A TIME SERIES ANALYSIS OF THE SHANGHAI AND NEW YORK STOCK PRICE INDICES

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Abstract: A time series analysis of the Shanghai and New York Stock Exchange composite price indices is provided to compare the weekly rates of return and volatilities of these two markets and to study their co-movement in 1992-2002. The rate of return and volatility of the Shanghai market were higher. The rates of returns in the two markets were approximately serially uncorrelated and mutually uncorrelated. Volatility, as measured by the absolute change in the rate of return, has positive serially correlations in both markets as expected, but the autoregressions are temporarily unstable. Most surprisingly the volatility measures of the two markets are significantly negatively correlated. Volatility in each market was found to Granger cause volatility in the other market negatively. This spurious correlation is explained by the negative correlations of macroeconomic fundamentals in the United States and China as indicated by a negative correlation between the rates of change in their GDP while their capital markets are not integrated. The analysis has implications for the use of autoregressions and Granger causality tests, and the interpretation of spurious correlation.

KEY WORDS: Time series analysis; Rate of return; Volatility; Autogressions; Granger causality; Spurious correlation; Shanghai stock price; New York stock price.

The purpose of this paper is to study the characteristics of the Shanghai and New York stock price indices comparatively and in relation to each other. The Shanghai stock market was established only in 1992 in the context of a rapidly growing developing economy (Chow, *et.al.*1999). It would be of interest to examine the characteristics of the movement of its price index in terms of the rate of return, its volatility and possible structural changes in the movements. Such characteristics would be especially interesting in comparison with the corresponding characteristics of the price index of the New York Stock Exchange as they can reveal the nature of stock price movements in an emergent market.

World economic integration is a main theme in the historical development of the 21st century. This study is concerned with one aspect of the integration between the U. S. and the Chinese economies, namely the co-movement of the stock prices in New York and Shanghai. It provides a set of measures of the degree to which the Chinese economy is integrated with the world economy. The Chinese economy is known to be integrated with the world economy in terms of trade flows. In 1999, the total value of imports and exports amounted to 36.5 percent of China's Gross Domestic Product (see Tables 3-1 and 17-1 of *China Statistical Yearbook 2000*). It is also understood that the capital market of China is less open. Our study provides a measure of openness of the Chinese capital market.

The rate of return and the volatility of the price indices are the two variables to be examined. As usual, the rate of return is measured by the change in the natural logarithm of the price index in a given period. Unlike most studies of stock price movements, volatility is measured by the absolute value of this change rather than by its variance. One advantage of using the absolute value is that the results are less sensitive to extreme values of the data, as compared with using ARCH-type models to study the residual variance of a time series model. In this paper we study the volatility of the rate of return itself, and not of the residual in a time series model of the rate of return. This choice was made for two reasons. First, the volatility of the rate of return itself, and not of the residual in a regression of the rate of return, is often the subject of interest in finance. Secondly, since log stock price behaves approximately as a random walk, or the rate of return is approximately serially independent, as is generally known and is seen later in this study, the rate of return itself and the residual of an autoregression of this rate are almost the same. We have chosen weekly observations of the rate of return and its volatility for analysis. Monthly observations would fail to reveal the finer or high-frequency movements. Daily data are noisy and create problems due to the difference in trading times of about half a day (depending on whether the United States is on day light saving time) and to the suspension of trade during weekends and special holidays. The use of weekly data appears to be a reasonable choice.

To characterize each market, we use the mean and variance of the rate of return, and mean and variance of the above measure of volatility. Both the variance of the rate of return and the mean of the absolute change in log price are measures of volatility. One can expect and casual observations reveal that Shanghai stock prices are more volatile than New York stock prices. This may reflect a higher degree of uncertainty on the part of the investors of Shanghai stocks regarding their future profitability. To examine the co-movements of the two price indices, we will use simple correlations and multiple regressions. The multiple regressions include autoregressions and regressions on both own-lagged values and on the current and lagged values of the corresponding variable for the other stock index. The last set of variables is used to test for Granger causality. In addition we study possible structural breaks in these regressions. Section 1 characterizes the two indices separately. Section 2 is concerned with their contemporaneous covariance. Section 3 presents multiple regressions on the rate of return, while section 4 presents multiple regressions on volatility as measured by the absolute value of the rate of return. Section 5 concludes.

1. Rate of Return and Volatility of Shanghai and New York Stock Price Indices

The two stock price indices used in this paper are the Shanghai Composite Index and the NYSE Composite Index, as reported in Datastream International (February 2002b, 2002d). We begin by showing the basic statistics on the rate of return, defined as *ln*index(t)-*ln*index(t-1), and its volatility, defined as the absolute value of this difference, where t refers to week t from January 1992 to February 2002, covering 10 years and 8 weeks or a total of 528 weekly observations.

