Volume Volatility in Dual Markets: Lessons from Chinese ADRs

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November 2010

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Abstract

We investigate the volume volatility relations of 14 Chinese ADRs and those of their underlying H-shares. Specifically we test whether a contemporaneous correlation or a lead-lag relation exists between volume and volatility for each ADR and its corresponding H-share. We perform Granger causality test to determine the direction of the lead lag relation, if it exists. Our results suggest that contemporaneous correlations are positive and statistically significant in only 3 of the 14 underlying H-shares. However, we find significant bidirectional relation between volume and volatility in 10 out of 14 ADRs, but only 4 out of 14 underlying H-shares. We also find that there are different patterns in leverage effect on 'bad news' between two markets, as well as various magnitude of volatility persistence over time between two markets. Finally, we use a bivariate GARCH in which the conditional volatility for each ADR and its underlying H-share are jointly determined by volume and volatility in each market. The GARCH model fits the data well. Further, in addition to the conventional GARCH parameters, expected and unexpected volumes significantly affect both the variance and the covariance function.

1. Introduction

The relation between trading volume and volatility has received considerable attention in the finance literature. Karpoff (1987) reports overwhelming evidence of a positive correlation between trading volumes and changes in prices in the US equity market. Lamoureux and Lastrapes (1990), Kim and Kon (1994), Anderson (1996), and Gallo and Pacini (2000) find evidence in support of a contemporaneous volume volatility relation from the US stock market.[1] Thus prices are more volatile during active trading. The so called 'smile' observed in both intraday volume and volatility in the equity market raises the suspicion that this volume volatility relation may be caused by impending information into the market.

[1] For international evidence on volume volatility commovement, please refer to Tse (1991), Chen and Tse (1993), Omran and McKenzie (2000), Zarraga (2003), Pyun et al. (2000), and Bohl and Henke (2003) and Saatcioglu and Starks (1998).

Contrary empirical evidence supporting a lead lag relation between volume and price changes or return volatility based on broad market indices also exists in the literature. Gallant et al. (1992), Campbell et al. (1993), Hiemstra and Jones (1995), Brooks (1998), Silvapulle and Choi (1999) find causality between trading volume and volatility, albeit the direction of such causality is inconclusive. Lee and Rui (2000) and Lee and Rui (2002) however find trading volumes in domestic or host markets do not Granger cause return variances in China and Japan respectively.

Two hypotheses, the Mixture of Distributions hypothesis (MDH later) and Sequential Information Arrival hypothesis (SIAH later), based on signaling and distribution theory justify the observed *contemporaneous* and bidirectional *causal* (lead lag) relations between stock prices changes and trading volume.

Admati and Pfleiderer (1988), Holden and Subrahmanyam (1992), and Harris and Raviv (1993) propose market microstructure based explanations of the volume volatility relation in a securities market with information asymmetry and predict a leader follower relation between volume and volatility for individual stocks.[2] Empirically, Harris (1987) and Smirlock and Starks (1988) find positive correlations between changes in trading volume and prices for a sample of NYSE stocks. Jones et al. (1994) find number of trades to be primary driver of the volume volatility relations for US securities and Darrat et al. (2003) find Granger causality from intraday trading volume to return volatility for 24 out of 30 Dow stocks.

[2] The academic literature generally sides with the idea of volume leading volatility while practitioners hold the viewpoint that volatility causes volume. Harris and Raviv (1993) argue that divergence of opinion among informed investors causes trading. Deuskar (2009) confirms a volatility leading volume hypothesis; however, since volatility is not observable but estimated, it is not clear what a leading volatility estimate truly implies.

With respect to volume and volatility of cross listed securities in multiple markets, Hauser et al. (1998) investigate the information flow between NYSE and Tel Aviv exchange for five stocks listed in both exchanges. Alaganar and Bhar (2002), Yang (2007), and Chen et al. (2010) fit bivariate GARCH models for return and volatility functions for home and host country securities. Poshakwale and Aquino (2008) study volatility transmission across home and host markets for 70 ADRs from 13 countries. However, we do not know of any published study on the dynamic relation between volume and volatility for individual securities traded in multiple markets.

In this paper, we examine the relation between trading volume and conditional return volatility of 14 Chinese ADRs listed at NYSE and their corresponding H-shares with primary listings in Hong Kong stock exchange (SEHK). We estimate volatility from a TARCH model that allows us to capture an asymmetric bad or good news effect. For each ADR and its underlying H-share, we determine whether volume and return volatility are contemporaneously correlated as predicted by the MDH or that a lead lag relation exists between volume and volatility as predicted by the alternative SIAH or market microstructure theories. We perform Granger causality tests to establish whether volume leads or lags volatility.

Finally, in order to explore the volume volatility dynamics, we fit a bivariate GARCH model where return volatilities for ADRs and their underlying securities are jointly determined by expected and unexpected volumes and volatility in each market.

The results from our bivariate GARCH model that decomposes volume into expected and unexpected components indicate a consistent and significant relation between conditional volatility and the covariance of unexpected volume in both host and underlying securities markets. These results have important implications for the role of trading volume in conveying information and affecting volatility.

The remainder of the paper proceeds as follows. In section 2, we provide a brief literature review; in section 3, we present a univariate analysis of volume followed by an empirical analysis of volume and volatility via a TARCH model; we introduce a bivariate GARCH model for returns of ADRs and their underlying H-shares and present the empirical results in section 4; we conclude in section 5.

2. Literature Review

Based on a survey of the literature, Karpoff (1987) reports a strong positive relation between changes in trading volume and absolute price changes. Two contrasting hypotheses, the Mixture of Distribution (MDH) and Sequential Information Arrival (SIAH) hypotheses attempt to explain the volume volatility relations. The MDH originally proposed by Clark (1973) indicates securities' return is drawn from a joint distribution of volume and prices conditional on the current information. Price and trading volume changes are driven by the same underlying information arrival process and hence volume and volatility are correlated. Lamoureux and Lastrapes (1990), Kim and Kon (1994), Anderson (1996), and Gallo and Pacini (2000) find evidence in support of a contemporaneous volume volatility relation as predicted by the MDH from the US stock market. Chen and Tse (1993), Omran and McKenzie (2000), Zarraga (2003), Pyun et al. (2000), and Bohl and Henke (2003) report similar evidence from the Japanese, UK, Spanish, Korean, and Polish stock markets respectively. Saatcioglu and Starks (1998) find positive correlation between changes in trading volume and price changes but mixed evidence on the direction of causality among Latin American markets.

The primary criticism with respect to MDH is twofold- first, it does not condition volatility on volume and thus fails to indicate volatility persistence after including volume; and second, as Fong (2003) and Xu et al. (2006) argue, MDH models do not allow for serial dependence in return volatility and volume.

In contrast, the SIAH (Copeland 1976, 1977) assumes that new information is disseminated sequentially to informed and uninformed traders. Due to the sequential information flow lagged absolute stock returns could have predictive power for current trading volume and vice versa, which imply bidirectional causality between volume and volatility. Campbell et al. (1993), Hiemstra and Jones (1995), and Brooks (1998) indicate the presence of bidirectional Granger causality between daily stock returns and changes in trading volume. Gallant et al. (1992) and Silvapulle and Choi (1999) however find one-way Granger causality from volume to return volatility in US and Korean stock markets respectively. Lee and Rui (2000) and Lee and Rui (2002) however find trading volume do not Granger cause returns in Chinese and

Japanese markets respectively.

