STOCK PRICE VOLATILITY AND ITS DETERMINANTS ON THE EMERGING FINANCIAL MARKET OF UKRAINE

by

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Abstract

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The paper investigates the issue of stock price volatility in a Ukrainian stock market as one of emerging financial markets. Data on the daily PFTS returns is utilized for an application of the threshold GARCH model with AR and MA components to estimate the stock price volatility. The model allows accounting for the impact the changes in conditional variance have on the expected stock returns. Consistent with findings for emerging financial markets, Ukrainian stock market is characterized by a high long-term volatility. Fundamental factors, as well as non-fundamental ones could be considered as possible sources of a high volatility. To examine the relationship between the stock returns volatility and a set of macro economic indicators a threshold GARCH model with macro components in the variance equation is applied to the respective monthly data. Model indicates a significant impact of the GDP growth and an openness of the market on the volatility of stock returns in the Ukrainian financial market. Among the non-fundamental factors so-called rational bubbles and fads could be named. Other very promising areas to be considered as the sources of volatility are the irrationality of agents, incomplete information, and learning effects.

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GLOSSARY

Autoregressive Conditional Heteroscedasticity (ARCH) models. The class of models proposed by Engle (1982) to capture the serial correlation of volatility of a dependent variable in the model. The time-variant volatility is represented here as a distributed lag of past squared innovations.

Bubbles. Arise usually in case of explosive return series when asset prices rise in response to expectations about higher prices in the future due to non-fundamental reasons, not due to fundamentals, e.g. the news about dividends.

Efficient Market Hypothesis (EMH). According to Fama (1970), "A market in which prices always 'fully reflect' available information is called 'efficient'." Due to this concept in an informationally efficient market price changes are unforecastable if they fully incorporate the expectations and information of all the market participants, which makes obtaining of abnormal profits on a portfolio impossible.

Fads (or 'overreactions'). Occur in case of high correlation between bubbles and fundamentals. 'Fads' model assumes that all economic agents are rational, but that there exist 'noise traders' who buy and sell stock for 'irrational' exogenous or psychological reasons. 'Fads' model argues that the trading by naïve investors creates the non-diversifiable risk that sophisticated investors must take into account.

Feedback traders. A type of stock market investors with adaptive expectations: they base their asset decisions on the past history of the market.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. The class of models proposed by Bollerslev (1986) as a way to model persistent movements in volatility without estimating a very large number of coefficients of the lag polynomial of an ARCH model. Changing volatility is conditional on past squared innovations and its own lagged values.

January effect. Refers to the fact that the daily rate of return appears to be unusually high during the early days of the month of January. In USA this happens due to year-end selling of stock in order to generate some capital losses which can be set against capital gains in order to reduce tax liability. In January investors want to return to their equilibrium portfolios, thus moving into the market to purchase stock.

Learning effects. Consist in that agents estimate parameters of the market each time the new information arrives. This is a small sample problem, which disappears when agents have full access to the information. In case of incomplete information market participants cannot determine the relation between the past and future events, resulting in a high volatility of asset prices as a large learning effect.

Leverage Effect. A negative correlation between volatility and past returns, which results in that negative returns have higher impact on the volatility than positive ones have.

Noise (or 'irrational') traders. A type of stock market investors who behave irrationally: they do not quote price equal to fundamental value, but act rather for some psychological reasons or the state of the mood.

'Smart money' traders. A type of stock market investors with rational expectations: they base their asset decisions on market fundamentals setting prices exactly equal to them.

Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) models. An alternative specification of the GARCH model, which allows to account for asymmetries. In particular, this model indicates whether the leverage effect is observed on the market.

Week-end effect. Refers to the fact that there appears to be a systematic fall in the daily rate of return on (some) stocks between the Friday closing and Monday opening. One explanation of this is that agents release 'good news' between Monday and Friday but wait until the weekend to release 'bad news', which is then reflected in 'low' stock prices on Monday.

C h a p t e r 1

INTRODUCTION

As numerous studies show, high stock price volatility is one of the characteristics of emerging financial markets, one of which is considered to be Ukrainian financial market. The question remains as to the source of this volatility. Can it be explained by fundamental or non-fundamental factors, or is it a shortcoming of the sample estimation.

Generally, emerging equity markets are characterized by high average returns and low correlations of returns with developed markets. Consequently, they provide large yield and diversifications potential, which attracts foreign investors. However, emerging markets are also characterized by large fluctuations of market returns, which cast doubt to efficiency and accuracy of the valuation of investment opportunities.

Generally speaking, many transition economies face a challenge of developing financial markets. In the process of transition, when central control over domestic savings and investment has ceased and new markets and market-based institutions are still developing, such economies tend to experience an overall economic decline. Thus, long-term investment credit becomes extremely crucial for the economy to revive production and make industries more competitive. Despite the fact that during the financial reforms process banks are usually given prior attention compared to non-banking institutions, banks do not provide the economy with long-term credit. At the same time, enterprises most likely are unable to distribute part of their profits to finance long-term investment into production.

Thus, it is difficult to overstate the importance of a stock market for an economy in transition. The primary benefits of a well-functioning stock market are: a) mobilization of savings; b) fund term matching with efficient allocation of investment resources; c) acceleration of economic growth.

A stock market allows investors to use various instruments to better satisfy their liquidity and risk preferences, thus, encouraging their savings and providing the non-financial corporations with equity finance possibilities. Singh and Hamid (1993) show evidence of a significant contribution of equity markets to investment expenditures of the corporate sector in developing countries. The efficiency of savings allocation is ensured through correct share pricing. Better-managed firms should face lower cost of capital while their shares are valued higher. Levine (1991) has shown that a stock market accelerates economic growth through a) elimination of premature liquidation of capital invested in firms, which increases firm productivity; and b) liquidity risk reduction, which encourages investment.

Basically, a large-scale privatization program is one of the most critical policy steps in a transition economy. Establishing the equity markets makes it possible to carry out privatization sales through stock exchanges. The resulting increase in capitalization of a stock market is considered as a direct effect of launching a privatisation program. Expanded diversification possibilities (which reduce volatility) through the new listings of privatized firms constitute an indirect effect of privatization on developing stock markets.

The concept of efficient markets [e.g. Fama (1970)] includes the necessary conditions for a market to exhibit a relatively higher efficiency level. In the context of a developing country these conditions appear to be the following: a) relatively low transactions costs which constitutes in a transparent and reliable clearing and settlement system, and also a proper legal protection of investors' rights and strict contract enforcement, b) all relevant information available at low costs (meaning the availability of stock quotes, comprehensive disclosure requirements and insider trading regulations), and c) an increasing number of participants that insures high liquidity. These conditions pertain to identification of the market as being well-functioning.

