Iranian Economic Review, Vol.13, No.21, Spring 2008

Interactions of returns and volatilities among different sizes of stocks: a Survey in Tehran Stock Exchange

Ezatollah Abbasian*
Vahid Abbasion**
Mehdi Moradpour Oladi***

Abstract

This paper investigates return and volatility spillover effects between the small, medium and large size firms using the multivariate GARCH framework (By size we mean a company's value on the stock market: the number of shares it has outstanding multiplied by the share price. This is known as market capitalization, or cap size). Using the monthly data from January 1995 to March 2006, we find that return and volatility transmission mechanisms between large and small firms in Tehran Stock Exchange market are asymmetric. In particular, there are significant spillover effects in returns from the portfolio of smaller stocks to the portfolio of larger stocks. For volatility, there is also evidence of limited feedback from the portfolios of smaller stocks to the portfolios of larger stocks.

Keywords: Return and Volatility Spillovers, Multivariate GARCH, VAR Analysis, IRF

---

* Assistant Professor in Economics, Department of Economics, Bu–Ali Sina University, Hamedan, Iran.E-mail: *Abbasian*@basu.ac.ir
** Master in Financial Management. Email: *V_Abbasion@Yahoo.com*
*** Master in Economics. Email: *Mehdi_Moradpour@Yahoo.com*

1- Introduction

This study, benefits from the existing literature by focusing on the dynamic relationships (transmission mechanisms) in returns and the volatilities of the returns in Tehran stock market. However, the transmission mechanisms which underpin the correlations have been more difficult to identify.

Transmission mechanisms between the returns and volatilities of different stocks are important for a number of reasons. Firstly, transmission mechanisms tell us something about market efficiency. In an efficient market, and in the absence of time-varying risk premia, it should not be possible to forecast the returns of one stock using the lagged returns of another stock. The finding that there are spillover effects in returns implies the existence of an exploitable trading strategy and, if trading strategy profits exceed transaction costs, potentially represents evidence against market efficiency. Secondly, transmission mechanisms may be useful for portfolio management, where knowledge of return spillover effects may be useful for asset allocation or stock selection. Thirdly, information about volatility spillover effects may be useful for applications in finance that rely on estimates of conditional volatility, such as option pricing, portfolio optimization, value at risk and hedging.

Many previous studies have documented that the returns of large and small stocks in the US stock market are cross-correlated[1]. Moreover, a number of these studies show that these cross-correlations are asymmetric: the returns of small stock portfolios tend to be correlated with the lagged returns of large stock portfolios, while the returns of large stock portfolios tend to be uncorrelated with the lagged returns of small stock portfolios. Lo and Mac Kinlay (1990a, 1990b) rule out non-synchronous trading as an explanation since implausible levels of non-synchronous trading are required to generate the size of the cross-correlations that exist in practice. A number of other explanations have therefore been proposed.

1- See, for example, Lo and MacKinlay (1990a, 1990b), Boudoukh, Richardson and Whitelaw (1994), Mech (1993), Badrinath, Kale and Noe (1995), McQueen, Pinegar and Thorley (1996) and Campbell, Lo and MacKinlay (1997, pages 74-78).

Mech (1993) suggests that asymmetry in the cross-correlation between returns on large and small stocks is due to transaction costs, and shows that the speed of price adjustment is associated with the standard deviation of returns and the bid-ask spread.

Chan (1993) suggests that differences in signal quality between large and small stocks induce asymmetry in their cross correlations. In particular, if the signal quality of large stocks is assumed to be better than that of small stocks, the covariance of the current returns of small stocks with the lagged returns of large stocks is larger than the covariance of the current returns of large stocks with the lagged returns of small stocks. Some studies (for example, Grinblatt, Titman and Wermers, 1995; Keim and Madhavan, 1995) argue that asymmetric spillover effects in the returns of large and small stocks are related to asymmetric trading patterns and the behavior of institutional investors.