The relative sizes of the two markets at the end of 1999 can be found in Bridge (2000) and are shown in Table 1.

Table 1. Sizes of the Shanghai and New York Stock Exchanges

	Shanghai Stock Exchange	New York Stock Exchange
Market capitalization (in US$ billion)	191.8	19,200
Number of total listed instruments	578	8476

Table 2 and 3 show the means and variances of the rate of return and of volatility computed from both the Shanghai and the NYSE composite price indices.

Table 2. Means and Variances of the Rates of Return

	Shanghai Rate of Return	New York Rate of Return
Mean	0.00310284	0.0017436
Variance	0.00486076	0.0003567

Table 3. Means and Variances of Volatility of Returns

	Shanghai Volatility	New York Volatility
Mean	0.04265396	0.01436957
Variance	0.0030476	0.00015283

The mean of weekly return to Shanghai stocks, 0.003103 (compounded to 17.5 percent annually) is much higher than the mean for NYSE, 0.001744 (compounded to 9.48 percent annually). These rates are computed in nominal terms since there are no weekly price indices to deflate them. To insure that the higher rate for Shanghai is not due mainly to a higher rate of inflation in China, we examine the relative inflation rates of the two countries. The rate of inflation in China from 1991 to 2001 according to the retail price index (equal to 213.7 in 1991 and to approximately 358.9 in 2001 – see *China Statistical Yearbook 2000*, Table 9.2) was about 5.3 percent annually. The rate of inflation in the United States (with the consumer price index equal to 134.6 in January 1991 and to 175.1 in January 2001) was about 2.6 percent annually. The difference of 2.7 percent in inflation rates can be used to adjust for the difference between 17.5 percent and 9.48 percent in the rates of return, still leaving a difference of about 5.3 percent in the latter. We can thus conclude that the rate of return from investing in stocks of a rapidly growing Chinese economy in the 1990's was higher than the return from investing in stocks of the United States.

Volatility as measured by both the variance of the rate of return and by the mean of the absolute value of the rate of return was much higher in Shanghai than in New York, suggesting a larger degree of uncertainty for investors in the former market. The variance of the second measure of volatility was also much higher for Shanghai than for New York, indicating that volatility is subject to a higher degree of variation in Shanghai than in New York. The relative magnitudes of all these statistics are as expected.

To find out whether the comparative statistics changed after 1997, we computed them for the two sub-samples. The first "before 1997" covers the five years from the first week of 1992 to the last week of 1996; the second "after 1997" covers five years and two weeks from the first week of 1997 to the end of February 2002.

Table 4: Rate of Return and Volatility in Two Sub-samples

	Shanghai Rate of Return		New York Rate of Return	
	Before 1997	*After 1997*	*Before 1997*	*After 1997*
Mean	0.00429886	0.00194253	0.0020894	0.001408
Variance	0.00874352	0.00110981	0.0001801	0.000529

	Shanghai Volatility		New York Volatility	
	Before 1997	*After 1997*	*Before 1997*	*After 1997*
Mean	0.06029907	0.02553557	0.0106528	0.017975
Variance	0.00511205	0.00045909	7.057E-05	0.000207

From table 4, we observe that the average rate of return in Shanghai decreased, as did the variance. The reduction in the mean rate of return, from 25.0 percent to 10.6 percent at an annual rate, is largely attributable to the reduction in the annual inflation rate from 11.4 percent in 1991-1996 to minus 1.0

percent in 1996-2001 which left the real rate of return almost the same in the two periods. To find out whether the scale effect due to inflation can explain the reduction in variance from 0.00874 to 0.00111, we compute the ratio of the standard deviations 0.0935 and 0.0333 to yield 2.81. This is higher than the ratio of the means 0.00430 and 0.00194 or 2.22, justifying the conclusion that volatility has decreased in real terms. In the later sample period, the mean volatility in Shanghai, measured by the absolute value of the rate of return decreased by a factor of 0.0603 to 0.0255 or 2.36, almost attributable to the scale effect of inflation, but the reduction of its standard deviation from 0.715 to 0.214 cannot be so attributed. It is important to note that in the second sample period, the mean and variance of the rate of return and the mean and variance of volatility for Shanghai all became closer to the corresponding statistics for New York. In New York, relatively smaller changes are observed in the means and variances of both variables, partly because the rate of inflation did not change as much. The differences in the statistics for the two sub-samples suggest that the rates of return and volatility of stock prices in nominal terms from January 1992 to February 2002 were not covariance stationary time series. If they were, the means and variances would be the same for both periods. Whether the same data generating process generated the data for each sub-sample remains an open question.

