thereby facilitating the entry of more informed traders. Moreover, Hong (2000) develops an equilibrium model of competitive futures markets in which investors trade to hedge positions and to speculate on their private information. He finds that when a futures market is opened investors are able to better hedge spot price risk and hence are more willing to take on larger spot positions. As a result the introduction of futures contracts reduces spot price volatility.

[7] The same results on price change variability also apply for nonbasket securities

[8] John et al. (2003) find that the introduction of option trading improves the informational efficiency of stock prices irrespective of whether binding margin requirements are in place or not. Intuitively, even though the addition of option trading enhances the ability of informed traders to disguise and profit from their trades, the informativeness of the trading process is greater because the market can now infer private information from two sources - order flow in the stock and option markets.

4 Empirical Evidence

A positive relationship between volume and volatility has often been reported in empirical research for cash and futures markets (Karpoff, 1987, Bessembinder and Seguin, 1992, Andersen 1996). A negative relationship between the two variables, though, is not precluded from economic theory (Holthausen and Verrecchia, 1990, Li and Wu, 2006) and empirical evidence (Daigler and Wiley,1999, Kawaller et al. 2001). For example, Daigler and Wiley (1999) find that the positive volatility-volume relationship is driven by the general public, a group of traders distant from the trading floor, less informed and with greater dispersion of beliefs. On the other hand clearing members and floor traders often decrease volatility and this is attributed mainly to the informational advantage from holding a seat in the futures market. Moreover, Avramov et al. (2006) show that informed (or contrarian) trades lead to a reduction in volatility while non-informational (or herding) trades lead to an increase in volatility.

As regards the empirical evidence, on the impact of futures trading on the spot market, Damodaran and Subrahmanayan (1992) survey a number of studies. They conclude that there is a consensus that listing futures on commodities reduces the variances of the latter. Edwards (1988) and Bessembinder and Seguin (1992) find that S&P 500 futures trading affects spot volatility negatively. Brown-Hruska and Kuserk (1995) also provide evidence, for the S&P 500 index, that an increase in futures volume (relative to spot volume) reduces spot volatility. The analysis in Board et al. (2001) suggests that in the UK futures trading does not destabilize the spot market.

Dennis and Sim (1999) document how the introduction of futures trading does not affect spot market volatility significantly in Australia and three other nations. Gulen and Mayhew (2000) find that spot volatility is independent of changes in futures trading in eighteen countries and that informationless futures volume has a negative impact on spot volatility in Austria and the UK. In general, mixed evidence is provided by studies that examine non-US markets. For example, Bae et al. (2004) find that the introduction of futures contracts in Korea is associated with greater spot price volatility. Overall, the impact of futures trading on the volatility of spot markets varies according to sample, data set and methodology chosen.

The impact of derivatives trading on the volatility of the cash market in India is explored in a few studies (Bandivadekar and Ghosh, 2003; Raju and Karande, 2003; Vipul, 2006). The empirical evidence suggests that as early as 2002-03 there was a reduction in the volatility of the cash market index after the introduction of index futures. Vipul (2006) find evidence of a reduction in the volatility of the prices of underlying securities after the introduction of futures contracts for individual stocks. However, these papers do not explore the volume-volatility link, nor separately the impact of futures and options trading on the underlying market. In what follows we will examine, within the context of a bivariate long-memory model, the effect of the opening of futures markets on spot price volatility and volume at the NSE.

5 Data and Estimation Procedure

The data set used in this study comprises 2814 daily trading volumes and prices of the NSE index, running from 3rd of November 1995 to 25th of January 2007. The data were obtained from the Indian NSE. The NSE index is a market value weighted index for the 50 most liquid stocks.

5.1 Price volatility

Using data on the daily high, low, opening, and closing prices in the index we generate a daily measure of price volatility. We employ the range-based estimator of Garman and Klass (1980) to construct the daily volatility ($y_t^{(g)}$) as follows

$$y_t^{(g)} = \frac{1}{2}u^2 - (2\ln 2 - 1)c^2, \quad t \in \mathbb{N},$$

where u and c are the differences in the natural logarithms of the high and low, and of the closing and opening prices respectively. Garman and Klass assume that the price follows a simple diffusion model without a drift and show that their range-based volatility measure is eight times more efficient than the daily squared return. The merits of using a range-based volatility measure are associated with Parkinson (1980) who proposes the use of high and low prices for estimating volatility in a constant volatility setting. The log range (high minus low) is not only more efficient as a volatility proxy but also is very well approximated as Gaussian (Alizadeh et al., 2002). Parkinson's estimator has been improved in several ways, including combining the range with opening and closing prices (Garman and Klass, 1980, Rogers and Satchell, 1991, Yang and Zhang, 2000). Andersen and Bollerslev (1998) show that the daily range is about as efficient a volatility proxy as the realized volatility based on returns sampled every three-four hours. Upon availability of high frequency data for the Indian stock market and to provide more robustness to our results, we aim to estimate realized volatility proxies either using minute-by-minute squared returns (Andersen et al., 2001) or squared ranges (Martens and vanDijk, 2007, Christensen and Podolskij, 2007). Shu and Zhang (2006) find that the range estimators are fairly robust toward microstructure effects and quite close to the daily integrated variance[9]. Various measures of range-based volatility have been employed in empirical finance research (Daigler and Wiley, 1999, Kawaller et al., 2001, Wang, 2002, Chen and Daigler, 2008)[10].

We also use an outlier reduced series for Garman-Klass volatility (see Figure 4B). In particular, the variance of the raw data is estimated, and any value outside four standard deviations is replaced by four standard deviations. Chebyshev's inequality is used as it i) gives a bound of what percentage ($1/k^2$) of the data falls outside of k standard deviations from the mean, ii) holds no assumption about the distribution of the data, and iii) provides a good description of the closeness to the mean,especially when the data are known to be unimodal as in our case[11]. Figure 4A plots the Garman-Klass volatility from 1995 to 2007.