Conrad, Gultekin and Kaul (1991) show that the same asymmetry that exists in the

Transmission of short horizon returns between large and small stocks in the US also exists in the transmission of volatility. They find that volatility shocks to large stocks are important for the future volatility of small stocks, but that volatility shocks to smaller stocks have little or no impact on the future volatility of large stocks. As with the results for return spillovers, simulation evidence suggests that the observed spillover effects in volatility are not caused by non-synchronous trading. Conrad, Gultekin and Kaul (1991) note that since stock price volatility is directly related to the rate of flow of information to the market (see Ross, 1989), the asymmetry in volatility spillovers between large and small stocks is consistent with a market in which the prices of large stocks respond to new information immediately, but the prices of small stocks respond with a lag. This explanation is supported by McQueen, Pinegar and Thorley (1996), who show that small stocks display a delayed reaction compared to large stocks when news reaches the market. Using longer horizon returns, Hasan and Francis (1998) also find that there are volatility spillovers between small and large stocks in the US, but in contrast with Conrad Gultekin and Kaul (1991), they find that these spillovers are approximately symmetric, acting both from large stocks to small stocks, and from small stocks to large stocks.

This paper investigates the return and volatility transmission mechanisms between large, small and medium cap firms in Tehran stock market using the monthly data from January 1995 to March 2006. We investigate these transmission mechanisms using the multivariate ARMA (1, 0)-GARCH (1, 1)-M model. The ARMA(1,0) process for returns is parsimonious which is selected by the Schwartz Bayesian Criterion (SBC). We model the spillover effects by introducing into the mean and variance equation for each group, the lagged shocks to the returns and volatilities of the other two groups.

Our results show that there are strong return transmission mechanisms between small and large stocks in Tehran stock market. Furthermore, consistent with the results of other studies for the US, we find that these return spillover effects are asymmetric. In particular, there are very significant return spillovers from the portfolios of small stocks to the portfolios of large stocks. For volatility, there aren't any spillovers from the portfolios of small stocks to the portfolios of large stocks.

The remainder of the paper is organized as follows. The following section gives details of the empirical methodology. Section 3 describes the data that we use in the study. Section 4 reports the results and section 5 offers a summary and conclusion.

2- Methodology

Two main approaches employed in this paper are the multivariate ARMA-GARCH-M model and the VAR model. The econometric part of the article uses the causality-in-variances GARCH model and VAR analysis to model conditional volatilities in stock market returns and the dynamic responses of volatilities to innovations in conditional variances.

2-1- The multivariate ARMA(1,0)-GARCH(1,1)-M model

The multivariate ARMA(1,0)-GARCH(1,1)-M specification used in this study can be written as:

$$R_{i,t} = \beta_{i,0} + \gamma_i h_{i,t} + \beta_{i,1} R_{i,t-1} + \epsilon_{i,t} \tag{1}$$

$$h_{ii,t} = c_{ii} + \delta_{ii} h_{ii,t-1} + \alpha_{ii} \epsilon^2_{i,t-1} \tag{2}$$

$$h_{ij,t} = \rho_{ij}(\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}) \qquad ; \text{for all } i, j = 1\ldots3 \text{ and } i \neq j, \qquad (3)$$

