Do Chinese stock markets share common information arrival processes?

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Abstract

According to the Mixture of Distributions Hypothesis (MDH), returns volatility and trading volume are driven by a common news arrival variable. Consequently, these two variables should be correlated. This paper extends, and to some extent, globalises the concept of a common information arrival process by hypothesising that this variable drives daily price (returns) volatility and trading volume changes in different financial markets. An implication is that returns volatility in one stock market should show positive and contemporaneous correlation with returns volatility in another stock market. This paper tests this implication using data from three separate, but geographically close, stock markets (Shenzhen, Shanghai and Hong Kong). A problem in the usual testing procedure is the likelihood that the news arrival process has long memory. This means that both volatility and volume (or external volatility) will have long memory and consequently, contemporaneous correlation between these variables is likely to be incorrectly rejected in cases where the test equation does not account for long memory. This paper uses fractionally integrated GARCH (FIGARCH) to test and account for long memory. The analysis finds that there is contemporaneous correlation between returns volatility in these stock markets and confirms the presence of long memory effects.

Keywords: mixture of distributions hypothesis, news arrival process, FIGARCH, volatility, long memory

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1. Introduction.

There is a growing literature on the modelling of temporal dependencies in financial market volatility. To some extent the theoretical under-pinning for these dynamic dependencies has lagged behind. However, the so-called mixture-of-distributions hypothesis ((MDH) does provide a rational for the many empirical studies that have found evidence of a strong positive correlation between returns volatility and trading volume. According to MDH, returns volatility and trading volume are driven by the same latent news (information) arrival variable. The arrival of good news results in increased trading, as the market adjusts to a new equilibrium, and a price increase, while the arrival of bad news results in increased trading and a price fall. Consequently, returns volatility and trading volume should be positively and contemporaneously correlated. A problem in testing this implication of the MDH is the likelihood that the news arrival process has a long memory property. It follows then that both volatility and volume will have the long memory property. Bollerslev and Jubinski (1999) show that in the presence of this long memory property the contemporaneous correlation between volatility and volume is likely to be incorrectly rejected in cases where the test equation does not account for long memory (or persistence). The use of fractionally integrated GARCH (FIGARCH) offers a way to take account of long memory (and indeed to test for long memory) in testing for contemporaneous correlation between volatility and volume (an implication of the MDH).

This paper extends, and to some extent, globalises the concept of shared common information arrival. Thus, we posit that a common latent news (information) arrival variable drives daily price (returns) volatility and trading volume changes in different financial markets around the world. An implication of this revised hypothesis is that returns volatility in one stock market should show contemporaneous correlation with returns volatility in another stock market. This effect is likely to be stronger if markets are geographically close or share similar hours of trading. In common with many of the papers that have tested the MDH, we don't test the hypothesis directly but rather the theoretical implications of the hypothesis. Therefore, this paper tests whether there is positive and contemporaneous correlation between the returns volatility of separate, but geographically close, stock markets (Shenzhen, Shanghai and Hong Kong). The test is carried out using FIGARCH in order to account for the persistence (or long memory) effects.

The remainder of the paper is organised as follows. The next section describes the MDH and reviews previous studies that have tested this hypothesis. In section 3 the common components in the information arrival process are defined. The propositions tested in this paper are developed and the testing procedures are explained in section 4. Some results are presented in section 5 and conclusions are drawn in a sixth and final section.

2. Literature Review

The mixture of distributions hypothesis (MDH) (Clark, 1973) suggests that a common information arrival process drives market returns volatility and trading volume changes. An implication of the MDH is that returns volatility and trading volume should be positively and contemporaneously correlated. The arrival of good or bad news results in a higher level of market activity than usual, an implication of which is increased volatility because of the adjustment to a new equilibrium state. The trading volume, which is a measure of the level of activity, should also increase. A problem in testing the MDH is that the news arrival variable is difficult to measure and as a result may researchers have resorted to using a proxy for this variable. The most widely used proxies have been trading volume, the number of transactions and volatility in an external market. The justification for the number of transactions as a proxy for the information flow is that this is another measure for the intensity of trading activity and as such is driven by the same information flow.

Studies by Epps and Epps (1976), Tauchen and Pitts (1983), Harris (1986, 1987) and Lamoureux and Lastrapes (1990) support the MDH and the conclusion that the trading volume can be a good proxy for the news arrival process. Other studies (Richardson and Smith,1994; Lamoureux and Lastrapes, 1994; and, Gallant *et al*. 1992) provide more mixed evidence on the validity of the MDH (when using trading volume as a proxy for news arrival).