[9] Realized volatility is estimated as the sum of squared high-frequency returns over a given sampling period (e.g., five-minute returns) and is subject to microstructure biases due to uneven trading times, bid-ask bounces and stale prices (Andersen et al., 2001).

[10] Chou (2005) propose a Conditional Autoregressive Range (CARR) model for the range (defined as the difference between the high and low prices). In order to be in line with previous research (Daigler and Wiley, 1999, Kawaller et al., 2001, and Wang, 2007) in what follows we model Garman-Klass volatility as an autoregressive type of process taking into account bidirectional feedback between volume and volatility, dual-long memory characteristics and GARCH effects.

[11] Carnero et al. (2007) investigate the effects of outliers on the estimation of the underlying volatility when they are not taken into account.

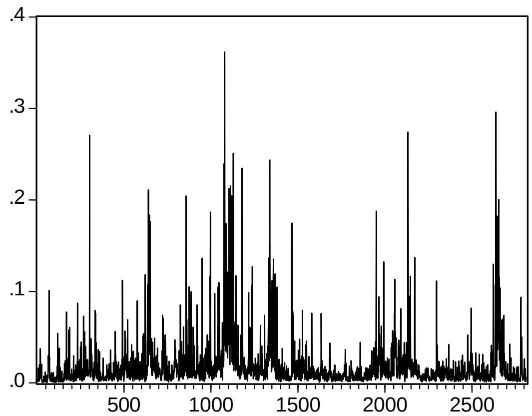

Figure 4A (Garman-Klass Volatility)

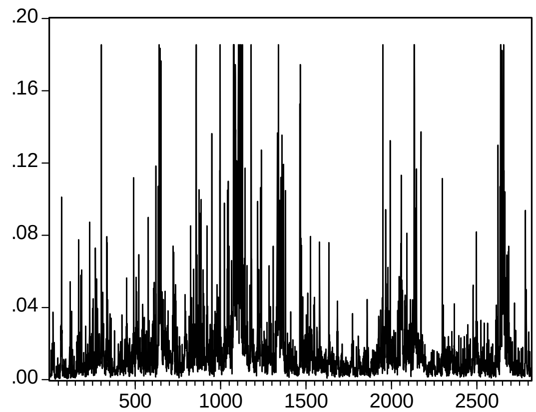

Figure 4B (Outlier reduced GK volatility)

5.2 Trading volume

Jones et al. (1994) find that on average the size of trades has no significant incremental information content and that any information in the trading behavior of agents is almost entirely contained in the frequency of trades during a particular interval. We also use the value of shares traded and the number of trades as two alternative measures of volume as we aim to capture and compare changes in the information content of trading activity over time and with the introduction of futures/options trading. Because trading volume is nonstationary several detrending procedures for the volume data have been considered in the empirical finance literature (Lo and Wang, 2000). Logarithmic transformations of trading activity are used in order to obtain better statistical inference and to linearize the near constant trend in trading volume evidenced in Figure 1. We form a trend-stationary time series of volume ($y_t^{(v)}$) by fitting a linear trend (t) and subtracting the fitted values for the original series ($\widetilde{y}_t^{(v)}$) as follows

$$y_t^{(v)} = \widetilde{y}_t^{(v)} - (\hat{a} - \hat{b}t),$$

where v denotes volume. The linear detrending procedure is deemed to provide a very good approximation of trading activity associated with the arrival of new information in the market. It is also a reasonable compromise between computational ease and effectiveness. We also extract a moving average trend from the volume series resulting in a detrended volume with downsized seasonal spikes from badla trades and futures contacts expiration. As detailed below, the results (not reported) for the moving average detrending procedure are qualitatively similar to those reported for the linearly detrended volume series[12]. In what follows, we will denote value of shares traded by vs and number of trades by n. Figures 5A and 5B and plot the number of trades and value of shares traded from November 1995 to January 2007.

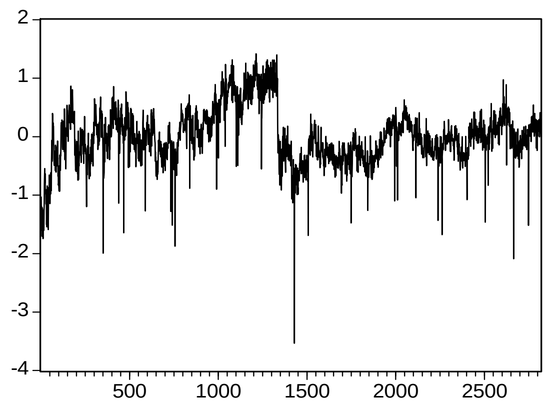

Figure 5A (Value of shares traded)

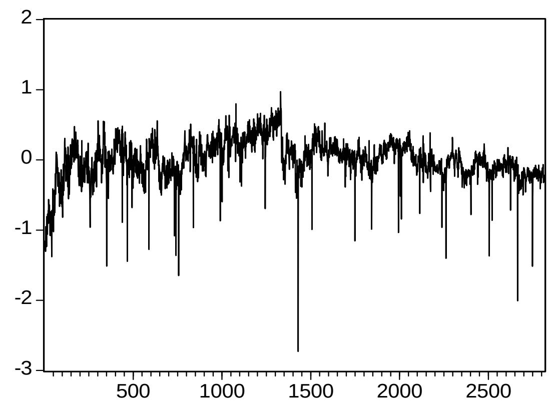

Figure 5B (Number of trades)

5.3 Structural breaks in volatility and volume

We also examine whether there are any structural breaks in both volume and volatility and, if there are, whether they are associated with the introduction of futures and options contracts. We test for structural breaks by employing the methodology in Bai and Perron (2003), who address the problem of testing for multiple structural changes in a least squares context and under very general conditions on the data and the errors. In addition to testing for the presence of breaks, these statistics identify the number and location of multiple breaks. Particularly, in the case of log volume we use a partial structural change model where we test for a structural break in the mean while at same time allowing for a linear trend of the form t/T. Granger and Hyung (2004) show that occasional level shifts in the mean give rise to the observed long memory property. Research along this line of models has produced some very interesting

[12] Bollerslev and Jubinski (1999) find that neither the detrending method nor the actual process of detrending affected any of their qualitative findings (see also, Karanasos and Kartsaklas, 2009 and the references therein).

results[13].

