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Stock market efficiency of Ukraine, China and Russia in comparison to USA.

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Abstract

This thesis test weak form efficiency in the stock markets of Ukraine, Russian, and China and compare the efficiency with USA stock market.

We employ Distribution test, Unit root test, Runs test, ARMA test and GARCH test to estimate the efficiency of the above four stock markets. In our study, we find that under unit root test and runs test, all of the four stock markets are not weak-form efficient. On the basis of ACF test, NYSE, PFTS and SSE are not weak-form efficient.

Key words: Ukraine, Russia, China, USA, Stock market Efficiency, Econometric Methodology.

Introduction

When money is put into the stock market, it is done with the aim of generating a return on the capital invested. Stock market efficiency has significant implication for investors and regulatory authorities. Lots of investors attempt not only to make a profitable return, but also to beat the market.

On the other hand, market efficiency – championed in the efficient market hypothesis (EMH) formulated by Eugene Fama in 1970, suggests that at any given time, prices fully reflect all accessible data on a particular stock and/or market. Thus, according to the EMH, no investor has an advantage in predicting a return on a stock price because no one has access to information not already available to everyone else. [1]

In efficient markets, prices turn out to be not predictable but random, so no investment pattern can be discerned. A planned approach to investment, therefore, cannot be successful. This "random walk" of prices, commonly spoken about in the EMH school of thought, results in the collapse of any investment strategy that aims to outperform consistently. In fact, the EMH suggests that given the transaction costs involved in portfolio management, it would be more profitable for an investor to put his or her money into an index fund. [1]

Accepting the EMH in its purest form may be difficult. The efficiency of capital markets is among the main problems of the financial sector's development. In the economics literature, there are three forms of efficiency: weak, semi-strong and strong. [1]

1. Strong efficiency – This is the strongest form, which states that all information in a market, whether public or private, is accounted for in a stock price. Not even insider information could give an investor an advantage.
2. Semi-strong efficiency – This type of EMH implies that all public information is calculated into a stock's current share price. Neither fundamental nor technical analysis can be used to reach superior gains.
3. Weak efficiency – This version of EMH claims that all past prices of a stock are reflected in today's stock price. Therefore, technical analysis cannot be used to predict and beat a market.[1]

In most cases this issue was studied in relation to developed countries, while little attention was paid to emerging markets, including Russia, China and Ukraine.

One of the most obvious modern trends in the development of the world financial system has been the increase in the share of emerging markets in the global capitalization and total liabilities under securities. At the same time the volatility of their stock markets has increased significantly. Judging from Asia's crisis of 1997-1998, the financial chaos in these countries could greatly affect the entire world economy.

In 1991, Russia and Ukraine started the difficult and complex path of transition towards a market economy. This process has resulted in a deep change in theirs economy, even though the transition is far from complete. The Russian stock market influences drastically Russian economic development by potentially providing mechanisms for resource re-allocation between different sectors of the Russian economy. The last decade has also seen a sharp rise in direct foreign investment, and the Russian market has become interesting to a increasing number of international investors. Nevertheless, despite its fast development and growing importance, the Russian stock market has been little investigated in the academic literature or the popular press.

The major objective of this paper is to test the market efficiency of the Russian, China, and Ukraine stock market and compare it to USA stock market efficiency; on the daily basis.

There are two biggest stock exchange in Russian: the Moscow International Stock Exchange (MISE) and the Moscow Central Stock Exchange (MCSE). Regular trading sessions started at the MCSE and the MISE in 1991. Two governing bodies were created in 1994: a Central Depository Clearing body and the Russian Federation Commission on Securities and the Capital Markets (FCSM). The MICEX Index is the real-time cap-weighted Russian composite index. It comprises 30 most liquid stocks of Russian largest and most developed companies from 10 main economy sectors. The MICEX Index was launched on September 22, 1997, base value - 100. The MICEX Index is calculated and disseminated by the MICEX Stock Exchange - the biggest Russian stock exchange for today which is successor of MCSE. For the Russian stock market, various indices are available, however in this study we use the MICEX index, the most important one. Its listing includes practically the largest and most liquid Russian companies. It is available on-line, and the information is updated every 30 minutes during trading hours. Due to the methodology of calculation, the MICEX index is quite stable with respect to sharp oscillations of a single stock price. [2]

Even though the size of Ukraine's stock market is not as large as those of emerging markets elsewhere (e.g., China, Russia), it has a significant potential growth and there is mounting interest by international investors in the country's securities. To study the efficiency of Ukraine's stock market, we used the values of the PFTS index (PFTS – abbreviation of the

Ukrainian Persha Fondova Torhivelna Systema, the name of the First Securities Trading System). [4]

China's equity market has been in existence since 1990, when both the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SHSE) were created. [8] Although China's equity market has developed rapidly, it is still qualified as less developed compared to US's equity market. Two types of shares are traded in the Chinese stock markets: A shares for domestic investors and B shares for foreign investors. [8] The market experienced an upward trend from the late 1990s to 2000. In 2000, the market capitalization, the liquidity and the trading volumes doubled from the previous year.[8]

Compared with Shenzhen Stock market, Shanghai stock market has been more active and represents Chinese stock market better. Therefore, in this paper, we select SSE to stand Chinese stock market index. [9]

Along with the collapse of the Soviet Union and the independence of Russian government, Russian stock market was founded in November, 1990. [9] After privatization, corporatization and chaos in capital markets resulted by long-term decline, Russian government published " Law of the Russian Federal Securities Market" to legalize the Russian Stock Market. From October 3, 1997, Russian began to adopt Russian Securities Index which is similar to US Dow Jones Index. [9] Soviet Union was the closest partner of China. They had the same political system ,set up their own stock markets almost at the same time and experienced reforms. [9] Therefore, it really meaningful to compare Chinese stock market with Russian stock market.

In this paper, we compare Chinese, Ukraine and Russian stock market with US's stock market. Because in our opinion, stock market in US is a developed market and should be efficient. For every market we will use daily data for the last 5 years (21 April 2005 – 21 April 2010).

Literature Review

During the past several years, lots of empirical research has concentrated on the efficiency of China's stock market. According to those studies, it is hard to obtain a definitive conclusion that China's stock market is efficient or not. Some of the studies claimed that China's stock market is already weak-form efficiency. Others objected the opinion. Song and Jin (1995) claimed that the Shanghai Stock Exchange has already been weakly efficient. However, Zhang and Zhou (2001) determined that China's stock market has not achieved weak-form efficiency.[7] Yudong Wang, Li Liu, Rongbao Gu, Jianjun Gao and Haiyan Wang(2010) pointed that Shanghai stock overall became more and more efficient.[10]

Natalia Abrosimova, Gishan Dissanaike, Dirk Linowski (2005) tested the weak-form efficiency of the Russian Stock Market , using random walk tests, and then applying ARMA and GARCH model trying to forecast future returns. Overall, the fact that they have not succeeded in identifying any notable weak-form inefficiencies using daily, weekly or monthly data could be viewed as somewhat surprising, especially given the relative infancy of the Russian market and its associated regulatory institutions. [2]

Adilya Batroshyna in her paper" The Efficiency Of Ukraine's Stock Market", try to demonstrate that Ukraine's stock market on the whole is a weak form of market efficiency. It explains the specific strategies for a market with a weak form of efficiency and offers recommendations on the continued development of Ukraine's stock market.[4]

We have searched for many articles about the US's stock market efficiency. Most of them considered the US's stock market is efficiency. Ky-Hyang Yuhn (1997) pointed that the US's stock market is an efficient market. [11] It is not possible to outperform the market average without luck.