Theoretical research in market microstructure revisits the volume volatility relation by assigning a critical role in the price discovery in the market to market makers, who infer information from observed gross and net order flows and set prices accordingly. Admati and Pfleiderer (1988), Holden and Subrahmanyam (1992), Harris and Raviv (1993), Wang (1994), and He and Wang (1995) derive several key equilibrium conditions linking trading volume and changes in prices. They find that trading volume and changes in prices may be positively correlated or follow a lead lag structure and further that trading volume (price) is serially positively (negatively) correlated, However, the debate continues as to whether information flows from volume to volatility via the buying/selling pressure hypothesis or the converse where trades occur only in response to an expected future price changes. Admati and Pfleiderer (1988), Holden and Subrahmanyam (1992) conclude that volume causes price change and thus volatility, while Harris and Raviv (1993) argue that volatility originating from the divergence of opinion about the effect of information on the value of a security causes trading volume. Admati and Pfleiderer (1988) predict an inverse relation between volume and volatility based on the inventory balancing needs of investors; Holden and Subrahmanyam (1992) suggest aggressive trading by informed traders spikes up volume containing presumed information that in turn drives volatility; in contrast, Harris and Raviv (1993) suggest that divergence of opinion as a proxy for volatility fuels trading.

These microstructure models' predictions are tested on individual securities primarily in US markets. Analyzing NYSE stocks, Harris (1987) reports a positive correlation between changes in trading volume and changes in volatility measured as squared returns; Jones et al. (1994) make the shocking discovery that trading frequency is at the essence of the volume volatility relations for individual securities; and Gervais et al. (2001) report a volume premium indicating higher returns for high volume portfolios. Smirlock and Starks (1988) find a positive relation between lagged volume and price changes while Bhagat and Bhatia (1996) find one-way causality where price changes lead volume but not the other way for US stocks. Darrat et al. (2003) use intraday data and find significant Granger causality from trading volume to return volatility for 24 out of 30 Dow stocks.

There is some evidence on volume and volatility for cross listed securities in multiple markets. Chan et al. (1996) compare the intraday volume, volatility, and spread of Japanese and European ADRs with those of the underlying securities and Hauser et al. (1998) investigate the information flow between NYSE and Tel Aviv exchange for five stocks listed in both exchanges. Karolyi (1995), Alaganar and Bhar (2002), and Xu and Fung (2002) fit bivariate GARCH models for two value weighted indexes of 24 Australian ADRs and their underlying stocks, where only the volatility functions are interrelated. Poshakwale and Aquino (2008) summarize the volatility transmission literature and apply appropriate volatility modeling techniques in the context of a global basket of ADRs. Yang (2007) and Chen et al. (2010) model information transmission and volatility spillover for Japanese and Chinese ADRs respectively. Yet there is no empirical study that we know of addresses the question of the dynamic relation between volume and volatility for cross listed securities in any emerging market.

3. Data, Methodology, and Empirical results

3.1. Descriptive statistics on host and home market return

Our data consists of daily prices and trading volumes on 14 Chinese ADRs listed on the New York Stock Exchange (hereafter NYSE) as of September 2010 and their corresponding underlying securities listed on the Stock Exchange of Hong Kong (hereafter SEHK).[3] We compute continuously compounded returns on the underlying stocks listed at SEHK and their corresponding ADR listings in NYSE as $r_t^i = \ln(P_t^i / P_{t-1}^i)$ where P_t^i denotes price of security *i* on day *t*. The sample period for each pair of ADR and the underlying security begins from the initial listing dates of the ADR and the underlying security and ends on 30 September 2010.

Table 1 provides descriptive statistics on returns on ADR and the underlying securities listed at SEHK. To provide a perspective we compare the returns of ADR and the underlying securities with respect to the US and Hong Kong market portfolios. The means and the standard deviations of returns of underlying H-shares

[3] As of September 2010, there are 51 Chinese ADRs listed on NYSE but only 14 of them have underlying shares in Hong Kong.

are not different from those of the ADRs. After a detailed comparative analysis of the returns on ADRs and the underlying H-shares, Dey and Wang (2009) find that in spite of equal means, the ADR and their underlying H-shares returns are not from identical distributions and those differ primarily in the tail areas statistics.

3.2. Trading Volume

Trading volume is the number of shares traded each day. Trading volume is documented to be non-stationary ([Dey [2005], Chae [2005]); however, the precise form of its non-stationarity may vary from one volume series to another. Testing for appropriate form of stationarity is complicated; known tests do not allow hypothesis testing against a specific alternative and hence we test for both difference and trend stationarity for each volume series. Table 2 contains the test results for each ADR and H-share. The null hypothesis that a unit root exists and thus volume is difference stationary is rejected by augmented Dickey-Fuller test while Kwiatkowski-Phillips-Schmidt-Shin test statistics cannot reject the null hypothesis of level trend stationary.

Our results showing volume as trend stationary validate the assumption that volume is trend stationary made by Girard and Biswas (2007) and Dale and Jitendranathan (2009). Hence we estimate the following function where volume is a deterministic function of time. Further since Gallant et al. (1992) report that trading volume may contain a nonlinear time trend as well, we include both a linear and quadratic time trend terms:

$$Vol_t = \alpha + \beta t + \chi t^2 + \varepsilon_t \qquad (3)$$

where Vol_t represents raw daily trading volume at time t. For the 14 Chinese ADRs and their underlying shares, the coefficients for both linear and non-linear trend term are significantly different from zero. In the following analysis we will employ detrended trading volume for the 14 Chinese ADRs and their underlying HK shares. The residuals from equation 3, detrended trading volumes denote unobservable information flow.

3.3. TARCH model

Volatility is not observable and hence we need to use a model for estimating volatility. The GARCH family of models has been widely used in the finance literature to estimate conditional volatility and hence a GARCH model is a natural candidate for volatility modeling. Nevertheless, we run a few diagnostics to determine whether the returns on the underlying H-shares listed in SEHK and their corresponding ADRs in NYSE are likely GARCH processes. We check heteroskedasticity conditions for each return series by computing Ljung-Box Q(6) and Q(12) statistics for return autocorrelations and report the test statistics in Table 3. Table 3 indicates that only 1 out of 14 ADRs have significant autocorrelation in both 6^{th} and 12^{th} orders; 4 out of 14 underlying H-shares have significant autocorrelation in both 6^{th} and 12^{th} orders. While the significant Ljung-Box test statistics $Q^2(6)$ and $Q^2(12)$ indicate the presence of conditional heteroskedasticity for 14 ADRs and their underlying H-shares. These findings suggest that GARCH models, which allow for conditional variance in returns, are appropriate for the returns on H-shares and their corresponding ADRs.

