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COMPARISON OF VOLATILITY ON AMERICAN AND CHINESE STOCK MARKETS DURING THE GLOBAL FINANCIAL CRISIS

Abstract: *This paper examines the volatility of the stock indices of two world powers – USA and China, before and during the global financial crisis. Generally, it is believed that markets of developing countries are riskier than the developed capital markets. The purpose of this study was to confirm or reject this common belief, to determine whether the characteristics of American stock market fluctuation changed during the crisis, and to compare its volatility to China. We used three different GARCH models to examine the volatility. The study confirmed that during the global financial crisis volatility significantly increased on both stock markets. The results of this study thus do not support the common belief that the developed capital market is subject to relatively lower volatility than the developing market. During the current global financial crisis, the developed American market has actually been more volatile than the Chinese one.*

Key words: *volatility, capital markets, GARCH, financial crisis, emerging markets.*

JEL-Classification: G15, G11, G01, C22

1 INTRODUCTION

The 2008 global financial crisis brought the risk management of capital markets to the forefront of investment in financial instruments. In financial literature, “risk” is a broad term that depends on the function and mission of a subject. On the capital market, risk is defined as an uncertain outcome of investment that results from a change in the price of financial instruments. The greater the price fluctuation of securities, the harder it is to predict the outcome of investment and the riskier the investment. Thus, volatility plays an important role in making investment decisions because it is a factor of uncertainty.

Generally, it is believed that markets of developing countries such as China, India, Brazil, and Russia are riskier than the developed capital markets. That is, the yields are potentially higher but so is the volatility. The purpose of this study was to confirm or reject this common belief, to determine whether the characteristics of American stock market fluctuation changed during the crisis, and to compare its volatility with that of the world's second-largest economic power.

In recent years, economists have been developing and studying various methods and approaches in volatility analysis. The mainstream of research is directed towards models that are based on studying past changes in volatility. Important researchers studying volatility using GARCH models include Bollerslev (1986; 1994), Baillie (1990), Chou (1988), Bera/Higgins (1993), Poterba/Summers (1986), and Pindyck (1984; 1998). Bollerslev is a pioneer in the development of GARCH models. Before the GARCH approach became widely accepted, conventional econometric models operated under the assumption of a constant variance of return. In 1982, Engle introduced the ARCH process or model, in which the conditional variance changes over time and is a function of previous error terms.

In 1986, Bollerslev published an article titled "Generalized Autoregressive Conditional Heteroskedasticity" (the origin of the acronym GARCH), in which he explained the general GARCH process that enables a more flexible lag structure. The process assumes that the conditional variance is a function of previous error terms and previous conditional variances. This is an improvement on the ARCH process.

The GARCH model was first used only for studying the developed capital markets, but gradually it also began to be applied to the markets of developing countries. Wang and Moore (2007) published a study in which they examined the changes in volatility of five stock indices of Eastern European countries. Based on the weekly data for 1994–2006, they discovered sudden changes in the variance of return and a persistence of variance shocks. According to Wang and Moore, sudden changes in return variance are the result of internal economic and financial factors of societies in transition, which result from the natural evolution of less-developed European capital markets. They highlighted the changes in interest-rate and stock-market policies, as well as the impact of financial crises.

Floros (2008) used GARCH models to explain the volatility of capital markets in Egypt and Israel. He established that time series can be modeled with statistical significance by means of the GARCH models. Alberg, Shalit, and Yosef (2006) used GARCH models in the analysis of returns and conditional variance of returns of two Israeli indices: the TA100 and the TA25. Their goal was to find the most suitable volatility model that could best explain the stylized facts. The study confirmed that the EGARCH model best described the behavior of returns of both indices from the viewpoint of fat tails and leverage effect.

The researchers that have studied the volatility of capital markets in the Middle East include Khedhiri and Muhammed (2008), who focused on Dubai and Abu Dhabi, where organized stock markets were officially established in 2000. Their study shows that a high uncertainty rate is the main reason for the high volatility level and thus lower returns. They also confirmed the statistically significant leverage effect for both indices.

Haque, Hassan, and Varela studied the volatility of the developing stock markets in Latin America (2001). Their analysis included weekly data relating to changes in the stock indices of Argentina, Brazil, Columbia, Mexico, and Venezuela from December 1988 to June 1998. The researchers confirmed the high mutual dependence of markets, except in the case of Venezuela, which had a low correlation with the other countries included in the study. The main reason for this lies in the sociopolitical environment. The relatively high correlation between the other markets offers little opportunity for the diversification of investments within the region. The researchers established that all markets except for the Venezuelan one showed ARCH/GARCH effects. Venezuela proved to be the most suitable market for the diversification within the region because the level of correlation with other markets was low. Volatility shocks were persistent only in Brazil. Other markets recovered from shocks in a year or even sooner. Prashant (2010) analyzed the volatility of Chinese and Indian stock markets and established that the persistence of volatility on the Chinese stock market was higher than that of the Indian one.