Kian-Ping Lim, Robert D. Brooks and Jae H.Kim (2007) test the efficiency of eight Asian stock markets after the 1997 financial crisis. They used daily data on the Istanbul Stock Exchange Composite Index by employing the rolling bicorrelation test statistics to investigate stock market efficiency from 1988 to 1993 on a yearly basis. The outcomes indicate that ISE became efficiency after the regulatory structure. And also, applied the rolling bicorrelation test statistic, the results show that Hong Kong is the most efficient, following Korea, Taiwan and Malalysia.[12]

Yudong Wang, Li Liu, Rongbao Gu, Jianjun Cao, Haiyan Wang (2009) applying detrended fluctuation analysis (DFA) and rolling window to test the Shanghai stock market efficiency. The results show that although, the inefficiency still exists in short-rum term, Shanghai stock market became more efficient in the long-run term. And it becomes more and more efficiency after the reform. [13]

Ramesh Chander, Kiran Mehta and Renuka Sharma (2008) using parametric and non-parametric test statistics to investigate the randomness in stock prices. The results tell that the stock return behavior was an independent behavior and it was supported by weak form market efficiency theory. [14]

Jae H.Kim and Abul Shamsuddin (2007) examined the market efficiency for Asian stock market by employing new multiple variance ratio test and Chow-Denning test. They found that Hong Kong, Japanese, Korea and Taiwanese markets is in the weak form market efficiency. And Indonesia, Malaysia and Philippines stock market have not shown any sign of the market efficiency. The markets of Singapore and Thai have become efficiency after the Asian crisis.[15]

Arusha Cooray, Guneratne Wickremasingle (2007) tests the weak form stock market efficiency of India, Sri Lanka, Pakistan and Bangladesh by employing the Augmented Dickey Fuller (ADF) test, the Phillips-perron (PP) test, the Dikcy-Fuller Generalized Least Square (DF-GLS) test and Elliot-Rothenberg-Stock (ERS) test. Also they use Cointegration and Granger causality tests to examine semi-strong form efficiency. However, the South Asian stock markets can not support the semi-strong form efficiency.[16]

Theoretical background

The nature of information does not have to be limited to financial news and research alone; in fact, information about political, economic and social events, combined with how investors identify such information, whether true or rumored, will be reflected in the stock price. According to EMH, as prices respond only to information available in the market, and, because all market participants are privy to the same information, no one will have the ability to out-profit anyone else. [1]

In the real world of investment, however, there are clear arguments against the EMH. There are investors who have beaten the market - Warren Buffett, whose investment strategy focuses on undervalued stocks, made millions and set an example for numerous followers. There are portfolio managers who have better track records than others, and there are investment houses with more renowned research analysis than others. So how can performance be random when people are noticeably profiting from and beating the market?

Counter arguments to the EMH state that consistent patterns are present. Here are a few examples of some of the predictable anomalies thrown in the face of the EMH: the January effect is a pattern that shows higher returns tend to be earned in the first month of the year; "blue Monday on Wall Street" is a saying that discourages buying on Friday afternoon and Monday morning because of the weekend effect, the tendency for prices to be higher on the day before and after the weekend than for the period of the rest of the week.

Studies in behavioral finance, which look into the effects of investor psychology on stock prices, also reveal that there are some predictable patterns in the stock market. Investors tend to buy undervalued stocks and sell overvalued stocks and, in a market of many participants, the result can be anything but efficient.

Paul Krugman, MIT economics professor, suggests that because of the mass mentality of the trendy, short-term shareholder, investors pull in and out of the latest and hottest stocks. This resulted in stock prices being distorted and the market being inefficient. So prices do not reflect all available information in the market. Prices are instead being manipulated by profit seekers. [1]

The EMH does not dismiss the possibility of anomalies in the market that result in the generation of superior profits. In fact, market efficiency does not require prices to be equal to fair value all of the time. Prices may be over- or undervalued only in random occurrences, so they eventually revert back to their mean values. As such, because the deviations from a stock's fair price are in themselves random, investment strategies that result in beating the market cannot be consistent phenomena.

Furthermore, the hypothesis argues that an investor who outperforms the market does so not out of skill but out of luck. EMH followers say this is due to the laws of probability: at any given time in a market with a large number of investors, some will outperform while other will remain average. [1]

In order for a market to become efficient, investors must perceive that a market is inefficient and possible to beat. Ironically, investment strategies intended to take advantage of inefficiencies are actually the fuel that keeps a market efficient.

A market has to be large and liquid. Information has to be widely available in terms of accessibility and cost and released to investors at more or less the same time. Transaction costs have to be cheaper than the expected profits of an investment strategy. Investors must also have enough funds to take advantage of inefficiency until, according to the EMH, it disappears again. Most importantly, an investor has to believe that she or he can outperform the market.

EMH propagandists will state that profit seekers will, in practice, exploit whatever abnormally exists until it disappears. In instances such as the January effect (a predictable pattern of price movements), large transactions costs will most likely outweigh the benefits of trying to take advantage of such a trend.

In the real world, markets cannot be absolutely efficient or wholly inefficient. It might be reasonable to see markets as essentially a mixture of both, wherein daily decisions and events cannot always be reflected immediately into a market. If all participants were to believe that the market is efficient, no one would seek extraordinary profits, which is the force that keeps the wheels of the market turning. [1]

Method

Data description

The data employed in this paper is composed of the closing index of the composite stock index for four stock markets—China, Russia, Ukraine and United States, in which China, Russia and Ukraine are emerging stock markets. The Chinese stock index is obtained from Shanghai Stock Exchange. The US stock index is obtained from New York Stock Exchange. Russian and Ukraine's stock index are from Moscow Central Stock Exchange and Ukrainian Persha Fondova Torhivelna Systema respectively. For every market we will use daily data for the last 5 years (21 April 2005 – 21 April 2010).

The main purpose of this paper is to analyze the risk of equity investments, daily data is specified in this study.

Emerging markets usually follow weak form of market efficiency. Since the test of EMH, in general, have come from the random walk literature, so we are interested in testing whether or not successive price changes were independent of each other.[5]

In this paper, we decided to use distribution test, Unit root test, Runs test, ARMA test, GARCH test and ACF test to estimate the market efficiency for China, Russia, Ukraine and USA.

Jarque–Bera test

As for any other research first of all we will plot our data and check normal with help of JB test.

The test was mentioned by Bowman & Shenton (1975), who noticed that the statistics JB can be used to test normality of a set of observations and will be asymptotically χ2(2)-distributed; however they also noted that "large sample sizes would doubtless be required for the χ2 approximation to hold". Bowman and Shelton did not study the properties of this test any further, preferring the D'Agostino's K-squared test. [17]

Around 1980, Anil K. Bera and Carlos M. Jarque while working on their dissertations, have applied the Lagrange multipliers test to the Pearson family of distributions and found that the JBtest was asymptotically optimal (although the sample size needed to "reach" the asymptotic level was quite large). In 1980 the authors published a paper (Jarque & Bera 1980), which treated a more advanced case of simultaneously testing the normality, homoscedasticity and absence of autocorrelation in the residuals from the linear regression. The JB test was mentioned there as a simpler case, but without giving sufficient details. A complete paper of the JB Test was published in the International Statistical Review in 1987 dealing with both testing the normality of observations and the normality of unobserved regression residuals. [17]

In statistics, the Jarque–Bera test is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness. The test is named after Carlos Jarque and Anil K. Bera. The test statistic JB is defined as

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}K^2\right) \tag{1}$$

where n is the number of observations (or degrees of freedom in general); S is the sample skewness, and K is the sample kurtosis:

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{3/2}} \tag{2}$$

$$K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} - 3 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{2}} - 3, \tag{3}$$

where $\hat{\mu}_3$ and $\hat{\mu}_4$ are the estimates of third and fourth central moments, respectively, $\bar{x}$ is the sample mean, and $\hat{\sigma}^2$ is the estimate of the second central moment, the variance. [17]

The statistic JB has an asymptotic chi-square distribution with two degrees of freedom and can be used to test the null hypothesis that the data are from a normal distribution. The null hypothesis is a joint hypothesis of the skewness being zero and the excess kurtosis being 0, since samples from a normal distribution have an expected skewness of 0 and an expected excess kurtosis of 0 (which is the same as a kurtosis of 3). As the definition of JB shows, any deviation from this increases the JB statistic.[17]

As we have data from stock markets it will be reasonable to assume, that it has trend and would not has a normal distribution.

After we check normality we can proceed to main part of our research, checking is this series are follows random walk hypothesis. We will do this with help of following tests: ACF, Runs and ADF tests. If this series are follow random walk hypothesis than we will receive proof of market efficiency, if not we will apply ARMA and GARCH models.