Besides the basic GARCH (1, 1) model, the GARCH family provides a rich suite of time varying and stochastic volatility models. Following Glosten et al. (1993) and Girard and Biswas (2007), we use an asymmetric GARCH model, Threshold GARCH or TARCH to model return volatility for individual securities. This model captures asymmetric characteristics such as the leverage effect, in which negative shocks have a greater effect on conditional volatility than positive shocks of the same magnitude. The TARCH specification also captures volatility clustering, i.e., when large (small) price changes tend to follow large (small) price changes. Further, the TARCH model allows a generalized error distribution (GED) as the unconditional error distribution, which nests the normal distribution along with several other possible probability density functions including ones which account for leptokurtosis and skewness both of which indicate departure from normality of the data but are well recognized characteristics of daily stock returns. Bollerslev et al. (1992) note that imposing the normality assumption leads to biased estimates.

We write the TARCH (1, 1) model representation of the mean return and volatility as follows:

$$R_t = \alpha + \sum_{r=0}^{p} \beta_r R_{t-1} + \varepsilon_t \qquad (2)$$

$$\sigma_t^2 = \alpha + \psi \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \lambda \sigma_{t-1}^2 \qquad (3)$$

where R_t is the realized return of the stock, expressed as an AR (1) process with an error term of mean zero and conditional variance σ_t^2. The conditional variance σ_t^2 is specified as a function of the mean volatility α, ε_{t-1}^2 which is the lag of the squared residual from the mean equation (the ARCH term) and which provides news about volatility clustering; σ_{t-1}^2 which is the last period's forecast variance (the GARCH term) and finally, the term for capturing the asymmetry $\varepsilon_{t-1}^2\, d_{t-1}$. The parameter d_t = 1 if ε_t <0, and 0 otherwise, so that good news (ε_t >0) and bad news (ε_t <0) are allowed to have different effects on the conditional variance. Good news has an effect of ψ, while bad news has an effect of $\psi + \gamma$. Accordingly, if γ >0, a leverage effect, exists, then bad news has greater effect than good news.

Persistence of volatility is measured by λ; when λ equals 1, current shocks persist indefinitely in conditioning the future variance. It also represents the change in the response function of shocks to volatility per period. A value greater than one implies that the response function of volatility is explosive and a value less than unity implies that the response to volatility shocks declines over time.

We present the results of TARCH (1, 1) model fit in Table 4 including the parameter estimates related to the leverage effect of 'good' and 'bad' news and the persistence of conditional volatility.[4] First, all Chinese ADRs and their underlying H-shares have significant coefficient of ε_{t-1}^2, which represents 'good news' in the market. The coefficients associated with squared residuals, ε_{t-1}^2 range from 0.047 (CHU) to 0.093 (CEA) for ADRs and from 0.005 (HNP) to 0.16 (LFC) for H-shares. With

[4] We find little differences between the parameter estimates from TARCH (1, 1) and EGARCH (1, 1). The likelihood ratios of both models reported in tables 3 and 4 show that for most securities TARCH (1, 1) values are slightly higher than those related to EGARCH (1, 1).

regard to reflection on ‘bad news’, the ADRs on the NYSE have different patterns than those associated with the underlying shares on the SEHK, the average coefficient is positive for ADRs whereas negative for H-shares, which suggests the investors’ different reaction to ‘bad news’ in two stock markets. On the NYSE, the leverage effect of ‘bad news’ is much greater than that on the SEHK. Also the number of significant and positive coefficients of ADRs is more than that of H-shares. On the other hand, we observe that the persistence of volatility in the NYSE is higher than that in the SEHK, which is consistent with the evidence in Xu and Fung (2002) that the Chinese ADRs listed on the NYSE play a bigger role in volatility spillover. However, none of the past volatility coefficient is close to unity, which implies that the response to volatility shocks declines quickly over time.

3.4. Volume volatility relation

We now proceed to test the contemporaneous volume volatility relation following Lamoureux and Lastrapes (1990), and Girard and Biswas (2007), who introduce a one-lag volume instead of a contemporaneous trading volume as an explanatory variable in the variance equation. They suggest that adding contemporaneous volume to the variance equation might cause a “simultaneity bias” since volume is endogenous to the system. We follow their model as below:

$$\sigma_t^2 = \alpha + \psi\ \varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2\ d_{t-1} + \lambda\sigma_{t-1}^2 + \kappa V_{t-1} \qquad (4)$$

where V_{t-1} is the one lag trading volume serving as a volume forecast while other terms have same definition as equation (3). We report the results in Table 5.

The results in Table 5 indicate limited evidence of significant correlation between one lag volume and volatility. We find significant correlation between volatility and volume for 9 ADRs and 5 H-shares; further, we find positive and significant correlation between volatility and one lag volume in 3 out of 14 underlying H-shares. Our finding provides limited support for MDH. We do not find any significant reduction in volatility persistence and thus our results confirm similar findings by Girard and Biswas (2007).

We now proceed to test SIAH following Darrat et al. (2003) in which we examine the lead-lag relations between volume and volatility using Granger causality test.

$$\sigma_t^2 = \alpha_1 + \sum_{k=1}^{p} \beta_k \sigma_{t-k}^2 + \sum_{k=1}^{q} \theta_k V_{t-k} + \varepsilon_{1t} \qquad (5)$$

$$V_t = \alpha_2 + \sum_{k=1}^{m} \delta_k \sigma_{t-k}^2 + \sum_{k=1}^{n} \phi_k V_{t-k} + \varepsilon_{2t} \qquad (6)$$

Table 6 contains results related to equations 5 and 6. With respect to Granger causality we use Wald test and find significant causality relation from trading volume to volatility in 14 ADRs and underlying shares in both markets, and find significant causality relation from volatility to trading volume in 10 ADRs and 4 underlying shares. This finding provides additional support for Darrat et al. (2003) and the SIAH.

In summary, our results are mixed. While we find positive contemporaneous relation between volume and volatility for 9 ADRs and 5 H-shares, we also find

Granger causality from volume to volatility. This calls for further probing into the volume volatility relation in a bivariate framework. We choose a model that allows for volatility in each market and the covariance between the host and home markets to be determined by its own volume and lagged volatility.