Moreover, Bai and Perron (2003) form confidence intervals for the break dates under various hypotheses about the structure of the data and the errors across segments. This allows us to estimate models for different break dates within the 95 percent confidence interval and also evaluate whether our inferences are robust to these alternative break dates. Our results (not reported) seem to be invariant to break dates around the one which minimizes the sum of squared residuals.

The overall picture dates two change points for volatility. The first is detected in July 2000 and the next one is in May 2006. As regards trading volume, both value of shares traded and the number of trades, have a common break dated in March 2001. Recall that the index futures and options trading started in June 2000 and June 2001 respectively. These dates fall within the confidence intervals estimated for volatility and volume This allows us to associate structural breaks in volatility and volume with the introduction of index futures and options and accordingly to construct dummy variables to capture their effect on the volatility-volume relationship. Accordingly, we break our entire sample into three subperiods. The first period is the period up to the introduction of futures trading (3rd November 1995 – 12th June 2000). The second period is the period from the introduction of futures contracts until the introduction of options trading (13th June 2000 - 2nd July 2001). Finally, the third period is the one which starts with the introduction of option contracts until the end of our sample (3rd July 2001 - 25th January 2007)[14].

[13] Lu and Perron (2010) consider the estimation of a random level shift model for which the series of interest is the sum of a short-memory process and a jump or level shift component. Once few level shifts are taken into account, there is little evidence of serial correlation in the remaining noise and, hence, no evidence of long-memory. When the estimated shifts are introduced to a standard GARCH model applied to the returns series, any evidence of GARCH effects disappears. Perron and Qu (2010) analyze the properties of the autocorrelation function, the periodogram, and the log periodogram estimate of the memory parameter for the random level shift model. Using data on various indices and sample periods, they show that all stock market volatility proxies considered clearly follow a pattern that would obtain if the true underlying process was one of short-memory contaminated by level shifts.

[14] The results in Lavielle and Moulines (2000) are valid under a wide class of strongly dependent processes, including long memory, GARCH-type and non-linear models. Our results show that there is no change in the number of break points estimated when we allow for long memory.

6 Econometric Model

6.1 Bivariate long-memory process

The MDH posits a joint dependence of both volatility and volume on new informational arrival and, thus, a bivariate model would better capture lagged and simultaneous correlations among the two variables. Several multivariate GARCH models have been proposed in the literature allowing for richer structures on the variable dynamics and time-varying correlations (see Bauwens et al., 2006, for a survey). Long memory conditional mean and variance models are desirable in light of the observed covariance structure of many economic and financial time series (Baillie, 1996; Baillie et al., 1996; Giraitis et al, 2000; Mikosch and Starica, 2000, 2003). For example, Chen and Daigler (2008) emphasize that both volume and volatility possess long memory characteristics. Baillie et al. (1996) show that the FIGARCH process combines many of the features of the fractionally integrated process for the mean together with the regular GARCH process for the conditional variance. The corresponding impulse response weights derived from the FIGARCH model also appear to be more realistic from an economic perspective when compared to the fairly rapid rate of decay associated with the estimated covariance stationary GARCH model or the infinite persistence for the IGARCH formulation[15].

Therefore we focus our attention on the topic of long-memory and persistence in terms of the first two moments of the two variables. Consequently, we utilize a bivariate ccc ARFI-FIGARCH model to test for causality between volume and volatility[16]. Within the framework of this dual long-memory model we will analyze the dynamic adjustments of both the conditional means and variances of volume and volatility, as well as the implications of these dynamics for the direction of causality between the two variables. The estimates of the various formulations were obtained by quasi maximum likelihood estimation (QMLE) as implemented by James Davidson (2008) in Time Series Modelling (TSM). To check for the robustness of our estimates we used a range of starting values and hence ensured that the estimation procedure converged to a global maximum.

[15] Tsay and Chung (2000) have shown that regressions involving fractionally integrated regressors can lead to spurious results. Moreover, in the presence of conditional heteroskedasticity, Vilasuso (2001) suggests that causality tests can be carried out in the context of an empirical specification that models both the conditional means and conditional variances.

[16] Karanasos and Kartsaklas (2009) applied the bivariate dual long-memory process to model the volume-volatility link in Korea.

Next let us define the column vector of the two variables $\mathbf{y}_t$ as $\mathbf{y}_t = (y_{1t}\ y_{2t})'$and the residual vector $\boldsymbol{\varepsilon}_t$ as $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}\ \varepsilon_{2t})'$. In order to make our analysis easier to understand we will introduce the following notation. $D_{t,f}$ is a dummy defined as: $D_{t,f} = 1$ during the period from the introduction of futures trading (that is 13th June 2000) until the end of the sample and $D_{t,f} = 0$ otherwise; similarly $D_{t,o}$ is a dummy indicating approximately the period which starts with the introduction of option contracts. That is, $D_{t,o} = 1$ in the period between 3rd July 2001 and 25th January 2007 and $D_{t,o} = 0$ otherwise. In addition, $D_{t,e}$ is a dummy defined as: $D_{t,e} = 1$ the last Thursday of every month -starting from the introduction of futures trading- and $D_{t,e} = 0$ otherwise.