The purpose of this study was to examine the volatility of the stock indices of two world powers—the American S&P 500 and the Chinese Shanghai Composite. The study covered two different time periods: one before the crisis (from 30 June 2004 to 30 June 2007) and one after the crisis began (from 30 June 2007 to 30 June 2010). Three volatility evaluation models were used to examine general risk before and during the crisis. Relative changes in volatility were assessed for both indices as well as relative changes in time.

The study confirmed that during the global financial crisis volatility significantly increased on both stock markets. On the American capital market volatility was higher, whereas the Chinese market was characterized by long memory. Patev (2003, 15) established the same in his study of the volatility of Eastern European indices during the Asian-Russian crisis: long memory increased during the period studied.

The results of this study thus do not support the common belief that the developed capital market is subject to relatively lower volatility than the developing market. During the current global financial crisis, the developed American market has actually been more volatile than the Chinese one. The reason for this is to be found in the origin of the crisis.

This paper consists of six parts. First, the analysis of stock markets included in the study is presented. This is followed by the presentation of the research method with an emphasis on the basic elements and presumptions of GARCH, IGARCH, and EGARCH models. Then the database and the basic characteristics of time series of index returns are presented. The paper then continues by presenting the empirical research findings and concludes with the main findings of the study.

2 ANALYSIS OF THE S&P 500 AND SHANGHAI COMPOSITE INDICES

The American capital market is the most developed markets in the world. Many researchers have studied its history. The American or the Anglo-Saxon financial system is based on three pillars: banking, money, and capital; all of them are equal, unlike in the European system where the banking system dominates the other two. The Constitution of the United States, ratified in 1788, provided the basis for the formation of a federal system that enabled a faster development of the financial system. There were only three banks operating at that time, but by 1800 their number had grown to 28. Organized stock trading started on local markets after 1790 (Philadelphia, New York, Boston), especially with government debt securities.

The S&P 500 is an index of the stock prices of 500 large publicly held companies actively traded on the American stock market exchanges. It has become one of the most widely known and well-established American stock indices. The company Standard & Poor began publishing this index in 1957. The S&P 500 focuses exclusively on U.S.-based companies (if a company moves its seat outside the U.S., it is no longer included in the index).

The Chinese financial system has developed in accordance with the country's economic reforms and its financial needs. The transition from a regulated or planned economy to a market economy was and still is gradual.

The capital market adapted to this pace of development as well, because its goals were to provide additional financial sources to companies, enable banks to transparently and effectively invest their sources (the deposit base grew more than thirty-fold from 1978 to 1990), as well as to improve the corporate management of domestic companies.

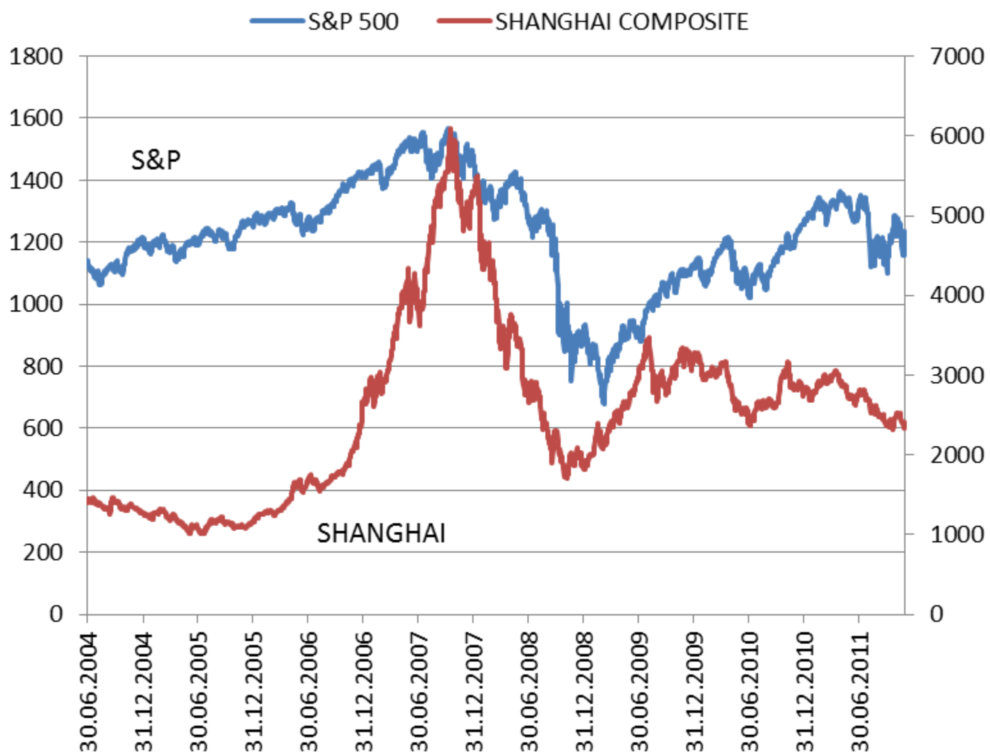
This development can be divided into three stages (Wei, 2007):

1. The first stage lasted from 1978 to 1990. It started with the issuing of government bonds, whereas the first stocks were issued no earlier than 1984. The market became better known and more successful when people discovered that the early investors had made large profits.
2. The second stage began with the foundation of two national stock exchanges in 1990. This stage lasted until 2001. The state established a legal framework and updated it occasionally. It introduced a system of quotas—that is, it limited companies' access to the capital market in order to maintain control of important state-owned companies. In addition, various classes of shares were introduced (A, B, H, and N).
3. In 2001 the market entered its adaptation stage. From 2001 to 2005 the index dropped to less than half of its previous value. The government introduced reforms to regain the investors' trust and reduced its shares in state-owned companies, which helped the market to expand after 2006.