We see that transition process produces a significant effect on the financial markets, resulting in high volatility of the stock prices. Examining the sources of the high volatility could help to investigate the efficiency of emerging markets. In particular, according to the efficient market hypothesis, the value of a security is the present discounted value of its future (risk-adjusted) cash flows, and fluctuations of the asset price are the subject of the news about its fundamentals. Many early studies suggest that stock price movements can be wholly attributable to this news. However, Shiller (1981), LeRoy and Porter (1981) while investigating U.S. security price movements found that large portion of those movements cannot easily be explained by the new information. Taking the estimates of the fundamental value of the stock price index as a present discounted value of ex-post dividends, Shiller was comparing the volatility of the actual price and its fundamental value. Because the actual price differs from the fundamental value only by a forecast error, then if the actual price is a rational forecast, its variance should be less than that of its fundamental value. On the contrary, as empirical results show, this variance bound condition is violated, which means that the asset prices are excessively volatile.

As Chiwon Yom (2000) suggests "movements in fundamentals also fail to explain substantial portion of volatility observed in emerging markets. Moreover, excess volatility in emerging markets is greater than that in developed markets. Actually, it appeared that neither small-sample bias rational bubbles nor standard models of expected returns adequately explain stock price volatility". This suggests a certain role for nonstandard models of expected returns, i.e. models aimed to explain the volatility by non-fundamental factors. Several factors identified in an attempt to explain the excess volatility are irrationality of agents, incomplete information, and learning effects.

Therefore, in order to indicate the problems of financial market and find better possibilities for improving the investment climate in Ukraine, the investigation of stock price volatility and its sources on the Ukrainian financial market becomes extremely useful.

Chapter 2

LITERATURE REVIEW

The phenomenon of stock price movements has always been of great interest for many researchers, since it helps to investigate the efficiency of the stock market. Numerous studies have attempted to explain the occurrence and foresee possible consequences, of those movements in order to examine whether the efficient market hypothesis holds. As a result, many works have been devoted to this and closely related topics. Thus, at present, we have a wide range of research studies examining whether stock prices fluctuate excessively due to the changes in fundamentals, or whether some other factors, such as bubbles, fads, incomplete information and learning, play a significant role in determining instability of stock prices.

The study of Chen, Roll, and Ross (1986) was one of those, which tried to explain the stock price volatility by reference only to the changes in fundamentals. It investigated the reaction of the stock market to "innovations" in macroeconomic variables. Authors recall that according to the financial theory, asset prices should be systematically affected by several factors, with innovations in the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low-grade bonds considered as sources of investment risk. A set of state economic variables is chosen to be candidates for sources of systematic asset risk. Several of those variables were then found to be statistically significant in explaining expected stock returns. The most significant sources of risk appeared to be innovations in industrial production, changes in the risk premium, and twists in the yield curve. The most surprising conclusion from the study was that although the stock market index explains a large portion of the stock returns variability, its influence is weak compared to the changes in state economic variables. The main inference was that the stock returns are determined by the economic news measured as innovations in state variables.

Although numerous studies were made on the stock prices instability, actually, Shiller was one of the first economists who argued that changes in fundamentals are not the only reason for stock prices fluctuations. Particularly, Shiller (1981) and LeRoy and Porter (1981) apply volatility tests in investigating the U.S. securities' price movements in the U.S. They found that large portion of those movements could not be explained by new information. Taking estimates of the stock price index's fundamental value as a present discounted value of ex-post dividends, Shiller was comparing the volatilities of the actual stock price and its fundamental value. Considering the actual price as a rational forecast he expected that the variance bound condition would hold, i.e. in case the actual price differs from its fundamental value only by a forecast error, its variance should be less than that of its fundamental value. However, the empirical results show that the variance bound condition is violated, which means that asset prices are excessively volatile.

West (1988a) developed the stock market volatility test of LeRoy and Porter. At that he has taken account of the criticism of Flavin (1983) and Kleidon (1985, 1986) about the small sample bias in estimates of the excess volatility and that of Marsh and Merton (1986) about the stationarity of the dividends around the time trend. West suggested that the small sample bias is caused by the nonstationarity in stock prices. The nonstationarity means that stock prices are expected to grow explosively, resulting in the "bubble" on the market. His inference is supported by the fact that studies allowing for the nonstationarity obtained significantly lower excess stock price volatility than those assuming stationarity of the series. West applied the test first suggested by Blanchard and Watson (1982). The test was based on the fact that if discount rates are constant, the variance of the innovation in the expected present discounted value of a given stock's dividend stream is smaller when expectations are conditional on the market's information set than when the expectations are conditional on a smaller information set. The author pointed out that stock price excess volatility is not likely to be caused by the small sample bias.

While studies made by Shiller (1981), LeRoy and Porter (1981), West (1988a), and others indicated excess volatility in U.S. stock prices, Bulkley and Tonks (1989) confirmed the generality of this by discovering excess volatility in U.K. stock prices.

However, Chiwon Yom (2000) using monthly data obtained the opposite results, i.e. the variance bound condition is satisfied for the developed markets. He suggested two possible explanations for this result. First, he uses the price-earnings ratios instead of prices alone, and the second is that he investigated monthly series for 14 years rather than annual data covering longer period. However, the more important result for our purposes from the study of Chiwon Yom is that he obtained larger ratios of standard deviation for emerging markets than those for developed markets, which means that emerging markets show higher volatility of stock prices than developed financial markets. This conclusion supports the results obtained from several previous studies.

Researchers have proposed a set of different explanations in their studies for the phenomena of high volatility on the financial markets. In act, the existing explanations can be divided into two categories: those attempting to tie stock price volatility with the changes in the fundamentals, and those based on the non-fundamental factors. The latter appears to be very important on the emerging financial markets.

Among the first studies on this issue were those of Flavin (1983) and Kleidon (1986). Authors pointed out that statistical methodology employed by Shiller is subject to small sample bias. In particular, they suggested a downward bias, since the variance was estimated as an average squared deviation around the sample mean rather than true mean. Flavin (1983) argued that the "volatility" or "variance-bounds" tests tend to be often severely biased in small samples, at that often toward rejection of the null hypothesis of market efficiency. She argues that downward bias for the perfect-foresight price is greater than that for actual price owing to higher autocorrelation. She suggests that the violation of market efficiency in the previous studies might be reflecting the sampling properties of the volatility measures, rather than a failure of the market efficiency hypothesis.