In the expressions below the subscripts 1 and 2 mean that the first equation represents the GK volatility and the second one stands for the volume. When the value of shares traded is used as a measure of volume we will refer to the expressions in equation (1) as model 1. Similarly, when we use the number of trades we will have model 2.

The best fitting specification (see equation 1 below) is chosen according to the minimum value of the information criteria (not reported). Ljung-Box test statistics for autocorrelation in normal and squared residuals are also used. For the conditional mean of volatility (y_{1t}), we choose an ARFI$(0, d)$ process for both measures of volume. For the conditional means of value of shares traded and number of trades, we choose an ARFI$(10, d)$ process. That is, $\Phi_2(L) = 1 - \sum_{j=1}^{10} \phi_2^{(j)} L^j$, with $\phi_2^{(4)} = \phi_2^{(6)} = \phi_2^{(7)} = \phi_2^{(9)} = 0$, for the value of shares traded, and only $\phi_2^{(4)} \neq \phi_2^{(5)} \neq \phi_2^{(9)} \neq \phi_2^{(10)} \neq 0$ for the number of trades. We do not report the estimated AR coefficients for space considerations.

The chosen estimated bivariate ARFI model is given by

$$
\begin{aligned}
&(1-L)^{d_{1,m}} \Big[y_{1t} - (\varphi_{12}^{(3)} + \varphi_{12,f}^{(3)} D_{t,f} + \varphi_{12,o}^{(3)} D_{t,o}) L^3 y_{2t} \\
&-(\mu_1 + \mu_{1,e} D_{t,e} + \mu_{1,f} D_{t,f} + \mu_{1,o} D_{t,o}) \Big] \;=\; \varepsilon_{1,t}, \\
&(1-L)^{d_{2,m}} \Phi_2(L) \Big[y_{2t} - (\varphi_{21}^{(1)} + \varphi_{21,f}^{(1)} D_{t,f} + \varphi_{21,o}^{(1)} D_{t,o}) L y_{1t} \\
&-(\mu_2 + \mu_{2,e} D_{t,e} + \mu_{2,f} D_{t,f} + \mu_{2,o} D_{t,o}) \Big] \;=\; \varepsilon_{2t}.
\end{aligned} \tag{1}
$$

where L is the lag operator, $0 < d_{i,m} < 1$ and $\mu_i, \mu_{i,e}, \mu_{i,f}, \mu_{i,o}$ are finite for $i = 1, 2$ (recall that 1 and 2 mean that the first equation represents the GK volatility and the second one stands for the volume).

The $\varphi_{12}^{(s)}$ coefficient captures the effect from volume on volatility while $\varphi_{21}^{(s)}$ represents the impact on the opposite direction. The information criteria (not reported) choose the model with the $\varphi_{12}^{(3)}$ and $\varphi_{21}^{(1)}$. Similarly, $\varphi_{12,f}^{(3)}$ and $\varphi_{21,f}^{(1)}$, correspond to the cross effects from the introduction of futures contracts onwards, while $\varphi_{12,o}^{(3)}$ and $\varphi_{21,o}^{(1)}$ stand for the volume-volatility feedback after the introduction of options trading. Thus, the link between the two variables is captured by $\varphi_{12}^{(3)}$ and $\varphi_{21}^{(1)}$, in the period up to the introduction of futures trading, by $\varphi_{12}^{(3)} + \varphi_{12,f}^{(3)}$ and $\varphi_{21}^{(1)} + \varphi_{21,f}^{(1)}$ in the second period, and by $\varphi_{12}^{(3)} + \varphi_{12,f}^{(3)} + \varphi_{12,o}^{(3)}$, $\varphi_{21}^{(1)} + \varphi_{21,f}^{(1)} + \varphi_{21,o}^{(1)}$ in the period which starts with the introduction of options contracts. The coefficients $\mu_{1,e}$, $\mu_{2,e}$ capture the impact of the expiration of derivatives contracts on the two variables[17].

We assume $\boldsymbol{\varepsilon}_t$ is conditionally normal with mean vector $\mathbf{0}$, variance vector $\mathbf{h}_t = (h_{1t}\ h_{2t})'$ and ccc $\rho = h_{12,t}/\sqrt{h_{1t}h_{2t}}$ $(-1 \leq \rho \leq 1)$, where 1 and 2 mean that the first equation represents the GK volatility and the second one stands for the volume. We also choose an ARCH(1) process for the volume and a FIGARCH$(0, d, 0)$ one for the volatility:

$$\begin{bmatrix} h_{1t} - \omega_1 \\ h_{2t} - \omega_2 \end{bmatrix} = \begin{bmatrix} 1 - (1-L)^{d_{1,v}} & 0 \\ 0 & \alpha_2 L \end{bmatrix} \begin{bmatrix} \varepsilon_{1t}^2 \\ \varepsilon_{2t}^2 \end{bmatrix}, \tag{2}$$

where $\omega_i \in (0, \infty)$ for $i = 1, 2$, and $0 < d_{1,v} < 1$[18]. Although we consider CCC between volatility and volume, we reestimate the ARFI-FIGARCH model using dynamic conditional correlations (DCC). A comparison of the results (not reported) with those obtained when the ccc model is used reveals that the results are qualitatively similar. Furthermore, we check the robustness of our results, by estimating the bivariate unrestricted extended DCC (UEDCC) GARCH model of Conrad and Karanasos (2010), allowing for volatility spillovers. Overall, the results (not presented) are in broad agreement with those

[17] Contracts of three different durations, expiring in one, two and three months, respectively, are traded simultaneously. On each trading day, they are traded simultaneously with the underlying stocks, between 8.55 am and 3.30 pm. The closing price for a trading day is the weighted-average of prices during the last hour and a half of the day, and this price is the basis for the settlement of these contracts. The futures and options contracts on the indices as well as those on individual stocks expire on the last Thursday of every month, resulting in a quadruple witching hour.