Bank loans and retained earnings remain the main sources for financing Chinese companies. The Chinese market is primarily dominated by large companies, which are majority state owned. Liquidity on the stock exchange cannot be compared to the standards on developed capital markets because only one-fourth of bonds issued are actively traded (European Central Bank 2010, 6). The base day for the Shanghai Composite index is 19 December 1990. This is an index of all stocks that are traded at the Shanghai Stock Exchange.

Figure 1 shows changes in the values of both indices in the period studied—that is, from 30 June 2004 to 30 June 2010. It is evident that share prices grew in the first half of the period studied. The Shanghai Composite index stands out with a more than triple increase. The reason for this is to be sought in the economic and capital market reforms that led to rapid economic growth in China. The downturn happened in the second half of 2007, when it became increasingly clear that the U.S. housing crisis was also threatening global economic growth. Global stock indices started 2008 with a negative trend and the crisis reached its peak on 15 September 2008 with the collapse of one of the largest investment banks, Lehman Brothers. The assistance provided by the Federal Reserve and the United States government made it possible to preserve and stabilize the American financial system. The effects of the world powers' economic programs helped revitalize economies. The S&P 500 index bottomed out in March 2009 and the Shanghai Composite bottomed out at the end of 2008.

Figure 1: Changes in the indices during the period studied

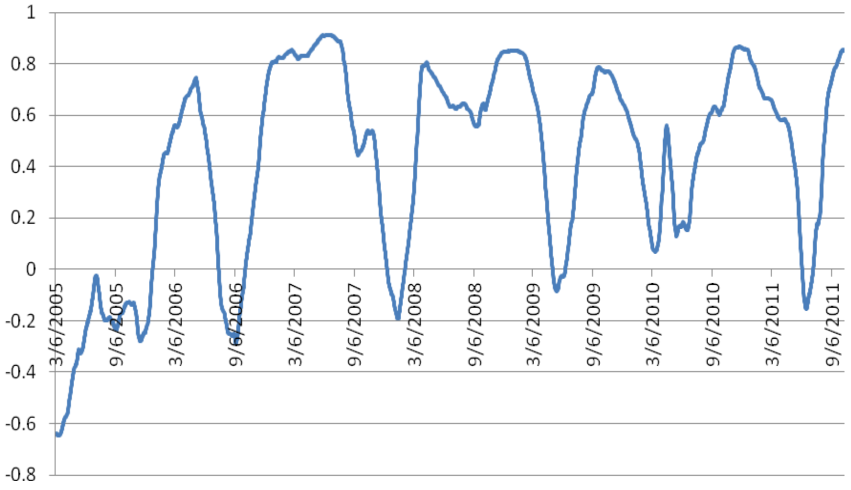


Source: Bloomberg 2011

Figure 2 shows the 250-day moving average correlation coefficient (the linear correlation between the S&P 500 and Shanghai Composite indices) for the period from 30 June 2004 to 30 June 2010. It is interesting that the correlation between the indices was negative until the beginning of 2006. This can also be seen in Figure 1: the S&P 500 index was growing and the Chinese index was falling. This trend changed in the second half of 2006, when the Chinese index began to rise sharply. The correlation coefficient became positive and approached the 0.8 threshold. This means that when the Chinese index increased by 1%, the American one increased by 0.8%. The correlation coefficient fell again due to the falling S&P 500 index in the first half of 2006. The strong correlation between the indices lasted until 2007, with the coefficient remaining above 0.8. The reason the coefficient fell into negative territory, even though both indices had a negative trend, is that the Chinese index fell significantly faster and more suddenly than the American one. The coefficient grew again because of a strong decrease in the American index. In the last period observed the value of the coefficient is falling again, primarily because the value of the Chinese index began to fall, whereas the American one was not under such pressure.

It can be concluded that the correlation between the indices is not one-sided, but that there are significant fluctuations. During most of the period, the value of the correlation coefficient was positive, which means that mutual dependence was increasing. Short negative periods are also evident, especially in the initial period and during the phases of extreme fluctuations that were the result of extreme circumstances due to the global financial crisis. It would thus make sense to check the volatility of both indices and the changes in their characteristics before and during the crisis.

Figure 2: The movement of the correaltion coefficient in the period observed (250 days)



Source:: author's calculations

3 RESEARCH METHOD

This section presents the GARCH, EGARCH, and IGARCH models. They are based on stochastic processes that are used for modeling selected time series and predicting future values (the size of change or at least its direction).

Campbell et al. (1997, 315) emphasized that it is statistically ineffective and illogical to use volatility measures that are based on the presumption of constant volatility in a given period because the time series changes over time. With regard to financial data, small changes are followed by small changes and big changes are followed by big ones, and this causes volatility clustering.