The weak form efficiency hypothesis requires that there should be no profit opportunities which are based on the past movement in asset prices. This means that an efficient market should be an unpredictable one. This has often been tested by carrying out simple regressions of the form:

$$r_t = \beta_0 + \sum_{i=1}^{p} \beta_i r_{t-i} + e_t \tag{4}$$

where r is the rate of return on an asset and weak form efficiency implies that b_i=0, i>0 , this will often be tested by estimating such equations, usually using OLS.

ACF

Autocorrelation is one of the statistical tools used for measuring the dependence of successive terms in a given time series. Therefore it is used for measuring the dependence of successive share price changes. It is the basic tool used to test the weak form of EMH. The autocorrelation function ACF (k) for the time series Y_t and the k-lagged series Y_{t-k} is defined as :

$$ACF(k) = \frac{\sum_{(t=1-k)}^{n} (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{(t=1)}^{n} (y_t - \bar{y})^2} \tag{5}$$

The standard error of ACF (k) is given by:

$$Se_{ACF(k)} = \frac{1}{\sqrt{(n-k)}} \tag{6}$$

where n is sufficiently large ($n \geq 50$), the approximate value of the standard error of ACF(k) is given by:

$$Se_{ACF(k)} = \frac{1}{\sqrt{(n)}} \tag{7}$$

To test whether ACF (k) is significantly different from zero, the following distribution of't' is used, i.e. t=ACF (k)/ SeACF(k). For both random variable series and series with trends, ACF (k) are very high and decline slowly as the lag value (k) increases. At the same time the ACF (k) of the first difference series (price changes or returns) are statistically insignificant when the series is a random walk series. A random walk series drifts up and down over time. In some situation it may be difficult to judge whether a trend or drift is occurring. Hence to determine whether a series has significant trend or whether it is a random walk, the t-test is applied on the series of first differences.[5]

After we apply ACF to our data we will proceed with unit root test and runs test.

ADF

" Three different unit root tests are used to test the null hypothesis of a unit root: namely, the Augmented Dickey-Fuller(ADF) test, the Phillips-Peron(PP) test, and the Kwiatkowski, Phillips, Schmidet and Shin(KPSS) test." [19] To begin with, the well-known ADF unit root test is conducted in the form of the following regression equation:

$$y_t = \boldsymbol{\gamma y_{t-1}} + \boldsymbol{\mu_t} \tag{8}$$

This is an AR(1) equation. We can transfer the above equation as the following:

$$(1 - \boldsymbol{\gamma L})\boldsymbol{y_t} = \boldsymbol{\mu_t} \tag{9}$$

In which, L is a lag factor. The condition for stationary is that the absolute value of the root of $1 - \boldsymbol{\gamma L}$ greater than 1. It means that $L = 1/\boldsymbol{\gamma}$ greater than 1. In the case of $\gamma = 1$, we can get the conclusion from equation 1 that this series is not stationary since the root equals to 1.

Because $\boldsymbol{\gamma}$ is unknown, we can not test the stationary of the series. However, we can test the stationary of the first difference of the equation. If the first difference of the equation is stationary, we can say that this series is not stationary. Then we can find whether the stock market is efficient or not. The first difference of the equation 1 is the following:

$$\Delta y_t = \boldsymbol{\delta y_{t-1}} + \boldsymbol{\mu_t} \tag{10}$$

In which, $\delta = y - 1$. Apparently, when $\delta = 0$ or $\gamma = 1$, the conclusion is the same. We can prove that when $|\gamma| < 1$, equation 1 is stationary. Otherwise, that is not stationary.

In this paper, we decide to choose ADF to test the stationary. The regression equation is the following:

$$\Delta y_t = \beta_1 + \beta_2 t + \boldsymbol{\delta y_{t-1}} + \boldsymbol{\alpha} \sum_{i=1}^{m} \boldsymbol{\Delta y_{t-1}} + \boldsymbol{\varepsilon_t} \qquad \boldsymbol{H_0 : \delta = 0} \tag{11}$$

Where y_t denotes the price for the market at time t, $\Delta y_t = y_t - y_{t-1}$, $\boldsymbol{\alpha}$ are coefficients to be estimated. $\boldsymbol{m}$ is the number of lagged terms, t is the time or trend term. β_2 is the estimated coefficient for the trend, β_1 is the constant and $\boldsymbol{\varepsilon}$ is white noise.

When we analyst the efficiency of the stock market, we employ return R_t as dependent variable.

$$\Delta R_t = \beta_1 + \beta_2 t + \boldsymbol{\delta y_{t-1}} + \boldsymbol{\alpha} \sum_{i=1}^{m} \boldsymbol{\Delta y_{t-1}} + \boldsymbol{\varepsilon_t} \qquad \boldsymbol{H_0 : \delta = 0} \tag{12}$$

If $\boldsymbol{\delta}$ equals to 0 statistically, the series R_t is not stationary. It means that $R_t = \boldsymbol{\gamma R_{t-1}} + \boldsymbol{\mu_t}$ and $\gamma = 1$. The series R_t is an random walk. The stock market is weak-form efficiency.

Otherwise, the series is stationary, $R_t = \boldsymbol{\gamma R_{t-1} + \mu_t}$ and $\gamma \neq 1$. It means that the stock price is not an random walk and the market is not efficiency.

Runs

Runs test is a non-parametric test, which applies to non-normal distribution samples. A "run" of a sequence is a series that has the same sign of the changes. There are three types of the changes of stock prices: positive , negative and no change. Accordingly there are three types of runs. “A positive (negative) run is a sequence of positive (negative) price changes preceded and succeeded by either negative (positive) or zero price change. Similarly, a zero run is sequence of zero price changes preceded and succeeded by either negative or positive price change.” [20]

The expected number of runs of all the three types is estimated as the following, (by Wallis, Robert(1956)).

$$M = \frac{N(N+1) - \sum_{i=1}^{3} n_i^2}{N} \tag{13}$$

Where M equals expected number of runs, n_i equals the number of price changes of each sign (i=1,2,3) and N equals total number of price changes.

$$N = n_1 + n_2 + n_3 \tag{14}$$

The standard error of the expected number of runs of all the sings can obtained as

$$\sigma_m = \left[\frac{\sum_{i=1}^{3} n(\sum_{i=1}^{3} n_i^2 + N(N+1)) - 2N\sum_{i=1}^{3} n_i^2 - N^3}{N^3(N-1)}\right]^{\frac{1}{2}} \tag{15}$$

When m is large enough, the sampling distribution is approximately normally distributed.[20]

Now we can apply ARMA and GARCH to the indexes which are not market efficient.

ARMA

An ARMA (p,q) model is obtained by combining the AR(p) and MA(q) models together. An AR (P) model is one that the current value of a variable y, depends on the only previous values plus an error term. The model can be expressed as the following:

$$y_t = \boldsymbol{\mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + u_t} \tag{16}$$

Where $\mathbf{u_t}$ is a white noise disturbance term. [21]

An MA (q) model is a linear combination of white noise process. The current value of a variable y depends on the current and previous values of a white noise disturbance term. An MA(q) model can be expressed as the follows:[21]

$$y_t = \boldsymbol{\mu + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q}} \tag{17}$$

"Such a model states that the current value of some series y depends linearly on its own previous values plus a combination of current and previous values of a white noise error term." [21]

An ARMA model can be written

$$\phi(L)y_t = \boldsymbol{\mu} + \boldsymbol{\theta}(\boldsymbol{L})\boldsymbol{u_t} \tag{18}$$

where

$$y_t = \boldsymbol{\mu} + \boldsymbol{\phi_1 y_{t-1}} + \boldsymbol{\phi_2 y_{t-2}} + \cdots + \boldsymbol{\phi_p y_{t-p}} + \boldsymbol{\theta_1 \mu_{t-1}} + \boldsymbol{\theta_2 \mu_{t-2}} + \cdots + \boldsymbol{\theta_q \mu_{t-q}} + \boldsymbol{u_t} \tag{19}$$

with

$$E(u_t) = 0; E(u_t^2) = \sigma^2; E(u_t u_s)0, t \neq s \tag{20}$$

The characteristics of an ARMA process will be a combination of that from the AR and MA parts. The mean of an ARMA process could be written [21]

$$E(y_t) = \frac{\mu}{1-\phi_1-\phi_2-\cdots-\phi_p} \tag{21}$$

GARCH

In econometrics, a model featuring autoregressive conditional heteroskedasticity considers the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the previous innovations. Such models are often called ARCH models (Engle, 1982), although a variety of other acronyms is applied to particular structures of model which have a similar basis. ARCH models are employed commonly in modeling financial time series that exhibit time-varying volatility clustering, i.e. periods of swings followed by periods of relative calm. [18]