[18] Brandt and Jones (2006) use the approximate result that if log returns are conditionally Gaussian with mean 0 and volatility h_t then the log range is a noisy linear proxy of log volatility. In this paper we model the GK volatility as an AR-FI-GARCH process.

presented below.

Note that the FIGARCH model is not covariance stationary. The question whether it is strictly stationary or not is still open at present (see Conrad and Haag, 2006). In the FIGARCH model, conditions on the parameters have to be imposed to ensure the non-negativity of the conditional variances (see: Conrad and Haag, 2006; Conrad, 2010)[19].

7 Empirical Results

7.1 Long-memory in volatility and volume

Empirical evidence supports the conjecture that daily volatility and trading volume are best described by mean-reverting long memory type processes (Bollerslev and Jubinski,1999; Lobato and Velasco, 2000; Chen et al., 2006; Chen and Daigler, 2008). These empirical findings are consistent with a modified version of the MDH, in which the dynamics of volatility and volume are determined by a latent informational arrival structure characterised by long range dependence (Andersen and Bollerslev, 1997).

Estimates of the fractional mean parameters are shown in table 1[20]. Several findings emerge from this table. Volatility and number of trades generated very similar long-memory parameters $d_{1,m}$: 0.43 and 0.47 respectively (see eq.'s 1 and 2 in model 2 in panel A). The estimated value of $d_{2,m}$, for value of shares traded, 0.60, is greater than the corresponding values for number of trades and volatility. In the mean equation for the volatility the long-memory coefficient $d_{1,m}$ is robust to the measures of volume used. In other words, the bivariate ARFI models 1 and 2 generated very similar $d_{1,m}$'s fractional parameters, 0.47 and 0.43 (see eq.'s 1 in panel A)[21].

Moreover, $d_{1,v}$'s govern the long-run dynamics of the conditional heteroscedasticity of volatility. The fractional parameter $d_{1,v}$ is robust to the measures of volume used. In other words, the two bivariate FIGARCH models generated very similar estimates of $d_{1,v}$: 0.57 and 0.58. All four mean long-memory

[19] Baillie and Morana (2009) introduce a new long-memory volatility process, denoted by Adaptive FIGARCH which is designed to account for both long-memory and structural change in the conditional variance process.

[20] Three tests aimed at distinguishing short and long-memory are implemented for the data. The statistical significance of the statistics (not reported) indicates that the data are consistent with the long-memory hypothesis. In addition, we test the hypothesis of long-memory following Robinson's (1995) semiparametric bivariate approach.

[21] It is worth mentioning that there is a possibility that, at least, part of the long-memory may be caused by the presence of neglected breaks in the series (see, for example, Granger and Hyung, 2004). Therefore, the fractional integration parameters are estimated taking into account the 'presence of breaks' by including the dummy variables for introduction of futures and option trading. Interestingly enough, the long-memory character of the series remain strongly evident.

coefficients are robust to the presence of outliers in volatility. When we take into account these outliers the estimated value of $d_{1,v}$ falls from 0.57 to 0.44 but remains highly significant.

Table 1. Long memory in volatility and levels

Panel A. Garman-Klass volatility			
Long memory & CCC	$d_{i,m}$	$d_{1,v}$	ρ
Model 1 (Value of shares traded)			
Eq. 1 Volatility y_{1t}	0.47 (0.10)***	0.57 (0.08)***	-
Eq. 2 Volume y_{2t}	0.60 (0.04)***	-	0.28 (0.03)***
Model 2 (Number of trades)			
Eq. 1 Volatility y_{1t}	0.43 (0.09)***	0.58 (0.09)***	-
Eq. 2 Volume y_{2t}	0.47 (0.03)***	-	0.30 (0.03)***
Panel B. Outlier reduced Garman-Klass volatility			
Model 1 (Value of shares traded)			
Long memory & CCC	$d_{i,m}$	$d_{1,v}$	ρ
Eq. 1 Volatility y_{1t}	0.42 (0.04)***	0.44 (0.08)***	-
Eq. 2 Volume y_{2t}	0.60 (0.04)***	-	0.30 (0.03)***
Model 2 (Number of trades)			
Eq. 1 Volatility y_{1t}	0.39 (0.04)***	0.44 (0.08)***	-
Eq. 2 Volume y_{2t}	0.48 (0.03)***	-	0.31 (0.03)***

Notes: The table reports parameter estimates of the long-memory and the ccc coefficients. $d_{i,m}$, $d_{1,v}$, $i = 1, 2$, and ρ are defined in equations (1) and (2) respectively.

*** denote significance at the 0.05 level respectively.

The numbers in parentheses are standard errors.

The variances of the two measures of volume generated very similar conditional correlations with the variance of volatility: 0.28, 0.30. Finally, the estimated values of the ARCH coefficients in the conditional variances of the value of shares and number of trades are 0.12 and 0.13 respectively. Note that in all cases the necessary and sufficient conditions for the non-negativitiy of the conditional variances are satisfied (see Conrad and Haag, 2006).

7.2 The relationship between volatility and volume

To recapitulate, we employ the bivariate ccc ARFI-FIGARCH model with lagged values of volume or volatility included in the mean equation of the other variable to test for bidirectional causality. The estimated coefficients $\varphi_{ij}^{(s)}$, $(\varphi_{12}^{(3)}, \varphi_{21}^{(1)})$ that are defined in equation (1), which capture the possible feedback between the two variables, are reported in the first column of table 2. All four $\varphi_{12}^{(3)}$ estimates are significant and negative (see eq.'s 1 in panels A and B). Note that both measures of volume have a similar impact on GK volatility (-0.013, -0.014). On the other hand, in all cases the $\varphi_{21}^{(1)}$ coefficients are insignificant, indicating that lagged volatility does not have an impact on current volume (see eq.'s 2 in panels A and B). In other words, in the period before the introduction of futures trading volume affects volatility negatively whereas there is no effect in the opposite direction.