GARCH models are methodologically improved ARCH[1] models because they have longer memory, are more flexible, and allow a less comprehensive process description. The GARCH concept overcomes some of the weaknesses of ARCH models, such as (Rachev et al. 2007, 284; Engel 2007, 4):

- Due to the structure of the model, only the square of ε_{t-i} affects the current volatility; the negative and positive values of the variable ε_t can actually have different effects on volatility;
- It is difficult to define the order *q* or the number of deviations of a random variable or errors;
- The effect of large shocks only lasts *q* periods;
- The ARCH model can predict the variance value in the time period *t*, based on the information known in the time period $t-1$;
- The prediction is conditionally deterministic because the model does not allow uncertainties about the expected value of the square of the random variable or errors in time *t*. Of course, the actual error may differ from the predicted one.

The advantage of GARCH models is that they can include certain characteristics of financial time series, such as the leverage effect,[2] volatility clustering,[3] and

[1] ARCH - Autoregressive Conditional Heteroskedasticity

Simple ARCH *(q)* model

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \tag{1}$$

where σ_t^2 is the conditional variance of a random variable or the error ε_t, depending on the information available in time *t*.

[2] The leverage effect was first introduced by Black in 1976, when he established that volatility increases with falling share prices and vice versa (Bouchaud et al. 2001, 4).

leptokurtosis.[4]According to some researchers (Bera & Higgins 1993, 315), the models are simple, and take into account the extent of changes in the variance and the fact that the ability to make predictions changes from one time period to another.

Because of the weaknesses of ARCH models mentioned above, Bollerslev (1986, 309) developed an expanded GARCH model.

GARCH *(ρ,q)* model for time series ε_t:

$$\varepsilon_t = \sqrt{\sigma_t^2}\eta_t , \qquad \eta_t \sim N(0,1) \tag{2}$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{\rho} b_j \sigma_{t-j}^2 \tag{3}$$

where:

$a_0 > 0$
$a_i \geq 0$ for $i = 1, \ldots, q$
$b_j \geq 0$ for $j = 1, \ldots, \rho$

The conditional variance σ_t^2 of random variable (or error) ε_t, depending on available information in time t and η_t, is an innovation characterized by *IID* (white noise) with $E(\eta_t) = 0$ and $Var(\eta_t) = 1$. GARCH *(ρ,q)* models the conditional variance σ_t^2, which is a linear combination of previous error terms and previous conditional variances. The GARCH model is unique precisely because it includes the previous values of the variable σ_t^2 in the modeling process.

The IGARCH or integrated GARCH model simulates the effect of shock on the variance, which persists indefinitely. This means that current information affects

[3] With regard to the movement of times series of returns, Mandelbrot (1963, 418) established that large changes in returns are followed by large changes and small changes in returns are followed by small changes (the sign of the change in the return value is not important).
[4] The distribution function of financial time series does not have the characteristics of normal distribution. Andersen et al. (2001, 44) studied the returns of shares in the Dow Jones Industrial Average index. They established that all the distributions of share returns are leptokurtic. Clustering around the mean, sharper peaks, and longer and fatter tails were typical.

the volatility predictions for all future periods. In this case, it is not necessary for the process to be stationary.

When *a* + *b* = *1* and *b* = *λ*, the GARCH *(1,1)* model is:

$$\sigma_t^2 = a_0 + (1-\lambda)\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 \,, \tag{4}$$

where the conditional variance is not set.

The conditional variance of the IGARCH process increases linearly when the period of prediction is getting longer and does not converge as is typical of the conditional variance in a GARCH model with weak stationarity.

GARCH models are effective in modeling time series with fat tails and volatility clustering. The models are symmetrical because they only take into account the size of the error and presuppose that the effects of positive and negative changes on the conditional variance are the same. On the other hand, asymmetrical models take into account the sign of the changes when analyzing the volatility of capital markets.

In 1991, Nelson developed the asymmetrical EGARCH model, which takes into account the negative correlation between volatility and past returns (Nelson 1991). The symmetrical ARCH model namely does not respond to the sign of ε_{t-i} and is thus uncorrelated with past errors. Nelson thus improved the previous model by defining the errors as $\varepsilon_t = \eta_t\sqrt{\sigma_t^2}$, where η_t is characterized by *IID* with a mean of *0* and a variance of *1*.

Nelson used a logarithmic formula to avoid the non-negativity constraints:

$$log(\sigma_t^2) = a_0 + \sum_{i=1}^{q} a_i g(\eta_{t-i}) + \sum_{i=1}^{p} b_i \log(\sigma_{t-1}^2) \tag{5}$$

where

$$g(\eta_t) = \theta\eta_t + \gamma[|\eta_t| - E|\eta_t|] \tag{6}$$

The EGARCH model is thus presented in Equations 5 and 6.