The volatility of returns in external (foreign) markets can also be used as a proxy for the (global) information process. Many of the empirical studies that have modelled the relationship between volatility in one market and volatility in another market have concentrated on testing for causality effects. For example, Cheung and Ng (1996) report that the Nikkei 225 index affects S&P 500 index, while Hu *et al*. (1997) investigate the existence of spillovers in the South China growth triangular. Indeed, the body of literature related to possible volatility spillovers among world equity markets is vast. Examples include Koch and Koch (1991), Brocato (1994), Eun and Shim (1989) using simultaneous equations modelling. The (G)ARCH type of models have been extensively used in such studies. Darbor and Deb (1997) used bivariate GARCH models for Canada, Japan , UK and USA to conclude that each bivariate pair of markets showed evidence of 'transitory correlation'. Koutmos and Booth (1995) found price spillovers (using trivariate EGARCH model) from USA to Japan and UK, and from Japan to UK. Many of these studies report evidence of 'transitory correlation' and infer directional 'causality'. Hilliard (1979) estimated mean coherences among equity markets and concluded that 'intra-continental' prices moved together, with little 'inter-continental' co-movements. This suggests that geographical proximity may be a major determinant for common information arrival process that determine markets co-movements. This result however may be partially due to the time period used. A study by Fischer and Palasvirta (1990) found that "the level of interdependence, as evidenced by the co-movement of index prices in the world's stock markets, has grown", thus suggesting increasing globalisation of world financial markets. Using a bivariate ARCH model with hourly data Susmel and Engle (1994) concluded that volatility spillovers last, 'only an hour or so'. This suggests that markets, which are closer in terms of trading hours, are more likely to be integrated.

The choice of information proxy in empirical studies has been subject to the observation by Epps and Epps (1976) that the mixing character of the information variable may cause the resulting returns to exhibit (G)ARCH properties. If this is the case, incorporating an appropriate information proxy in the variance equation of a GARCH process may lead to a decline in its persistence (sum of GARCH coefficients) and similarly to a decrease in excess kurtosis. Such effects have been shown for example in Lamoureux and Lastrapes (1990). However, if the information arrival proxy is poor (in that it does not adequately capture the mixing properties of the news arrival process) then these desirable effects may not materialise (e.g. Hu *et* *al*. 1997) and it may be necessary to find alternative proxies. It is likely that the trading volume may be a poor proxy, as it does not distinguish between a large number of small transactions and a small number of large transactions.

Bollerslev and Jubinski (1999) find that both volatility and volume have a hyperbolic decay rate in their respective autocorrelations, which is indicative of long memory in these variables and the news arrival process. They explain the potential existence of long memory in the information arrival rate as follows, "Suppose that each day a particular piece of new "news" hits the market. Suppose also that the impact of a given day's "news" will last for a random number of days. It follows from Parke (1999) that, under reasonable assumptions about the corresponding survival probabilities, the resulting latent aggregate information-arrival process will be fractionally integrated". They further explain that if the news arrival rate has the long memory property, it follows that both volatility and volume will have the long memory property, and "the long-run decay rates should be the same across the two series". Bollerslev and Jubinski (1999) introduce a fractionally integrated process I(d), with $0<d<1$, to account for the long memory in volatility and volume. They show that in the presence of this long memory property the contemporaneous correlation between volatility and volume is likely to be incorrectly rejected in cases where the test equation does not account for long memory (or persistence).

3. Specification of common and specific information arrival components

The information arrival process for any particular stock market can be considered to consist of two components: information *specific* to this market only and *common* information relevant to this and other markets. If the common information arrival process drives returns volatility in a set of markets, then the returns volatility in these markets is expected to be positively and contemporaneously correlated. In other words, including the volatility of one market into the variance specification of another should increase the explanatory power of the latter.

Given an information arrival rate I_t (expressing the number of pieces of 'news' arriving during the period (say a day), the MDH implies that the conditional distribution of the returns for market *i* will be:

$$R_{it} \mid I_t \sim N(\mu_i, \sigma_i^2 I_t) \tag{1}$$

News can be decomposed into two components: news specific to market *i* and news that is relevant (common) to market *i* and other markets. Denoting these component information arrival rates (specific and common) as i_t and l_t, equation (1) can be rewritten as follows:

$$R_{it} \mid I_t \sim N(\mu_i, \sigma_i^2 (i_t + l_t - k_t)) \tag{2}$$

The variable k_t denotes the number of information arrivals containing information that is common to from both sets. ($0 \le k_t \le I_t$). If strict inequalities are assumed for k_t, then equation (2) can be rewritten as follows:

$$R_{it} \mid I_t \sim N(\mu_i, \sigma_i^2 (i_t - k_t) + \sigma_i^2 l_t) \tag{3}$$

Equation (3) postulates that volatility in market *i* consists of two distinct components. The component $(i_t - k_t)$ is the information arrival rate of news specific to market *i* and this rate is conditional on the information set common to all markets (l_t) in the sense that the former does not contain information relevant to other markets. Similarly, for another market, say market *j*, characterised by information arrival rate J_t, the following equation can be specified.