Where $R_{i,t}$ is a one period return of portfolio i at time t, $\in_{i,t}$ is a residual term of portfolio i and $\in_t|\psi_{t-1} \sim N(0, H_t)$, $h_{ii,t}$ is a conditional variance of $R_{i,t}$ given a set of all information available at time t-1 (ψ_{t-1}), $h_{ij,t}$ is a conditional covariance between $R_{i,t}$ and $R_{j,t}$ given a set of all information available at time t-1 (ψ_{t-1}), H_t is a conditional covariance matrix ($H_t = [h_{ij,t}]$), ρ_{ij} is a conditional correlation coefficient of $R_{i,t}$ and $R_{j,t}$. Equation 1 models a return as an ARMA(1,0) process with a GARCH-M term. The ARMA(1,0) process for returns is parsimonious which is selected by the Schwartz Bayesian Criterion (SBC). The GARCH-M term captures a response of a return to its time-varying risk premium. The conditional variance ($h_{i,t}$) in equation 2 is a function of its past squared residuals and conditional variances. To ensure that the conditional variance is non-negative and the process is stationary, it is necessary to assume that c_{ii}, δ_{ii}, α_{ii}, ≥ 0 and $\delta_{ii} + \alpha_{ii} < 1$ (or $\delta_i + \alpha_i = 1$ in the case of IGARCH). A number of studies have shown that the GARCH(1,1) specification is adequate to model conditional variances of stock returns[1]. Furthermore, in practice, a high order of the multivariate GARCH(r,m) is difficult and complicate to estimate. Equation 3 restricts the conditional covariance between $R_{i,t}$ and $R_{j,t}$ to be proportional to the product of the conditional standard deviations. Thus, the conditional correlation coefficient of $R_{i,t}$ and $R_{j,t}$ is constant. Hence, this multivariate GARCH approach is so called the Constant Correlation (CCORR) model.

The advantage of using the multivariate approach is that it estimates the ARMA-GARCH-M model for all returns simultaneously. Hence, it utilizes the information in the entire variance-covariance matrix of the errors. The estimation of the parameters in the models is therefore more precise. In addition, since all parameters are estimated jointly, this approach avoids the *generated regressor* problem associated with the univariate approach.[2]

1- See Bollerslev (1987), French, Schwert and Stambaugh (1987), Akgiray (1989), Schwert and Seguin (1990), Conrad et al (1991) and Bollerslev, Chou and Kroner (1992).

2- See Conrad et al (1991).

To address an issue of transmission mechanisms of returns and volatilities, exogenous variables will be introduced into returns and conditional variances to capture potential return and volatility spillovers across large, medium and small size groups. To model return spillovers from index *j* to index *i*, past returns of each index *j* are separately added into the return of an index *i*. Also, past squared residuals of each index *j* are separately added into the conditional variance of an index *i* to capture volatility spillovers from index *j* to an index *i*.

$$R_{i,t} = \beta_{i,0} + \gamma_i h_{i,t} + \beta_{i,1} R_{i,t-1} + w_{i,j} R_{j,t-1} + \in_{i,t} \quad (4)$$

$$h_{ii,t} = c_{ii} + \delta_{ii} h_{ii,t-1} + \alpha_{ii} \in^2_{i,t-1} + z_{i,j} \in^2_{j,t-1} \quad ; i, j = 1…3 \text{ and } i \neq j \quad (5)$$

where $w_{i,j}$ and $z_{i,j}$ measure the *partial* impacts of the return and volatility spillovers from index *j* to an index *i* respectively.

The *simultaneous* effects can also be estimated by including return and volatility spillovers from index *j* to the return and conditional variance of an index *i* respectively in the same time.

$$R_{i,t} = \beta_{i,0} + \gamma_i h_{i,t} + \beta_{i,1} R_{i,t-1} + \sum_{j=1, j\neq i}^{3} w_{i,j} R_{j,t-1} + \varepsilon_{i,t} \quad (6)$$

$$h_{ii,t} = c_{ii} + \delta_{ii} h_{ii,t-1} + \alpha_{ii} \varepsilon^2_{i,t-1} + \sum_{j=1, j\neq i}^{3} z_{i,j} \varepsilon^2_{j,t-1} \quad ; i, j = 1…3 \text{ and } i \neq j \quad (7)$$

Where $w_{i,j}$'s measure the joint impacts of the return spillovers from index *j* to an index *i*, while $z_{i,j}$'s capture the joint impacts of the volatility spillovers from index *j* to an index *i*.

The optimization technique used to estimate the ARMA-GARCH-M model is the Quasi-maximum likelihood estimation since the maximum likelihood estimation under the assumption of conditional normality can be quite restrictive and the tails of even conditional distributions often seem to be fatter than those of the normal distributions. However, the Quasi-maximum likelihood estimator (QMLE) is generally consistent and the related test statistics are valid under non-normality.[1]

1- See, for example, Bollerslev (1987), Bollerslev and Wooldrige (1992) and Glosen, Jagannathan and Runkle (1993).