Equation 6 defines the following characteristics of the EGARCH model (Bera & Higgings 1993, 332):

- The function of innovation $g(\eta_t)$ to the conditional variance depends linearly on the innovation η_t. The incline is $a_i(\theta + \gamma)$ if the innovation η_t is positive $(0 > \eta_t < \infty)$, and $a_i(\theta - \gamma)$ if the innovation η_t is negative $(-\infty > \eta_t \leq 0)$. The function $g(\eta_t)$ enables the conditional variance to be asymmetric. The effect of the positive and negative changes on the conditional variance can thus be modeled;
- The first term in Equation 6 allows a correlation between the errors and future conditional variances. If $\gamma = 0$ and $\theta < 0$, where θ is the measure of asymmetrical influence of past innovations on the current conditional variance, a negative innovation η_t will cause the error to be negative and the current effect of the innovation on the conditional variance will be positive;
- The second term defines the ARCH effect or the size of the effect. We presuppose that $\theta = 0$ and $\gamma > 0$. When the absolute value of the innovation η_t exceeds the expected value, the innovation $g(\eta_t)$ has a positive effect on the conditional variance.

4 RESEARCH DATA

This study is based on data collected over a period of 6 years, which was divided into two parts: the period before the crisis, from 30 June 2004 to 30 June 2007, and the period during the crisis, from 30 June 2007 to 30 June 2010. We were not interested in the movement of the indices but in the movement of the volatility of the daily returns of the indices, which is a big risk factor for investments in capital markets. Continuous daily returns of indices were calculated using the natural logarithm:

$$R_t = \ln(P_t / P_{t-1}), \qquad (7)$$

where R_t is the daily return and P_t is the price on day t.

The data required were obtained from the Bloomberg data system, and the EVIEWS software was used for the calculations. GARCH, IGARCH, and EGARCH models were used in the study.

In financial econometrics, the modeling of conditional variance is based on indirect construction of models. According to Pagan (1996), the goal of all models is to encompass the entire process of shaping the conditional density of returns, which means that the models have become increasingly complex. In the past two decades, the univariate ARCH model has been most widely used. Bollerslev (2001) stressed that ARCH models, even though they are incorrectly specified, serve as filters and means for predicting the persistent stochastic volatility used in the theory of valuation.

4.1 Basic characteristics of time series of index returns

Table 1 shows the statistics of the indices' returns for the period from 30 June 2004 to 30 June 2007. The ratio between the return and the risk is evident already in the first two moments of distribution. The mean of the Chinese index is almost four times higher and its standard deviation is more than two times higher than that of the American index. In the period observed, investments in the Chinese shares were substantially more profitable, but also riskier. The greater difference between the maximum and minimum values of the Shanghai Composite index confirms the greater risk. The coefficient of asymmetry is negative in both cases, which means that the distribution is left-skewed. Most of the distribution is concentrated to the right of the mean with a longer left tail. The coefficient of kurtosis shows acute peaks in the distribution of returns or leptokurtosis.

The Jarque-Berra[5] test was used to determine whether the returns of the S&P 500 and Shanghai Composite indices in the period studied had normal distribution. Based on the results of the tests the null hypothesis of normally distributed returns was rejected. The index returns in the period studied did not have normal distribution.

Table 1: Time series statistics of continuous returns of the S&P 500 and Shanghai Composite indices from 30 June 2004 to 30 June 2007

	S&P 500	**SHANGHAI COMPOSITE**
Mean	3.65×10^{-4}	13.82×10^{-4}
Median	7.39×10^{-4}	14.21×10^{-4}
Maximum	0.0213	0.0789
Minimum	-0.0353	-0.0926
Standard Deviation	0.0066	0.0159
Skewness	-0.2554	-0.5214
Kurtosis	4.3529	7.2084
Jaque Berra test	65.7893*	568.5202*
Probability	0.0000	0.0000
Observations	755	727

*Statistical significant at 5%; Source: author's calculations

[5] The Jarque-Berra test is used to determine whether the distribution of a time series is normal. The null hypothesis is that the time series has normal distribution. If the calculated value is higher than the test statistic, the null hypothesis is rejected. The time series thus does not have normal distribution.

Table 2: Time series statistics of continuous returns of the S&P 500 and Shanghai Composite indices from 30 June 2007 to 30 June 2010

	S&P 500	**SHANGHAI COMPOSITE**
Mean	-4.99×10^{-4}	-6.35×10^{-4}
Median	8.23×10^{-4}	10.59×10^{-4}
Maximum	0.1096	0.0903
Minimum	-0.0947	-0.0804
Standard Deviation	0.0194	0.0225
Skewness	-0.1359	-0.1402
Kurtosis	8.3072	4.4937
Jarque Berra test	889.5582	70.5418
Probability	0.0000	0.0000
Observations	756	733

*Statistical significant at 5%
Source: author’s calculations

Table 2 shows the statistics of index returns for the period from 30 June 2007 to 30 June 2010. In this period, the indices had negative returns and higher volatility. The developed capital market had a relatively greater increase in volatility. The standard deviation grew from 0.0066 to 0.0194, which is a growth of almost 200 percent. On the other hand, the risk of the Shanghai Composite rose by more than 40 percent. Compared to the period before the crisis, the asymmetrical coefficients approached one another, whereas the index of the developed capital market shows a relatively higher coefficient of kurtosis. In both cases, the null hypothesis of normal distribution of returns was rejected.

