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1 Introduction

The rapid growth in the market for financial derivatives, and the presumption that they are responsible for more volatile financial markets, perhaps even responsible for the financial crash of 1987, have resulted in continual exploration of the impact of these financial instruments on volatility in the spot equity (or cash) market. The effect of derivatives trading on cash market volatility is theoretically ambiguous and depends on the specific assumptions of the model (see Mayhew 2000). In keeping with this, 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).

Even as the sophistication of financial markets improve around the world, and trading in financial derivatives spreads across emerging markets, the aforementioned literature is almost entirely restricted to developed country contexts. 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). However, the volume-volatility relationship and how has this changed after the introduction of derivatives market remains an open empirical question in the emerging market context.[1]

This study complements the literature about the impact of derivatives trading on the volatility of cash markets in emerging market economies. Specifically we examine how the introduction of futures and options affects the volume-volatility link at the National Stock Exchange (NSE), the largest stock exchange in India. We estimate the two main parameters driving the degree of persistence in the two

[1] Tauchen and Pitts (1983) paper was the first to speak about an inverse volatility-volume relationship. As pointed out by Kawaller et al. (2001), empirical evidence of an inverse relation between the two variables is rare in the literature, and the widely held perception is that the two are positively related. However, evidence about a negative relationship between volume and volatility is not absent altogether. Daigler and Wiley (1999) find that the activity of informed traders is often inversely related to volatility. Wang (2007) argues that foreign purchases tend to lower volatility, especially in the first few years after market liberalization when foreigners are buying into local markets. Karanasos and Kartsaklas (2009) show that, in Korea, the causal negative impact from total volume to volatility reflects the causal relation between foreign volume and volatility. Therefore, we investigate the significance and the sign of the causal effect as well.

variables and their respective uncertainties using a bivariate constant conditional correlation (ccc) Generalized ARCH (GARCH) model that is Fractionally Integrated (FI) in both the Autoregressive (AR) and variance specifications. We refer to this model as the AR-FI-GARCH. It provides a general and flexible framework with which to study complicated processes like volume and volatility. In order to be able to examine the volume-volatility relationship, we estimate the bivariate ccc AR-FI-GARCH model with lagged values of one variable included in the mean equation of the other variable.

Aside from using the AR-FI-GARCH framework that allows us to capture the long memory aspect of 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

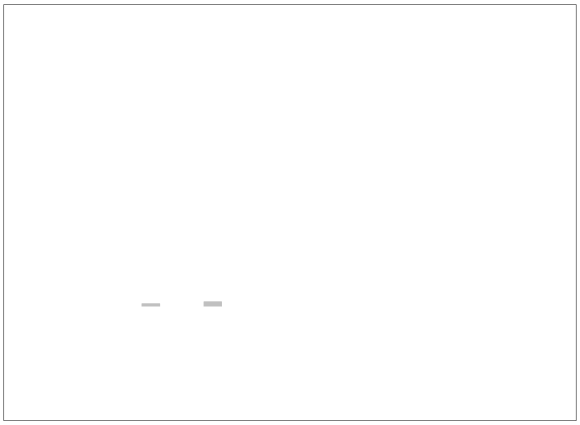

Figure 2

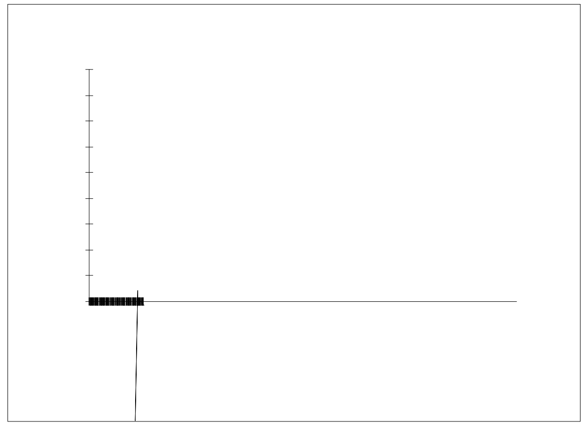

Figure 3

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 signi…cant structural changes in the Indian equity market by the turn of the century.[2] 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.[3] 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.