2. Simple Correlations of Price Movements

To get a preliminary picture of the degree of integration of the two markets, we compute the simple correlation coefficients between the variables of the two markets. Table 5 shows correlation matrices of the Shanghai, New York and Hong Kong (given by the Hong Kong Stock Exchange All Ordinaries price index, also available in Datastream 2002c) rate of return and stock price volatility.

Table 5: Correlation Matrices of Rate of Return and Volatility

	Rate of Return (528 obs.)			Volatility (528 obs)		
	Shanghai	NY	Hong Kong	Shanghai	NY	Hong Kong
Shanghai	1.0000			1.0000		
New York	-0.0117	1.0000		-0.1388	1.0000	
Hong Kong	0.0638	0.3957	1.0000	-0.0128	0.1876	1.0000

Observe first that the New York and Hong Kong markets show highly significant positive correlations in both rate of return and in volatility, suggesting that the two markets are highly integrated. By contrast, the Shanghai and New York markets show negative correlations in both rates of return and in volatility, being much stronger and very significant for volatility. This fact rules out the possibility that the same set of factors affect both markets in the same directions. In this sense, the Shanghai and New York markets are not integrated.

The almost zero and insignificant correlation between the rates of return to Shanghai and New York stocks indicates that the two markets are not integrated. Since the negative correlation between the volatility measures for New York and Shanghai is statistically significant at the 0.001 level, an explanation is required. We start with the proposition that volatility in each market is affected by some economic fundamentals of the economy. The United States and China experienced very different economic histories during the sample period. For most of the period the United States had a sustained economic growth, possibly driven by a revolution in information technology. China, on the other hand, started this period with the aftermath of the Tiananmen incident, followed by Deng Xiaoping's policy announced in Shenzhen in 1992 to deepen market reform that led to expansion and inflation, and then by the tight monetary policy of Zhu Rongji to control inflation beginning in 1995, only to experience the negative impact of the Asian financial crisis of 1997-9. The fact that the macro-economic fundamentals of the two countries had different time paths can be seen by the correlation between *ln*GDP(t)-*ln*GDP(t-1) in the two countries. Since quarterly data for China are not available, we computed the correlation coefficient between the annual changes in *ln*GDP from 1992 to 2000 (Datastream International 2002a, 2002e) and found a value of –0.632. With only 8 annual observations this negative correlation coefficient is significant at the 5 percent level. Therefore, we can interpret the negative correlation between the volatility measures for New York and Shanghai as being driven by two different sets of economic fundamentals in the two countries. Although we are unable to specify the fundamentals precisely we can observe their effects as manifested in the changes in GDP. To the extent that the changes in GDP of the two economies are negatively correlated, we can say that the fundamentals are mostly negatively correlated and can account for the negative correlation of volatility. The fundamental economic variables in the United States and China were probably structurally unrelated to each other but happened to be negatively correlated during our sample period.

If so, we can say that the negative correlation of volatility in stock return in the New York and Shanghai stock exchanges was spurious.

While the above correlation matrices provide very useful information on the degree of integration of the two markets in terms of the rate of return and volatility, it is important to examine the correlation in the context of multiple regressions after netting out the delayed effects of the lagged dependent variables.

3. Rates of Return

We first consider the rate of return, as measured by the change in the natural logarithm of stock price in week *t*. According to the efficient market hypothesis, rates of return are difficult to predict. We wish to find out to what extent this hypothesis is valid and whether the rates of return to Shanghai and New York stocks are correlated after netting out the effects of their own lagged values.

3.1 Autoregressions of the Rate of Return

Shanghai Rate of Return

To construct a model to explain the Shanghai rate of return by its own past values we have calculated the AIC values for models including one through eight lags and found that the AIC is minimized when the number of lags equals one. Furthermore, the Breusch-Godfrey test confirms the absence of serial correlation in the residual of this model with one lagged dependent variable. This first-order autogression is given in column 2 of Table 6.

Under the null (efficient market) hypothesis that the rate of return is serially uncorrelated, we find that the coefficient 0.1035 to be significant at the 0.035 level using a two-tail t test. In this sense the efficient market hypothesis did not hold exactly in the Shanghai market over this time period. We will comment on this hypothesis later when the data are divided into two sub-samples.

New York Rate of Return

To select the number of lags to explain the rate of return of New York stocks, we calculated the AIC values for models including one through eight lags and found a minimized AIC at the number of lags equal to one. Furthermore, the Breusch-Godfrey test applied to the model using one lag confirms the absence of serial correlation in the residual. The result is given in the fifth column of Table 6.

The negative coefficient –0.0833 is significant at a 0.057 level, suggesting that the weekly rate of return to New York stocks might have a small negative serial correlation. This phenomenon will be further investigated when we divide the sample into two sub-periods.