An adapted Dickey/Fuller test was used to check if both indices were non-stationary before and during the crisis. In both cases, the calculated absolute value of the test was higher than the critical theoretical value. The null hypothesis of non-stationarity was thus rejected. The indices of both periods show stationary time series of continuous daily returns.

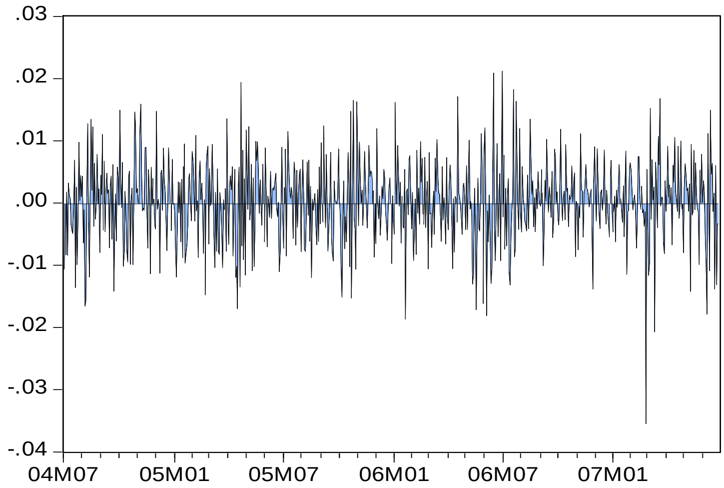
Table 3: Testing the stationarity of time series of the returns of indices using the Dickey/Fuller test

	S&P 500	SHANGHAI COMPOSITE
Dickey - Fuller test (before the crisis)	-28.6727	-26.7786
Dickey - Fuller test (during the crisis)	-23.4835	-26.9497
Critical value α = 0,01	3.44	

Source: author's calculations

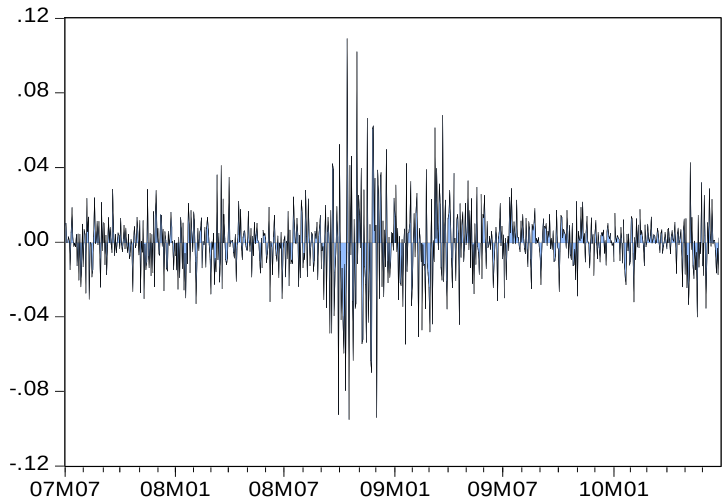
Figures 3–6 show the movement of daily returns of the S&P 500 and Shanghai Composite indices in the periods studied. The figures show that, at the end of 2008 and at the beginning of 2009, when the crisis reached its peak, there was much more volatility than before the crisis.

Figure 3: Movement of the S&P 500 index daily returns from 30 June 2004 to 30 June 2007



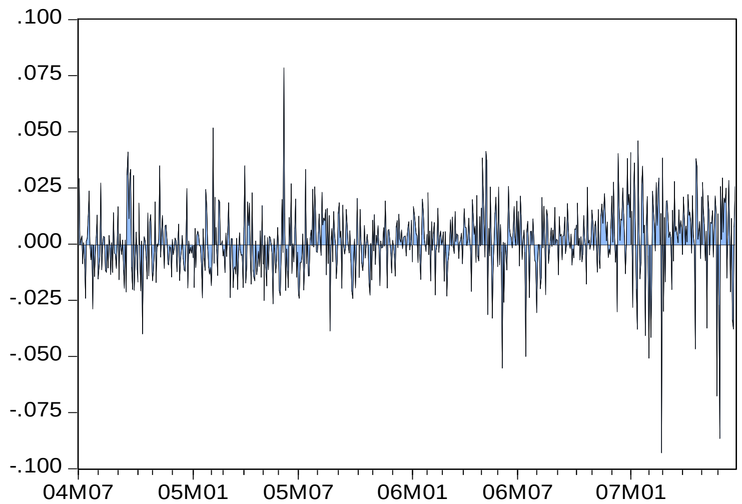
Source: author's calculations

Figure 4: Movement of the S&P 500 index daily returns from 30 June 2007 to 30 June 2010