If an autoregressive moving average model (ARMA model) is assumed for the error variance, the model is a generalized autoregressive conditional heteroskedasticity (GARCH, Bollerslev(1986)) model. In that case, the GARCH(p, q) model (where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ϵ^2) is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \cdots + \alpha_q\epsilon_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_p\sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2 \tag{22}$$

Generally, when testing for heteroskedasticity in econometric models, the best test is the White test. However, when dealing with time series data, as we have, this means to test for ARCH errors (as described above) and GARCH errors (below). [18]

GARCH (p, q) model specification

The lag length *p* of a GARCH (p, q) process is established in three steps:

1. Estimate the best fitting AR(q) model

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_q y_{t-q} + \epsilon_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i} + \epsilon_t \quad . \tag{23}$$

2. Compute and plot the autocorrelations of ε^2 by

$$\rho = \frac{\sum_{t=i+1}^{T} (\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)(\hat{\epsilon}_{t-1}^2 - \hat{\sigma}_{t-1}^2)}{\sum_{t=1}^{2} (\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)^2} \tag{24}$$

3. The asymptotic, that is for large samples, standard deviation of ρ (i) is $1/\sqrt{T}$. Individual values that are larger than this indicate GARCH errors. To estimate the total number of lags, use the Ljung-Box test until the value of these are less than, say, 10% significant. The Ljung-Box Q-statistic follows χ^2 distribution with *n* degrees of freedom if the squared residuals ϵ_t^2 are uncorrelated. It is recommended to consider up to T/4 values of *n*. The null hypothesis states that there are no ARCH or GARCH errors. Rejecting the null thus means that there are existing such errors in the conditional variance.[18]

The presence of ARCH processes implies that the time series follows some sort of nonlinear dynamic process despite a lack of any significant autocorrelations among past observations.

Therefore, if ARCH is present, it may lead to a serious linear model misspecification. For this reason, we test the time series for ARCH effects. Engle (1982) proposed the class of ARCH models which allowed one to model variance directly in terms of past observations (see Bollerslev, Chou, and Kroner (1992) for an extensive survey of the development and application of these models). These models represent conditional variance as a distributed lag of past squared innovations:

$$\begin{aligned} &\varepsilon_t \sim N(0, h_t) \\ &h_t = \omega + \alpha(L)\varepsilon_t^2 \end{aligned} \tag{25}$$

where e represents past innovations, L denotes the lag operator, and w>0, α>0.

To avoid estimation of a large number of coefficients in a high-order polynomial α(L), Bollerslev (1986) generalizes the order of the ARCH(q) model into the Generalised Autoregressive Conditional Heteroskedasticity model of orders p and q:

$$\begin{aligned} &\varepsilon_t \sim N(0, h_t) \\ &h_t = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)h_t \end{aligned} \tag{26}$$

This process is covariance stationary if and only if α (L)+β(L)<1, in which case the model could also be written as an infinite order ARCH model.[2]

Comparison of the above tests

The methods we employed above in this thesis are common to test the market efficiency and all of them have advantages and disadvantages.

(1) Distribution test: this method is easy to understand and operate. However, distribution test is employed under the assumption that all the data has the same variance. This assumption is opposite to the reality. Therefore, the result of the test could be not accurate.

(2) Unit root test: this method is also easy to understand and operate. However, the statistics is easy to be influenced by abnormal value. Therefore, when we use this method to test the efficiency of market, it is necessary to eliminate the abnormal value. This method can not give a detailed description of the reality.

(3) Run test: compared with other methods, runs test is more intuitive. However, this method is not so comprehensive. Because the absolute values of the data are ignored.

(4) ARAM test: this method can give more details about the reality. However, this method is also not comprehensive enough.

(5) GARCH test: this method also can give more detaials and catch volatility of the series. [9]

Empirical Results

As we see on the graphs 1-4 every index has trend. We can assume that the next test (Jarque-Bera) would not show normality of our data because of these trends.

Jarque-Bera

According to the p-values of JB test, we reject the null of normality for all given series with 5% level of significance, although we see that the distribution is slightly platykurtic and negatively skewed for NYSE and MICEX.

Tests for Random Walk

ACF Test

To determine whether a series has significant trend or whether it is a random walk, the t-test is applied on the series of first differences for 36 lags of daily indexes.

Table 1

Index	NYSE	PFTS	SSE	MICEX
Significant lags	1,2,3	1,2,3,4,5,7,9	3,4	No significant lags

We can see from the table that NYSE, PFTS and SSE have significant lags (i.e. they are significantly different from zero) at the 95% confidence level.

Conclusion: On the basis of ACF test, the null hypothesis of the random walk cannot be accepted for any index except MICEX.

ADF Test

The unit root test indicates that NYSE, PFTS, SSE and MICEX indexes are non-stationary. Since all the P-values of the four market indexes are significantly larger than 5% level. After making first difference of NYSE, PFTS, SSE and MICEX indexes index, all of the variables have no unit root, which means they become stationary.

Apparently, all of the variables have a unit root. All of the series are not stationary. Therefore, according to $y_t = \gamma y_{t-1} + \mu_t, |\gamma| < 1.$ All of the series are not random walk. The changes of the prices of the stocks are not random. Historical information can not be fully reflected in current prices. Investors can obtain excess value through analyzing historical information. In conclusion, NYSE, PFTS, SSE and MICEX are not weak-form efficient.

Runs test

We employed runs test under the null hypothesis that price changes are independent. The results show that all of the stock markets are not weak-form efficient. Since all the P-values are significantly less than 0.005. Therefore, we reject the null hypothesis and accept the alternative hypothesis. The series are not random. Thus, NYSE, PFTS, SSE and MICEX are not weak-form efficient.

On the basis of all the performed tests, the null hypothesis of the random walk can be rejected for daily data for all indexes. Therefore, we proceed further in our analysis of daily returns.

It means that this data may follow some predictable patterns. Therefore, we perform linear and non-linear modeling for daily data.

Daily Returns Modeling

All the modeling is performed for the in-sample period 21 April 2005 – 21 April 2010. The dependent variable is stock index.

To choose best AR (p) and MA (q) we will build table with SBC and AIC for different models.

ARMA Model Building

Table 2

Index	Best ARMA model
NYSE	ARMA (1,1)
PFTS	ARMA (2,2)
SSE	ARMA (1,0)
MICEX	ARMA (1,0)

As we see from the table 2 (in detail tables 21-24), we will choose p=1 and q=1 for NYSE index, p=2 and q=2 for PFTS index, p=1 and q=0 for SSE index and p=1 and q=0 for MICEX index. Because of the lowest SBC from models which are possible. Since the two criteria are different in this test. And "it will always be the case that SBC selects a model that is at least as small (i.e. with fewer or the same number of parameters) as AIC, because the former criterion has a stricter penalty term. This means that SBC penalizes the incorporation of additional terms more heavily." [21]

GARCH Model Building

Table 3

Index	Best GARCH model
NYSE	GARCH (2,0)
PFTS	GARCH (2,0)
SSE	GARCH (1,1)

MICEX	GARCH (2,1)

In order to build a GARCH model, we selected the best fitting AR (p) and MA (q) model. As we see from the table 3 (in detail tables 33-36), we will choose p=2 and q=0 for NYSE index, p=2 and q=0 for PFTS index, p=1 and q=1 for SSE index and p=2 and q=1 for MICEX index. We found that the AR (p) and MA(q) are different for different indexes. Therefore we will choose different models for different indexes. According to the Jarque-Bera statistic, the skewness and kurtosis of distribution differ significantly from the normal distribution parameters as we said before. Tests for heteroscedasicity confirm the presence of the ARCH effects. Therefore, a GARCH-type model can be a suitable for us. Now build table 4 with α and β for different indexes.