$$R_{jt} \mid J_t \sim N(\mu_j, \sigma_j^2 (j_t - m_t) + \sigma_j^2 l_t) \tag{4}$$

Re-specifying equation (3) in a volatility model, the volatility of market returns for market *i* will be (contemporaneously) cross-correlated with volatility from another market, say market *j*, as volatility in both markets are driven the common element of the information arrival process (l_t). This correlation will be higher where the impact of $(i_t - k_t)$ is smaller, that is when the common information component (l_t) dominates the information set. However, if the impact of $(j_t - m_t)$ is large (indicating that market *j* is more independent than other markets), then the degree of correlation will decrease, because the volatility measure for market *j* is less correlated with the common information component (l_t) of the news arrival process. Epps and Epps (1976) observe that the information arrival process may cause returns volatility to exhibit GARCH properties. The volatility persistence in a GARCH model where the volatility of an external market is a dependent variable should decrease. This decrease is negatively related to the degree of independence of market *i* and market *j*.

The 'revised' MDH model described above is used in specifying a volatility model where the volatility in market *i* is positively and contemporaneously correlated to the volatility in market *j*. The causal relationship is between the common component of the news arrival process and returns volatility in both markets. Thus, the MDH does not suggest a causal relationship between returns volatility in markets *i* and *j*.

Many researchers have searched for directional returns volatility causality between two separate markets (see section 2). There are a number of reasons why directional causality (non-spurious and spurious) may be found in studies modelling returns volatility in one market as a function of return volatility in another market. One reason may arise from using daily data for the separate markets in circumstances where the trading hours of these markets only partially overlaps. In this case, three distinct information components can be identified: information arriving when only the first market is open (and the second is closed), information arriving when both are open and information arriving when only the first market is closed. It is clear that if a further distinction is made between information that is relevant to only one of these markets and information that is commonly relevant, then inference about causal effects could become contaminated by the above effects and the possibility of reaching spurious conclusions about causality increases. However, careful treatment of the issue of partial overlaps in hours of trading can help avoid the associated problems.

In addition, although the common information arrival process may affect two markets simultaneously, the characteristics of each market will determine to what extend and how the news will impact on its level of trading and returns. This may result in some small differences in the timing of the reaction to the news, which may result in the erroneous identification of a causal effect. On the other hand, a non-spurious causal relationship may be found between volatility in two markets in circumstances where returns volatility changes in one market becomes information which is specific to the other market. The news arrival process for any market can be thought of as having two components, one containing information that is relevant (*common*) to all markets and one containing market *specific* information.

4. Methodology

This paper tests whether the volatility of returns in two mainland Chinese stock markets, namely, Shanghai and Shenzhen, is positively and contemporaneously correlated with the returns volatility in the Hong Kong stock. Given that the news arrival process is likely to have long memory and therefore returns volatility in these markets will also have long memory it is important to use a model that takes accounts of these effects. Using a FIGARCH specification has three advantages. Firstly, it provides a test for the presence of long memory in the news arrival process. Secondly, if the parameter for volatility is positive and significant then evidence in support of the 'revised' MDH is found. Thirdly, if long memory is present, then the order of fractional integration due to the common information component should be same for both markets. A formal test on this provides another indirect test on the validity of the 'revised' MDH.

The analysis is based on the Fractionally Integrated General Auto-Regressive Conditional Heteroscedasticity Model (FIGARCH) introduced by Baillie *et al*. (1996). The FIGARCH specification proposed by these authors does not apply fractional differencing to the constant term, which causes problems when interpreting the results. Therefore, an alternative FIGARCH specification, which was suggested by Chung (1999), is used. The variance equation in this is expressed as:

$$\xi_t = z_t \sigma_t \tag{5}$$

where $z_t \sim \text{iid } D(0,1)$ (6)

where D(.) is some unknown probability density function (the usual normality assumption is relaxed), ξ_t is the innovations process and σ_t^2 is the conditional variance, which can be presented as:

$$\sigma_t^2 = \sigma^2 + \lambda(L)(\xi_t^2 - \sigma_t^2) \tag{7}$$

where L is a lag operator, σ is the unconditional variance and the infinite summation polynomial $\lambda(L)$ is given by:

$$\lambda(L) = \sum_{i=1}^{\infty} \lambda_i L^i \xi_t^2 = 1 - [1 - \beta(L)]^{-1} \phi(L)(1-L)^d \tag{8}$$

where the fractional differencing parameter $0 \le d \le 1$, and $\phi(L)$ is given by

$$\phi(L) = [1 - \alpha(L) - \beta(L)](1-L)^{-1} \tag{9}$$

In (8) and (9) above $\alpha(L)$ and $\beta(L)$ are polynomials with coefficients given by the GARCH coefficients (i.e. the coefficients of ξ_{t-i}^2 (i = 1, ..q) and σ_{t-j}^2 (j= 1,..,p) in the conditional variance equation of the standard GARCH (p, q) model).