Later, Kleidon (1986) examining Flavin's conclusion attempted to explain why the perfect-foresight price has higher serial correlation than the actual price. He conducted his research based on the weak form of the 'efficient market hypothesis' (Fama, 1970) which consists of the observation that the present price of the stock incorporates all information about the past stock price movements and it is not possible to make profits by observing those movements. The author recalls that actually, according to a standard efficient market model, stock prices change by the present value of expected future dividends. The latter cause much larger changes in present value than the current dividend change. Generally, the perfect-foresight price uses full knowledge of the ex-post dividends, thus, it fluctuates only by the change in current dividend. Hence, the change in perfect-foresight prices appears to be smaller than that in actual prices. As a result, the time-series of the perfect-foresight price would be smoother than that of actual price. West (1988a) claimed that under the assumption of a constant discount rate, stock prices are too volatile to be equal to expected present discounted value of dividends. To explain this result he considered the possibility of discount rate fluctuations be the reason for the excess volatility. However, this hypothesis was disproved. Therefore, he suggested a detailed investigation of bubbles and fads as more likely to be an explanation for the excess volatility.

The main drawback of the theory proposed by Flavin and Kleidon is that it fails to explain excess volatility observed in emerging markets. Generally speaking, the same explanation could be applied to developed markets as well as to emerging ones. Chiwon Yom suggested that small sample bias could be more severe in the emerging market as its dividends are more serially correlated. However, the data he uses in his study does not support this suggestion.

The second explanation of the high volatility of stock prices in emerging financial markets is that of time varying discount rates. In general, in the models for stock prices the expected rate of return is assumed to be constant over time. However, as Fama and French (1988) found, the U.S. stock market returns are predictable. What is more, Harvey (1995) argued for the predictability of the emerging market returns. Authors suggested that the actual variation in the discount rate as well as the change in dividends should be reflected in the change of the price. Otherwise, the researcher would falsely reject the variance bound condition.

The remaining explanations for the difference between the stock price movements on developed and emerging markets are based on non-fundamental factors. One of them is a speculative price bubble, which arises when asset prices rise in response to expectations about higher prices in the future arising from non-fundamental reasons. In this case the price varies simply because of rational expectations about the future, not due to the news about dividends. West (1988b) investigated bubbles that are not correlated with fundamentals and suggests that even if bubbles are ruled out, the excess asset price volatility will still be observed. West came to the conclusion that neither a sample bias (as discussed above) nor an explosive rational bubble (indicated using the backward recursion from the maturity date), can produce an adequate explanation of the volatility of the stock prices. He argued that factors other than bubbles should be considered, and the appropriate parametric model would be preferable in explaining the excess stock price volatility.

In cases of high correlation between bubbles and fundamentals, then "overreactions", or "fads", occur. However, bubbles can continuously exist only when certain conditions (e.g. new investors continuously enter the market) hold. Otherwise, bubbles collapse. Since on emerging markets those conditions are usually unlikely to be satisfied, bubbles in such markets are expected to collapse. On the contrary, Sarno and Taylor (1999) based on empirical evidence suggest the existence of bubbles on the emerging financial markets of East Asian countries. The authors even argue that those bubbles can explain stock price volatility.

There are other studies that do not find empirical support for the hypothesis that stock price volatility is subject to rational bubbles. Ahmed, Rosser, and Uppal (1999) find that at best the presence of bubbles could not be rejected, and in the study of Chan, McQueen, and Thorney (1999) it is concluded that asset returns do not conform completely to the theory of bubbles.

Thus, authors attempted to consider some nonstandard models for expected returns in order to explain stock price volatility on emerging financial markets. One of the models is a so called "fads" model, which assumes that all economic agents are rational, but that there exist "noise traders" who buy and sell stock for "irrational" exogenous or psychological reasons. So, those naïve investors create risk, which should be taken into account by the sophisticated investors. In their study devoted to noise trading, DeBondt and Thaler (1985) showed that stock prices change to the large extent due to the market participants' overreaction to news. Later De Long et al. (1990) suggested the noise traders' misinterpret information about future dividends or just do not care about it and, as a result, may cause an increase in assets' prices when they suddenly (following their psychological trends) start to buy securities. Moreover, Palomino (1996) found that noise traders could even dominate the market for a certain time obtaining higher utility, since in a market with imperfect information all agents have some market power in influencing stock prices. West (1988b) suggests evidence, however, largely indirect, in favour of fads rather than bubbles or traditional models for returns as a tool to explain stock price volatility.

One more non-fundamental factor used to explain excessive volatility is incomplete information and learning models, which relax the assumption that agents have full information about changes in asset fundamentals. Instead, as Timmerman (1993) suggests, there are so called learning effects reflected in an agents estimated parameters of the market each time new information arrives. Some studies, such as Bray and Savin (1986), Marcet and Sargent (1989), Timmerman (1993), consider learning effects as a small sample problem, which disappears when agents have full access to the information. However, later Timmerman (1996) argued that learning effects need not disappear with the structural breaks in dividend process, since they could be unique events not connected to the past experience. Hence, in case of incomplete information market participants cannot determine the relation between the past and future events, which results in a high volatility of asset prices as a large learning effect.

Naturally, researchers investigate not only reasons for the volatility of stock prices, but also tried to find more efficient methods for that volatility estimation. A significant problem that arises in this context is the problem of heteroscedasticity in stock prices. In many early papers, such as those by Martin and Klemkosky (1975), Bey and Pinches (1980), and Barone-Adesi and Talwar (1983), it is suggested that heteroscedasticity is a purely statistical problem, not the problem of security returns. This conclusion stems from the fact that the market return is a pure estimate of the market volatility.

Schwert and Seguin (1990) continued investigation of the question of fluctuating stock returns, particularly, the question of heteroscedasticity in aggregate stock returns. They argued that any predictable heteroscedasticity observed in stock prices series should be incorporated into the studies of stock returns distributional properties. In particular, studies of "mean reversion" in stock returns, such as those by French, Schwert, and Stambaugh (1987), Fama and French (1988), or Poterba and Summers (1988), should adjust for predictable heteroscedasticity effects. The main conclusion from their work is that the volatility of monthly returns to the size-ranked portfolios is highly related to the autoregressive predictions of this market volatility factor.

As suggested in the studies mentioned above, all the attempts to estimate and explain high volatility of stock prices lead to the conclusion that movements in fundamentals fail to explain a substantial portion of the observed stock price volatility. Moreover, several studies found that the volatility of stock prices on emerging financial markets is much higher than that on developed markets. A large number of studies were devoted to the investigation of the volatility problem. It appears that neither the small-sample bias or rational bubbles nor fundamental models of expected return could adequately explain stock price fluctuations. Therefore, it is expected that a certain role could be given to non-fundamental models of expected returns. Those are "bubbles", "fads" models or models assuming incomplete information and the existence of learning effects on the markets.

An investigation of the financial markets, and particularly the stock price fluctuations on the emerging markets, appears to be interesting for academicians and important from the practical point of view. Generally, there is a low correlation of returns on developed and emerging markets. This makes the latter particularly attractive for foreign investors as it presents portfolio diversification opportunities. Therefore, the more information about the stock market that is available, the more foreign capital might be attracted to the market. Since the financial market of Ukraine is an emerging one, it makes sense to investigate stock prices behaviour. This knowledge may help to increase the flow of foreign capital into the economy.