This negative volume-volatility link is in line with theoretical models which associate price movements to an increasing number of active traders and consensus among investors when new information arrives in the markets (Tauchen and Pitts, 1983; Holthausen and Verrecchia, 1990). It is also consistent with the empirical evidence of Daigler and Wiley (1999) and Avramov et al. (2006) which associate informed trading with a reduction in volatility.

We cannot argue with certainty that liquidity is a contributing factor to the above negative relation because we use the detrended volume which is often related to informed trading. Though, liquidity trading absorbs the price impact of information-based trading and in this way higher intensity of liquidity trading helps lower volatility. By 1996-97, i.e., within two years of initiation of trading at the NSE, more than 100,000 trades were being executed per day, leading to an exchange of more than 13 billion shares over the course of the year. The corresponding figures at the turn of the century, in 1999-2000, were about 400,000 - a four-fold increase - and 24 billion. These are fairly large numbers given that fewer than 1000 companies were listed at the exchange during this period. Therefore, a market with an increasing number of active traders and liquidity is more able to absorb the price impact of information-based trading especially when combined with increased consensus among investors when new information is released.

Table 2. Mean Equation: Cross effects

Panel A. Garman-Klass volatility	(1)	(2)	(3)
Cross Effects	$\varphi_{ij}^{(s)}$	$\varphi_{ij,f}^{(s)}$	$\varphi_{ij,o}^{(s)}$
Model 1 (Value of shares traded,)			
Eq. 1 Volatility $y_{1t}(i=1,\, j=2,\, s=3)$	-0.013 (0.006)***	0.003 (0.008)	0.009 (0.006)*
Eq. 2 Volume $y_{2t}(i=2,\, j=1,\, s=1)$	-0.110 (0.259)	-0.161 (0.507)	0.117 (0.461)
Model 2 (Number of Trades,)			
Eq. 1 Volatility y_{1t} $(i=1,\, j=2,\, s=3)$	-0.014 (0.008)***	0.006 (0.010)	0.008 (0.007)
Eq. 2 Volume y_{2t} $(i=2,\, j=1,\, s=1)$	0.120 (0.177)	-0.006 (0.330)	-0.255 (0.317)
Panel B. Outlier reduced Garman-Klass volatility			
Cross Effects	$\varphi_{ij}^{(s)}$	$\varphi_{ij,f}^{(s)}$	$\varphi_{ij,o}^{(s)}$
Model 1 (Value of shares traded)			
Eq. 1 Volatility y_{1t}	-0.008 (0.004)**	-0.001 (0.006)	0.009 (0.005)**
Eq. 2 Volume y_{2t}	-0.065 (0.302)	-0.340 (0.586)	-0.558 (0.694)
Model 2 (Number of Trades)			
Eq. 1 Volatility y_{1t}	-0.009 (0.005)**	0.001 (0.008)	0.008 (0.007)
Eq. 2 Volume y_{2t}	0.195 (0.201)	-0.031 (0.365)	-1.006 (0.523)***

Notes: The table reports parameter estimates of the cross effects. $\varphi_{ij}^{(s)}$, $\varphi_{ij,f}^{(s)}$, and $\varphi_{ij,o}^{(s)}$, $ij = 12, 21$, defined in equation (1). s is the order of the lag. *,**,*** denote significance at the 0.15, 0.10, and 0.05 level respectively. The numbers in parentheses are standard errors.

We now turn to the impact of the introduction of derivatives trading on the volume-volatility link. Estimated values of the dummy coefficients for the cross-effects are presented in the last two columns of table 2. Recall that the relation between the two variables in the second period is captured by the sum of the coefficients in the first two columns, $(\varphi_{ij}^{(s)} + \varphi_{ij,f}^{(s)})$, while the sum of the coefficients in all three columns, $(\varphi_{ij}^{(s)} + \varphi_{ij,f}^{(s)} + \varphi_{ij,o}^{(s)})$, captures the link commencing with the introduction of options contracts. All $\varphi^{(s)}_{ij,f}$ ($\varphi^{(3)}_{12,f}$, $\varphi^{(1)}_{21,f}$) estimates are insignificant (see the second column in table 2). Thus, it appears that the introduction of futures trading does not influence the volume-volatility link. As far as the introduction of options contracts is concerned, there seems to be a change in the influence of the value of shares traded on volatility. In particular, when we have the value of shares traded, the estimated $\varphi^{(3)}_{12,o}$ coefficient is positive and significant (0.009). However, it is less than the estimate of $|\varphi^{(3)}_{12}|$: (0.013). Thus in the period which starts with the introduction of options trading the impact of the value of shares traded on volatility is still negative but much smaller in size $\varphi^{(3)}_{12} + \varphi^{(3)}_{12,o} = -0.004$. As can be seen from Panels A and B of table 2 the volume-volatility link is, in general, robust to the presence of outliers in volatility.

Our empirical results indicate that the introduction of the futures trading does not induce a significant migration of informed trading, but the introduction of the option trading does. This weakening of the volume-volatility link after the introduction of options contracts is consistent with the possibility that options trading may have weakened the impact volume has on volatility through the information route. The argument is as follows: In the Indian context, in keeping with the arguments of Kumar, et al. (1995), the introduction of derivatives trading may have led to a migration of informed or sophisticated traders from the cash to the derivatives markets. It has been argued that badla trades pooled together characteristics of cash and futures trading[22]. However, while badla traders had to pay interest to the financiers who provided the mezzanine finance to facilitate this roll over, there was no daily mark to market and margin call, unlike in a futures market. Hence, it can also be argued that badla trading worked quite similarly to options markets, with the interest paid to the financiers acting as the price for the implicit call option on the underlying shares. In other words, in the aftermath of introduction of futures trading, badla traders, who were generally more sophisticated and informed than smaller/retail investors, were likely to have migrated from the cash to the derivatives market[23]. There is some evidence

[22]Recall that in the pre-derivatives era, week-long trading cycles co-existed with badla trading whereby take a position on a stock, not take delivery at the end of the trading cycle, and roll it over to the following trading cycle.