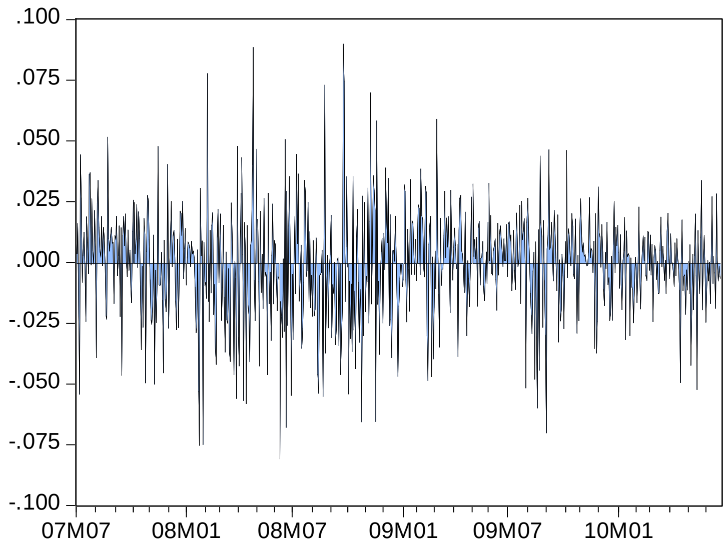
Source: author's calculations

Figure 5: Movement of the Shanghai Composite indes daily returns from 30 June 2004 to 30 June 2007



Source: author's calculations

Figure 6: Movement of the Shanghai Composite index daily returns from 30 June 2007 to 30 June 2010



Source: author's calculations

5 ANALYSIS AND RESULTS

The results of this study are outlined below. Table 4 shows the results of the volatility analysis of the S&P 500 and Shanghai Composite indices before the financial crisis. All parameters are statistically significant at the 10% level. As stressed, the value of short memory[6] determines how fast the conditional variance will respond to new information on the market. Long memory[7] is used to measure the persistence of shocks in the conditional variance.

First, the results for the period before the crisis are analyzed. The conditional variance of the developing Chinese capital market was almost twice as sensitive to new information as the developed market. The GARCH coefficient, which shows the persistence of shocks, was also higher for China. This means that the shocks (their effect on the variance) needed more time to abate. The volatility persistence measured by the sum of short and long memory is higher for the Shanghai Composite index.

[6] The ARCH parameter is referred to as "short memory."
[7] The GARCH parameter is referred to as "long memory."

IGARCH (1,1) was used to model conditional variance, which assumes that the shocks to the variance are constant. The new information has a continuous effect on volatility in all future periods. The sum of short and long memories always equals 1 and is in accordance with the assumption that shocks have a permanent effect on the movement of conditional variance. All parameters are statistically significant at the 10% level. In the period before the crisis the value of the GARCH parameter (long memory) of the S&P 500 index was above 1, whereas the value of the ARCH parameter (short memory) was negative. The new information thus had a positive effect on the volatility of the index. On the other hand, the value of short and long memories of the Shanghai Composite index was below 1.

The symmetrical GARCH models describe the processes that assume the effects on volatility are the same, regardless of whether the changes are positive or negative. On the other hand, the asymmetrical models take into account the different effects of negative and positive changes on the conditional variance. The results of the analysis for the period before the crisis show that the EGARCH (1,1) model is not suitable for the analysis of the Shanghai Composite index. This is because the leverage effect is not statistically significant and is, unlike the theoretical recognition, positive. The leverage effect of the S&P 500 index is statistically significant and negative. The model adequately describes the volatility movement.

Finally, it can be summed up that before the financial crisis, the Chinese index was subject to higher volatility than the developed market index. This finding is in accordance with the common belief that developing markets offer potentially higher returns but also carry greater risk. The sum of the short and long memory parameters of the Shanghai Composite index was higher than that of the S&P 500.

A comparison of parameters between the models shows that the value of the Akaike information criterion (AIC)[8] and the BIC information criterion[9] is highest for the EGARCH (1,1) model for the S&P 500, and GARCH (1,1) for the Shanghai Composite. This is because the results of the EGARCH model are not in accordance with the theoretical findings.

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[8] AIC – Akaike Information Criterion

$$AIC_{\rho,q} = ln\hat{\sigma}^2_{\rho,q} + \frac{2}{T}(\rho + q) \tag{8}$$

When selecting a model, the most appropriate combination is p,q, which minimizes the value of the AIC.

[9] BIC – Schwarz Information Criterion

$$BIC_{\rho,q} = ln\hat{\sigma}^2_{\rho,q} + \frac{\ln T}{T}(\rho + q) \tag{9}$$

Compared to the *AIC*, the *BIC* information criterion prefers models with fewer parameters because the penalty for the use of additional parameters is higher.

Table 4: Estimated parameters of the models for the period before the crisis

	Parameters	S&P 500	(P)*	SHANGHAI COMPOSITE	(P)*
GARCH (1,1)	C	$3.62x10^{-6}$	0.1782**	$5.41x10^{-6}$	0.052
	ARCH	0.0366	0.0823	0.0772	0.0000
	GARCH	0.8793	0.0000	0.9073	0.0000
	AIC	-7.2312		-5.565	
	BIC	-7.1944		-5.5271	
IGARCH (1,1)	ARCH	-0.0066	0.0000	0.0591	0.0000
	GARCH	1.0066	0.0000	0.9409	0.0000
	AIC	-7.2101		-5.5487	
	BIC	-7.1861		-5.5234	
EGARCH (1,1)	ARCH	-0.0438	0.0999	0.1552	0.0000
	GARCH	0.8662	0.0000	0.9839	0.0000
	L	-0.1746	0.0000	0.0165	0.1864**
	AIC	-7.2861		-5.5805	
	BIC	-7.2432		-5.5363	