It is worth to say, that there is some empirical works which use from ARMA-GARCH model to analyze the other aspects of Stock Exchange market behavior. For example, TANG Him John, CHIU K C, XU Lei.(2003), Finite Mixture of ARMA-GARCH Model for Stock Price Prediction, paper presented in the In Proc. of 3rd International Workshop on Computational Intelligence in Economics and Finance(CIEF) of 7th Joint Conference on Information Sciences, North Carolina, USA, Sep. 26-30, 2003, 1112-1119 pgs. In this paper, the authors derive a GEM algorithm for the mixture of ARMA-GARCH model. Its relative empirical performance in stock price prediction against the conventional ARMA-GARCH and mixture of AR-GARCH model is investigated. Results reveal that both mixture models outperform the conventional ARMA-GARCH model, with the best results obtained by the mixture of ARMA-GARCH model.

2-2- The VAR analysis

A p^{th} -order VAR in standard form of returns (conditional variances) can be written as:

$$x_t = A_0 + \sum_{i=1}^{p} A_i x_{t-i} + e_t \qquad (8)$$

Where x_t is a (3×1) vector of returns (conditional variances), A_0 is a (3×1) vector of constants, A_i are (3×3) matrices of coefficients, e_t is a (3×1) vector of residuals (e_t ~ i.i.d. $N\ (0,\sigma_t^2)$). In addition, the VAR model such equation 8 can also be written as a Vector Moving Average (VMA).

$$x_t = \mu + \sum_{i=0}^{p} A_1^i e_{t-i} \qquad (9$$

In fact, VAR residuals, e_t, are shocks to variables in the system, and they are serially uncorrelated by construction. However, the components of e_t may be contemporaneously correlated. They can be orthogonalized into a set of uncorrelated residual components (structural VAR residuals) by using the Choleski Decomposition. In other words, equation 9 can be transformed to:

$$x_t = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i} \tag{10}$$

Where ε_t is a (3×1) vector of structural VAR residuals? Equation 10 shows responses of each return (conditional variance) in the system to the time paths of its own structural shock vs. shocks to the other returns (conditional variances). The responses are measured as ϕ_i, and the sets of ϕ_i are so called Impulse Response Functions (IRFs). Plotting the IRFs is a practical way to visualize the responses.

3- Data Description

The data used in this paper is monthly stock returns from January 1995 to March 2006 for Tehran Stock Exchange. According to the market capitalization, three portfolios including the large, medium and small size firms are defined. All firms with market capitalization less than 0.1 percent of total market are included in portfolio I where the firms with market capitalization between 0.1 and 0.5 percent of total market are included in portfolio II and the rest (market capitalization is more than 0.5 percent of total market) go to portfolio III[1]. Firstly, we use the multivariate ARMA-GARCH-M model and secondly adopt the VAR model to investigate the transmission mechanisms between large versus small stocks. The VAR model is alternative approach to the ARMA-GARCH model and has been widely used for examining dynamic relations among the multiple time-series. Unlike the ARMA-GARCH model, the VAR model allows us to trace out the time-path of impacts of shocks to each variable in a system on all variables in the system without adding some extra exogenous variables to capture spillover effects as using the ARMA-GARCH model. Furthermore, it has been shown by some studies that transmission mechanisms between assets persist for many periods.[2] Hence, the VAR model is suitable to be

---

1- Keep in mind that classifications such as "large cap" or "small cap" are only approximations that change over time. Also, the exact definition can vary between brokerage houses. In the Tehran Stock Exchange market most brokers and dealers prefer to use proportions (as is employed in this paper) to define market capitalization.

2- See, for example, Chan, Chan, Karolyi (1991), Wen-Ling Lin (1996) and Tay and Zhu (2000).

used to examine the transmission mechanisms with long lags, whereas it would be difficult and complicate to estimate using the ARMA-GARCH model.