Parameter Stability of Autoregressions of Rates of Return

To find out whether the parameters of the autoregressive models changed after the beginning of 1997, we estimated the models separately for the samples "before 1997" and "after 1997" as reported in columns 3 and 4 of table 6 for Shanghai and columns 6 and 7 of the same table for New York.

For Shanghai the positive coefficient of the lagged variable for the entire sample becomes insignificant (at the 5 percent level) in both sub-samples. This suggests that the positive serially correlation, if present, was only a temporary phenomenon prevailing in an initial period of growth. A Chow test of parameter stability in the two sub-periods gives an $F(2,523)$ statistic of only 0.2489, much smaller than the 20 percent critical value of 1.61, and fails to reject the null hypothesis of no structural change. The large standard errors of the coefficients account for the failure to reject the null hypothesis. We can also conclude that the efficient market hypothesis is valid for both sub-periods.

For New York the negative serial correlation as revealed by the regression coefficient was larger in absolute value for the first sub-period than for the second sub-period. Again, because of the large standard errors of the coefficients in both periods, a Chow statistic of $F(2, 523) = 0.6936$ fails to reject the hypothesis that the coefficients for the two sub-samples are identical. The efficient market hypothesis can be maintained based on the evidence of the second sub-period.

3.2 Examining Additional Effects of Current and Lagged Rates of Return of Other Market

Bekeart and Harvey (1995) have observed that the correlation between returns of an emerging market and a developed market is low. Using the markets of Shanghai and New York, we can examine the extent to which this observation is true. First, we examine this relationship with current Shanghai rate of return as the dependent variable and lagged Shanghai and current and lagged New York rates of return as explanatory variables. The results are reported in column 2 of table 7. With a t statistic of -.0.10, the coefficient of the contemporaneous New York rate has no effect on the Shanghai rate of return. In the multivariate setting the possible effect of the New York market is shown by the combined effect of both the current and lagged New York rate of return on the current Shanghai rate of return. As indicated by the small t statistics of the coefficients of both New York rates of return, an F test of the hypothesis that they are both zero renders no rejection and supports the conclusion that the two markets are not integrated. Furthermore, testing the significance of the three variables combined, including the lagged Shanghai variable, yields and $F(3, 523)$ statistic of 2.13, significant only at the 9.6 percent level. In this sense the efficient market hypothesis is further supported based on the Shanghai rate of return.

We perform the same exercise with the New York rate of return as the dependent variable. The results are seen in column 5 of table 7. Again, no contemporaneous integration is found as the coefficient of the current Shanghai rate of return is very insignificant. (Note that its t statistic is the same as the t static of the coefficient of the current New York rate in the regression of the Shanghai rate, since both are based on the same partial correlation of the two current rates holding the same two lagged values constant.) Also the coefficients of both Shanghai variables are jointly insignificant, confirming that the two markets are not integrated from the viewpoint of explaining the New York rate of return. We also test the joint significance of all three variables, including the lagged New York variable, and obtain an $F(3, 523)$ statistics of 1.53, significant only at the 20.7 percent level. Again this is an additional piece of evidence supporting the efficient market hypothesis.

Does this relationship change after 1997?

Columns 3 and 4 of tables 7 show the sub-sampled models of Shanghai rate of return, and columns 5 and 7 of the same table show those of New York rate of return.

For the explanation of the Shanghai rate of return, after the possible effects of New York rates are accounted for, the coefficient of Shanghai's own lagged value became insignificant for both sub-periods. As the standard errors of the coefficients are large, a Chow test based on $F(4, 523) = 0.3961$, with a 20 percent critical value of 1.50, fails to reject the constancy of the coefficients of the model in the two periods. Regressions of the New York rate of return in the two sub-samples reveal that only the lagged New York rate was significant in the first sub-period, but a Chow test based on $F(4, 523) = 0.5014$ does not reject that the hypothesis that coefficients of the two sub-sample regressions are the same.

4. Multiple Regressions of Volatility

4.1 Autoregressions of Volatility

To construct a model to explain volatility in the Shanghai and New York markets, the effects of their own past values will first be accounted for. To determine the appropriate number of lagged dependent variables to include in the respective models we rely on three criteria: the significance of the individual parameter estimates, the minimized AIC value, and the presence of serial correlation in the residual. Including one lagged dependent variable at a time, we look at these three criteria to construct a model to explain current volatility in each market.

To explain the volatility of Shanghai stock price, we found the coefficients of the first, second, and fourth lags to be highly significant. The AIC values for models including one through eight lags had a minimum at four lags. Furthermore, the Breusch-Godfrey test for serial correlation applied to the model using four lagged values yields a coefficient of the lagged residual with a t-statistic of –1.02 and p-value of 0.308. A positive serial correlation in the residual was found when only three lags were included. Column 2 of Table 8 shows the results of this model with four lags.