UKRAINIAN FINANCIAL MARKET

Let us consider Ukrainian stock market as one of the emerging financial markets. According to the January 2003 data provided by the rating agency Standard & Poor's (which is, actually, one of the main sources of information for the international investors concerning emerging financial markets), the stock market of Ukraine is classified as 'Frontier' (a category in the classification). Besides the Ukraine, 20 other countries belong to the S&P Frontier group (among them Romania, Slovak Republic, Croatia, Bulgaria, Estonia, Latvia, Lithuania, etc.). Table 3.1 below summarizes the data for those countries belonging to the S&P Frontier Group.

Table 3.1. The stock markets classified as S&P Frontier, January 2003*

Parameter/ Country	***Capitalization (January), mln.USD***	***Monthly average trading volume in 2002, mln.USD***	***Local index (January)***	***change (%, during the year)***
Ukraine	3 119.40	10.56	52.7	-8.03
Romania	4 561.50	33.6	1 774.60	6.96
Slovenia	4 606.30	83.62	3 305.80	-1.03
Croatia	3 975.60	12.21	1 096.10	-6.52
Bulgaria	733.3	14.37	—	—
Lithuania	1 462.60	15.19	944.6	3.59
Estonia	2 429.90	20.11	208.6	-1.84
Latvia	714.5	10.35	162	0.56

*Sourse: S&P data

Comparing local stock market indicators according to S&P data (which are calculated based on PFTS data) for January 2003 with those of other underlying countries one can see that:

- the level of capitalization of Ukraine's stock market is the fourth ranked after that of Slovak Republic, Romania, and Croatia;
- average monthly trading volume is lower than that of Slovak Republic, Romania, Estonia, Lithuania, Bulgaria, Croatia, and Latvia;
- 9 Ukrainian securities were included by the February 1, 2003 into the index "basket" of IFCG Frontier Comp.

After it was proclaimed independent, Ukraine set about creating a national banking structure and a stock market. In four years a twin-level banking structure was established. It includes the National Bank of Ukraine and a network of commercial banks of all types over all the Ukraine's administrative regions. The Ukrainian stock market started to develop. It consists of 2 stock, 2 hard currency interbank and 91 commodity exchanges; 65 investment funds and companies, 500 trust partnerships, 660 insurance companies and 250 audit firms.

With the objective of investigating the current state of the system of financial markets in Ukraine and to lay down guidelines as to how it might be developed, four research groups of academics from the Institute of World Economy and International Relations of the Ukrainian Academy of Science, Kiev State University of Economics (Department of Finance), University of Valencia, Spain, and coordinators of the project from Napier University, Edinburgh, United Kingdom were established. They studied various aspects of the issue, respectively: 1) fundamental problems in relation to the formation of financial markets in an economy in transition and their support for the transition process; 2) the regulatory system surrounding financial operations and ways of broadening the system of financial markets; 3) a comparison of the financial markets system in Spain with a view to making recommendations for the development of financial markets in Ukraine, and also make suggestions for the integration of Ukraine in global financial system; 4) implications from the United Kingdom financial system which may bear on the developing system of Ukrainian financial markets. The results of the investigation were used for making the recommendations for the development of financial market in Ukraine.

The investigation found that, although the Ukrainian Government, through enacting appropriate legislation, has been proactive in facilitating the structural development of the financial markets and institutions, the attraction of inward investment into the economy is being frustrated by other wider structural factors of a political, economic and cultural nature.

Foreign inward investment is also discouraged by Ukrainian foreign investment legislation, which changes frequently and factors that frustrate the creditable advances made in terms of stock market regulation and transparency. Moreover, since inward investment is dependent upon Western perceptions of how the Ukrainian economy and society function, it is contended that such perceptions cannot be ignored. Furthermore, while it is accepted that effective regulation of the financial markets is necessary to attract more inward investment, it was suggested that this should be the responsibility of the Government. The financial system is not yet ready for self-regulation.

According to Mr. Johann Jonach, President of Alfa Capital (Ukraine), in 1995 there was no such thing in Ukraine as a securities market, which should act as a link between the interests of Ukrainian companies, on the one hand, and investors, particularly foreign ones who are looking for attractive investment targets, on the other. During 1997 the sector of energy production and distribution mainly attracted portfolio investors. Today's situation in the securities market is much more complex. It has been affected by the crisis started in South-East Asia, which still continues to depress equity prices in Ukraine. At the same time Ukrainian share prices are now probably among the cheapest in the world, which offers lots of opportunities for the astute investor. Currently investments into Ukrainian treasury bills and private equity investments are on top of the agenda. There are a few strategic investors who want to invest into projects in Ukraine in order to get a position in this ***big and quickly developing market***. At the same time it has to be said that the further development of Ukraine's enormous potential depends greatly on economic reforms, and a source of legal basis for property rights. In principal, interest among strategic investors is very high, but concrete results are much more difficult to achieve. The investment banking and corporate finance activities should help to contribute to a sizeable increase in direct investment into Ukraine, which should be promoted as an attractive country for investment worldwide, via conferences, seminars and many direct contacts.

Chapter 4

METHODOLOGY

In my thesis research study I will follow the idea of Chiwon Yom (2000), which consists of the two main steps described in detail below.

First, I will estimate the volatility of stock returns on the Ukrainian stock market. Actually, the volatility of the Ukrainian financial market is expected to be high, in line with that on other emerging financial markets. Several models exist for volatility estimation from historical data. Moreover, volatility can be identified with the second moments of returns suggesting the application of GARCH-type models.

Second, I will attempt to explain the estimated volatility considering two approaches:

1) volatility is attributable to econometric properties of estimation, such as small sample bias, at that it is explained by the fundamental factors;

2) volatility is viewed as an indication of market inefficiency. Thus, there are rather non-fundamental factors causing asset prices to fluctuate excessively. This explanation includes bubbles, fads, and incomplete information and learning.

4.1. VOLATILITY ESTIMATION

Before constructing our final model for volatility estimation, let us look at the stochastic process a stock price is usually assumed to follow. The estimation of the volatility from the historical data is based on this assumption. Namely, as suggested by Hull (2000), stock prices follow a generalized Wiener process, according to which they have constant rates of an expected drift and variance. The drawback of this form of stochastic process is that it does not account for the fact that the expected percentage return from a stock is independent of the stock's price. In the model proposed by Hull (2000) the expected return (which is expected drift divided by the stock price) is taken as constant. Denoting *stock price at time* t by S, and the *expected rate of return on the stock* by μ we can derive the expected drift as μS. Then in the short interval of time the expected increase in S would be $\mu S\Delta t$. In case of zero stock price volatility, this model implies $\Delta S = \mu S\Delta t$. When Δt approaches zero, this gives $dS = \mu Sdt$ or $dS/S = \mu dt$. Thus, we obtain $S_T = S_0 e^{\mu T}$, which means that when the variance is zero, the stock price grows at a constant rate μ per unit of time. However, in practice stock prices exhibit volatility, which leads to the model $dS = \mu Sdt + \sigma Sdz$ or $dS/S = \mu dt + \sigma dz$, where σ is the *volatility of the stock price*.