4. Bivariate GARCH model

The above analysis for ADRs and H-shares assumes that the innovations in the mean equations are independent, which is perhaps untrue given the cash flows for those securities are identical and there may be arbitrage opportunities between the two trading locations. A bivariate GARCH model is appropriate for modeling volatility feedbacks from the two markets. The model below combines elements of Xu and Fung (2002), Darrat et al. (2003), and Girard and Biswas (2007).

$$R_{n,t} = \alpha_0^n + \sum_r \alpha_r^n R_{n,t-r} + \sum_s \beta_s^h R_{h,t+1-s} + \varepsilon_{n,t} \text{......(7)}$$

$$R_{h,t} = \alpha_0^h + \sum_r \alpha_r^h R_{h,t-r} + \sum_s \beta_s^n R_{n,t-s} + \varepsilon_{h,t} \text{......(8)}$$

$$\varepsilon_t \mid \Omega_{t-1} = \begin{bmatrix} \varepsilon_{n,t} \\ \varepsilon_{h,t} \end{bmatrix} \sim N(\mathrm{O}, H_t)$$

$$H_{n,t} = M_{11} + A_{11}\varepsilon_{n,t-1}^2 + B_{11}H_{n,t-1} + C_{11}EV_{n,t-1} + D_{11}UV_{n,t-1} + e_{n,t} \text{.......(9)}$$

$$H_{h,t} = M_{22} + A_{22}\varepsilon_{h,t-1}^2 + B_{22}H_{h,t-1} + C_{22}EV_{h,t-1} + D_{22}UV_{h,t-1} + e_{h,t} \text{......(10)}$$

$$H_{hn,t} = M_{12} + A_{12}\varepsilon_{n,t-1}\varepsilon_{h,t-1} + B_{12}H_{hn,t-1} + C_{12}EV_{n,t-1}EV_{h,t-1} + D_{12}UV_{n,t-1}UV_{h,t-1} + e_{hn,t} \text{..(11)}$$

Following Girard and Biswas (2007), we examine whether surprises in trading activity convey more information and thus have a larger effect on return volatility than forecastable activity. Accordingly, we apply ARMA (p, q) processes to partition activity into expected and unexpected components as follows:

$$V_t = \alpha + \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{j=1}^{q} \delta_j \varepsilon_{t-j} + \eta_k dum_k + \varepsilon_t \text{ ....(12)}$$

where V_t is the residual from equation 3 or the detrended volume at time *t* and 'dum_k' is a dummy variable that denotes *kth* day of the week. We select the optimal length of the lags, p=1 and q=1 on the basis of AIC and SBC criteria. In the model, EV_t is the expected volume at time *t* and UV_t, the unexpected volume at time *t* is the residual, ε_t. Hence we break up volume into expected and unexpected volume as in Bessembinder and Seguin (1993) and Lee and Rui (2002), although we use an ARMA (1, 1) instead of a trend model. As in Girard and Biswas (2007), we obtain our initial daily volume forecast using parameter estimates from the data for the prior six months approximately 60 observations; thereafter, the ARMA models forecasts are estimated using a moving window which drops the first day of the series and adds the following day. Consequently, the ARMA model always uses information from the immediately preceding three months. The empirical results indicate good fit for the ARMA model while showing lack of consistency in terms of day of the week effect with respect to the individual securities.

There are a few salient features of the above bivariate GARCH model. First, we break up total volume into expected and unexpected components and estimate their impact on volatility. Second, we assume a lagged dependence structure for the covariance function similar to that of the variance function; in addition, the covariance term includes one lag values of expected and unexpected volumes. Thus volume impacts not only inter temporal volatility directly but may also cause contemporaneous correlation in return and volatility.

Ding & Engle (2001) and Bauwens et al. (2006) comment that compared to the large number of diagnostic tests available for univariate models, few tests are suitable for multivariate models and three moment conditions should be tested about the standardized error term, $z_t = H_t^{-1/2}\varepsilon_t$. We use the most widely used diagnostics test, the Box–Pierce/Ljung–Box portmanteau test to detect the autocorrelation of the residuals. The test results are contained in Tables 7 and 8.

Table 7 reports the parameter estimates associated with the variance and covariance functions (equations 9-11) of the corresponding bivariate GARCH model. The parameter estimates, A_{11} through B_{22} denote the variance and covariance functions as linear functions of the ARCH and GARCH parameters without the volume effects. Table 8 reports the parameter estimates, A_{11} through D_{22} which relate to the variance and covariance functions, and the one lag expected and unexpected volume effects in addition to the ARCH and GARCH effects.

The empirical results for the bivariate GARCH model without expected and unexpected volume effects strongly support the model and hence its assumptions. The ARCH and GARCH parameters are all significant at less than 1% level for all the 14 pairs of ADRs and their underlying H-shares. The parameters associated with lagged covariance and correlation coefficients in the covariance function are also positive and significant at 1% level.

For the full model with expected and unexpected volumes as additional determinants of volatility, again the ARCH and GARCH parameters are largely positive and significant at less than 1% level.

The remaining six parameters C_{11} through D_{22} associated with one lag expected and unexpected volumes show mixed results in terms of significance and sign consistency. Among those parameters, C_{11} (12 out of 14 significant), C_{12} (only 8 out of 14 significant, 1 negative, 7 positive), and C_{22} (6 positive significant, 1 negative significant, and 7 insignificant) are particularly unstable perhaps due to the fact that correlation itself may be non-stationary. The parameters related to one lag covariance are generally stable- D_{11} is significant for 9 out of 14 securities, D_{12} is positively significant for all securities, and D_{22} is positively significant for 5 out of 14 securities. While stability and consistency might be an issue for a couple of parameters, which can be easily attributed to a few securities e.g., CHU has been an exception in for three parameters, in general the bivariate GARCH model with expected and unexpected volume effects seems to do very well for the data in terms of model fit. That lagged volume explains a part of volatility confirms the notion of information content in volume driving volatility.

5. Conclusions

We examine the information content in volume and volatility and their relation with respect to securities traded in multiple markets. Specifically we test whether there is a contemporaneous versus a lead lag relation between volume and volatility in 14 Chinese ADRs listed on the NYSE and their underlying H-shares listed on the SEHK. We use an asymmetric GARCH model, TARCH to estimate volatility and its dependence on trading volume. We find there are different patterns in leverage effect on 'bad news' between two markets, as well as various magnitude of volatility persistence over time between two markets. Our results also suggest that contemporaneous correlations are positive and statistically significant in only 3 of the 14 underlying H-shares on the SEHK. However, all ADRs and the remaining 11 underlying H-shares do not exhibit significant and positive correlation between trading volumes and return volatility. Thus we find weak evidence of contemporaneous correlations between volume and volatility as predicted by the Mixture of Distribution Hypothesis. On the contrary, our results also show limited support for the Sequential Information Arrival Hypothesis. We find significant bidirectional relation between volume and volatility in 4 out of 14 ADRs and 2 out of 14 underlying H-shares. However Granger causality test confirm a strong volume to volatility causality for all 14 pairs of ADRs and their underlying H-shares whereas only 4 (2) NYSE (SEHK) securities show causality the reverse way. Finally a comprehensive bivariate GARCH model is fitted where in addition to the volatility of the corresponding security, expected and unexpected lagged volumes are determinants of volatility. The covariance function is a non-trivial function of past covariance, expected volume, and volume surprises.