In order to estimate this process the infinite order of $\lambda(L)$ needs to be truncated. Baillie *et al*. (1996) suggest truncation at 1000 lags, which seems a rather arbitrary choice. Chung (1999) suggests truncation at the number of observations in the information set (i.e. t-1) which makes full use of all available information. Consequently the approach suggested by Chung (1999) is used here.

The specified model used in the analysis includes *n* explanatory variables, x_i, (i=1, n) in the variance equation, the term as follows:

$$\sigma_t^2 = \sigma^2 + \lambda(L)(\xi_t^2 - \sigma_t^2) + \left(\sum_{i=1}^{n} w_i x_{it} \right) [1 - \beta(L)]^{-1} \tag{10}$$

Note, that in the specification used (unlike the model proposed by Baillie *et al*., 1996) there is no constant amongst the explanatory variables. A constant term is incorporated via the unconditional variance and thus the fractional differencing operator will apply to the constant, but not to the other explanatory variables.

In this study the dependent variables are logarithmic daily returns for the two mainland market indices. An important explanatory variable is the squared returns (a widely used measure of volatility) for the Hong Kong Hang Seng index, which are used in partially explaining the volatility of the dependent variables. All the returns are multiplied by 100 prior to analysis in order to make the estimation more tractable and may be interpreted in percentage terms. An important consideration is the treatment of cases where there has been trading in one market, but not in the other. In the case where there is no trading in Hong Kong, the volatility variable is set to zero. Where there is no trading in the mainland markets, but trading is taking place in Hong Kong, the corresponding volatility measure is calculated as the squared logarithmic return (i.e. the difference in the index at the being and the end of the period of non-trading) for the whole period of non-trading. An alternative approach would be to use an aggregate volatility measure for the period of non-trading. However, it is argued that an aggregated volatility measure might exaggerate the real news arrival process in circumstances where there is considerable global turbulence followed by calm during the period of non-trading.

The other explanatory variables are dummy variables, which are specified to account for systematic microstructure effects. These include days-of-the-week dummies and two dummies indicating where the mainland markets re-open after a longer period of inactivity (during a period when the Hong Kong market was active). The dummy variable, DUM1, takes the value 1 in the time period following a period where the mainland markets were closed for 1 or 2 days while the Hong Kong market was open and zero, otherwise. The dummy variable, DUM2, is specified in a similar way but refers the to case where the mainland markets are closed for a period of 3 or more trading days (while the Hong Kong market remained open). The day of the week effects are considered a stylised fact in empirical finance and their effects on volatility have been found to be significant in Chinese stock markets (Xu, 2000; Friedmann and Sanddorf-Köhle, 2002). Xu (2000) notes that these effects are likely to be model dependent.

A specific case of the FIGARCH model is the integrated GARCH (IGARCH) in which d=1. In other words the GARCH coefficients sum up to one[1] as follows:

$$\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j = 1 \tag{11}$$

There is a tendency for the standard GARCH model fitted to financial data to display a nearly integrated character. In other words, it approximates the FIGARCH model. Baillie *et al*. (1996) demonstrates that if the underlying process is indeed a FIGARCH representation then fitting a GARCH process to the data biases the estimated parameters towards a nearly integrated process. An additional rationale for choosing the FIGARCH specification is that financial data tends to exhibit long memory properties (see for example Ding *et al*., 1993). The standard GARCH model represents an I(0) process in the variance and as such exhibits an exponential rate of decay. This characteristic means that although the GARCH model can capture the short-memory properties of volatility well, but it is a disadvantage when trying to capture the long memory effects. Similarly the IGARCH specification uses an I(1) process that leads to infinite persistence in volatility, which is something that lacks a convincing economic interpretation. It is therefore desirable to use a formulation that allows for both short and long memory properties in volatility to be captured.

Note, also, that estimating the model in the form of a conventional GARCH without imposing the stationarity restriction may result in the counterintuitive result of over persistence (i.e sum exceeding 1) where no explanatory variables are included in the variance equation. Furthermore, the conventional GARCH is likely to approximate IGARCH when explanatory variables are included.

In this study the standard GARCH model is also estimate both without and with explanatory variables (the latter case exactly corresponding to the estimated FIGARCH specification). The reason for this is twofold. Firstly, it allows examination of whether the common tendency for the standard GARCH model fitted to financial data to display a nearly integrated character holds for the data used in this study. Secondly, it provides an opportunity to compare the results produced by the FIGARCH specification with those of the standard GARCH.