The discrete version of this model known as geometric Brownian motion is $\Delta S / S = \mu\Delta t + \sigma\varepsilon\sqrt{(\Delta t)}$ or $\Delta S = \mu S\Delta t + \sigma S\varepsilon\sqrt{(\Delta t)}$. Here ε denotes a random drawing from a standard normal distribution, $\Delta S / S$ is a return on the stock provided in a short period of time, $\mu\Delta t$ is an expected value of this return, $\sigma\varepsilon\sqrt{(\Delta t)}$ is the stochastic component of the return. Thus, the variance of the return is $\sigma^2\Delta t$, and the return $\Delta S / S$ is normally distributed with mean $\mu\Delta t$ and standard deviation $\sigma\sqrt{(\Delta t)}$, i.e. $\Delta S / S \sim \varphi(\mu\Delta t, \sigma\sqrt{(\Delta t)})$.

Now, let us consider another example, namely an estimation of the excess stock price volatility from the historical data. In this approach we define the number of observations as ($\boldsymbol{n}$+1), the stock price at the end of interval $\boldsymbol{i}$ as $\boldsymbol{S_i}$ ($\boldsymbol{i}$ = 0,1,…,$\boldsymbol{n}$), length of time interval $\boldsymbol{\tau}$ in years, and continuously compounded return is $\boldsymbol{u_i} = \ln(\boldsymbol{S_i}/\boldsymbol{S_{i-1}})$ for $\boldsymbol{i}$ = 1, 2,…,$\boldsymbol{n}$.; therefore, $\boldsymbol{S_i} = \boldsymbol{S_{i-1}e^{ui}}$. Considering $\bar{u}$ as a mean of $\boldsymbol{u_i}$'s, the standard deviation of those returns is then given by:

$$s=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(u_i-\bar{u}\right)^2} \quad \text{or} \quad s=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}u_i^2-\frac{1}{n(n-1)}\left(\sum_{i=1}^{n}u_i\right)^2}\ .$$

However, the standard deviation of the return $\boldsymbol{u_i}$ is $\boldsymbol{\sigma\sqrt{\tau}}$, and $\boldsymbol{s}$ is its estimate. Therefore, the stock price volatility can be estimated as $\boldsymbol{\sigma^*} = \boldsymbol{s/(\sqrt{\tau})}$. A problem here is to appropriately choose the value for $\boldsymbol{n}$. According to the frequently used rule of thumb, the time period $\boldsymbol{n}$ over which the volatility is measured is set equal to the time period over which it is to be applied.

The next approach, which can be utilized to estimate stock price volatility, is the GARCH or General Autoregressive Conditional Heteroscedasticity model.

Denoting the stock price volatility estimated at the end of the day n-1 as $\boldsymbol{\sigma_n}$, we can calculate the variance rate as $\boldsymbol{\sigma_n^2}$. As we stated above, the compounded return during day $\boldsymbol{i}$ is set as $\boldsymbol{u_i} = \ln(\boldsymbol{S_i}/\boldsymbol{S_{i-1}})$. We are interested here in estimating the stock price volatility at each period, i.e. we want to estimate the current volatility of the stock returns. To obtain the required estimation we account for the set of information we have at the end of the period *n-1*. It is evident that the more recent information is more detailed. Logically, it may be appropriate to give higher weight to the recent data during estimation.

The current volatility is very likely to be affected by the most recent information, which we can account for by assigning higher weights to the most recent data and the lowest weights to the events happened long ago. Then denoting weights by α_i we obtain

$$\sigma_n^2 = \sum_{i=1}^{m} \alpha_i u_{n-i}^2 , \qquad (1a)$$

which is a weighted sum of the squared compounded returns calculated for each interval *n* of the entire period under observation.

To extend this idea, we assume that there exists the long-run volatility *V* with the weight *γ* assign to it. Then the model becomes $\sigma_n^2 = \gamma V + \sum_{i=1}^{m} \alpha_i u_{n-i}^2$, at that all the weights must sum to unity, i.e. $\gamma + \sum_{i=1}^{m} \alpha_i = 1$. In this model the estimate of the variance is based on a long-run average variance and *m* observations. The older the observation, the less weight it is given. And denoting $\omega = \gamma V$ we simplify the expression to

$$\sigma_n^2 = \omega + \sum_{i=1}^{m} \alpha_i u_{n-i}^2 \qquad (1b)$$

This is the version of the model used in estimation. Engle (1982) first suggested the following form of the model:

$$\begin{aligned} u_t &= \varepsilon_t h_t^{1/2}, \\ h_t &= \alpha_0 + \alpha_1 u_{t-1}^2 \end{aligned} \qquad (2)$$

with variance $V(\varepsilon_t) = 1$. Here $h_t = \sigma_n^2$. This representation then was called an autoregressive conditional heteroscedasticity (ARCH) model.

Specific characteristics of the ARCH regression model make it useful for economic applications, particularly, in econometric forecasts. According to

McNees (1979), "large and small errors tend to cluster together (in contiguous time periods)." Thus the ARCH model allows changing forecast variance over time and its prediction by the past forecast errors. In this respect, given our previous analysis the usefulness of the model appears to be obvious.

As suggested by Engle (1982), ARCH model appears to have many applications in finance. According to the simplest assumptions, financial assets portfolios are held as functions of the expected means and variances of the rates of return. Changes in expected means and variances are associated with shifts in asset demand. Add to that the fact that in the used model the variance is constrained to be constant over time so that no exogenous variable can explain changes in variance.

The ARCH model proposed by Engle explicitly models time varying conditional variances, relating them to the information set from previous periods, in particular, modelling them as a linear function of past squared innovations. According to previous studies concerning conditional variances, "large changes tend to be followed by large changes, and small changes tend to be followed by small changes" – at that, sign of the change does not matter.

In order to account for the impact the conditional variance makes on the mean of the model, Engle et al. (1987) introduce the ARCH-M, or ARCH-in-mean model, which is an extended version of the ARCH. With this specification we can now model the direct effect made by changes in conditional variances on the expected return of securities. Now the conditional variance is included as a regressor into the model and determines the relation between the risk of holding the asset and return on this asset. Basically, when a risk-averse person holds risky asset, she requires a compensation for the risk she bearing. A compensation for the risk is measured by the rise in the expectation of the return.