[2] 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 …nanciers 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.

[3] On January 10, 2000, rolling settlement was introduced for the …rst 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.

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 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.[4]

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

[4] 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.

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 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 in which 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.[5]

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 basket has no effect on the variance of price changes in component securities.[6]

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.[7] 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, 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

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

$$y_t^{(g)} = \frac{1}{2}u_t$$

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.[10] Figure 4A plots the Garman-Klass volatility from 1995 to 2007.

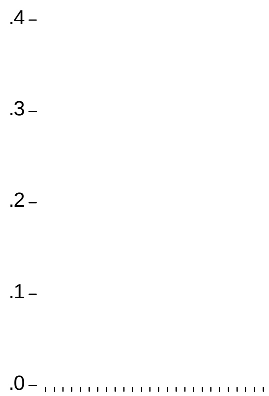

Figure 4A (Garman-Klass Volatility)

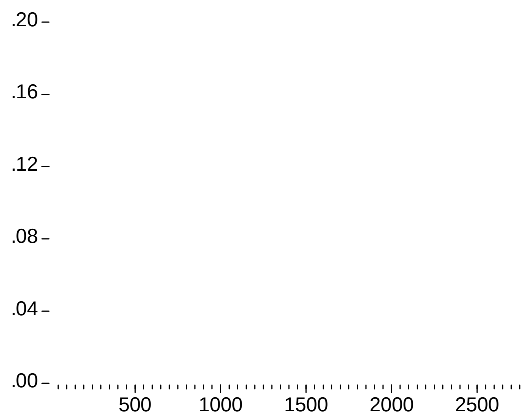

Figure 4B (Outlier reduced GK volatility)

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

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.

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

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 ($\tilde{y}_t^{(v)}$) as follows

$$y_t^{(v)} = \tilde{y}_t^{(v)} \quad (\hat{a} \quad \hat{b}t);$$

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 baddla 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. [11] 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.

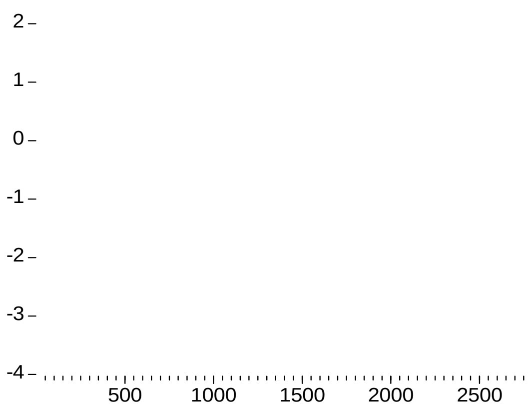

Figure 5A (Value of shares traded)

Figure 5B (Number of trades)

[11] 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).

5.3 Structural breaks in volatility and volume

their effect on the volatility-volume relationship. Accordingly, we break our entire sample into three sub-periods. 1st period (the period up to the introduction of futures trading): 3rd November 1995 –12th June 2000; 2nd: 13th June 2000 - 2nd July 2001 that is, the period from the introduction of futures contracts until the introduction of options trading; the 3rd period is the one which starts with the introduction of option contracts: 3rd July 2001 - 25th January 2007.[13]

6 Econometric Model

6.1 Bivariate long-memory process

The Mixture of Distributions Hypothesis 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, Laurent and Rombouts, 2004, 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, Bollerslev and Mikkelsen, 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.[14]

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 AR-FI-GARCH model to test

[13] Lavielle and Moulines (2000) extended the results of Bai and Perron (1998). Their results 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 strongly dependent process or long memory.