[23]Indeed, there is evidence to suggest that after the introduction of derivatives trading, price discovery was more likely to take place in the futures market than in the cash market (Raju and Karande, 2003). There is also evidence to suggest that in the post-derivatives era a large proportion of traders in the cash market were unsophisticated. The Economic Survey for 2005-06, published by the Government of India, as of 2005, states that the number of accounts held by retail investors at the two depositories in the country, NSDL and CSDL, stood at 8.5 million, confirming that a large proportion of cash market traders were unsophisticated. Support for the preponderance of retail investors in the cash market in the post-derivatives regime can also be found by way of a comparison between the percentage changes in the number of trades and those in the number of shares traded in the cash market since 2001-02. The number of trades kept increasing at a rapid pace, but since

to suggest that much of this migration may have been to the options market[24]. It is also worth mentioning here that badla trades were banned when index and individual options (as well as rolling settlement) were introduced and this may have partly caused this migration of informed investors to the options market. Additionally, options contracts are more leveraged than futures contracts and share similar characteristics with badla trades. The issue of migration is also supported by the significantly lower value of shares traded and number of trades in the cash market after the introduction of options (see results in Table 4).

In the event of such a migration, private information of the sophisticated traders in the options markets may not have reached the relatively less sophisticated traders in the cash market, given the informational inefficiency in the Indian stock market (Sarkar and Mukhopadhyay, 2005). In any event, the retail investors, who are presumably counterparties to a very significant proportion of the trades, are possibly not sophisticated enough to interpret information signals given out by trades involving options contracts. Table 3 below gives an overview of the volume-volatility link over the three different periods considered.

Table 3. The Volume-Volatility link

Period:	Period 1	Period 2	Period 3
Panel A. The effect of Volume on Volatility			
Value of shares traded	negative	negative	negative (smaller)
Number of trades	negative	negative	negative
Panel B. The impact of Volatility on Volume			
Value of shares traded	insignificant	insignificant	insignificant
Number of trades	insignificant	insignificant	insignificant

Overall, in all cases volume is not affected from changes in volatility. Causality runs only from volume- whether value of shares traded or number of trades- to volatility (see also eq.'s 2 in table 2). In particular, in all three periods the number of trades affects volatility negatively with the introduction of derivatives

2004-05 the number of stocks changing hands has increased at a much slower rate. In other words, since the introduction of derivatives trading in general, and options trading in particular, an increasing proportion of the trades in the cash market possibly involved retail investors.

[24] Between 2004-05 and 2006-07, the number of options contracts traded at the NSE quadrupled from 12.94 million to 50.49 million.

trading leaving the sign and the magnitude of this relationship unaltered (see also eq.1 in model 2 in table 2). In other words, the introduction of the two financial instruments is not affecting the information role of the number of trades in terms of predicting future volatility. One possible explanation is that the use of number of trades as a proxy for volume does not reflect the fact that traders might take larger spot positions after the introduction of derivatives trading due to increased risk sharing opportunities. Similarly, in all three periods the value of shares traded has a negative effect on volatility (see also eq.1 in model 1 in table 2). This result is consistent with the views that the activity of informed traders is inversely related to volatility when the marketplace: has increased liquidity, an increasing number of active investors, and high consensus among investors when new information is released. It is noteworthy that in the period from the opening of the options market until the end of the sample the impact of volume on volatility, although still significantly negative, is much smaller in size. Hence, introduction of options trading may have weakened this impact through the information route.

7.3 Expiration and other effects of derivatives trading

In this Section we investigate whether the opening of the futures and options markets affects spot price volatility and trading volume. Recall that the coefficients $\mu_{i,f}$, $\mu_{i,o}$, $i = 1, 2$, capture the effects of derivatives trading on spot volatility and volume. The estimate $\mu_{1,f}$ is negative and significant, indicating that the introduction of futures trading leads to a decrease in spot volatility (see eq.'s 1 in the second column of table 4). Our result is in line with the empirical findings of Bessembinder and Seguin, 1992. One possible explanation is provided by Stein (1987). Once futures are introduced increases in the number of uniformed traders are beneficial even though such increases lower the average informedness of market participants. The latter is mitigated by the increase in risk sharing and the fact that spot traders tend to offset any mistakes the secondary traders make[25].

On the other hand, options trading has no significant impact on spot volatility since the coefficient $\mu_{1,o}$ is insignificant in all cases (see eq.'s 1 in the third column of table 4). This result is consistent with that of Bollen (1998), who did not find any impact of options trading on the volatility of the underlying

[25] Subrahmanyam (1991) and Hong (2000) also argue in favor of introducing a futures market in terms of reducing or stabilising spot price volatility.

stock. But it is at odds with Kumar et al. (1995, 1998) among others[26], who point out that options reduce the volatility of the underlying stock because (i) they improve the efficiency of incomplete asset markets by expanding the opportunity set facing investors, (ii) speculative traders migrate from the underlying market to the options market since they view options as superior speculative vehicles. As a result the amount of noise trading in the spot market is reduced. They also argue that liquidity in the underlying market improves because informed traders, since they view options as superior investment vehicles, shift to the options market. Finally, they argue that options may improve the efficiency of the underlying market by increasing the level of public information in the market. We have already noted the inefficiency in the Indian market. Further, with speculators with superior information migrating to the options (and generally speaking derivatives) market, and with the consequent preponderance of retail investors in the cash market, noise trading in the latter market may have actually increased. Hence, many of the possible ways in which the introduction of options contracts might have increased the quality of the underlying cash markets were unlikely to have worked out in the Indian context.