Another version of the model is GARCH (1,1) or generalized autoregressive conditional heteroscedasticity model proposed by Bollerslev (1986). In this model, conditional variance, or volatility, σ^2_n is based on the most recent observation of u^2 and the most recent observation of the variance rate, i.e. model allows accounting for the impact of the previous changes in variance on the current volatility. The model then appears as follows:

$$\sigma_n^2 = \gamma V + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2 \qquad (3)$$

where γ, α, β, are the weights assigned to V, u^2_{n-1}, and σ^2_{n-1} respectively. As the weights must sum to one, $\gamma + \alpha + \beta = 1$.

Denoting once again $\omega = \gamma V$, we obtain GARCH (1,1) written as:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2 \qquad (4)$$

which is usually used for parameters estimation. Having ω, α, and β estimated from the regression and recalling that all the coefficients must sum to one, we can calculate the coefficient near the long-term variance, i.e. $\gamma = 1 - \alpha - \beta$. The long-term variance V then is $\dfrac{\omega}{\gamma} = \dfrac{\omega}{1-\alpha-\beta}$.

For a stable GARCH (1,1) process, estimated coefficients are required to satisfy $\alpha + \beta < 1$ in order to ensure finite conditional variance.

The more general GARCH (p, q) model calculates σ^2_n from the recent p observations on u^2 and the most recent q observations of the variance rate.

The typical form of the GARCH-M model suggested in Greene (2000), which we will use in the same context as in Chiang and Doong (1999), is the following:

mean equation: $$r_t = a_0 + \gamma h_t + \varepsilon_t \tag{5a}$$

where $$\varepsilon_t / \Omega_{t-1} \sim N(0, h_t)$$

variance equation: $$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{5b}$$

where $\boldsymbol{r}_t$ is an expected return. The inequality restrictions $\omega > 0, \alpha \geq 0, \beta \geq 0$ are imposed in order to ensure that conditional variance $\boldsymbol{h}_t$ is positive. Ω_{t-1} is an information matrix containing all the information available at the previous period. Equation (5*a*) is a mean equation, showing the relationship between the expected return and conditional variance. And equation (5*b*) is the variance equation showing how the conditional variance is determined by the innovations and lagged conditional variance values. The two equations are estimated jointly and recursively using an iteration procedure to maximize the log-likelihood function with respect to the parameters in the mean and variance equations. Because of the nonlinear nature of the model, the OLS method is applied to obtain the initial values for the parameters in two equations. Then the series of squared regression errors are derived, and then used to calculate the conditional variance, which in turn used as an argument in the mean equation.

The coefficient γ in the model captures the influence of the conditional variance on expected stock returns. A significant and positive γ implies that investors are compensated by higher returns for bearing higher levels of risk. A significant negative coefficient indicates that investors were penalized for the risk bearing. In the second, i.e. variance, equation the size and significance of α indicate the magnitude of the effect of the lagged squared error ε^2_{t-1} on the conditional variance h^2_t. Moreover, the significance of α indicates the existence of the ARCH process in the variance equation.

To account for possible asymmetries and leverage effects in the stock market the TARCH or the EGARCH model can be applied. In the TARCH model the variance equation takes the form

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \delta\varepsilon_{t-1} I_{t-1} \qquad (6a)$$

where indicator variable $\boldsymbol{I_{t-1}} = 1$ if $\boldsymbol{\varepsilon_{t-1}} < 0$. The estimated coefficients must satisfy the following non-negativity constraints: $\boldsymbol{\alpha} + \boldsymbol{\delta} \geq 0$ and $\boldsymbol{\alpha} \geq 0$. Here positive $\boldsymbol{\delta}$ coefficient suggests the presence of the leverage effects on the market, i.e. the negative returns have greater impact on the conditional variance than the positive returns.

In the EGARCH model suggested by Nelson (1991) in order to take care of the non-negativity constraints the variance equation appears to be in logarithms (which guarantee the non-negative variance) and takes the following form:

$$\log h_t = \omega + \beta \log h_{t-1} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \delta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (6b)$$

It includes the term $\boldsymbol{\varepsilon_{t-1}/\delta_{t-1}}$, thus making the model asymmetric as $\boldsymbol{\delta}$ is different from zero. When $\boldsymbol{\delta < 0}$, positive shocks have an impact on the volatility, however less than negative shocks do suggesting the leverage effects on the market.

4.2. EXAMINING THE DETERMINANTS OF VOLATILITY

High volatility on the emerging financial markets can be caused by many factors. To determine what are the most likely sources of the stock price volatility we model the relation between the stock prices and a set of real and financial macroeconomic variables among them GDP, exports and imports of the country, and also the calculated indicator of the openness of the market which is the ratio of the trade balance to the real GDP value in the respective period. This is a basis of the approach applied by Chiwon Yom (2000), which I mainly follow in my study.

One of the researches devoted to the analysis of the stock-real variables cross-effects is the study by Burgstaller (2002), in which the author investigates the long-run relations between the stock prices and other macroeconomic variables as well as short-term dynamics. Employing time series data, the author analyses empirical relations using a vector autoregression (VAR) model. The reduced form of this model is set up as follows:

$$X_t = \mu + \sum_{i=1}^{p} \Theta_i X_{t-i} + e_t \qquad (7)$$

This is of order $\boldsymbol{p}$, with $\boldsymbol{X}$ being a vector of $\boldsymbol{n}$ time series, which are the exogenously introduced explanatory variables. The corresponding vector error correction representation (VECM) is the following:

$$\Delta X_t = \mu + \prod X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + e_t \qquad (8)$$

which is equivalent to the VAR equation. Here $\boldsymbol{\Gamma_i}$'s are parameter matrices and $\boldsymbol{e_i}$ is a vector of normally distributed random errors that are contemporaneously correlated, thereby having a non-diagonal covariance matrix. If $\boldsymbol{\Pi}$ has a reduced rank, it can decomposed as $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta'}$ with $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ being $\boldsymbol{n}$ by $\boldsymbol{r}$ matrices.

The estimated coefficients will measure the speed of adjustment of the series under consideration towards the long-run relations after a shock to the equilibrium has taken place. Burgstaller claims that at least one of the long-run variables must be responsible for the adjustment. A standard $\boldsymbol{F}$-test is then employed to assess how one variable affects predictions of another. It is according to the weak form efficiency concept that stock prices should reflect all historical changes in macroeconomic variables. If this is the case, stock prices should follow a random walk and stock returns should be stationary.

Another approach to the investigation of the volatility in emerging financial markets was proposed by Harvey and Becaert (1997). They analyzed the relative importance of the changes in macroeconomic indicators in different countries for the expected return and conditional variance processes. Namely, authors examined the reasons for different volatility levels across emerging markets considering particularly the timing of the capital market reforms implemented in the respective country. The findings of the study consist in that capital market liberalizations do not drive up the market volatility in the country at the same time increasing the correlation between country's local returns and the world market. And, as we noted above, emerging markets are characterized by the low correlation of returns with the world market.