In this paper maximum likelihood (ML) and quasi-maximum likelihood (QML) techniques are used to estimate the FIGARCH models. Under the normality assumption, the QML estimator is consistent subject to the correct specification of the conditional mean and the conditional variance (Weiss, 1986). However, the QML estimator is inefficient (Engle and Gonzalez-Rivera, 1991). The greater the departure from the assumption of normality, then the more inefficient the QML estimator becomes. An additional consideration is that although a GARCH process with normally distributed innovations exhibits fat tails, it cannot capture all of the observed kurtosis in empirical data. Due to the importance of fat tails in empirical finance the use of alternative distributions to the normal distributions (as in (6) above) is more likely to reduce the excess kurtosis of the residuals of GARCH type of models. Therefore, the assumption of normality is relaxed. Four information criteria (Akaike, Hannan-Quinn, Schwartz and Shibata) are used in selecting the appropriate distribution in (2) from the following candidates: normal, student t, Generalised Error Distribution (GED), and skewed t-distribution. The GED distribution and the skewed t-distribution are fat –tailed, and so is the student t distribution given the appropriate choice of the tail parameter (i.e. tail parameter = 1 (the Caushy distribution) or alternatively in the range (2-5)). The use of these alternative distributions is likely to result in a situation where more of the excess kurtosis is captured.

The Box -Pierce test for serial correlation based on the standardised residuals and on the standardised squared residuals (McLeod and Li, 1983) is used in this study. Using the F-test version of the LM ARCH test the adequacy of the estimated model is assessed by testing for residual ARCH effects (Engle, 1982). The sign bias t-test, the negative size bias t-test, the positive size bias t-test and the joint test for the three effects are used to identify possible misspecification of the conditional variance equation based on the news impact curve (Engle and Ng, 1993). Finally, the adjusted Pearson goodness-of-fit test can be used to compare the empirical distribution of the innovations with the theoretical distribution in order to provide a measure of goodness-of-fit.

Data

Data for the Shanghai Stock Exchange Composite Index (SSEC), Shenzhen Stock Exchange Composite index (SZSC) and Hong Kong’s Hang Seng index (HSI) for the period 2 July 1997 - 8 February 2002 were used to formulate and test the presence of common component in the news arrival process.

5. Empirical Results

The FIGARCH models are estimated using maximum likelihood (ML) and quasi-maximum likelihood (QML) techniques. Both the ML and the QML standard errors for the parameter estimates are computed (the point estimates for the parameters are the same). Two equations are estimated, one for returns volatility calculated from the Shanghai Composite Index (SSEC) and one for returns volatility calculated from the Shenzhen Composite Index (SZSC). The explanatory variables are, namely, the volatility (VOL) of the Hong Kong returns calculated from the Hang Seng Index and the dummy variables (FRI, MON, DUM1 and DUM2) discussed in section 4. These variables are included in both the mean and variance equations within the two FIGARCH models for Shenzhen and Shanghai.

During the estimation process, explanatory variables associated with insignificant parameters were excluded and the model re-estimated. The results of the final estimation are presented in Tables 1 and 2. The results indicate that FRI, a day-of-the-week dummy variables for Friday, is the only significant explanatory variable in the mean equations for both the Shenzhen and Shanghai models. This result agrees with the finding of Xu (2000) and suggests that there are higher Friday market returns on the China stock exchanges. The explanatory variables, VOL, MON and DUM1 are all significant in the variance equations for both the Shenzhen and Shanghai models. Therefore, the same explanatory variables are significant in each model.

In the variance equations, the only systematic day of the week effect is the increased volatility on Monday, again in agreement with the empirical findings reported in the literature. The other significant variable in the variance equations is DUM1 indicating a considerable increase in volatility after short (1 or 2 days) breaks in trading. Note, however, that the presence of this effect is marginal in terms of statistical significance and although the QML standard errors show it to be significant at the 95% confidence level, it is only significant at 90% confidence level, according to the ML standard errors. The consistency of the ML results depends upon the correct specification of the distributional assumption (i.e. equation 6), while the consistency of the QML results are more robust to alternative distributional assumptions. Consequently, the presence of this effect (described by DUM1) can be accepted.

The other inactivity dummy DUM2 (indicating a break in trading of 3 or more days) was found to be insignificant in both the SSEC and SZSC cases. This may indicate that the external volatility proxy cannot capture contemporaneous volatility during shorter periods of inactivity. But, that when these breaks are longer, the common information arrival component fully explains the deviation from the normal level of volatility.

The less restrictive nature of the QML significance levels can be further exploited. It can be seen that the standard error for the Friday effect in the mean equation increases in the QML case compared to the ML case and its significance becomes questionable (at least for the SZSC case). This agrees with the findings of Xu (2000). On the other hand, the significance of VOL and MON, as well as that of DUM1, increases in the QML case compared to the ML errors.

The best distributional assumption (equation 6) among the pre-determined alternatives in both cases and according to all informational criteria employed was found to be the skewed student t-distribution. For details on its log-likelihood function and other properties see Lambert and Laurent (2001). The skewed student t-distribution is an asymmetric fat-tailed distribution and thus the resulting model is intrinsically asymmetric. Tests for asymmetry of the parametric specification are negative, which indicates that there is no additional asymmetry attributable to mis-specification.