Table 4

Index	GARCH model	α	β	α+β
NYSE	GARCH(2,0)	0.001194	-0.998382	-0,997188
PFTS	GARCH(2,0)	-2.948220	-0.996019	-3,944239
SSE	GARCH(1,1)	-1.522410	-0.994125	-2,516535
MICEX	GARCH(2,1)	-0.275380	-0.999640	-1,27502

As we see from the table above α+β for all indexes <1 it means that this process is covariance stationary, in which case the model could also be written as an infinite order ARCH model. And we can use these models to forecast future indexes.

Conclusions

In this paper, we tested for weak-form efficiency using daily indexes time series of NYSE, PFTS, SSE and MICEX. It was found that the null hypothesis of the random walk could be rejected for the daily data for every given index. It is a little bit strange, because in introduction part we supposed that stock market in US is a developed market and should be efficient. But it can be easily explained by financial crisis of 2008-2009, and we think, that in 2 years USA stock market became efficient again. Also we think that in next 10 years Russia, China and Ukraine markets will become efficient too.

In order to study linear and non-linear dependence in the daily data, ARMA and GARCH models were built. To select the best fitting model, the parameters of MA (q) with AR(p) and GARCH (p,q) processes were compared with AIC and SBC.

In the study for ARMA model, we choose p=1 and q=1 for NYSE index, p=2 and q=2 for PFTS index, p=1 and q=0 for SSE index and p=1 and q=0 for MICEX index. You can see this in table 2.

Similarly, for GARCH model we choose p=2 and q=0 for NYSE index, p=2 and q=0 for PFTS index, p=1 and q=1 for SSE index and p=2 and q=1 for MICEX index (table3).

Under distribution test, we can say that all of the four stock markets are not normally distributed. Since all p-values are evidently less than 5% level. We rejected the null hypothesis.

On the basis of ACF test, the null hypothesis of the random walk cannot be accepted for any index except MICEX. Because table 1 shows that NYSE, PFTS and SSE have significant lags (i.e. they are significantly different from zero) at the 95% confidence level.

The unit root test shows that NYSE, PFTS, SSE and MICEX are not weak-form efficient. Since all of the P-values of the four market indexes are significantly larger than 5% level. They are not random walk. Current price can reflect historical information. Informed investors can obtain excess value.

We can see from runs test that NYSE, PFTS, SSE and MICEX are still not weak-form efficient. Since we reject the null hypothesis with p-values are remarkable less than 0.005.

After obtaining results of ACF, ADF and Runs test we can conclude that on daily basis none of four indexes show market efficiency. As we mentioned in theoretical part there are portfolio managers who have better track records than others, and there are investment houses with more renowned research analysis than others. So how can performance be random when people are noticeably profiting from and beating the market? Market inefficiency is the answer. It means that lots of investors can not only to make a profitable return, but also to beat the market.

We made a conclusion that this data follows some predictable patterns. Therefore, we perform linear and non-linear modeling for daily data. And we can conclude that ARMA and GARCH models can be used to predict stock market indexes of USA, China, Russia and Ukraine on daily basis.

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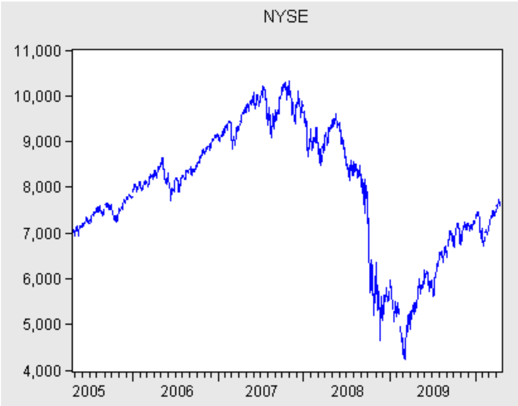
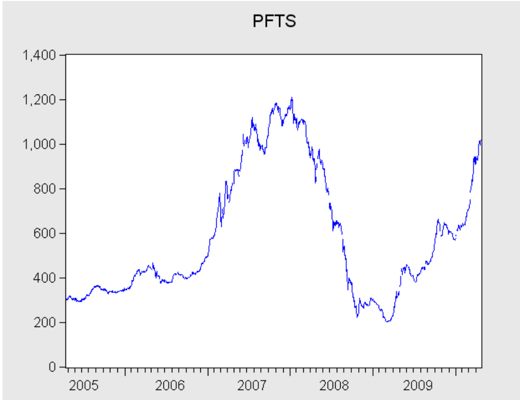
Appendix