Table 1 shows preliminary statistics of all portfolios returns. In addition, the distributions of the returns are not normal since the return series of each portfolio exhibit significant skewness and kurtosis.

Table 1: Preliminary statistics of the returns

Portfolio	Mean	Variance	Skewness	Kurtosis	No. of obs.
I	0.0218	0.0295	1.0048	5.2160	132
II	0.0295	0.0413	0.4537	3.1573	132
III	0.0332	0.0621	1.5127	7.3095	132

Table 2 indicates the significant autocorrelations in all the returns and the squared returns with the exception of the case of the large return. The autocorrelations in the returns may be due to some form of market inefficiency, whereas the autocorrelations in the squared returns can be captured by the ARCH and GARCH models.

Table 2: A test of autocorrelations in the returns (R_t) and the squared returns (R_t^2)

ρ_t	R_t			R_t^2		
	I	**II**	**III**	**I**	**II**	**III**
ρ_1	0.394**	0.397**	0.478**	0.277**	0.211*	0.321**
ρ_2	0.262**	0.236**	0.224**	0.272**	0.142*	0.079**
ρ_3	0.265**	0.253**	0.237**	0.151**	0.120*	0.095**
ρ_4	0.353**	0.275**	0.262**	0.221**	0.125*	0.146**
ρ_5	0.225**	0.132**	0.270**	0.187**	0.043*	0.104**
ρ_6	0.200**	0.154**	0.196**	0.179**	0.006*	0.021**

ρ_t is the autocorrelation coefficient at lag t. Ljung-Box statistic is utilised to test the hypothesis that autocorrelations of the returns and squared returns up to lag t are jointly zero. (*) indicates significance at the 5% level, while (**) indicates significance at the 1% level.

Table 3 exhibits the lead-lag relationship of the returns and the squared returns. The lag (lead; given by negative lag) refers to the number of periods II lag (lead) III in the first column, I lag (lead) III in the second column and I lag (lead) II in the third column. For the returns, the LB test shows a feedback relation between III's return and II's return and a feedback relation between II's return and I's return. Although there is a feedback relation between III's return and I's return, the impact of III's on I's is much stronger than the opposite direction. For the squared returns, the test shows that cross-correlations in the squared returns are all significant. Thus, this suggests strong linkages in the second moment of the returns of these portfolios in mutual directions. It is worth to say that, according to the results, all variables are stationary at the 1% significance level.

Table 3: Cross-correlations in the returns (R_t) and the squared returns (R_t^2)

Lag	II & III		I & III		I & II	
	R_t	R_t^2	R_t	R_t^2	R_t	R_t^2
-3	0.1893*	0.1301*	0.2895*	0.0858*	0.3041*	0.2309*
-2	0.1311*	0.2191*	0.1952*	0.0832*	0.2621*	0.1902*
-1	0.3735*	0.1647*	0.3108*	0.2812*	0.4101*	0.1622*
0	0.7060*	0.6459*	0.3221*	0.1427*	0.5551*	0.2937*
1	0.3867*	0.1733*	0.2080*	0.0764*	0.2289*	0.2873*
2	0.1886*	0.0001*	0.0863*	0.0718*	0.1489*	0.1401*
3	0.3075*	0.0833*	0.1117*	0.1013*	0.2251*	0.1948*

Ljung-Box statistic is utilised to test the hypothesis that cross-correlations of the returns and the squared returns are jointly zero up to lag t. (*) indicates significance at the 5% level, while (**) indicates significance at the 1% level.

4. Empirical Results

Table 5 reveals the estimate results of the multivariate ARMA (1,0)-GARCH(1,1)-M model for returns. In general, the results provide strong evidence that this specification is adequate to model returns and conditional variances of all three portfolios. Considering the mean return equation, the first lagged returns of medium and small size groups significantly predict their own current returns, where the first lagged return of large almost significantly explains its own current return at the 5% level. The γ corresponding to each portfolio indicates no response of each return to its own time-varying risk (a conditional variance). Turning to the conditional variance equation, δ and α of all conditional variances are strongly significant and, the sums of $\delta + \alpha$ are under unity. This suggests the strong degree of persistence in the conditional variances and confirms that the conditional variances follow a stationary process.