[14] 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.

for causality between volume and volatility.[15]

The chosen estimated bivariate ARFI model is given by

$$(1 \quad L)^{d_m^{(g)}} \left[y_t^{(g)} \quad (\;\; ^{(} \right.$$

where $\omega^{(i)} \in (0; \infty)$ for $i = g; v$, and $0 < d_v^{(g)} < 1$.[17] Although we consider the correlation between volatility and volume, our specification excludes the causal interaction of the ARCH effects of volatility and volume. We use the diagonal representation where variances depend solely on past own squared residuals, and covariances depend solely on past own cross-products of residuals. Chen and Daigler (2008) take a constant correlation coefficient (ccc) GARCH, in which the ARCH terms of the volume and volatility have potential effects on each other. 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).[18]

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, Daigler and Parhizgari, 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.[19] Several findings emergTf15.0ts7s s7-3.6i3(Se)-1(v the long-memory coefficient $d_m^{(g)}$ is robust to the measures of volume used. In other words, the bivariate ARFI models 1 and 2 generated very similar $d_m^{(g)}$'s fractional parameters, 0.47 and 0.43 (see eq.'s 1 in panel A).[20]

Moreover, $d_v^{(g)}$'s govern the long-run dynamics of the conditional heteroscedasticity of volatility. The fractional parameter $d_v^{(g)}$ is robust to the measures of volume used. In other words, the two bivariate FIGARCH models generated very similar estimates of $d_v^{(g)}$: 0.57 and 0.58. All four mean long-memory coefficients are robust to the presence of outliers in volatility. When we take into account these outliers the estimated value of $d_v^{(g)}$ falls from 0.57 to 0.44 but remains highly significant.

[20] 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.

Table 1. Long memory in volatility and levels

Panel A. Garman-Klass volatility

Long memory & ccc	$d_m^{(i)}$	$d_v^{(i)}$

7.2 The relationship between volatility and volume

To recapitulate, we employ the bivariate ccc AR-FI-GARCH 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 $_{s}^{(ij)}$, ($_{3}^{(gv)}$; $_{1}^{(vg)}$) 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 $_{3}^{(gv)}$ 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 $_{1}^{(vg)}$ 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 the theoretical results which associate trading with consensus between investors when new information arrives in the markets and an increasing number of active traders (Tauchen and Pitts, 1983, Holthausen and Verrecchia, 1990). It is also consistent with the empirical evidence of Daigler and Wiley (1999) and Avramov, Chordia and Goyal (2006) which associate informed trading with a reduction in volatility.

We cannot argue with certainty that liquidity is a contributing factor to the above relationship 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	$_s^{(ij)}$	$_s^{(ij;f)}$	$_s^{(ij;o)}$
Model 1 (Value of shares traded, vs)			
Eq. 1 Volatility $y_t^{(g)}(i = g; j = vs; s = 3)$	-0.013 (0.006)***	0.003 (0.008)	0.009 (0.006)*
Eq. 2 Volume $y_t^{(vs)}(i = vs; j = g; s = 1)$	-0.110 (0.259)	-0.161 (0.507)	0.117 (0.461)
Model 2 (Number of Trades, n)			
Eq. 1 Volatility $y_t^{(g)}$ $(i = g; j = n; s = 3)$	-0.014 (0.008)***	0.006 (0.010)	0.008 (0.007)
Eq. 2 Volume $y_t^{(n)}$ $(i = n; j = g; s = 1)$	0.120 (0.177)	-0.006 (0.330)	-0.255 (0.317)
Panel B. Outlier reduced Garman-Klass volatility			
Cross Effects	$_s^{(ij)}$	$_s^{(ij;f)}$	$_s^{(ij;o)}$
Model 1 (Value of shares traded)			
Eq. 1 Volatility $y_t^{(g)}$	-0.008 (0.004)**	-0.001 (0.006)	0.009 (0.005)**
Eq. 2 Volume $y_t^{(vs)}$	-0.065 (0.302)	-0.340 (0.586)	-0.558 (0.694)
Model 2 (Number of Trades)			
Eq. 1 Volatility $y_t^{(g)}$	-0.009 (0.005)**	0.001 (0.008)	0.008 (0.007)
Eq. 2 Volume $y_t^{(n)}$	0.195 (0.201)	-0.031 (0.365)	-1.006 (0.523)***

Notes: The table reports parameter estimates of the cross effects. $_s^{(ij)}$, $_s^{(ij;f)}$, and $_s^{(ij;o)}$, $ij = vg; gv$, 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 relationship. Estimated values of the dummy coefficients for the cross-effects are presented in the last two

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 $v = vs$, the estimated ${}_{3}^{(gv;o)}$ coefficient is positive and significant (0:009). However, it is less than the estimate of $j\,{}_{3}^{(gv)}j$ (0:013). Thus in the period which starts with the introduction of options trading the impact of the value of shares traded on

trading leaving the sign and the magnitude of this relationship unaltered (see also eq.1 in model 2 in stock. But it is at odds with Kumar et al. (1995, 1998) among others,[25] 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.