*two-sided test; **parameter is not statistical significant
Source: author’s calculations

Table 5: Estimated parameters of the models for the period during the crisis

	Parameters	S&P 500	(P)*	SHANGHAI COMPOSITE	(P)*
GARCH (1,1)	C	4.46×10^{-6}	0.006	8.20×10^{-6}	0.031
	ARCH	0.1066	0.0000	0.0616	0.0000
	GARCH	0.8820	0.0000	0.9222	0.0000
	AIC	-5.5147		-4.8291	
	BIC	-5.480		-4.7914	
IGARCH (1,1)	ARCH	0.0895	0.0000	0.0451	0.0000
	GARCH	0.9105	0.0000	0.9549	0.0000
	AIC	-5.4912		-4.819	
	BIC	-5.4667		-4.7939	
EGARCH (1,1)	ARCH	0.1394	0.0001	0.1287	0.0000
	GARCH	0.9722	0.0000	0.9561	0.0000
	L	-0.1403	0.0000	-0.0847	0.0000
	AIC	-5.5477		-4.8469	
	BIC	-5.5048		-4.8029	

*two-sided test
Source: author's calculations

Based on the data presented in Table 5, it can be concluded that the level of volatility of the developing markets remained the same during the crisis, whereas the volatility of the developed capital market increased. The standard deviations of the time series approached one another during the crisis, whereas before the crisis the standard deviation in the Chinese data was more than twice as high as that for the developed market data.

During the financial crisis the value of the ARCH parameter (short memory) increased, whereas the value of the GARCH parameter (long memory) did not change significantly. On the Chinese market the opposite occurred. The value of short memory fell and the value of long memory rose. The new information had less effect on market volatility than before the crisis. The comparison of volatilities during the crisis shows that the S&P 500 index was much more influenced by short memory than the Chinese index. The financial crisis affected U.S. investors in such a way that their decisions were much more often impulsive, which caused the conditional variance to be much more responsive to new information. The Shanghai Composite index had a much higher value of the long memory, which means that the shocks lasted longer.

In contrast to the period before the crisis, the EGARCH (1,1) model is suitable for the analysis of the volatility of the Chinese index. The leverage effect is statistically significant and, in accordance with the theoretical findings, positive. On the American capital market, the absolute value of the leverage effect fell from $|-0.1746|$ to $|-0.1403|$. During the crisis, the effect of long memory on volatility increased from 0.866 to 0.9722.

A comparison of parameters between the models shows that the value of the Akaike information criterion (AIC) and the BIC information criterion is highest in the EGARCH (1,1) model for the S&P 500 and the Shanghai Composite.

Based on the comparison of both periods, one may conclude that volatility was higher on the developed capital market, and that during the crisis significant changes occurred in the structure itself. Before the crisis, long memory tended to influence volatility. The effect of new information became stronger during the crisis because the value of the ARCH parameter (short memory) grew. A reverse process was evident on the developing market, where the value of the ARCH parameter during the crisis fell and the value of the GARCH parameter (long memory) grew. The Chinese stock market index did not show significant changes in volatility either. This finding differs from the most common belief that the developing markets with potentially higher returns also carry greater risk. The reason for this may be found in the origin of the financial crisis, which has its roots in the bursting of the U.S. housing bubble.

4 CONCLUSIONS

This study examines stock market volatility. The global financial crisis brought volatility and risk management of financial institutions to the forefront. The study investigated the volatility of returns of the S&P 500 and Shanghai Composite indices during two time periods: from 30 June 2004 to 30 June 2007 and from 30 June 2007 to 30 June 2010. The purpose of the study was to analyze volatility changes of the stock market indices before and during the global financial crisis. The study examined two things: (1) whether stock-market volatility increased during the global financial crisis, and (2) whether the developed capital market had lower volatility than the Chinese developing market during the financial crisis.

The GARCH, IGARCH, and EGARCH models were used in modeling stationary time series. The EGARCH model best explained the volatility of the S&P 500 index in both periods studied. In studying the volatility of the Shanghai Composite index before the crisis, the EGARCH model did not prove to be useful because the parameter of the leverage effect was positive.

The study proved that general volatility was higher during than before the financial crisis. This provided the answer to the first question of the study. On the American capital market, the volatility coefficients were higher, whereas the Chinese market only had a higher long memory (GARCH) coefficient. Patev (2003, 15) came to a similar conclusion when he studied the volatility of the indices of the Eastern European stock markets during the Asian-Russian crisis. The value of the long memory parameter increased in the period studied.

A common belief in the financial world is that developing markets are riskier than developed markets. The results of this study of index volatility do not confirm a higher volatility of the Shanghai Composite index. During the financial crisis, the developed American market had relatively greater volatility than the Chinese market, and significant changes in the structure of volatility also occurred. The origin of the crisis itself is most likely the main reason the biggest economic crisis since 1930 has caused a relatively greater increase in the volatility of the developed market compared to that of the developing one.

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