Table5: The multivariate ARMA(1,0)-GARCH(1,1)-M model for the returns on

Portfolio	β_0	γ	β_1	c	δ	α
1	0.01070	0.00000092	0.03752	-0.00253	0.00000105	0.00002678
2	0.01661	0.0000012	0.14582	-0.00052349	0.00000308	0.00009985
3	0.01449	0.00000103	0.43590	0.00228	0.000000503	0.00002435

The model is

$$R_{i,t} = \beta_{i,0} + \gamma_i h_{i,t} + \beta_{i,1} R_{i,t-1} + \in_{i,t}$$

$$h_{ii,t} = c_{ii} + \delta_{ii} h_{ii,t-1} + \alpha_{ii} \in^2_{i,t-1} \qquad ; \text{for all i, j} = 1 \ldots 3 \text{ and } i \neq j$$

where Port. 1, 2 and 3 = the portfolios of small (I), medium(II) and large(III) firms respectively.

Table 6 reports the simultaneous estimates of return and volatility spillovers across large, medium and small size groups using the multivariate ARMA(1,0)-GARCH(1,1)-M model as in equations 6 and 7. For return spillovers, the results show that small firms' returns are important in predicting the future dynamics of larger firms' returns rather than the opposite direction. There is strong evidence of uni-directional return spillovers from small to large and from large to medium size groups. In contrast, there is no evidence of return spillovers from large to small and from medium to large size groups in turn. Turning to volatility spillovers, the results show no direction of volatility spillovers between large, medium and small size firms. Thus, the results of table 6 tend to weaken the evidence of the asymmetry in the predictability of the returns and volatilities of the small vs. large firms.

Table 6: Estimates of simultaneous return and volatility spillovers at lag 1 using the multivariate ARMA (1,0)-GARCH(1,1)-M model

Return spillovers	$R_{1,t}$	$R_{2,t}$	$R_{3,t}$
$R_{1,t-1}$	0.25238	0.05598	0.10580
$R_{2,t-1}$	0.15415	0.22061	0.05826
$R_{3,t-1}$	0.03752	0.14582	0.43590
Volatility spillovers			
$\in^2_{1,t-1}$	2.73E-11	-4.76E-11	-4.38E-11
$\in^2_{2,t-1}$	-1.4E-12	1.11E-10	1.91E-10
$\in^2_{3,t-1}$	1.25E-11	4.81E-11	2.50E-11

The numbers in this table are the coefficients of returns and volatility spillovers across all portfolios.

Turning to the VAR analysis, we first estimate VAR models for the returns of large, medium and small size groups. Using the Schwartz Bayesian Criterion (SBC), the VAR model with one lag is chosen as a parsimonious specification for modeling the returns. Once the VAR systems for the returns are estimate, we then conduct the dynamic analyses of IRFs.

Table 7: The Variance decompositions of returns (IRF)

A. Percentage of the returns of small size firms explained by shocks to the returns of:					
	Lag				
	1	5	10	20	26
Portfolio I	0.36349	0.05754	0.00993	0.00030078	0.00003690
Portfolio II	0.20525	0.4205	0.00719	0.00021756	0.00002669
Portfolio III	0.05173	0.03868	0.00688	0.00020835	0.00002556
B. Percentage of the returns of medium size firms explained by shocks to the returns of:					
	Lag				
	1	5	10	20	26
Portfolio I	0.22716	0.0703	0.01237	0.00037465	0.00004596
Portfolio II	0.29934	0.05138	0.00895	0.00027099	0.00003324
Portfolio III	0.16772	0.04931	0.00857	0.00025952	0.00003183
C. Percentage of the returns of large size firms explained by shocks to the returns of:					
	Lag				
	1	5	10	20	26
Portfolio I	0.25566	0.0940	0.01646	0.00049854	0.00006115
Portfolio II	0.12718	0.06735	0.01191	0.00036060	0.00004423
Portfolio III	0.45507	0.06669	0.01141	0.00034533	0.00004236