Data plot

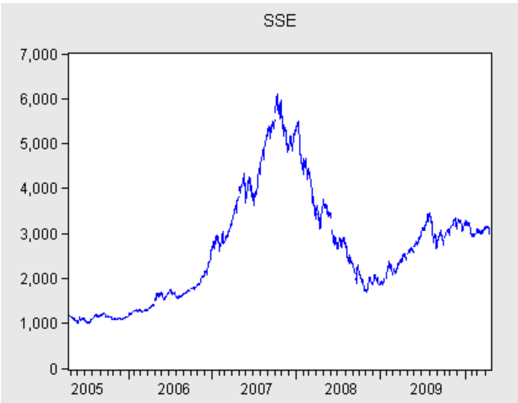
Graph 1



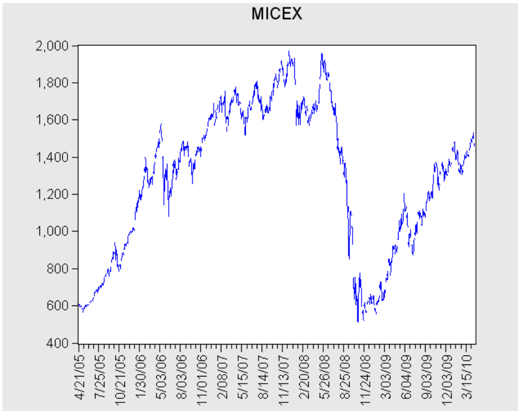
Graph 2



Graph 3

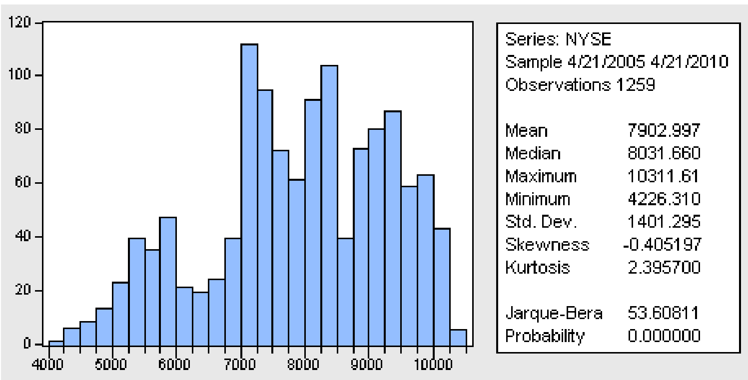


Graph 4

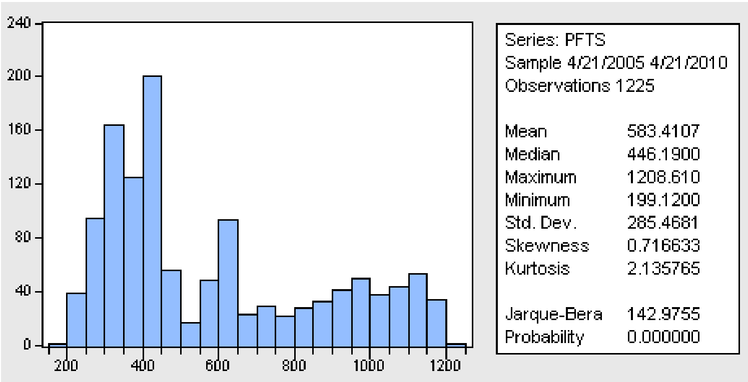


Jarque-Bera

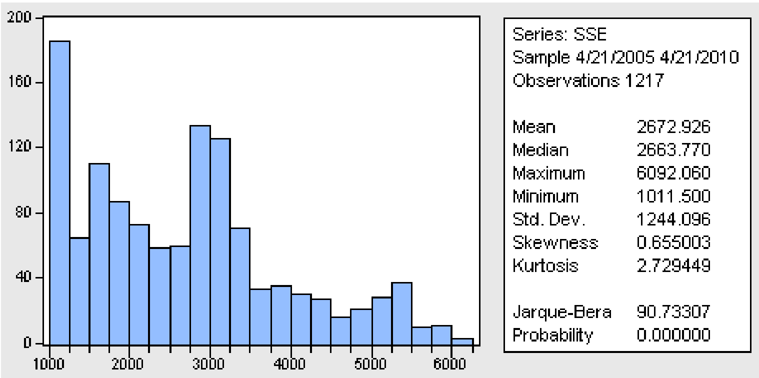
Graph 5



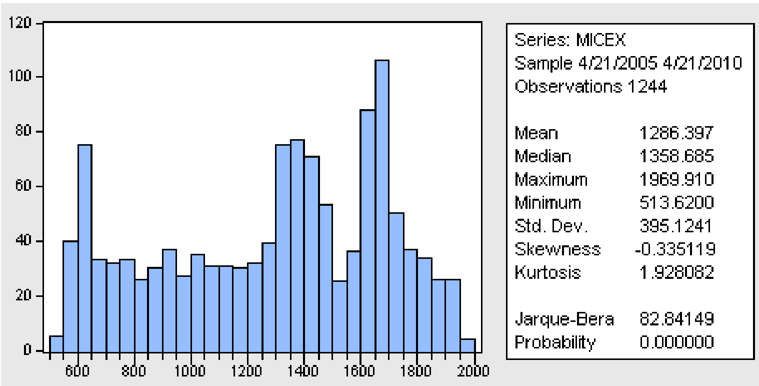
Graph 6



Graph 7



Graph 8



ACF

Table 5

Correlogram of D(NYSE)

Date: 05/20/10 Time: 19:29
Sample: 4/21/2005 4/21/2010
Included observations: 1258

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.109	-0.109	15.016	0.000
		2	-0.069	-0.082	21.103	0.000
		3	0.056	0.040	25.097	0.000
		4	-0.017	-0.012	25.458	0.000
		5	-0.008	-0.004	25.540	0.000
		6	-0.014	-0.020	25.789	0.000
		7	-0.026	-0.030	26.642	0.000
		8	0.025	0.017	27.412	0.001
		9	-0.001	0.001	27.415	0.001
		10	0.038	0.044	29.214	0.001

Table 6

Correlogram of D(PFTS)

Date: 05/20/10 Time: 19:30
Sample: 4/21/2005 4/21/2010
Included observations: 1224

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.240	0.240	70.454	0.000
		2	0.045	-0.014	72.901	0.000
		3	0.065	0.061	78.099	0.000
		4	0.078	0.052	85.615	0.000
		5	0.094	0.066	96.481	0.000
		6	0.035	-0.006	97.978	0.000
		7	0.043	0.031	100.21	0.000
		8	0.024	-0.003	100.95	0.000
		9	0.066	0.055	106.28	0.000
		10	0.029	-0.009	107.31	0.000

Table 7

Correlogram of D(SSE)

Date: 05/20/10 Time: 19:31
Sample: 4/21/2005 4/21/2010
Included observations: 1216

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.011	0.011	0.1596	0.689
		2	-0.037	-0.037	1.8611	0.394
		3	0.068	0.069	7.5632	0.056
		4	0.069	0.067	13.451	0.009
		5	-0.011	-0.007	13.587	0.018
		6	-0.048	-0.048	16.456	0.012
		7	0.021	0.013	17.016	0.017
		8	-0.033	-0.041	18.367	0.019
		9	-0.042	-0.033	20.578	0.015
		10	0.020	0.023	21.082	0.021

Table 8

Correlogram of D(MICEX)

Date: 05/20/10 Time: 19:32
Sample: 4/21/2005 4/21/2010
Included observations: 1243

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.026	-0.026	0.8275	0.363
		2	0.020	0.020	1.3437	0.511
		3	-0.012	-0.011	1.5115	0.680
		4	-0.032	-0.033	2.8181	0.589
		5	0.034	0.033	4.2986	0.507
		6	-0.020	-0.017	4.7903	0.571
		7	0.004	0.001	4.8075	0.683
		8	-0.016	-0.015	5.1289	0.744
		9	0.016	0.017	5.4380	0.795
		10	-0.028	-0.029	6.4332	0.778

ADF

Table 9

ADF (level)

Augmented Dickey-Fuller Unit Root Test on NYSE

Null Hypothesis: NYSE has a unit root
Exogenous: None
Lag Length: 2 (Automatic based on SIC, MAXLAG=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.031803	0.6721
Test critical values:	1% level	-2.566804	
	5% level	-1.941076	
	10% level	-1.616530	

*MacKinnon (1996) one-sided p-values.

Table 10

Augmented Dickey-Fuller Unit Root Test on PFTS

Null Hypothesis: PFTS has a unit root
Exogenous: None
Lag Length: 1 (Automatic based on SIC, MAXLAG=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.092461	0.9290
Test critical values:	1% level	-2.566854	
	5% level	-1.941082	
	10% level	-1.616525	

*MacKinnon (1996) one-sided p-values.

Table 11

Augmented Dickey-Fuller Unit Root Test on SSE

Null Hypothesis: SSE has a unit root
Exogenous: None
Lag Length: 0 (Automatic based on SIC, MAXLAG=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.207677	0.7465
Test critical values:	1% level	-2.566865	
	5% level	-1.941084	
	10% level	-1.616524	

*MacKinnon (1996) one-sided p-values.

Table 12

Augmented Dickey-Fuller Unit Root Test on MICEX

Null Hypothesis: MICEX has a unit root
Exogenous: None
Lag Length: 0 (Automatic based on SIC, MAXLAG=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.224149	0.7512
Test critical values:	1% level	-2.566824	
	5% level	-1.941078	
	10% level	-1.616528	

*MacKinnon (1996) one-sided p-values.

Table 13

ADF (1 difference)

Augmented Dickey-Fuller Unit Root Test on D(NYSE)

Null Hypothesis: D(NYSE) has a unit root
Exogenous: None
Lag Length: 1 (Automatic based on SIC, MAXLAG=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.63727	0.0000
Test critical values:	1% level	-2.566804	
	5% level	-1.941076	
	10% level	-1.616530	

*MacKinnon (1996) one-sided p-values.

Table 14

Augmented Dickey-Fuller Unit Root Test on D(PFTS)			
Null Hypothesis: D(PFTS) has a unit root			
Exogenous: None			
Lag Length: 0 (Automatic based on SIC, MAXLAG=22)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.30036	0.0000
Test critical values:	1% level	-2.566854	
	5% level	-1.941082	
	10% level	-1.616525	
*MacKinnon (1996) one-sided p-values.			

Table 15

Augmented Dickey-Fuller Unit Root Test on D(SSE)			
Null Hypothesis: D(SSE) has a unit root			
Exogenous: None			
Lag Length: 0 (Automatic based on SIC, MAXLAG=22)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-34.41739	0.0000
Test critical values:	1% level	-2.566867	
	5% level	-1.941084	
	10% level	-1.616524	
*MacKinnon (1996) one-sided p-values.			

Table 16

Augmented Dickey-Fuller Unit Root Test on D(MICEX)			
Null Hypothesis: D(MICEX) has a unit root			
Exogenous: None			
Lag Length: 0 (Automatic based on SIC, MAXLAG=22)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.12773	0.0000
Test critical values:	1% level	-2.566825	
	5% level	-1.941078	
	10% level	-1.616528	
*MacKinnon (1996) one-sided p-values.			