To explain the volatility of New York stock prices, we found that the significance of the individual coefficients dropped off after the inclusion of the fifth lag. Adding one lag at a time and looking at the significance level of the last lag, it is observed that the first, second, fourth, and fifth lags are individually significant to within a 0.05 level and that the third, sixth, seventh, and eighth lags are not. The AIC value reaches a minimum with the inclusion of the fourth lag. However, the Breusch-Godfrey test strongly indicates the presence of serial correlation in the model with only four lags. By including an additional lag variable, the serial correlation is eliminated and the AIC increases by only a negligible amount. We thus chose five lags in the autoregression for New York volatility, as presented in the fifth column of Table 8.

The positive and significant coefficients of the lagged variables for both markets indicate that volatility tends to have positive correlations with its own lagged values, as is well-known. The Root MSE of the model of the New York volatility (0.01208) is much lower than that of the model of Shanghai volatility (0.05102), suggesting that the former can be predicted with a higher degree of precision. The comparison of residual variances of volatility confirms the conclusion from comparing the unconditional variances that the volatility in Shanghai has a higher degree of variation and is less predictable.

To test for structural change in each market, we divided the sample into two halves, before and after 1997. The autoregressions for Shanghai are shown in columns 3 and 4, and for New York are shown in columns 6 and 7 of Table 8. A Chow test of equality between the coefficients in the two Shanghai sub-samples gives an $F(5, 514)$ statistic of 4.26, strongly rejecting the hypothesis of stability of the parameters (the critical level for 0.001 level of significance being only 0.71). A Chow test for the two New York sub-samples gives an $F(6, 511)$ statistic of 4.53, also strongly rejecting the hypothesis of parameter stability in the explanation of New York volatility.

4.2. Examining Additional Effects of Lagged Volatilities of the Other Market

We next introduce lagged values of the variable for the other market to determine whether they "Granger" caused the volatility in the former market by performing F-tests for the significance of the set of coefficients the lagged independent variables.

If we explain Shanghai volatility we choose the number of lagged values of New York volatility according to AIC and the absence of serial correlation in the residuals. The AIC value with two New York lags is very close to its minimum value with only one lag but eliminates the serial correlation of the residuals in the latter. Hence two New York lags are chosen, and the results reported in column 2 of Table 9. These results confirm the negative relation between volatility in Shanghai and New York. The negative coefficients of the two lagged New York variables are significant at the 0.053 and 0.061 levels respectively. An F-test on the joint significance of the coefficients of these two lagged New York variables returns an F-statistic of 3.92 and a p-value of 0.0204. Statistically, New York volatility Granger caused Shanghai volatility in an opposite direction. This negative relation was already explained by the difference in the time paths of economic fundamentals in the two countries.

When five lagged values of Shanghai volatility was added to explain New York volatility only the coefficient of the first Shanghai lagged variable is found to be significant at the 0.10 level. The AIC value calculated by varying the number of lagged Shanghai variables is minimized at the inclusion of the first Shanghai lag. Furthermore, the Breusch-Godfrey test reveals the absence of serial correlation in this model. The model with one Shanghai lagged variable is reported in column 6 of table 9. The negative coefficient of the one Shanghai lag is significant at the 0.034 level, suggesting that. an increase in past Shanghai volatility is associated with a decrease in New York volatility. Statistically Shanghai volatility also Granger caused New York volatility. Furthermore, comparing the best models of volatility in the two markets, we find again that the regression of New York volatility has a smaller residual variance and thus is more easily predictable than Shanghai volatility..

4.3 Is covariation of volatility significant in a multivariate setting?

To incorporate instantaneous causality in explaining Shanghai volatility we add the current value of the variable in the other market in the regression. The result for Shanghai is reported in column 3 of Table 9, and the result for New York is reported in column 7 of Table 9.

The coefficients of all New York variables are negative, again revealing the negative relationship found previously, although the coefficient of the current New York volatility is significant only at a 0.138 level. The simple regression of current Shanghai volatility on current New York volatility, without controlling for past values of either market, has an estimated coefficient of –0.62, significant at a 0.001 level. After controlling for own lagged values and the lagged values of volatility in the other market, this estimate decreased in magnitude to –0.272, with a significant level of 13.8 percent. However in a dynamic setting, we should test the combined effect the current and two lagged New York volatility variables on Shanghai volatility using an $F(3, 516)$ statistic which equals 3.36 and is significant at the 1.87 percent level. This reinforces the negative relationship of current volatilities in the two markets.