5. Summary and concluding results

In this paper, we investigate return and volatility spillover effects between large, medium and small stocks in Tehran Stock Exchange market using the multivariate ARMA(1,0)-GARCH(1,1)-M model. This approach seems particularly attractive in predicting future returns, especially when previous returns of specific size groups of firms in the financial market are known. One interesting observation about the collected variables used in the study is that the average return (3.32%) and standard deviation (0.08%) of large size firms are higher than of small and medium size firms. The autocorrelation between returns is weak for all groups and the highest autocorrelation exists with the one lag period.

The highest cross correlation is between large and medium size groups for the leads. However, the correlation between small and medium size groups is higher than the others for the lags.

According to the Dickey-Fuller test, all variables are stationary at the 1% significance level. In this study, we used a multivariate ARMA (1, 0)-GARCH (1, 1)-M model to predict future returns and estimate volatility. Our results indicate that in each size group, the return is a function of one lag return and this relation is positive.

We find that the returns of small firms are important in predicting the future dynamics of large firms, but that the returns of larger stocks have much less impact on the future dynamics of smaller stocks. The results are potentially useful for a range of applications in finance that rely on forecasts of returns.

References

1- Aggarwal, R., C. Inclan, and R. Leal (1999), 'Volatility in Emerging Stock Markets', Journal of Financial and Quantitative Analysis, Vol. 34, No. 1, pp. 33-55.

2- Badrinath, S.G., J.R. Kale, and T.H. Noe (1995), 'Of Shepherds, Sheep and the Cross-Autocorrelations in Equity Returns', Review of Financial Studies, Vol. 8, No. 2, pp. 401-430.

3- Bae, K.-H., and G.A. Karolyi (1994), 'Good News, Bad News and International Spillovers of Stock Return Volatility between Japan and the U.S.', Pacific-Basin Finance Journal, Vol. 2, pp. 405-438.

4- Bollerslev, T. (1990), 'Modelling the Coherence in Short Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model', Review of Economics and Statistics, Vol. 72, pp. 498-505.

5- Bollerslev, T., R.Y. Chou, and K.F. Kroner (1992), 'ARCH Modelling in Finance: A Review of Theory and Empirical Evidence', Journal of Econometrics, Vol. 52, pp. 5-59.

6- Bollerslev, T. and J. Wooldridge (1992), 'Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances', Econometric Reviews, Vol. 11, pp. 143–172.

7- Boudoukh, J., M. Richardson, and R. Whitelaw (1994), 'A Tale of Three Schools: Insights on Autocorrelations of Short-Horizon Returns', Review of Financial Studies, Vol. 7, pp. 539-573.

8- Campbell, J., A. Lo and A. MacKinlay (1997), The Econometrics of Financial Markets, Princeton University Press, New Jersey.

9- Chan, K. (1993), 'Imperfect Information and Cross-autocorrelation among Stock Prices' Journal of Finance, Vol. 48, pp. 1211-1230.

10- Conrad, J., M. Gultekin, and G. Kaul (1991), 'Asymmetric Predictability of Conditional Variances', Review of Financial Studies, Vol. 4, pp. 597-622.

11- Draper, P., and K. Paudyal (1997), 'Microstructure and Seasonality in the UK Equity Market', Journal of Business Finance and Accounting, Vol. 24, pp. 1177-1204.

12- Engle, R.F., and K.F. Kroner (1995), 'Multivariate Simultaneous Generalized ARCH', Econometric Theory, Vol. 11, No. 1, pp.122-150.

13- Engle, R.F., and V.K. Ng (1993), 'Measuring and Testing the Impact of News on Volatility', Journal of Finance, Vo. 48, No. 5, pp. 1749-1778

14- Glosten, L., R. Jagannathan, and D. Runkle (1993), 'Season Patterns in the Volatility of Stock Index Excess Returns', Journal of Finance, Vol. 48, pp. 1779-1801.