The idea of the approach proposed by Harvey and Becaert was suggested first by Engle (1982). Before, the volatility was modelled on the basis of the past history of returns. However, we can add some exogenous explanatory variable into the model. So, the idea consists in that exogenous variables are introduced directly to the variance equation of the GARCH model used to estimate stock returns volatility on the market. This allows direct estimation of the relation between the conditional variance, i.e. stock returns volatility, and macroeconomic indicators, i.e. fundamental factors. Then the model takes the following form:

mean equation: $$r_t = a_0 + \varepsilon_t \tag{9a}$$

where $$\varepsilon_t / \Omega_{t-1} \sim N(0, h_t)$$

variance equation: $$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma X_{t-1} + \delta\varepsilon_{t-1} I_{t-1} \tag{9b}$$

where indicator variable $\boldsymbol{I_{t-1}} = 1$ if $\boldsymbol{\varepsilon_{t-1}} < 0$. The estimated coefficients must satisfy the following non-negativity constraints: $\boldsymbol{\alpha} + \boldsymbol{\delta} \geq 0$ and $\boldsymbol{\alpha} \geq 0$. Here again positive $\boldsymbol{\delta}$ coefficient suggests the presence of the leverage effects on the market. Matrix $\boldsymbol{X_{t-1}}$ is a matrix of macroeconomic variables introduced to the variance equation to examine a possible impact they can have on the conditional variance, which is stock returns volatility.

Monthly series of the respective variables are used in this approach. In our case when the monthly data is accessible only for 5 years, namely for the period January 1998 – December 2002, the number of observations is equal to 60 for all the considered variables. In particular, we use the monthly data on the stock returns, real GDP, GDP growth over the year, exports and imports values and their growth over the month, and a market openness index calculated as a ratio of the country's trade balance to the real GDP values for the respective period.

C h a p t e r   5

DATA DESCRIPTION

For the empirical part of my research two data sets are required. One of them is to estimate the excess stock price volatility and the other is to determine which economic forces can explain any excess volatility in the emerging Ukrainian financial market.

Data for the analysis of the stock price volatility will be taken from the Annual Report of PFTS Association, which can be found on its web site. Particularly, data on PFTS index is taken daily for the period from November 3, 1997 till March 13, 2003. Since in the GARCH model, which will be utilized for volatility estimation, returns and not index values on the stocks are required, those returns are calculated from the values of the stock price indices by the formula for calculating the log-returns.

To specify determinants of the excess stock price volatility on the Ukrainian financial market, monthly data on Real Gross Domestic Product (real GDP), imports, and exports of Ukraine will be used. Besides, an index of the market openness to the world economy is calculated as a ratio of the trade balance of Ukraine to he real GDP values for respective periods. Yearly and monthly data for the period 1997-2001 is taken from the on-line database of the International Monetary Fund's International Financial Statistics (IFS).

Chapter 6

EMPIRICAL RESULTS

6.1. VOLATILITY ESTIMATED

Having the daily data on PFTS index values we calculated the daily log-returns for the entire period. Figures 6.1 and 6.2 below present the PFTS stock price index (***P***) and log-return series (***R***) for the entire sample period, i.e. 1323 observations from the beginning of the Ukrainian on-the-counter trading system PFTS, the 11th November 1997 till 13th March 2003.

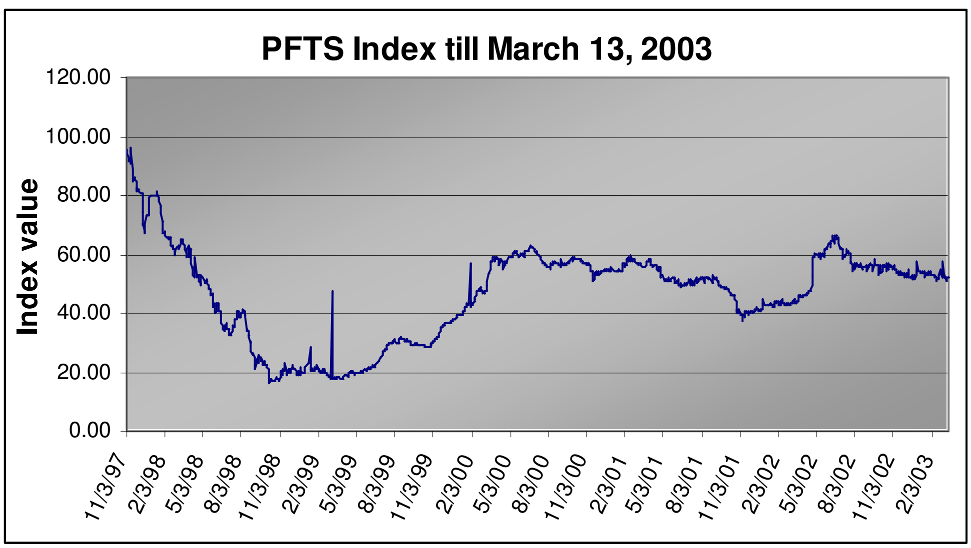

Figure 6.1. PFTS stock price index: 11th November 1997 – 13th March 2003

As empirical evidence suggests the returns on the emerging financial markets, one of which is Ukrainian market, are not highly volatile comparing to the returns on the assets of the world-recognized companies on the developed markets. We see that the volatility is observed during the first year of the first Ukrainian over-the-counter PFTS system functioning until the first shock in January 1999. After the largest shock in March 1999 damped oscillations were observed for almost one year and then again smaller shock occurred. Returns started to volatile again for approximately the last two years.