To explain New York volatility by the inclusion of the current Shanghai volatility, we find, in column 7 of table 9, the coefficient –0.0166 of the current Shanghai variable to be significant only at the 10 percent level, but the coefficients of both Shanghai variables are significant at the 2.84 percent level based on the $F(2, 515)$ statistic being equal to 3.58. Before allowing for the effects of past volatility in both markets, the simple regression of New York volatility on current Shanghai volatility alone has a coefficient of –0.03 with a 0.1 percent significance level. Both results support the negative relation of volatility in the two markets.

Was there a structural change after 1997?

In the autoregressions of volatility we have found that the parameters are highly unstable for both Shanghai and New York. It is of interest to find out whether parameter instability remains when volatilities of the other market are added as explanatory variables to improve the model. We have estimated the model for the two sub-periods, before and after 1997, as reported in columns 4 and 5 for Shanghai and columns 8 and 9 for New York in Table 9..

In the regression of Shanghai volatility for the 'before 1997' period none of the negative coefficients of New York volatility, current or past, is significant, and the $F(3, 248)$ statistic for the three coefficients is only 1.06, with a p-value of 0.368, showing the combined effect to be insignificant. For the post 1997 period, the corresponding $F(3, 260)$ statistic is only 1.31, significant only at the 27.0 per cent level. Hence for the two periods separately, there is no significant negative correlation between Shanghai volatility and the New York volatilities, after adjusting for the effects of the lagged Shanghai variables. This result is in contrast with the significant negative correlation found for the entire sample period. Furthermore, the root MSE of the model in the post-1997 sub-sample became smaller, suggesting that, even if the model is not a correct data generating process, the conditional variation in volatility was reduced as the Shanghai market became more mature. A Chow test of the equality of all coefficients in the two sub-periods gives an $F(8, 508)$ statistic of 2.209 and is extremely significant since the critical value of this statistic at the 0.1 per cent level is only 0.592. Given such temporal instability of the coefficients, one may even question the assumption that the model is valid within each sub-period. If the assumption is invalid, the statistical analysis presented can be interpreted only as descriptive statistics summarizing certain aspects of economic history, and not as estimation and testing of a correctly specified statistical model.

Looking at the model for New York volatility, we find the combined effects of the two Shanghai variables to be insignificant for the first sub-period, with an $F(2, 247) = 0.41$ and a p-value of 0.664. So is the combined effect in the second sub-period, based on an $F(2, 260)$ statistic of 2.21 and a p-value of 0.112. Recall that the combined effect of the two Shanghai volatility variables for the entire sample is significant at 2.84 percent based on $F(2, 515) = 3.58$. Thus the two Shanghai variables show a combined negative effect on New York volatility for the entire period but no significant effect for each sub-period separately. This is similar to the result concerning the negative combined effect of the New York variables in a regression on Shanghai volatility. The parameters of the regression of New York volatility are far from temporarily stable as indicated by the $F(8, 507)$ statistic of 3.34 from the Chow test, with a p-value much smaller than .01. From such temporal instability of the parameters, one can question whether the equation truly represents the data generating process even within each sub-sample period.

5. Conclusions.

We draw two sets of conclusions from this study, one on empirical findings and the second on econometric method.

There are six empirical findings. The first two are concerned with the time series properties respectively of the rate of return and of volatility that are valid for both markets. The second and third deal with comparison of the Shanghai and New York markets based on these two variables. The remaining two are findings on the co-movements of the two variables in the two markets.

First, concerning the dynamic property of the rate of return common to both markets, we can say that the efficient market hypothesis is essentially valid in the sense that the weekly rate of return in both Shanghai and New York is approximately serially uncorrelated for both sub-periods. There are two minor qualifications to this statement. A weak positive effect of the own lagged rate on the Shanghai rate of return was found but it disappeared in the second sub-period. A stronger negative effect of the own lagged rate on the New York rate of return was found but it also disappeared in the second sub-period. For the entire period, an F test of the combined effect of all variables on the rate of return in both Shanghai and New York turned out to be insignificant, failing to reject the hypothesis that the rate of return is random and serially uncorrelated. Secondly, concerning the dynamic property of volatility, we find positive effects of own lagged variables in both markets, thus confirming the well-know result that volatility has positive serial correlations. However the autogressions of volatility and the regressions including current and lagged volatilities of the other market are all temporarily unstable, for both Shanghai and New York. This indicates that although volatility has positive serial correlations it is difficult to specify a regression equation for it that is temporarily stable.