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Table 1: Descriptive statistics on daily return on Chinese ADRs on NYSE and their underlying shares on the Stock Exchange of Hong Kong; return is computed as $r_t^i = \ln(P_t^i / P_{t-1}^i)$ where P_t^i denotes price of security *i* on day *t*

Symbol	Obs.	Mean	Sd. Dev	Min	Max	Skewness	Kurtosis
ACH [2600.hk]	2084	0.0008 (0.0008)	0.038 (0.037)	-0.164 (-0.22)	0.221 (0.277)	0.404 (0.306)	5.95 (7.11)
LFC [2628.hk]	1632	0.001 (0.001)	0.029 (0.027)	-0.129 (-0.278)	0.166 (0.149)	0.37 (-0.39)	6.819 (12.64)
CHL [0941.hk]	3109	0.0006 (0.0006)	0.030 (0.027)	-0.157 (-0.165)	0.186 (0.156)	0.412 (0.296)	7.05 (6.91)
CHA [0728.hk]	1891	0.0005 (0.0005)	0.030 (0.027)	-0.163 (-0.206)	0.209 (0.186)	0.407 (0.006)	8.76 (9.36)
CEO [0883.hk]	2302	0.001 (0.001)	0.028 (0.027)	-0.17 (-0.20)	0.222 (0.201)	0.113 (-0.01)	8.12 (8.08)
GSH [0525.hk]	3449	-0.00001 (-0.00002)	0.03 (0.03)	-0.20 (-0.29)	0.268 (0.194	0.376 (-0.11)	9.25 (10.15)
PTR [0857.hk]	2517	0.0008 (0.0007)	0.026 (0.025)	-0.149 (-0.249)	0.15 (0.181)	0.074 (-0.09)	7.957 (11.43)
CHU [0762.hk]	2464	-0.0001 (-0.0001)	0.032 (0.029)	-0.161 (-0.135)	0.203 (0.147)	0.20 (-0.135)	7.158 (6.50)
CEA [0670.hk]	3062	0.0003 (0.0003)	0.04 (0.042)	-0.27 (-0.371)	0.505 (0.488)	0.987 (0.673)	15.13 (15.45)
SNP [0386.hk]	1465	0.0006 (0.0006)	0.029 (0.027)	-0.169 (-0.187)	0.187 (0.162)	0.191 (0.024)	7.69 (7.51)
ZNH [1055.hk]	2387	0.0001 (0.0001)	0.04 (0.041)	-0.327 (-0.324)	0.242 (0.357)	0.273 (0.332)	7.20 (9.07)
HNP [0902.hk]	3032	0.0002 (0.0003)	0.031 (0.031)	-0.175 (-0.167)	0.168 (0.207)	0.118 (0.231)	6.231 (6.71)
SHI [0338.hk]	4130	0.0001 (0.0001)	0.035 (0.038)	-0.194 (-0.393)	0.270 (0.254)	0.415 (0.08)	7.539 (10.9)
YZC [1171.hk]	2877	0.0008 (0.0008)	0.039 (0.039)	-0.202 (-0.189)	0.237 (0.263)	0.278 (0.368)	6.852 (6.51)

Table 2: Stationary test for volume for both ADR and their underlying HK shares

Symbol	ACF H_0: series has a unit root	KPSS H_0: series is level stationary without trend
ACH	-5.776*(0.00)	0.236
2600.hk	-10.438*(0.00)	0.210
LFC	-3.465**(0.04)	0.148
2628.hk	-8.307*(0.00)	0.179
CHL	-19.026*(0.00)	0.128
0941.hk	-19.456*(0.00)	0.203
CHA	-13.00*(0.00)	0.098
0728.hk	-9.852*(0.00)	0.068
CEO	-13.85*(0.00)	0.227
0883.hk	-32.10*(0.00)	0.059
GSH	-18.152*(0.00)	0.122
0525.hk	-13.771*(0.00)	0.099
PTR	-7.028*(0.00)	0.203
0857.hk	-12.682*(0.00)	0.256
CHU	-8.916*(0.00)	0.270
0762.hk	-12.587*(0.00)	0.103
CEA	-13.289*(0.00)	0.053
0670.hk	-7.792*(0.00)	0.087
SNP	-8.218*(0.00)	0.150
0386.hk	-17.721*(0.00)	0.130
ZNH	-12.587*(0.00)	0.150
1055.hk	-12.025*(0.00)	0.098
HNP	-10.677*(0.00)	0.157
0902.hk	-14.419*(0.00)	0.073
SHI	-10.049*(0.00)	0.062
0338.hk	-10.361*(0.00)	0.107
YZC	-10.109*(0.00)	0.099
1171.hk	-14.221*(0.00)	0.089

KPSS is calculated as LM statistics with critical value 0.7390, 0.463 and 0.347 at 10%, 5%, and 1% levels respectively.

Table 3: Ljung-Box Q statistics for returns and squared returns, respectively distributed as Chi-square statistics with 6 and 12 degrees of freedom

Symbol	Exchange	Q(6)	Q(12)	$Q^2(6)$	$Q^2(12)$
ACH	NYSE	12.99**	15.81	26.54*	49.60*
2600.hk	SEHK	11.54**	20.19***	24.46*	78.80*
LFC	NYSE	10.48	13.21	87.04*	163.05*
2628.hk	SEHK	6.53	8.02	81.74*	95.75*
CHL	NYSE	6.88	10.76	94.35*	179.26*
0941.hk	SEHK	21.94*	31.60*	210.31*	341.12*
CHA	NYSE	3.29	7.18	83.58*	117.22*
0728.hk	SEHK	9.81	12.57	34.44*	83.56*
CEO	NYSE	1.97	3.32	20.03*	43.90*
0883.hk	SEHK	7.77	9.28	17.90*	66.12*
GSH	NYSE	23.98*	36.22*	198.43*	259.87*
0525.hk	SEHK	7.76	15.17	102.96*	174.17*
PTR	NYSE	5.97	14.73	99.02*	222.16*
0857.hk	SEHK	13.41**	16.08	56.84*	103.35*
CHU	NYSE	7.31	11.37	17.39*	38.57*
0762.hk	SEHK	4.54	6.65	28.73*	67.07*
CEA	NYSE	8.86	11.49	73.39*	144.02*
0670.hk	SEHK	9.63	25.62*	98.77*	155.92*
SNP	NYSE	10.59	20.94**	109.52*	126.16*
0386.hk	SEHK	15.87*	18.69***	58.43*	103.74*
ZNH	NYSE	3.52	13.63	71.63*	119.69*
1055.hk	SEHK	5.88	16.36	71.65*	174.19*
HNP	NYSE	8.81*	11.84	150.50*	313.92*
0902.hk	SEHK	18.51*	21.30**	67.00*	223.88*
SHI	NYSE	6.85	11.24	123.89*	294.58*
0338.hk	SEHK	1.57	9.67	204.25*	489.49*
YZC	NYSE	8.11	13.53	24.26*	41.68*
1171.hk	SEHK	9.43	12.10	125.96*	179.82*

Note: * indicates statistical significance at less than 1%, ** indicates statistical significance at less than 5%, *** indicates statistical significance at less than 10%

Table 4: Volatility persistence in an asymmetric conditional heteroskedasticity model TARCH (1, 1) without volume. LL1 and LL2 are the values of likelihood functions for a TARCH and a corresponding EGARCH model respectively; *t*-statistics are inside parentheses.