Importantly, the two mainland China markets are found to follow similar dynamics. This is not only because the same parameters are significant in the respective equations, but also because the magnitudes of the estimated parameter values are similar. This is particularly evident when one compares the fractional integration parameters (*d*) (from equation 8). The significance of the VOL variable in both the SSEC and SZSC equations indicates that there is correlation between the volatility in these two markets and volatility in the Hong Kong market. This finding supports the assertion that a common news arrival variable drives volatility in Shanghai and Hong Kong, as well as in Shenzhen and Hong Kong. The near equality of the fractional integration coefficients *d* in the estimated equations[2] for SSEC and SZSC implies that the volatility all three stock market has a common cause. Given the near equality of the fractional integration coefficients in the two estimated equations there is validity in comparing the estimated parameters from these equations. Comparing the coefficients of VOL from the estimated equations for Shanghai (0.014953) and Shenzhen (0.02287), it is clear that the latter is considerably higher. This implies that Hong Kong has more influence on Shenzhen. Although Shenzhen is geographically closer to Hong Kong, than Shanghai, the most likely reason for this close relationship is the type of the stocks traded in Shenzhen. Indeed, the B-shares traded in Shenzhen are traded in Hong Kong dollars, while those traded in Shanghai are traded in US dollars.

Another interesting difference is in the parameters of the skewed t-distribution. The tail coefficient for Shenzhen exceeds that of Shanghai (see Tables 1 and 2), although both coefficients show potential for fatter tails. The asymmetry coefficient for Shenzhen is also higher (in absolute value) demonstrating a greater degree of asymmetry in the returns.

The diagnostic test statistics for the both models are satisfactory. Table 3 presents the result from the Box -Pierce test for serial correlation based on the standardised residuals and on the standardised squared residuals (McLeod and Li, 1983). There is no strong evidence for serial correlation, although the evidence at lag 3 in the residuals from SZSC is marginal (significant at 90% significance level). Using the F-test version of the LM ARCH test (Engle, 1982) no residual ARCH effects are detected (see Table 4)

Table 5 presents the results for a range of tests designed to identify possible misspecification of the conditional variance equation based on the news impact curve (Engle and Ng, 1993). The sign bias test examines the impact of positive and negative return shocks on volatility not predicted by the model, i.e. whether there are such effects. The negative size bias test (positive size bias test) focuses on the different affects that large and small negative (positive) return shocks have on volatility, which is not predicted by the volatility model. Finally, a joint test for these affects is also carried out. Another way to view these tests is as tests for asymmetric effects that have not been captured in the GARCH specification. For this reason they are usually employed to test for EGARCH (or any other asymmetric GARCH specification against the alternative of symmetric GARCH. Note however that the model estimated in this paper is asymmetric due to the use of the asymmetric skewed t-distribution in its specification (eq.(6)). The tests results presented in Table 5 reject possible misspecification.

Table 6 shows the results from the adjusted Pearson goodness-of-fit test that compares the empirical distribution of the innovations with the theoretical distribution. Since the residuals are non-normal (by construction) it is pointless to carry out the usual tests for normality. Therefore, in this case normality tests are replaced by the Pearson goodness-of-fit test, which is used to test the appropriateness of the distributional assumption. It is useful to note that the preliminary results from this test allowed us to exclude both the Gaussian and the GED distribution as appropriate specifications[3]. In order to carry out this testing procedure, it is necessary to first classify the residuals in cells (categories) according to their magnitude. The choice of number of cells is, however, far from obvious (Palm and Vlaar, 1997). In this case three alternative choices for the number of cells are specified. These choices (40, 50 and 60) represent a reasonable range within which the optimal choice would be expected to fall. The results indicate that the empirical distribution of the innovations correspond to the assumed distribution (skewed t-distribution with the parameters estimated and given in tables 1 and 2).

Due to the widespread use of standard GARCH models in empirical finance, it might be useful to ask, what are the gains in applying the more involved FIGARCH specification? Are the efficiency gains associated with the better test statistics and improved economic interpretability of the results justified in terms of significant improvements in the quality of the results? To help answer these questions some comparable GARCH models are also estimated. It is a standard practice in estimating GARCH models to impose the following stationarity restriction:

$$\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j < 1$$

This restriction ensures the consistency of the estimation algorithm. Failure to impose this restriction may mean that counter-intuitive results are obtained. Nevertheless, unrestricted estimation may be very useful in identifying potential misspecifications. Table 7 reports the results from the unrestricted estimation of a number of alternative GARCH specifications for SSEC and SZSC. The GARCH (1,1) model does not contain any explanatory variables while the reference model contains the same explanatory variables as in the FIGARCH model estimated above. Results for both the normal distribution and the skewed t-distribution (which are used in the reference model) are presented.