Third, the Shanghai stocks had a higher mean rate of return than New York stocks. The higher mean rate of return in Shanghai for the entire period is partly but not mainly the result of a higher rate of inflation in China. Even after the rate of inflation became zero or slightly negative in China in the second sub-period, the rate of return in Shanghai remained higher than that of New York, but the difference in the rate of return between the two markets narrowed in the second sub-period. Fourth, volatility as measured by both the variance of the rate of return and the mean absolute change in return was higher in Shanghai than in New York and this phenomenon cannot be explained entirely by a higher inflation rate in China. The second measure of volatility itself was subject to a higher degree of uncertainty in Shanghai. As an emerging market the Shanghai market had a higher volatility and the volatility itself had a higher variance, but the difference from the New York market was reduced in the second sub-period as the Shanghai market became more mature.

Fifth, while the rates of return in the two markets were uncorrelated, there was a significant negative correlation between volatilities in the two markets. The negative correlation in volatility persisted after allowing for the effects of own lagged values, as demonstrated by regressions of volatility of both markets on own lagged values and current and lagged values of volatility in the other market. The negative combined effect of volatility variables in the other market is significant in the explanation of volatility of both markets for the entire sample period, but not significant in the two sub-periods separately. All regressions explaining volatility in both Shanghai and New York, while showing positive serial correlations, are highly unstable temporarily. Sixth, in view of the lack of positive correlations in both the rate of return and volatility we can conclude that the Shanghai and New York stock markets were not integrated during our sample period from January 1992 to February 2002. The negative correlation of volatility has to be explained by the movements of omitted variables in both markets. The above result is one indication that the Chinese capital market was not integrated with the world market, but the degree of integration may increase in the future as China has become a member of WTO. On the whole the empirical results of this study serve as a record of a part of the financial history of China in the process of its economic development.

There are four observations to make on the practice of econometrics. The first is on the use of auto-regressions as a standard tool for time series analysis. Without much knowledge about the economics of the time series to be studied, econometricians often choose vector autoregressions as the data generating process. Our study of the volatility in the rates of return to Shanghai and New York stocks suggests that this specification of the data generating process could sometimes be invalid. The measured volatility of Shanghai stocks was unlikely to be explained adequately by its own lagged values and the current and lagged values of volatility of New York stocks. Many unknown variables are missing. Economic data are sometimes the outcome of a variety of factors interacting in a very complicated way that cannot be modeled adequately by the theoretically simple and attractive bivariate autoregressions. .

The second is on the use of Granger causality tests to determine the existence of causal effects. This paper illustrates that Granger causality tests can give misleading results if one important simplifying assumption is incorrect. Reviewing an econometrics text by Chow (1983, p. 212) we find: "X causes Y, given an information set A_t which includes at least (X_t, Y_t), if Y_t can be predicted better by using past X_t than by not using it… In order to define causality in a bivariate time-series model involving X_t and Y_t we make two simplifying assumptions. First, the set A_t includes X_t and Y_t only and not a third variable…" If other variables than those included in the model affect the dependent variable in question, as in the case of our bivariate model of volatility, the conclusions obtained by Granger causality tests can be misinterpreted. If we interpreted the test results under the erroneous assumption that no other important variables were present we would conclude incorrectly that New York volatility Granger caused Shanghai volatility negatively, and Shanghai volatility also Granger caused New York volatility negatively. This negative relationship can be interpreted as resulting from the different time paths of the yet unspecified economic fundamentals in the two countries. It illustrates the well-known effects of omitted variables on the estimates of regression coefficients.

Third, the existence of "spurious correlations" in time series analysis are often the result of omitted variables rather than the existence of unit roots. Although independent time series each having a unit root can give rise to spurious correlations, perhaps in econometric practice the spurious correlations often encountered are not due to the presence of unit roots. If unit roots are the cause, they can be eliminated in a co-integration analysis by first-differencing to convert a non-stationary model to a stationary one. The problem of spurious correlations can persist in stationary models because of omitted variables. This study illustrates the spurious negative correlation between volatility of returns to stocks traded in the Shanghai and New York Stock Exchanges when the measure of volatility was not expected to have a unit root.

Fourth, this study has suggested that the absolute value of the change in log price is a convenient measure of volatility of stock prices and possibly of other economic variables. The use of absolute value, if applied to residuals of time serious models, may provide an alternative to the commonly used ARCH-type models. The relative merits of these two types of models remain to be investigated.