Symbol	Exchange	ε^2(t-1)	ε^2(t-1)d(t-1)	σ^2(t-1)	LL1	LL2
ACH	NYSE	0.061(7.13)*	0.002(0.39)	0.92(119.2)*	2508	2498
2600.hk	SEHK	0.066(4.74)*	0.039(2.70)*	0.90(59.36)*	2381	2375
LFC	NYSE	0.078(5.97)*	0.007(0.38)	0.909(66.05)*	1733	1730
2628.hk	SEHK	0.16(8.90)*	0.07(2.42)*	0.759(30.70)*	1728	1722
CHL	NYSE	0.052(5.11)*	0.025(1.96)**	0.925(103.66)*	4836	4827
0941.hk	SEHK	0.053(5.43)*	0.05(3.80)*	0.90(84.42)*	4897	4891
CHA	NYSE	0.076(5.49)*	-0.006(-0.33)	0.92(79.39)*	2476	2474
0728.hk	SEHK	0.083(5.67)*	-0.01(-0.70)	0.915(68.9)*	2398	2392
CEO	NYSE	0.073(6.45)*	0.018(1.81)***	0.905(71.63)*	1631	1633
0883.hk	SEHK	0.093(5.05)*	0.007(0.37)	0.89(60.62)*	1562	1564
GSH	NYSE	0.088(8.80)*	0.029(1.89)***	0.89(89.40)*	5659	5645
0525.hk	SEHK	0.15(5.92)*	0.05(1.44)	0.77(32.20)*	5356	5346
PTR	NYSE	0.07(6.04)*	0.009(1.86)***	0.91(82.13)*	3844	3844
0857.hk	SEHK	0.06(5.39)*	0.008(0.78)	0.92(87.43)*	3857	3855
CHU	NYSE	0.047(4.49)*	0.017(1.76)***	0.94(106.61)*	3345	3348
0762.hk	SEHK	0.052(4.75)*	0.027(1.41)	0.92(76.96)*	3435	3437
CEA	NYSE	0.093(24.14)*	0.011(1.83)***	0.90(92.56)*	4674	4662
0670.hk	SEHK	0.10(53.66)*	0.027(2.22)*	0.88(99.39)*	4343	4297
SNP	NYSE	0.069(5.64)*	-0.004(-0.93)	0.91(76.73)*	3466	3465
0386.hk	SEHK	0.065(4.76)*	0.022(1.30)	0.90(62.43)*	3437	3435
ZNH	NYSE	0.07(6.29)*	0.056(2.91)*	0.89(73.12)*	4046	4012
1055.hk	SEHK	0.09(5.22)*	0.07(2.62)*	0.84(46.06)*	3867	3846
HNP	NYSE	0.054(5.53)*	0.037(2.56)*	0.925(108.26)*	4703	4688
0902.hk	SEHK	0.005(5.96)*	0.026(1.85)***	0.935(119.77)*	4251	4231
SHI	NYSE	0.068(6.94)*	0.03(2.39)*	0.90(88.46)*	5947	5945
0338.hk	SEHK	0.082(40.93)*	0.06(3.03)*	0.871(60.56)*	5432	5426
YZC	NYSE	0.05(5.91)*	0.01(0.96)	0.93(99.71)*	3671	3667
1171.hk	SEHK	0.05(5.92)*	0.009(0.66)	0.931(97.47)*	3567	3562
Mean	NYSE	0.068	0.022	0.912		
	SEHK	0.079	-0.0029	0.814		
Maximum	NYSE	0.093	0.056	0.94		
	SEHK	0.16	0.07	0.935		
Minimum	NYSE	0.047	-0.006	0.89		
	SEHK	0.005	-0.01	0.759		
Nos. Significant (+)	NYSE	15 (15)	9 (9)	15 (15)		
	SEHK	15 (15)	7 (7)	15 (15)		

Table 5: Contemporaneous volume-volatility relation test with trading volume; LL1 and LL2 are the values of likelihood functions for a TARCH and a corresponding EGARCH model respectively; *t*-statistics is reported in parenthesis. De-trended volume is multiplied by 10^8.

Symbol	Market	ε^2(t-1)	ε^2(t-1)d(t-1)	σ^2(t-1)	V(t-1) x10^8	LL1	LL2
ACH	NYSE	0.063(11.98)*	0.005(0.49)	0.92(98.83)*	1.50(1.45)	2508	2498
2600.hk	SEHK	0.06(4.72)*	0.03(1.96)**	0.90(59.73)*	-2.37(-0.99)	2381	2375
LFC	NYSE	0.078(4.36)*	0.004(0.36)	0.868(34.00)*	2.41(2.64)*	1733	1730
2628.hk	SEHK	0.11(4.76)*	0.069(1.87)***	0.81(27.63)*	0.0005(0.51)	1728	1722
CHL	NYSE	0.14(4.96)*	0.049(1.85)***	0.60(27.66)*	0.002(26.30)*	4836	4827
0941.hk	SEHK	0.054(5.41)*	0.05(3.78)*	0.85(83.62)*	-0.002(-0.38)	4897	4891
CHA	NYSE	0.076(5.65)*	-0.006(-0.37)	0.921(79.06)*	0.20(0.34)	2476	2474
0728.hk	SEHK	0.078(5.03)*	-0.007(-0.39)	0.915(69.08)*	0.006(1.77)*	2398	2392
CEO	NYSE	0.076(4.95)*	0.02(1.89)***	0.884(54.17)*	5.36(4.15)*	1631	1633
0883.hk	SEHK	0.094(3.40)*	0.007(0.31)	0.85(11.83)***	0.07(12.84)*	1562	1564
GSH	NYSE	0.08(8.43)*	0.03(1.78)***	0.89(83.09)*	1.04(1.28)	5659	5645
0525.hk	SEHK	0.087(6.30)*	0.02(0.58)	0.89(84.92)*	0.06(1.15)	5356	5346
PTR	NYSE	0.07(5.61)*	0.003(1.83)***	0.90(69.93)*	1.82(1.68)***	3844	3844
0857.hk	SEHK	0.05(4.86)*	0.006(0.81)	0.94(93.10)*	0.009(2.52)*	3857	3855
CHU	NYSE	0.045(4.81)*	0.018(1.63)	0.93(102.20)*	0.5(1.61)	3345	3348
0762.hk	SEHK	0.054(4.93)*	0.019(1.31)	0.92(78.35)*	-0.03 (-1.03)	3435	3437
CEA	NYSE	0.07(6.09)*	0.06(2.75)*	0.912(81.34)*	-3.87(-0.43)	4674	4662
0670.hk	SEHK	0.10(5.60)*	0.32(7.14)*	0.89(74.39)*	-0.017(-0.65)	4343	4297
SNP	NYSE	0.029(2.96)*	0.075(2.91)*	0.90(60.60)*	7.44(3.96)*	3466	3465
0386.hk	SEHK	0.11(3.70)*	0.18(3.25)*	0.90(59.80)*	0.009(1.95)**	3437	3435
ZNH	NYSE	0.14(5.29)*	0.047(2.91)*	0.89(71.12)*	14.1(1.73)**	4046	4012
1055.hk	SEHK	0.059(3.03)*	0.08(3.02)*	0.83(53.29)*	0.14(1.53)	3867	3846
HNP	NYSE	0.05(4.42)*	0.038(2.58)*	0.924(97.30)*	2.83(2.42)*	4703	4688
0902.hk	SEHK	0.05(5.94)*	0.02(1.76)***	0.935(96.23)*	-0.005(-0.45)	4251	4231
SHI	NYSE	0.069(6.62)*	0.037(2.49)*	0.89(67.65)*	24.4(2.35)*	5947	5945
0338.hk	SEHK	0.064(5.41)*	0.08(4.34)*	0.87(67.91)*	0.05(2.15)**	5432	5426
YZC	NYSE	0.05(4.73)*	0.01(0.75)	0.928(88.72)*	4.21(2.51)*	3671	3667
1171.hk	SEHK	0.067(5.34)*	0.009(0.62)	0.927(92.37)*	-0.003(-1.18)	3567	3562
Mean	NYSE	0.074	0.027	0.882	4.42		
	SEHK	0.074	0.063	0.887	-0.14		
Maximum	NYSE	0.14	0.075	0.93	24.4		
	SEHK	0.11	0.32	0.94	0.14		
Minimum	NYSE	0.029	-0.006	0.60	-3.87		
	SEHK	0.05	-0.007	0.81	-2.37		
# significant (+)	NYSE	15 (15)	9 (9)	15 (15)	9(9)		
	SEHK	15 (15)	8 (8)	15 (15)	5 (5)		