15- Grinblatt, M., S. Titman, and R. Wermers (1995), 'Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior', American Economic Review, Vol. 85, pp. 1088-1105.

16- Hamao, Y., R.W. Masulis, and V.K. Ng (1990), 'Correlations in Price Changes and Volatility across International Stock Markets', The Review of Financial Studies, Vol. 3, No. 2, pp. 281-307.

17- Hasan, I., and B.B. Francis (1998), 'Macroeconomic Factors and the Asymmetric Predictability of Conditional Variances', European Financial Management, Vol. 4, No. 2, pp. 207-230.

18- Hung, M.W., C.F. Lee, and L.C. So (2003), 'The Impact of Foreign-listed Single Stock Futures on the Domestic Underlying Stock Markets', Applied Economics Letters, Vol. 10, No.9, pp. 567-574.

19- Keim, D., and A. Madhavan (1995), 'Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders', Journal of Financial Economics, Vol. 37, pp. 371-398.

20- Kroner, K., and V.K. Ng (1998), 'Modeling Asymmetric Comovement of Asset Returns', Review of Financial Studies, Vol. 11, No. 4.

21- Lakonishok, J., and S. Smidt (1988), 'Are Seasonal Anomalies Real?: A Ninety Year Perspective', Review of Financial Studies, Vol. 1, pp. 403-425.

22- Lo, A. W., and A. C. MacKinlay (1990a), 'An Econometric Analysis of Nonsynchronous Trading', Journal of Econometrics, Vol. 45, pp. 181-211.

23- Lo, A. W., and A. C. MacKinlay (1990b), 'When are Constrarian Profits due to Shock Market Overreaction?', Review of Financial Studies, Vol. 3, pp. 175-205.

24- McQueen, G., M. Pinegar, and S. Thorley (1996), 'Delayed Reaction to Good News and the Cross-Autocorrelation of Portfolio Returns', Journal of Finance, Vol. 51, No. 3, pp. 889-919.

25- Mech, T. (1993), 'Portfolio Autocorrelation', Journal of Financial Economics, Vol. 34, pp. 307-44.

26- Ng, V.K., R.P. Chang and R. Chou (1991), 'An Examination of the Behavior of International Stock Market Volatility, in: S. Ghon Rhee and Rosita P. Chang, eds.', Pacific-Basin Capital Market Research, Vol. 2 (North-Holland, Amsterdam), Pp. 245-260.

27- Roll, R. (1988), 'The International Crash of October 1987', Financial Analysts Journal, September-October, pp. 19-35.

28- Ross, S.A. (1989), 'Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy', Journal of Finance, Vol. 44, pp. 1-7.

29- Schwert, G.W. (1990), 'Stock Volatility and the Crash of '87', The Review of Financial Studies, Vol. 3, No. 1, pp. 77-102.

30- Sharpe, W.F. (Sept. 1964), 'Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk', Journal of Finance, pp. 425-442.

31- TANG Him John, CHIU K C, XU Lei.(2003), Finite Mixture of ARMA-GARCH Model for Stock Price Prediction, paper presented in the In Proc. of 3rd International Workshop on Computational Intelligence in Economics and Finance(CIEF) of 7th Joint Conference on Information Sciences, North Carolina, USA, Sep. 26-30, 2003, 1112-1119 pgs.

32- Thedossiou, P. and U. Lee (1993), ‘Mean and Volatility Spillovers across Major National Stock Markets: Further Empirical Evidence’, Journal of Financial Research, Vol. 16, No. 4, pp. 337-350.

33- Tinic, S. M. and R.R. West (1984), ‘Risk and Return: January vs the Rest of the Year’, Journal of Financial Economics, Vol. 13, pp. 561-74.

34- Wang, S.S., O.M. Rui, and M. Firth (2002), ‘Return and Volatility Behavior of Dually-traded Stocks: the Case of Hong Kong’, Journal of International Money and Finance, Vol. 21, pp.265-293.

35- White, H., 1982, “Maximum Likelihood Estimation of Misspecified Models”, Econometrica 50, 1-25.