In the models without explanatory variables (GARCH(1,1) in Table 7) the sum of the GARCH coefficient is found to be consistently greater than 1. This counterintuitive result (implying that the unconditional variance does not exist) suggests that there is something wrong with the model, as it is specified. Imposing the stationarity restriction will simply lead to a nearly integrated GARCH. This result is not dependent on distributional assumptions[4]. Using IGARCH in this context however seems to contradict the economic rationale. The inclusion of explanatory variables (reference model in Table 7) seems to reduce the volatility persistence. Nevertheless, the models remain nearly integrated. The higher levels of reduction in volatility persistence that are observed under the model where a normal distribution is assumed are likely to spurious because of the inadequacy of this distributional assumption. The results contained in Table 7 suggest that a FIGARCH specification is more appropriate for the problem in hand.

Another interesting inference from the reference model presented in table 7 is that all variables in the model were significant, except for VOL. Interestingly, the same holds for the IGARCH specification (unreported results, available from the authors)[5]. Actually, when the normal distribution is used the VOL variable is significant according to the ML standard errors, but not according to the QML standard errors. This result, however, is likely to be due to the incorrect specification of the conditional variance, which is evident from the test statistics (unreported results, available from the authors).

6. Conclusions

The Mixture of Distributions Hypothesis (MDH) postulates that price volatility and trading volume are driven by a common news (information) arrival variable. Consequently, returns volatility and trading volume should be positively and contemporaneously correlated. This paper extends the MDH and proposes that common information arrival process drives daily price (returns) volatility and trading volume changes in different financial markets around the world. An implication of this revised hypothesis is that returns volatility in one stock market should show contemporaneous correlation with returns volatility in another stock market. This paper tests this implication of the extended MDH. The analysis indicates that there is positive and contemporaneous correlation between volatility in two mainland China stock markets, Shenzhen and Shanghai, and volatility in the Hong Kong stock market. This finding supports the view that these two mainland China stock markets share a common information arrival component with the Hong Kong market.

The analysis is carried out using a FIGARCH specification for the conditional variance, in order to account for the presence of long memory effects, which were found to be present. The estimated long memory process is nevertheless stationary (d

< 0.5) which conforms to the theoretical expectations for a model of market returns. Using a standard GARCH(1,1) specification[6] rejects positive and contemporaneous correlation between volatility in Shenzhen and Shanghai and volatility in the Hong Kong stock market, which rejects the existence of a common information arrival component. However, the results produced are unsatisfactory from the point of view of economic interpretation. Therefore, testing for common components crucially depends on correctly specifying the conditional variance. The diagnostic tests for the FIGARCH models were all satisfactory and an advantage of the FIGARCH specification is its ability to capture both shot and long memory effects.

In carrying out the analysis the assumption of normality in the innovations was relaxed. The final results were not dependent on the relaxation of this assumption. The assumption of normality was rejected due to the existence of unexplained excess kurtosis in the residuals (from the model where normal innovations are assumed), which resulted in unsatisfactory diagnostic tests. There was evidence that these asymmetric effects (that were present when normal innovations were assumed) were properly captured when an alternative distributional assumption was used. In addition, some systematic affects were found, which were invariant to model specification. These include higher returns on Friday and increased volatility on Monday and after short breaks in trading. The systematic appearance of these affects probably reflects the micro-structure of the markets, although the latter two are commonly observed on stock markets and the former is not new in the stock market studies.

Although not formally tested, the similar magnitudes of the coefficients in the models specified for SSEC (Shanghai) and SZSC (Shenzhen) suggests that they follow common dynamics (i.e. stochastic trends). This is something that follows from the similarity of the fractional differencing parameter implying that a common component of the news arrival process drives these stochastic trends. The influence of the Hong Kong market was found to be greater in relation to the Shenzhen market compared to the Shanghai market.

Notes

1. i.e. the first part of $\phi(L)$ contains unit root.
2. We do not explicitly test the latter, although one may use e.g. the test due to Robinson (1995).
3. The Gaussian could also be rejected by the high values of excess kurtosis and the highly significant normality test statistics.
4. It is invariant to the use of distributions other than the referred above..
5. Additionally in the IGARCH specification (estimated by restricting the GARCH coefficient beta1) the DUM1 variable is only marginally significant (significant at 90% confidence level, but not and 95%).
6. Including the IGARCH specification.