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

Table 4. Mean Equation: Dummy e¤ects for constants

Panel A. Garman-Klass volatility	(1)	(2)	(3)
Constant E¤ects	$^{(i;e)}$	$^{(i;f)}$	$^{(i;o)}$
Model 1 (Value of shares traded, vs)			
Eq. 1 Volatility $y_t^{(g)}$, $i = g$	-0.003 (0.002)**	-0.12 (0.009)*	-0.003 (0.005)
Eq. 2 Volume $y_t^{(vs)}$, $i = vs$	0.108 (0.022)***	-0.030 (0.154)	-0.746 (0.344)***
Model 2 (Number of trades, n)			
Eq. 1 Volatility $y_t^{(g)}$, $i = g$	-0.003 (0.002)**	-0.014 (0.009)*	-0.003 (0.002)
Eq. 2 Volume $y_t^{(n)}$, $i = n$	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 E¤ects	$^{(i;e)}$	$^{(i;f)}$	$^{(i;o)}$
Eq. 1 Volatility $y_t^{(g)}$	-0.003 (0.002)**	-0.013 (0.007)***	-0.004 (0.005)
Eq. 2 Volume $y_t^{(vs)}$	0.105 (0.022)***	-0.033 (0.154)	-0.743 (0.342)***
Model 2 (Number of trades)			
Eq. 1 Volatility $y_t^{(g)}$	-0.003 (0.002)**	-0.014 (0.006)***	-0.004 (0.005)
Eq. 2 Volume $y_t^{(n)}$	0.001 (0.016)	0.065 (0.105)	-0.505 (0.299)**

Notes: The table reports parameter estimates of the constant dummy e¤ects.

$^{(i;e)}$, $^{(i;f)}$ and $^{(i;o)}$; $i = v; g$, are de…ned in equation (1):

The numbers in parentheses are standardt84-23.914(.)-7(0)-14d[()]ts already noted above that there is evidence to suggest that this may have happened in the Indian market.

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

References

[1] Alizadeh, S., Brandt, M., and Diebold, F. X., 2002. Range-based estimation of stochastic volatility models, Journal of Finance, 57, 1042-1092.

[2] Alkeback, P., and Hagelin, N., 2004. Expiration day e¤ects of index futures and options: evidence from a market with a long settlement period. Applied Financial Economics, 14, 6, 385-396.

[3] Andersen, T., 1996. Return volatility and trading volume: an information ‡ow interpretation of stochastic volatility. Journal of Finance, 1, 169-204.

[4] Andersen, T., and Bollerslev, T., (1996). Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long-Run in High Frequency Returns. Journal of Finance, 52, 975-1005.

[5] Andersen, T., and Bollerslev, T., (1998). Answering the Skeptics: Yes, Standard Volatility Models

[12] Baillie, T. R, and Morana, C., 2009. Modelling long memory and structural breaks in conditional variances: An adaptive FIGARCH approach. Journal of Economic Dynamics and Control, 33, 1577-1592.

[13] Bandivadekar, S., and Ghosh, S., 2003. Derivatives and volatility in the Indian stock markets. Reserve Bank of India Occasional Papers, 24(3), 187-201.

[14] Bauwens, L., Laurent, S., and Rombouts, J., 2006. Multivariate GARCH models: a survey. Journal of Applied Econometrics, 21, 79-109.

[15] Bessembinder H., and Seguin, P., 1992. Futures-trading activity and stock price volatility. Journal of Finance, 47, 2015-2034.

[16] Bhaumik, S. K., and Bose, S., 2009. Impact of derivatives trading on emerging stock markets: Some evidence from India. Comparative Economic Studies, 51, 118-137.