Table 6: Granger causality between volume and volatility, Granger causality Wald tests are used, and Chi-square statistics with *p*-value in parenthesis are reported.

Symbol	Market	$H_{0:}\ V_t \nrightarrow h_t^2$	$H_{0:}\ h_t^2 \nrightarrow V_t$
ACH	NYSE	57.25(0.00)*	1.83(0.03)**
2600.hk	SEHK	13.72(0.00)*	15.61(0.00)*
LFC	NYSE	64.70(0.00)*	3.25(0.00)*
2628.hk	SEHK	22.39(0.00)*	2.95(0.00)*
CHL	NYSE	53.217(0.00)*	1.18(0.28)
0941.hk	SEHK	12.1(0.000)*	1.48(0.11)
CHA	NYSE	24.97(0.00)*	4.44(0.00)*
0728.hk	SEHK	33.54(0.00)*	1.23(0.25)
CEO	NYSE	18.56(0.00)*	6.63(0.00)*
0883.hk	SEHK	9.02(0.000)*	1.20(0.27)
GSH	NYSE	17.58(0.00)*	6.61(0.00)*
0525.hk	SEHK	11.53(0.00)*	1.39(0.18)
PTR	NYSE	73.67(0.00)*	2.11(0.01)*
0857.hk	SEHK	22.22(0.00)*	1.91(0.02)**
CHU	NYSE	23.31(0.00)*	1.18(0.28)
0762.hk	SEHK	29.68(0.00)*	1.05(0.39)
CEA	NYSE	34.33(0.00)*	5.49(0.00)*
0670.hk	SEHK	20.73(0.00)*	2.16(0.01)*
SNP	NYSE	44.48(0.00)*	1.38(0.16)
0386.hk	SEHK	10.13(0.00)*	1.22(0.26)
ZNH	NYSE	28.51(0.00)*	1.39(0.18)
1055.hk	SEHK	28.57(0.00)*	1.38(0.18)
HNP	NYSE	22.92(0.00)*	5.74(0.00)*
0902.hk	SEHK	19.53(0.00)*	1.03(0.41)
SHI	NYSE	66.72(0.00)*	3.31(0.00)*
0338.hk	SEHK	26.49(0.00)*	1.25(0.25)
YZC	NYSE	19.77(0.00)*	2.31(0.00)*
1171.hk	SEHK	39.97(0.00)*	1.02 (0.40)
Nos. Significant	NYSE	14	10
	SEHK	14	4

Table 7: Determinants of conditional volatility estimates from a bivariate GARCH model

The parameter estimates, A_{11} through B_{22} appear under each ADR are related to the following model without expected and unexpected volumes. We also report the diagnostic test, Portmanteau Autocorrelation Test which computes the multivariate Box-Pierce/Ljung-Box Q-statistics for standardised residual serial correlation up to the order of 12. The critical value of the distribution of χ^2 at 10% with df at 48 is 60.906, 65.15 at 5% level, and 73.68 at 1%.

$$H_{n,t} = M(1,1) + A(1,1) \times \varepsilon^2_{n,t-1} + B(1,1) \times H_{n,t-1} + \epsilon_{n,t}$$

$$H_{h,t} = M(2,2) + A(2,2) \times \varepsilon^2_{h,t-1} + B(2,2) \times H_{h,t-1} + \epsilon_{h,t}$$

$$H_{nh,t} = M(1,2) + A(1,2) \times \varepsilon_{n,t-1} \times \varepsilon_{h,t-1} + B(1,2) \times H_{nh,t-1} + \epsilon_{nh,t}$$

Symbol	A_{11}	A_{12}	A_{22}	B_{11}	B_{12}	B_{22}	Q(12)
ACH	0.053* (12.18)	0.045* (11.81)	0.057* (12.35)	0.939* (214.59)	0.942* (202.79)	0.930* (155.73)	40.59
LFC	0.089* (11.50)	0.095* (11.58)	0.12* (16.57)	0.884* (102.05)	0.863* (82.24)	0.83* (63.63)	53.71
CHL	0.05* (12.31)	0.037* (9.68)	0.056* (13.63)	0.929* (202.52)	0.947* (213.87)	0.924* (154.03)	49.72
CHA	0.06* (11.47)	0.06* (10.37)	0.097* (11.19)	0.926* (151.61)	0.908* (107.09)	0.88* (80.41)	44.78
CEO	0.06* (10.29)	0.05* (8.15)	0.056* (10.05)	0.922* (124.36)	0.935* (156.43)	0.933* (151.29)	58.57
GSH	0.074* (23.06)	0.055* (18.15)	0.057* (20.77)	0.91* (294.37)	0.932* (259.17)	0.936* (377.29)	55.22
PTR	0.069* (16.23)	0.060* (14.46)	0.061* (15.63)	0.913* (159.46)	0.923* (181.63)	0.924* (185.38)	52.39
CHU	0.058* (14.54)	0.051* (10.76)	0.061* (13.85)	0.927* (166.82)	0.919* (122.98)	0.907* (101.56)	58.50
CEA	0.085* (27.62)	0.072* (21.63)	0.087* (17.07)	0.904* (101.15)	0.911* (129.26)	0.901* (128.52)	54.31
SNP	0.073* (12.34)	0.062* (11.84)	0.074* (11.25)	0.901* (107.87)	0.909* (111.09)	0.906* (95.38)	58.65
ZNH	0.078* (17.96)	0.060* (17.80)	0.058* (16.19)	0.907* (175.6)	0.924* (204.92)	0.929* (203.64)	62.12
HNP	0.064* (16.64)	0.051* (14.87)	0.059 (14.13)	0.927* (220.68)	0.938* (254.85)	0.934* (206.40)	58.13
SHI	0.086* (20.98)	0.087* (21.31)	0.104* (21.13)	0.890* (113.62)	0.885* (130.56)	0.875* (121.54)	56.01
YZC	0.052* (13.33)	0.047* (13.79)	0.056* (13.31)	0.939* (227.23)	0.944* (267.59)	0.936* (222.77)	58.02