[26] See Skinner (1989) and Detemple and Jorion (1990), for example.

Table 4. Mean Equation: Dummy effects for constants

Panel A. Garman-Klass volatility	(1)	(2)	(3)
Constant Effects	$\mu_{i,e}$	$\mu_{i,f}$	$\mu_{i,o}$
Model 1 (Value of shares traded,)			
Eq. 1 Volatility y_{1t}, $i = 1$	-0.003 (0.002)**	-0.12 (0.009)*	-0.003 (0.005)
Eq. 2 Volume y_{2t}, $i = 2$	0.108 (0.022)***	-0.030 (0.154)	-0.746 (0.344)***
Model 2 (Number of trades)			
Eq. 1 Volatility y_{1t}, $i = 1$	-0.003 (0.002)**	-0.014 (0.009)*	-0.003 (0.002)
Eq. 2 Volume y_{2t}, $i = 2$	0.004 (0.015)	-0.073 (0.106)	-0.503 (0.295)**
Panel B. Outlier reduced Garman-Klass volatility			
Model 1 (Values of shares traded)			
Constant Effects	$\mu_{i,e}$	$\mu_{i,f}$	$\mu_{i,o}$
Eq. 1 Volatility y_{1t}	-0.003 (0.002)**	-0.013 (0.007)***	-0.004 (0.005)
Eq. 2 Volume y_{2t}	0.105 (0.022)***	-0.033 (0.154)	-0.743 (0.342)***
Model 2 (Number of trades)			
Eq. 1 Volatility y_{1t}	-0.003 (0.002)**	-0.014 (0.006)***	-0.004 (0.005)
Eq. 2 Volume y_{2t}	0.001 (0.016)	0.065 (0.105)	-0.505 (0.299)**

Notes: The table reports parameter estimates of the constant dummy effects.

$\mu_{i,e}$, $\mu_{i,f}$ and $\mu_{i,o}$, $i = 1, 2$, are defined in equation (1).

The numbers in parentheses are standard errors.

By contrast, since the estimates $\mu_{2,f}$ are insignificant, it appears that the average levels of value of shares traded and of number of trades remain the same before and after the introduction of futures trading (see eq.'s 2 in the second column of table 4). However, the negative and significant estimated values of $\mu_{2,o}$ indicate that on average the value of shares traded and the number of trades decrease after the introduction of option contracts. This result is in line with the theoretical argument in Kumar et al. (1995). They argue that the migration of some speculators to options markets on the listing of options is accompanied by a decrease in trading volume in the underlying security. We have already noted above that there is evidence to suggest that this may have happened in the Indian market.

Finally, we examine the impact of derivatives contracts expiration on trading volume and range-based volatility[27]. When the value of shares traded is used as a measure of volume the model indicates that there is a significant expiration day effect. In both equations of model 1 the estimates of $\mu_{i,e}$, $i = 1, 2$, are statistically significant (when we use the value of shares traded), albeit with opposite signs (see the first column of model 1 in table 4). The value of shares traded on expiration days is higher, on average, than their value on non-expiration days, while volatility is lower on expiration days than on other days. By contrast there is no evidence that the expiration of derivatives contract affects the number of trades; the estimated value of $\mu_{2,e}$ is insignificant when we use the number of trades (see the last figures in the first column of panels A and B in table 4). Our estimates from the bivariate dual long-memory model also suggest that the impact of derivatives expiration on volatility is negative. This, is consistent with the results in Bhaumik and Bose (2009), who found that derivatives contract expiration affects GARCH volatility negatively. These results are quite robust across models 1 and 2 and across panels A and B. In other words, in all cases the results are not qualitatively altered by changes in the measures of volume and they are not sensitive to the presence of outliers in volatility. Table 5 below gives an overview of the expiration and other effects of derivatives trading.

Table 5. Effects of derivatives trading

	Futures Trading	Option Trading	Expiration of Derivatives contracts
Volatility	Decreases	Unchanged	Decreases
Value of shares traded	Unchanged	Decreases	Increases
Number of trades	Unchanged	Decreases	Unchanged

[27] We have also explored the effect of the expiration of derivatives contracts on some aspects of the underlying cash market using simple parametric and non-parametric tests (results are not reported).

8 Conclusions

This paper has investigated the issue of temporal ordering of the range-based volatility and trading volume in the NSE, the largest cash and derivatives exchange in India, for the 1995-2007 period. We examined the nature of the volume-volatility link and the impact of derivatives trading on this link, as well as on volume and volatility on their own. Our results suggest the following:

First, in all three periods the impact of number of trades, one of the measures of volume, on volatility is negative. Similarly the value of shares traded, the other measure of volume, has a negative effect on volatility as well. This result is consistent with the views that the activity of informed traders is inversely related to volatility when the marketplace has increased liquidity, an increasing number of active investors and high consensus among investors when new information is released. However, the magnitude of this negative impact of volume on volatility was much reduced after the introduction of options trading. Introduction of options trading may have weakened the impact volume has on volatility through the information route. In sharp contrast, volume is independent of changes in lagged volatility.

Second, the introduction of futures trading leads to a decrease in spot volatility. This finding offers support to the theoretical arguments of Stein (1987) and Hong (2000). However, option listings have a (negative but) insignificant effect on spot volatility. It is therefore evident that the possible ways in which the introduction of options might have increased the quality of the underlying cash markets were unlikely to have worked out in the Indian context.

Thirdly, volume decrease after the introduction of option contracts, offering support to the view that the migration of some speculators to options markets on the listing of options, is accompanied by a decrease in trading volume in the underlying security. Volume, however, is unaffected by the introduction of futures trading.

Finally, expirations of equity based derivatives have significant impact on the value of shares traded on expiration days and on the range-based volatility. Our results reinforce the conclusions of Bhaumik and Bose (2009).

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