[17] Black, F., 1975. Fact and fantasy in the use of options, Financial Analysts Journal 31, 36-72.

[18] Black, F., 1986. Noise. Journal of Finance, Vol. 41, 529-543.

[19] Blume, D., Easley, L., and O'Hara, M., 1994. Market Statistics and Technical Analysis: The Role of Volume. Journal of Finance, 49. 153-181.

[20] Board, J., Sandmann, G., and Sutcli¤e, C., 2001. The e¤ect of futures market volume on spot market volatility. Journal of Business, Finance and Accounting, 28, 799-819.

[21] Bollen, N. P. B., 1998. A note on the impact of options on stock volatility. Journal of Banking and Finance, 22, 1181-1191.

[22] Bollen, N.P.B., and Whaley, R.E., 1999. Do expirations of Hang Seng index derivatives a¤ect stock market volatility? Paci…c Basin Finance Journal, 7, 453-470.

[23] Bollerslev, T., and Jubinski, D., 1999. Equity trading volume and volatility: latent information arrivals and common long-run dependencies. Journal of Business & Economic Statistics, 1, 9-21.

[24] Brandt, M. W., and Jones, C. S., 2006. Volatility forecasting with range-based EGARCH models. Journal of Business & Economic Statistics, 24, 470-486.

[25] Brown-Hruska, S., and Kuserk, G., 1995. Volatility, volume and the notion of balance in the S&P 500 cash and futures markets. Journal of Futures Markets, 15, 677-689.

[26] Carnero, M. A., Peña, D., and Ruiz, E., 2007. E¤ects of outliers on the identi…cation and estimation of GARCH models. Journal of Time Series Analysis, 28, 471-497.

[27] Chen, Z., and Daigler, R., 2008. An examination of the complemenary volume-volatility information theories. Journal of Futures Markets, 28, 963-992.

[28] Chen, Z., Daigler, R., and Parhizgari, A., 2006. Persistence of volatility in future markets. Journal of Futures Markets, 26, 571-594.

[29] Chow, Y. F., Yung. H. H. M., and Zhang, H., 2003. Expiration day e¤ects: The case of Hong Kong. Journal of Futures Markets, 1, 67-86.

[30] Chou, R. Y., 2005. Forecasting …nancial volatilities with extreme values: the conditional autoregressive range (CARR) model. Journal of Money, Credit, and Banking, 37, 561-582.

[31] Clark, P., (1973). A Subordinated Sttor0lZSTlagba95(au)-1(s:)-569(the)-396(.)-385(alue)-1

[37] Daigler, R., and Wiley, M., 1999. The impact of trader type on the futures volatility-volume relation. Journal of Finance, 6, 2297-2316.

[38] Damadoran, A., and Lim, J., 1991. The e¤ects of option listing on the underlying stocks' return processes, Journal of Banking and Finance 15, 647-664.

[39] Damodaran, A., Subrahmanayan, M., 1992. The e¤ects of derivative securities on the markets for the underlying assets in the United States: a survey. Financial Markets, Institutions and Instruments, 2, 1-21.

[40] Davidson, J., 2008. Time Series Modelling 4.27. http://www.timeseriesmodelling.com.

[41] Dellas, H. and Hess, M., 2005. Financial development and stock returns: A cross-country analysis. Journal of International money and Finance, 24, 891-912.

[42] DeLong, B., Shleifer, A., Summers, L., and Waldman, R., (1990a). Noise trader risk in …nancial markets. Journal of Political Economy, 98, 703-739.

[43] DeLong, B., Shleifer, A., Summers, L., and Waldman, R., (1990b). Positive feedback investment strategies and destabilizing rational speculation. Journal of Finance, 45, 379-395.

[44] Dennis, S. A., Sim, A. B., 1999. Share price volatility with the introduction of individual share futures on the Sydney Futures Exchange. International Review of Financial Analysis, 8, 153-163.

[45] Detemple, J., Jorion, P., 1990. Option listing and stock returns: An empirical analysis, Journal of Bunking and Finance 14(4), 781-802.

[46] Detemple, J., Selden, L., 1991. A general equilibrium analysis of option and stock market interactions, International Economic Review 32(2), 279-303.