Runs test

Table 17

Runs Test for NYSE

	7049.18
Test Value[a]	8032,0000
Cases < Test Value	629
Cases >= Test Value	629
Total Cases	1258
Number of Runs	23
Z	-34,241
Asymp. Sig. (2-tailed)	,000

a. Median

Table 18

Runs Test for PFTS

	301.89
Test Value[a]	446,0000
Cases < Test Value	611
Cases >= Test Value	613
Total Cases	1224
Number of Runs	16
Z	-34,142
Asymp. Sig. (2-tailed)	,000

a. Median

Table 19

Runs Test for SSE

	1172.56
Test Value[a]	2665,0000
Cases < Test Value	608
Cases >= Test Value	608
Total Cases	1216
Number of Runs	12
Z	-34,254
Asymp. Sig. (2-tailed)	,000

a. Median

Table 20

Runs Test for MICEX

	603.79
Test Value[a]	1359,0000
Cases < Test Value	621
Cases >= Test Value	622
Total Cases	1243
Number of Runs	38
Z	-33,171
Asymp. Sig. (2-tailed)	,000

a. Median

ARMA

Table 21

information criteria for ARMA models of the percentage changes about NYSE

AIC						
p/q	0	1	2	3	4	5
0	17.32897	16.05878	15.11129	14.45685	13.99441	13.72275
1	12.21865	12.20667	12.20489	12.20367	12.20492	12.20623
2	12.20926	12.20722	12.20462	12.20567	12.20592	12.20578
3	12.20487	12.20458	12.2061	12.2007	12.19734	12.19603
4	12.20535	12.20681	12.20274	12.20995	12.2046	12.19946
5	12.20763	12.20907	12.19752	12.19721	12.21174	12.20422
SBIC						
p/q	0	1	2	3	4	5
0	17.33306	16.06694	15.12354	14.47318	14.01482	13.74724
1	12.22682	12.21893	12.22122	12.22409	12.22942	12.23481
2	12.22152	12.22357	12.22505	12.23019	12.23452	12.23847
3	12.22122	12.22503	12.23064	12.22932	12.23005	12.23283
4	12.2258	12.23136	12.23138	12.24268	12.24142	12.24038
5	12.2322	12.23773	12.23027	12.23406	12.25268	12.24925

Table 22

information criteria for ARMA models of the percentage changes about PFTS

AIC						
p/q	0	1	2	3	4	5
0	14.14695	12.79251	11.68306	10.78218	10.18531	9.68574
1	7.66635	7.6092	7.610279	7.610242	7.610551	7.604911
2	7.609466	7.610791	7.587186	7.607894	7.609378	7.605618
3	7.611758	7.606651	7.589573	7.585987	7.587123	7.58868
4	7.610433	7.608797	7.586389	7.607372	7.583635	7.586389
5	7.610074	7.610046	7.588741	7.590358	7.585904	7.587675
SBIC						
p/q	0	1	2	3	4	5
0	14.15113	12.80086	11.69558	10.79887	10.20617	9.710772
1	7.6747	7.621724	7.626978	7.631116	7.635599	7.634135
2	7.621998	7.627501	7.608073	7.632959	7.63862	7.639038
3	7.628478	7.627552	7.614655	7.615249	7.620565	7.626302
4	7.631348	7.633895	7.61567	7.640836	7.621282	7.628219
5	7.635188	7.639346	7.622227	7.62803	7.627761	7.633718

Table 23

information criteria for ARMA models of the percentage changes about SSE

AIC						
p/q	0	1	2	3	4	5
0	17.09103	15.76516	14.82079	13.92521	13.42054	13.00032
1	11.17443	11.17592	11.17623	11.17284	11.16966	11.17127
2	11.17674	11.1754	11.177	11.17268	11.17211	11.17116
3	11.1778	11.17822	11.16261	11.16774	11.17386	11.16154
4	11.17536	11.17464	11.16467	11.16412	11.16331	11.16263
5	11.17316	11.17479	11.16703	11.15084	11.15862	11.17589
SBIC						
p/q	0	1	2	3	4	5
0	17.09522	15.77354	14.83337	13.94199	13.44151	13.02549
1	11.18282	11.18851	11.19302	11.19382	11.19484	11.20065
2	11.18934	11.1922	11.198	11.19788	11.20151	11.20476
3	11.19461	11.19923	11.18782	11.19716	11.20748	11.19937
4	11.19639	11.19987	11.19411	11.19776	11.20115	11.20468
5	11.19841	11.20425	11.2007	11.18871	11.2007	11.22218

Table 24

information criteria for ARMA models of the percentage changes about MICE

AIC						
p/q	0	1	2	3	4	5
0	14.79708	13.51432	12.57356	11.88159	11.4247	11.10448
1	9.658961	9.659992	9.661134	9.662556	9.663308	9.663582
2	9.66077	9.662136	9.663503	9.664056	9.664088	9.665603
3	9.662752	9.664345	9.659051	9.659947	9.666452	9.668012
4	9.665014	9.665441	9.660444	9.658588	9.66498	9.661835
5	9.666218	9.666324	9.667903	9.665622	9.655296	9.66348
SBIC						
p/q	0	1	2	3	4	5
0	14.8012	13.52256	12.58593	11.89808	11.4453	11.12921
1	9.667208	9.672362	9.677627	9.683173	9.688048	9.692445
2	9.673148	9.67864	9.684133	9.688812	9.69297	9.698611
3	9.679267	9.684988	9.683823	9.688847	9.699482	9.70517
4	9.685671	9.690229	9.689363	9.691639	9.702162	9.703149
5	9.691022	9.695262	9.700975	9.702828	9.696637	9.708954

Table 25

Dependent Variable: NYSE
Method: Least Squares
Date: 05/24/10 Time: 00:23
Sample (adjusted): 4/22/2005 4/21/2010
Included observations: 1258 after adjustments
Convergence achieved after 9 iterations
MA Backcast: 4/21/2005

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8101.104	1115.405	7.262929	0.0000
AR(1)	0.997583	0.001911	522.0117	0.0000
MA(1)	-0.124416	0.028091	-4.429077	0.0000

R-squared	0.994060	Mean dependent var	7903.675
Adjusted R-squared	0.994050	S.D. dependent var	1401.645
S.E. of regression	108.1163	Akaike info criterion	12.20667
Sum squared resid	14669876	Schwarz criterion	12.21893
Log likelihood	-7674.998	Hannan-Quinn criter.	12.21128
F-statistic	105005.2	Durbin-Watson stat	1.985956
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00
Inverted MA Roots	.12

Table 26

Dependent Variable: PFTS
Method: Least Squares
Date: 05/24/10 Time: 02:23
Sample (adjusted): 4/25/2005 4/21/2010
Included observations: 1223 after adjustments
Convergence achieved after 34 iterations
MA Backcast: 4/21/2005 4/22/2005

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	656.1867	29.92885	21.92489	0.0000
AR(1)	1.998397	0.001471	1358.652	0.0000
AR(2)	-0.998462	0.001469	-679.6566	0.0000
MA(1)	-0.777908	0.027990	-27.79230	0.0000
MA(2)	-0.218643	0.028027	-7.801190	0.0000

R-squared	0.998593	Mean dependent var	583.8713
Adjusted R-squared	0.998588	S.D. dependent var	285.4740
S.E. of regression	10.72540	Akaike info criterion	7.587186
Sum squared resid	140111.6	Schwarz criterion	7.608073
Log likelihood	-4634.564	Hannan-Quinn criter.	7.595047
F-statistic	216125.6	Durbin-Watson stat	2.000725
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	1.00
Inverted MA Roots	1.00	-.22

Table 27

Dependent Variable: SSE
Method: Least Squares
Date: 05/24/10 Time: 10:59
Sample (adjusted): 4/22/2005 4/21/2010
Included observations: 1216 after adjustments
Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3473.861	1152.914	3.013113	0.0026
AR(1)	0.998090	0.001488	670.7698	0.0000

R-squared	0.997309	Mean dependent var	2674.160
Adjusted R-squared	0.997307	S.D. dependent var	1243.863
S.E. of regression	64.55085	Akaike info criterion	11.17443
Sum squared resid	5058510.	Schwarz criterion	11.18282
Log likelihood	-6792.052	Hannan-Quinn criter.	11.17759
F-statistic	449932.1	Durbin-Watson stat	1.975476
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00

Table 28

Dependent Variable: MICEX
Method: Least Squares
Date: 05/24/10 Time: 12:35
Sample (adjusted): 4/22/2005 4/21/2010
Included observations: 1243 after adjustments
Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1457.304	230.6487	6.318285	0.0000
AR(1)	0.995945	0.002172	458.4987	0.0000