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Table 6 Autoregressions of Rate of Return of Shanghai and New York Stock Prices												
	Shanghai						New York					
	All Data (527 obs.)		Before 1997 (259 obs.)		After 1997 (268 obs.)		All Data (527 obs)		Before 1997 (259 obs.)		After 1997 (268 obs.)	
Lag	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**
S1	.1035	2.39	.1132	1.82	.0290	0.48						
N1							-.0833	-1.91	-.1669	-2.70	-.0564	-0.92
Cons.	.0027	0.91	.0037	0.64	.0019	0.93	.0019	2.28	.0024	2.90	.0015	1.06
R-squared	.0102		.0128		.0009		.0069		.0275		.0032	
Root MSE	.0695		.0933		.0334		.0189		.0133		.0230	

Table 7 Regressions of Rate of Return of Shanghai and New York Stock Prices												
	Shanghai						New York					
	All Data (527 obs.)		Before 1997 (259 obs.)		After 1997 (268 obs.)		All Data (527 obs)		Before 1997 (259 obs.)		After 1997 (268 obs.)	
Lag	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**
S0							-.0012	-0.10	.0020	0.22	-.0226	-0.53
S1	.1038	2.39	.1140	1.83	.0290	0.48	-.0111	-0.94	-.0096	-1.08	-.0248	-0.59
N0	-.0167	-0.10	.0973	0.22	-.0475	-0.53						
N1	.1322	0.82	.4192	0.95	.0365	0.41	-.0837	-1.92	-.1675	-2.70	-.0573	-0.93
Cons.	.0026	0.83	.0027	0.44	.0019	0.93	.0019	2.32	.0025	2.93	.0016	1.11
R-squared	.0120		.0162		.0027		.0087		.0320		.0056	
Root MSE	.0696		.0935		.0335		.0189		.0133		.0231	

Table 8 Autoregressions of Volatility of Shanghai and New York Stock Prices						
	Shanghai			New York		
	All Data (524 obs.)	Before 1997 (256 obs.)	After 1997 (268 obs.)	All Data (523 obs)	Before 1997 (255 obs.)	After 1997 (268 obs.)
Lag	Coef. t	Coef. t	Coef. t	Coef. t	Coef. t	Coef. t
S1	.2762 6.41	.2434 3.92	.1463 2.37			
S2	.1088 2.43	.0826 1.28	.0938 1.70			
S3	-.0388 -0.87	-.0795 -1.23	.0201 0.38			
S4	.1933 4.49	.1760 2.78	.0419 0.82			
N1				.0645 1.47	.0854 1.34	-.0051 -0.08
N2				.1002 2.30	.0099 0.16	.0609 0.99
N3				.0235 0.54	.0356 0.56	-.0403 -0.66
N4				.1468 3.37	.0246 0.39	.1191 1.94
N5				.0927 2.11	-.0546 -0.86	.0850 1.38
Cons.	.0198 5.79	.0356 4.92	.0176 7.09	.0083 6.61	.0096 6.53	.0140 5.64
R-squared	.1572	.1021	.0552	.0600	.0122	.0268
Root MSE	.0510	.0686	.0210	.0121	.0085	.0143

Table 9 Regressions of Volatility of Shanghai and New York Stock Prices								
	Shanghai				New York			
	All Data (524 obs.)	All Data (524 obs.)	Before 1997 (256 obs.)	After 1997 (268 obs.)	All Data (523 obs)	All Data (523 obs)	Before 1997 (255 obs.)	After 1997 (268 obs.)
Lag	Coef. T	Coef. t	Coef. t	Coef. t	Coef. t	Coef. t	Coef. t	Coef. T
S0						-.0166 -1.62	-.0018 -0.23	-.0675 -1.62
S1	.2611 6.05	.2554 5.90	.2351 3.76	.1398 2.26	-.0209 -2.13	-.0160 -1.56	-.0061 -0.79	-.0423 -1.02
S2	.0965 2.16	.0942 2.11	.0753 1.16	.0827 1.49				
S3	-.0486 -1.09	-.0480 -1.08	-.0802 -1.23	.0241 0.45				
S4	.1874 4.37	.1827 4.25	.1781 2.81	.0380 0.74				
N0		-.2722 -1.49	-.0951 -0.19	-.1490 -1.66				
N1	-.3549 -1.94	-.3354 -1.83	-.7432 -1.44	.0063 0.07	.0556 1.27	.0491 1.12	.0820 1.28	-.0136 -0.22
N2	-.3445 -1.88	-3163 -1.72	-.4565 -0.88	-.0895 -0.99	.0898 2.06	.0834 1.91	.0035 0.05	.0510 0.83
N3					.0133 0.30	.0123 0.28	.0323 0.50	-.0478 -0.78
N4					.1426 3.28	.1365 3.14	.0262 0.41	.1105 1.81
N5					.0852 1.94	.0851 1.94	-.0551 -0.86	.0786 1.28
Cons.	.0317 5.82	.0354 5.91	.0503 4.21	.0222 5.60	.0098 6.83	.0106 7.00	.0102 6.25	.0176 5.81
R-squared	.1698	.1722	.1124	.0694	.0682	.0720	.0154	.0421
Root MSE	.0507	.0507	.0686	.0210	.0120	.0120	.0085	.0143