[47] Easley, D., Hvidkjaer, S., and O'Hara, M., 2002. Is information risk a determinant of asset returns? Journal of Finance, 57, 2185-2221.

[48] Easley, D., Kiefer, N., O'Hara, M., and Paperman J., 1996. Liquidity, information, and infrequently traded stocks. Journal of Finance, 51, 1405-1436.

[49] Edwards, F. R., 1988. Does futures trading increase stock market volatility?. Financial Analysts Journal, Jan.-Feb. 63-69.

[50] Epps, T. and Epps, M. L., 1976. The stochastic dependence of security price changes and transaction volumes: implications for the mixture-of-distributions hypothesis. Econometrica, 44, 305-321.

[51] Gammill, J. F., Marsh, T., 1988. Trading activity and price behavior in the stock and stock index futures markets in October 1987. Journal of Economic Perspectives, 2, 25-44.

[52] Gammill, J. F., Perold, A. F., 1989. The changing character of stock market liquidity. Journal of Portfolio Management, Spring, 13-18.

[53] Garman, M., and Klass, M., 1980. On the estimation of security price volatilities from historical data. Journal of Business, 1, 67-78.

[54] Ghysels, E., Seon, J., 2005. The Asian …nancial crisis: the role of derivative securities trading and foreign investors in Korea. Journal of Intenational Money and Finance, 24, 607-630.

[55] Granger, C., and Hyung, N., 2004. Occasional structural breaks and long memory with an appli-

[61] Harris, L. 1989. S&P 500 Cash stock price volatilities, Journal of Finance 44, 1155-l175.

[62] Harris, M. and Raviv, A., 1993. Di¤erences of Opinion Make a Horse Race. Review of Financial Studies, Vol. 6, No. 3. (1993), pp. 473-506.

[63] Holthaussen, R. W., and Verrecchia, R., 1988. The E¤ect of Informedness and Consensus on Price and Volume Behavior. Accounting Review, 65, 191-208.

[64] Hong, H., 2000. A model of returns and trading in futures markets. Journal of Finance, 55, 959-988.

[65] He, H., and Wang, J., 1994. Di¤erential information and dynamic behavior of stock trading volume. Review of Financial Studies, 8, 919-972.

[66] Jones, C., Kaul, G., and Lipson, M., (1994a). information, trading and volatility. Journal of Financial Economics, 36,127-154.

[67] Karanasos, M., and Kartsaklas, A., 2009. Dual long-memory, structural breaks and the link between turnover and the range-based volatility. Journal of Empirical Finance, 16, 838-851.

[68] Karpo¤, J., 1987. The relation between price changes and volume: a survey. Journal of Financial and Quantitative Analysis, 22, 109-126.

[69] Kawaller, I., Koch, P., and Peterson, J., 2001. Volume and volatility surrounding quarterly redesignation of the lead S&P 500 futures contract. Journal of Future Markets, 12, 1119-1149.

[70] Kim, J., Kartsaklas, A., and Karanasos, M., 2005. The volume-volatility relationship and the

[73] Lavielle, M., and Moulines, E., 2000. Least-squares estimation of an unknown number of shifts in a time series. Journal of Time Series Analysis, 21, 33-59.

[74] Li, J., and Wu, C., 2006. Daily return volatility, bid-ask spreads, and information ‡ow: analyzing the information content of volume. Journal of Business, 79, 2697-2740.

[75] Lobato, I., and Velasco, C., 2000. Long memory in stock-market trading volume. Journal of Business & Economic Statistics, 18, 410-427.

[76] Mayhew, S., 2000. The impact of derivatives on cash market: What have we learnt? Mimeo. University of Georgia at Athens.

[77] Megginson, W. L., and Weiss, K. A., 1991. Venture capitalist certi…cation in initial public o¤erings. Journal of Finance, Papers and Proceedings, 3, 879-903.

[78] Pok, W.C., Poshakwale, S., 2004. The impact of the introduction of futures contracts on the spot market volatility: The case of Kuala Lumpur stock exchange, Applied Financial Economics 14, 143–154..