R-squared	0.994131	Mean dependent var	1286.946
Adjusted R-squared	0.994127	S.D. dependent var	394.8079
S.E. of regression	30.25732	Akaike info criterion	9.658961
Sum squared resid	1136142.	Schwarz criterion	9.667208
Log likelihood	-6001.044	Hannan-Quinn criter.	9.662062
F-statistic	210221.0	Durbin-Watson stat	2.048883
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00

GARCH

Table 29

Dependent Variable: NYSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/21/10 Time: 16:00
Sample (adjusted): 4/25/2005 4/21/2010
Included observations: 1257 after adjustments
Convergence achieved after 110 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8134.768	1153.257	7.053731	0.0000
AR(1)	0.879037	0.021116	41.62976	0.0000
AR(2)	0.118176	0.021307	5.546379	0.0000
Variance Equation				
C	24968.47	595.2327	41.94742	0.0000
RESID(-1)^2	0.001194	0.000419	2.850628	0.0044
GARCH(-1)	-0.998382	0.000205	-4874.927	0.0000

R-squared	0.994046	Mean dependent var	7904.382
Adjusted R-squared	0.994023	S.D. dependent var	1401.979
S.E. of regression	108.3920	Akaike info criterion	12.18444
Sum squared resid	14697769	Schwarz criterion	12.20895
Log likelihood	-7651.918	Hannan-Quinn criter.	12.19365
F-statistic	41774.86	Durbin-Watson stat	1.998107
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	-.12

Table 30

Dependent Variable: PFTS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/21/10 Time: 16:06
Sample (adjusted): 4/25/2005 4/21/2010
Included observations: 1223 after adjustments
Convergence achieved after 60 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	586.1437	31.25389	18.75426	0.0000
AR(1)	1.600223	0.051742	30.92683	0.0000
AR(2)	-0.628946	0.051494	-12.21385	0.0000
		Variance Equation		
C	52085.39	3026.842	17.20783	0.0000
RESID(-1)^2	-2.948220	0.184588	-15.97187	0.0000
GARCH(-1)	-0.996019	0.000355	-2801.839	0.0000

R-squared	0.997558	Mean dependent var	583.8713
Adjusted R-squared	0.997548	S.D. dependent var	285.4740
S.E. of regression	14.13495	Akaike info criterion	11.82832
Sum squared resid	243152.6	Schwarz criterion	11.85338
Log likelihood	-7227.015	Hannan-Quinn criter.	11.83775
F-statistic	99445.30	Durbin-Watson stat	1.732945
Prob(F-statistic)	0.000000		
Inverted AR Roots	.91	.69	

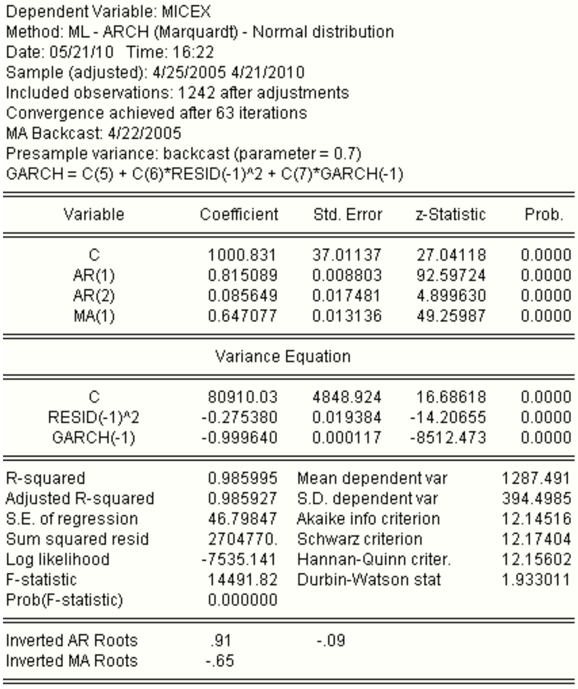
Table 31

Dependent Variable: SSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/21/10 Time: 16:16
Sample (adjusted): 4/22/2005 4/21/2010
Included observations: 1216 after adjustments
Convergence achieved after 31 iterations
MA Backcast: 4/21/2005
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2674.938	158.9842	16.82518	0.0000
AR(1)	1.052065	0.010340	101.7435	0.0000
MA(1)	0.721892	0.053598	13.46858	0.0000
		Variance Equation		
C	1004848.	62150.78	16.16791	0.0000
RESID(-1)^2	-1.522410	0.240807	-6.322122	0.0000
GARCH(-1)	-0.994125	0.000867	-1147.076	0.0000

R-squared	0.993659	Mean dependent var	2674.160
Adjusted R-squared	0.993632	S.D. dependent var	1243.863
S.E. of regression	99.25684	Akaike info criterion	14.87398
Sum squared resid	11920823	Schwarz criterion	14.89916
Log likelihood	-9037.377	Hannan-Quinn criter.	14.88345
F-statistic	37919.92	Durbin-Watson stat	2.882117
Prob(F-statistic)	0.000000		
Inverted AR Roots	1.05		
	Estimated AR process is nonstationary		
Inverted MA Roots	-.72		

Table 32



Dependent Variable: MICEX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/21/10 Time: 16:22
Sample (adjusted): 4/25/2005 4/21/2010
Included observations: 1242 after adjustments
Convergence achieved after 63 iterations
MA Backcast: 4/22/2005
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1000.831	37.01137	27.04118	0.0000
AR(1)	0.815089	0.008803	92.59724	0.0000
AR(2)	0.085649	0.017481	4.899630	0.0000
MA(1)	0.647077	0.013136	49.25987	0.0000
Variance Equation				
C	80910.03	4848.924	16.68618	0.0000
RESID(-1)^2	-0.275380	0.019384	-14.20655	0.0000
GARCH(-1)	-0.999640	0.000117	-8512.473	0.0000

R-squared	0.985995	Mean dependent var	1287.491
Adjusted R-squared	0.985927	S.D. dependent var	394.4985
S.E. of regression	46.79847	Akaike info criterion	12.14516
Sum squared resid	2704770.	Schwarz criterion	12.17404
Log likelihood	-7535.141	Hannan-Quinn criter.	12.15602
F-statistic	14491.82	Durbin-Watson stat	1.933011
Prob(F-statistic)	0.000000		

Inverted AR Roots	.91	-.09
Inverted MA Roots	-.65	

Table 33 – NYCE

	q\p	AR(0)	AR(1)	AR(2)
AIC	MA(0)	16.43977	13.98358	***12.18444***
SBC		16.45610	14.00400	***12.20895***
AIC	MA(1)	16.04724	15.23550	15.24549
SBC		16.06765	15.26000	15.27410
AIC	MA(2)	15.38057	15.28767	15.48634
SBC		15.40506	15.31625	15.51903

Table 34 – PFTS

	q\p	AR(0)	AR(1)	AR(2)
AIC	MA(0)	13.22166	12.01987	***11.82832***
SBC		13.23835	12.04074	***11.85338***
AIC	MA(1)	12.79182	12.14118	11.83824
SBC		12.81268	12.16622	11.86748
AIC	MA(2)	11.66468	12.31756	12.44194
SBC		11.68971	12.34678	12.47536

We choose GARCH (2,0), because on 5% significance level GARCH(0,2) is insignificant.

Table 35 – SSE

	q\p	AR(0)	AR(1)	AR(2)
AIC	MA(0)	16.07928	14.61850	14.78516
SBC		16.09606	14.63949	14.81036
AIC	MA(1)	15.79143	***14.87398***	13.16962
SBC		15.81240	***14.89916***	13.19901
AIC	MA(2)	14.74531	14.37716	13.17094
SBC		14.77047	14.40654	13.20453

We choose GARCH (1,1), because on 5% significance level other models with lower AIC and SBC are insignificant.

Table 36 – MICEX

	q\p	AR(0)	AR(1)	AR(2)
AIC	MA(0)	13.77772	12.52726	12.41006
SBC		13.79420	12.54788	12.43482
AIC	MA(1)	13.53140	12.46428	***12.14516***
SBC		13.55200	12.48902	***12.17404***
AIC	MA(2)	12.73694	9.623850	12.42242
SBC		12.76166	9.652713	12.45542

We choose GARCH (2,1), because on 5% significance level GARCH(1,2) is insignificant.