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Table 1 Estimated FIGARCH Model for SSEC (Shanghai)

		Maximum likelihood		Quasi Maximum likelihood	
	Coefficient	**Std.Error**	**Prob.**	**Std.Error**	**Prob.**
FRI (M)[1]	0.139920	0.070033	0.0460	0.078515	0.0750
VOL (V)	0.014953	0.006310	0.0181	0.005330	0.0051
MON (V)	0.302292	0.139031	0.0299	0.131124	0.0213
DUM1 (V)	1.697110	0.916812	0.0644	0.873551	0.0523
d-Figarch	0.420155	0.061416	0.0000	0.048370	0.0000
GARCH(Beta1)	0.454840	0.148224	0.0022	0.171581	0.0081
ARCH(Alpha1)	0.207296	0.148457	0.1629	0.188766	0.2724
Asymmetry	-0.108370	0.037199	0.0036	0.038044	0.0045
Tail	5.818128	0.674571	0.0000	0.628426	0.0000

1. The letter M in brackets following the name of an explanatory variable indicates that the variable appears in the mean equation within the FIGARCH model. The letter V indicates that a variable appears in the variance equation.

Table 2. Estimated FIGARCH Model for SZSC (Shenzhen).

		Maximum Likelihood		Quasi Maximum Likelihood	
	Coefficient	**Std. Error**	**Prob**	**Std. Error**	**Prob**
FRI (M)[1]	0.125493	0.072873	0.0853	0.080574	0.1196
VOL (V)	0.022827	0.006782	0.0008	0.005335	0.0000
MON (V)	0.361157	0.155868	0.0207	0.147774	0.0147
DUM1 (V)	1.632036	0.915255	0.0748	0.785495	0.0380
d-Figarch	0.429418	0.060515	0.0000	0.050802	0.0000
GARCH(Beta1)	0.425498	0.132511	0.0014	0.134847	0.0016
ARCH(Alpha1)	0.178036	0.131316	0.1754	0.147182	0.2267
Asymmetry	-0.163094	0.042251	0.0001	0.047154	0.0006
Tail	6.608929	0.866680	0.0000	0.818569	0.0000

1. The letter M in brackets following the name of an explanatory variable indicates that the variable appears in the mean equation within the FIGARCH model. The letter V indicates that a variable appears in the variance equation.

Table 3 Box-Pierce test results

Box-Pierce Q-statistics on residuals				
	Shanghai		Szenshen	
	Test statistic	P-value	Test statistic	P-value
Q(1)	0.68568	0.407637	1.38745	0.238837
Q(2)	1.21996	0.543363	2.05406	0.35807
Q(3)	5.17874	0.159167	6.49803	0.0897402
Q(4)	5.18264	0.269065	6.64331	0.155981
Q(5)	7.04424	0.217371	7.98416	0.157111
Q(10)	8.42632	0.587270	10.0275	0.43808
Q(20)	15.52440	0.745656	20.7249	0.413478
Box-Pierce Q-statistics on squared residuals				
	Shanghai		**Szenshen**	
	Test statistic	**P-value**	**Test statistic**	**P-value**
Q(2)	1.54160	0.214380	0.717925	0.396825
Q(3)	1.59525	0.450397	0.718781	0.698102
Q(4)	1.61540	0.655904	0.895537	0.826505
Q(5)	1.72009	0.787066	0.902503	0.924201
Q(10)	2.29704	0.985853	1.162860	0.998961

Table 4 ARCH test results

Up to lag	Shanghai		Szenshen	
	Test statistic	Prob.	Test statistic	Prob.
1	0.79888	0.3716	0.58406	0.4449
2	0.72301	0.4855	0.31085	0.7329
3	0.46955	0.7036	0.15702	0.9252
4	0.35731	0.8390	0.25058	0.9094
5	0.42843	0.8290	0.29454	0.9161
10	0.43609	0.9292	0.26610	0.9882

Table 5. Diagnostic tests based on the news impact curve

	Shanghai		Szenshen	
	Test	Prob	Test	Prob
Sign Bias t-Test	0.16276	0.87071	0.06255	0.95013
Negative Size Bias t-Test	0.84875	0.39602	0.92571	0.35460
Positive Size Bias t-Test	1.40282	0.16067	1.25187	0.21062
Joint Test for the Three Effects	5.67891	0.12832	4.35017	0.22605

Table 6. Adjusted Pearson Chi-square Goodness-of-fit test

	Shanghai		Szenshen	
Cells	**Statistic**	**P-Value(lag 1)**	**Statistic**	**P-Value(lag 1)**
40	46.9458	0.178960	40.6167	0.399011
50	50.6643	0.407698	42.3697	0.737094
60	67.8484	0.201084	60.6894	0.414753

Table 7. Results from unconstrained estimation of standard GARCH models

	GARCH(1,1)		Reference model	
	SSEC	**SZSC**	**SSEC**	**SZSC**
Normal distribution				
GARCH(Beta1)	0.860481	0.854330	0.719480	0.706269
ARCH(Alpha1)	0.179560	0.186012	0.215490	0.221892
SUM	1.040041	1.040342	0.93497	0.928161
Skewed t-distribution				
GARCH(Beta1)	0.887819	0.876084	0.783795	0.760113
ARCH(Alpha1)	0.143591	0.154484	0.170112	0.194197
SUM	1.03141	1.030568	0.953907	0.95431