[79] Raju, M.T., and Karande, K., 2003. Price discovery and volatility on NSE futures market. Working paper series no. 7, Securities and Exchange Board of India.

[80] Robinson, P., 1995. Log-periodogram regression of time series with long-range dependence. Annals
and95.Inoni6(14,)]ge. Ap5(ce20.475-23.91Boar)mer293(an)-1(g91BoarM0.475-23er)1(s)-3(an)-1(34(eki1n)-1(gs,)-33T1(s
3(E)-1(xl)kl()-31.w9ae0(and95.)--283(NSE)ak ol2t,rand95.5nce.et,orr theorking

[85] Skinner, D., 1989. Options markets and stock return volatility, Journal of Financial Economics 23, 61-78.

[86] Smirlock, M., and Starks, T. L., 1988. An Empirical analysis of the stock price-volume relationship. Journal of Banking and Finance, 12, 31-41.

[87] Stein, J. C., 1987. Informational externalities and welfare-reducing speculation. Journal of Political Economy, 95, 1123-1145.

[88] Stephan, J., Whaley, R., 1990. Intraday price change and trading volume relations in the stock and stock option markets, Journal of Finance 45, 191-220.

[89] Stoll, H.R., and Whaley, R.E., 1997. Expiration day effects of the All Ordinaries Share Price index futures: Empirical evidence and alternative settlement procedures. Australian Journal of Management, 22, 139-174.

[90] Subrahmanyan, A., 1991. A theory of trading in stock index futures. The Review of Financial Studies, 4, 17-51.

[91] Tauchen, G. and Pitts, M., 1983. The Price Variability-Volume Relationship on Speculative Markets. Econometrica, 51, 485-505.

[92] Trennepohl, G., Dukes, W., 1979. CBOE options and stock volatility, Review of Business and Economic Research 14, 49-60.

[93] Tsay, W., and Chung, C., 2000. The spurious regression of fractionally integrated processes. Journal of Econometrics, 96, 155-182.

[94] Vilasuso, J., 2001. Causality tests and conditional heteroscedasticity: Monte Carlo evidence. Journal of Econometrics, 1, 25-35.

[95] Vipul, 2005. Futures and options expiration-day effects: The Indian evidence. The Journal of Futures Markets, 11, 1045-1065.

[96] Vipul, 2006. Impact of the introduction of derivatives on underlying volatility: Evidence from India. Applied Financial Economics, 16(9), 687-697.

[97] Wang, C., 2002. The effect of net positions by type of trader on volatility in foreign currency futures markets. Journal of Future Markets, 5, 427-450.

[98] Wang, J., 2007. Foreign equity trading and emerging market volatility: evidence from Indonesia and Thailand. Journal of Development Economics, 84, 798-811.

[99] Christensen, K., and Podolskij, M., 2007, Realized range based estimation of integrated variance. Journal of Econometrics, 141, 323-349.

[100] Giraitis, L., Kokoszka, P., and Leipus, R., 2000, Stationary ARCH models, model dependence structure and central limit theorem. Econometric Theory, 16, 3-22.

[101] Lobato, I., 1997, Consistency of the average cross-periodogram in long memory time series. Journal of time series analyisis, 18, 137-155.

[102] Lu, Y., and Perron, P., 2010, Modelling and forecasting stock return volatility using a random level shift model. Journal of Empirical Finance, 17, 138-156.

[103] Martens, M., and van Dijk, D., 2007, Measuring volatility with the realized range. Journal of Econometrics, 138, 181-207

[104] Mikosch, T., and Starica, C., 2000, Is it really long memory we see in financial returns? Extremes and Integrated risk Management,

[105] Mikosch, T., and Starica, C., 2003, Long range dependence effects and arch modelling. Theory and applications of long range dependence.

[106] Perron, P., and Qu, Z., 2010, Long memory and level shifts in the volatility of stock market return indices. Journal of Business and Economic Statistics, 28, 275-290.

[107] Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. Journal of Business, 53, 61-65.

[108] Yang, D., and Zhang, Q., (2000). Drift-independent volatility estimation based on high, low, open, and close prices. Journal of Business, 73, 477–491.