Table 8: Determinants of conditional volatility estimates from a bivariate GARCH model

The parameter estimates, A_{11} through D_{22} appear in the adjacent column are related to the full model below. we also report the diagnostic test, Portmanteau Autocorrelation Test which computes the multivariate Box-Pierce/Ljung-Box Q-statistics for standardised residual serial correlation up to the order of 12. The critical value of the distribution of χ^2 at 10% with df 48 is 60.906, 65.15 at 5% level, and 73.68 at 1%. Expected volume and unexpected volume are multiplied by 10^{-6}, the covariance of expected volume and the covariance of unexpected volume are multiplied by 10^{-10}.

$$H_{N,t} = M(1,1) + A(1,1) \times \varepsilon^2_{N,t-1} + B(1,1) \times H_{N,t-1} + C(1,1) \times EV_{N,t-1} + D(1,1) \times UV_{N,t-1} + \epsilon_{N,t}$$

$$H_{H,t} = M(2,2) + A(2,2) \times \varepsilon^2_{H,t-1} + B(2,2) \times H_{H,t-1} + C(2,2) \times EV_{H,t-1} + D(2,2) \times UV_{H,t-1} + \epsilon_{H,t}$$

$$H_{hn,t} = M_{12} + A_{12}\varepsilon_{n,t-1}\varepsilon_{h,t-1} + B_{12}H_{hn,t-1} + C_{12}EV_{n,t-1}EV_{h,t-1} + D_{12}UV_{n,t-1}UV_{h,t-1} + e_{hn,t}$$

Symbol	A_{11}	A_{12}	A_{22}	B_{11}	B_{12}	B_{22}	C_{11}	C_{12}	C_{22}	D_{11}	D_{12}	D_{22}	Q(12) (eq1)	Q(12) (eq2)	Q(12) (eq3)
ACH	0.04*	0.042*	0.043*	0.95*	0.921*	0.93*	0.065**	0.005*	-0.003*	0.015*	0.417*	0.068*	57.30	54.57	47.42
	(8.53)	(6.02)	(6.64)	(202.13)	(123.81)	(125.05)	(2.27)	(2.89)	(-2.78)	(2.31)	(2.99)	(3.58)			
LFC	0.057*	0.05*	0.072*	0.89*	0.87*	0.865*	0.057*	0.01*	-0.0001	0.028*	0.007*	0.03*	42.58	40.26	25.35
	(5.28)	(9.11)	(10.87)	(45.08)	(83.7)	(38.13)	(6.77)	(4.31)	(-0.75)	(2.97)	(3.16)	(3.91)			
CHL	0.051*	0.024*	0.059*	0.917*	0.923*	0.90*	0.005*	-0.074	0.027*	0.20*	0.003*	-0.001*	40.62	34.82	32.93
	(10.68)	(9.69)	(12.53)	(183.67)	(196.37)	(137.65)	(4.77)	(-0.62)	(5.70)	(5.81)	(2.75)	(-2.82)			
CHA	0.04*	0.057*	0.081*	0.906*	0.901*	0.85*	0.01*	0.69	0.028	0.11	0.021*	0.0001	59.67	44.78	38.04
	(9.85)	(8.08)	(8.99)	(125.59)	(97.11)	(55.79)	(2.30)	(0.78)	(1.34)	(0.61)	(5.69)	(0.82)			
CEO	0.064*	0.002*	0.05*	0.88*	0.891	0.928*	0.021*	0.67**	0.006	0.0009	0.001**	0.00001	54.87	47.14	42.15
	(6.10)	(2.36)	(8.27)	(49.66)	(62.42)	(116.30)	(3.26)	(1.96)	(0.42)	(0.55)	(1.99)	(0.75)			
GSH	0.072*	0.052*	0.058*	0.903*	0.913*	0.935*	0.235*	-18.34	3.64	0.04	0.52*	0.0007*	48.84	49.05	46.49
	(16.12)	(16.90)	(17.04)	(193.29)	(205.43)	(268.32)	(3.37)	(-0.10)	(0.62)	(0.33)	(6.52)	(3.81)			
PTR	0.068*	0.029*	0.04*	0.90*	0.93*	0.941*	0.03*	0.45***	-0.013	0.032*	0.0005*	0.0001*	41.28	40.70	41.45
	(11.12)	(6.47)	(10.20)	(123.86)	(112.71)	(159.56)	(3.02)	(1.69)	(-0.79)	(1.92)	(2.88)	(5.97)			
CHU	0.045*	0.047*	0.057*	0.932*	0.92*	0.90*	0.007	-0.25*	0.07**	0.044*	0.011*	-0.0001	53.78	47.83	43.48
	(9.31)	(9.55)	(10.46)	(175.84)	(108.03)	(100.1)	(1.56)	(-2.49)	(4.87)	(3.73)	(4.54)	(-0.85)			
CEA	0.085*	0.07*	0.047*	0.90*	0.89*	0.94*	-0.028	119.37*	-0.18	0.18*	0.36*	0.0001	57.30	54.57	47.42
	(14.42)	(13.51)	(14.73)	(61.04)	(135.23)	(71.19)	(-0.68)	(2.91)	(-0.96)	(2.99)	(17.80)	(-0.67)			
SNP	0.068*	0.072*	0.075*	0.88*	0.88*	0.86*	0.07*	1.89***	0.33*	0.04	0.004*	-0.00002	42.32	40.12	43.84
	(8.59)	(8.84)	(9.88)	(77.42)	(57.88)	(43.74)	(3.21)	(1.82)	(4.64)	(1.46)	(4.49)	(-0.74)			
ZNH	0.069*	0.083*	0.055*	0.91*	0.848*	0.911*	0.11**	202.4**	4.75*	0.21	0.83*	0.0007***	56.29	50.45	48.47
	(10.11)	(13.45)	(12.35)	(110.67)	(128.73)	(150.11)	(2.17)	(1.92)	(2.42)	(1.09)	(8.59)	(1.72)			
HNP	0.034*	0.039*	0.04*	0.95*	0.95*	0.954*	0.016*	0.99*	0.10*	0.067*	0.02**	-0.0005	52.32	48.69	46.63
	(13.35)	(12.79)	(10.17)	(206.87)	(198.9)	(196.03)	(2.87)	(0.78)	(7.57)	(3.36)	(2.18)	(-0.53)			
SHI	0.06*	0.055*	0.058*	0.916*	0.929*	0.928*	0.196*	6.91	0.833*	0.33**	0.29*	-0.0004	52.01	44.97	48.25
	(17.21)	(19.73)	(20.23)	(132.96)	(117.31)	(116.36)	(2.89)	(0.72)	(2.58)	(2.12)	(4.99)	(-0.35)			
YZC	0.044*	0.045*	0.053*	0.946*	0.946*	0.942*	0.023*	-0.187*	0.026	0.036**	0.054*	-0.0005	48.84	49.05	46.49
	(12.12)	(7.75)	(12.96)	(215.09)	(161.83)	(197.04)	(2.58)	(-0.39)	(1.34)	(2.38)	(2.88)	(-0.90)			