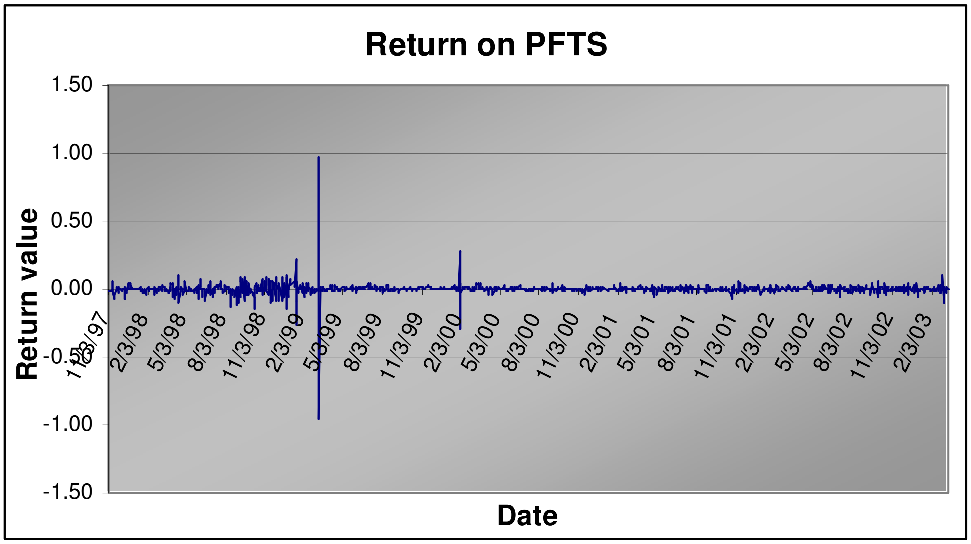

Figure 6.2. Log–returns: 11th November 1997 – 13th March 2003

Before proceeding with the analysis, the curious thing about the data should be noticed. As it is evident from Figure 6.2, two last and the largest spikes in the returns series seem to be not the results of the episodes of higher volatility. One can see that during that period the volatility was on its lower levels comparing to the entire sample period. The reason for those spikes could be rather the fact that exactly on these days, i.e. on the 6th March 1999 and 30th January 2000 zero trading volumes were observed. And then, namely on the 7th March 1999 and 31st January 2000, the trading volumes enormously increased most likely causing the sharp fall in price. On the other hand, the first spike in the return series, namely the one occurred on the 13th January 1999, was rather due to the volatility, since the trading volume during this day was greater than zero and did not change with the change in return during this day.

As we can see, after the graduate decrease the sharp rise in price on the 6th March 1999 (from almost the lowest point) an immediate fall to the previous level on the 9th March 1999 occurred which correspond to the largest swings of the return series along the whole PFTS history (returns constituted **96.69%** and **–96.31%** respectively). During these days there was no crucial fundamental news. Thus, the observed momentary price change could have happened due to the "bubble" on the market. However, since prices sharply rose on Friday and fell on Monday, this could be a vivid example of the weekend effect anomaly, when investors release "bad news" during the weekend. Those "bad news" are then reflected in the low stock prices on Monday.

Besides, two smaller swings were observed along the sample period. One of them occurred on the 13th January 1999, when during one day the price rose and immediately fell to the previous level (return constituted **22.64%** and **–26.38%** respectively). Before this day the results of the Ukrainian economy in 1998 taken from the preliminary national accounts were announced to the public. The production increase in the industries, the enterprises of which are encountered into the PFTS index, could lead to the momentary price rise due to the momentary increase in the demand for stocks of those enterprises. The second swing occurred in a year. Prices rose on the 30th January 2000 and fell on the 31st January 2000 (returns constituted **27.76%** and **–29.78%** respectively). This swing was observed at the end of January, again after the preliminary national economy results were announced. Moreover, those results suggested an increase of the PFTS trading volumes and positive dynamics of the PFTS system. In particular, the total trading volume constituted three times the volume of the previous year and the index value increased by the 72% in comparison to the previous year. This tendency was an indication of the situation on the stock market as a whole in 1999. The stable increase started at the end of October 1999 and was caused by optimistic forecasts and president elections. December 1999 with the highest trading volume observed was characterized as the most active month. And January 2000 was the least active. Hence, the momentary increase in the index value could be an example of the "bubble", since it could happen as a result of the expectations about the resurgence of the PFTS index.

For high frequency (daily) data as in our case we expect that returns are not normally distributed but rather the distribution is leptokurtic, which would suggest the presence of the ARCH/GARCH process in the series. The test for normality appears to be as shown on Figure 6.3:

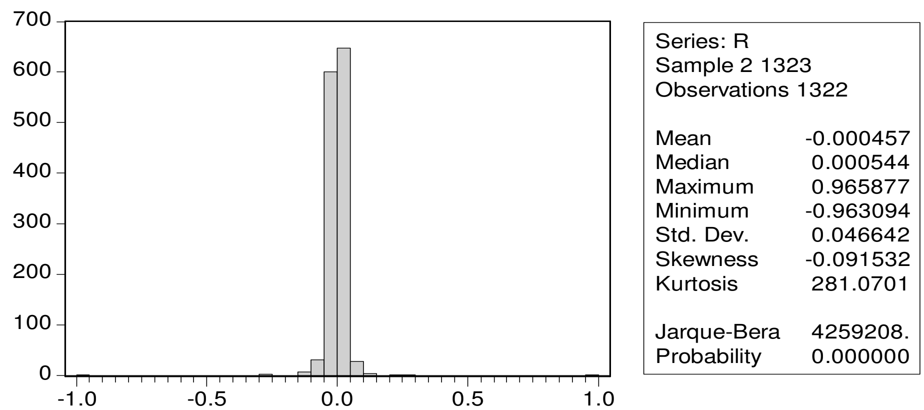

Figure 6.3. A normality test for the daily log-returns.

The mean and median values are almost zero; however, max and min values are very high. From the histogram we see the presence of several outliers. Those are reflection of the sharp swings in price and return, which we mentioned above. Extremely high kurtosis value suggests that our returns series is highly leptokurtic, which is the sign of the ARCH/GARCH process in the return series.

The histogram and test statistic for the cleared (i.e. without underlying six outliers) series is presented in Table 6.4 below. It shows lower kurtosis value, however high enough to indicate the leptokurtic returns, i.e. fat-tailed distribution, thus non-normality (which is also suggested by the high Jargue-Bera statistic with zero p-value). Thus, it is an evidence of the ARCH/GARCH process in the series.

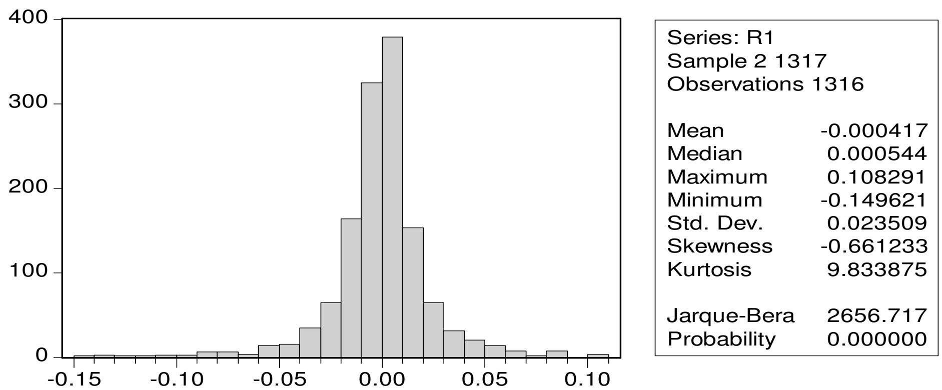

Figure 6.4. A normality test for the "cleared" log-return series.

Correlogram for the return series is presented in Appendix A, which indicates the presence of autocorrelation in the returns (all the p-values equal to zero). Namely there are significant autoregressive components of the lags 1, 2, 39, and moving average components of the lags 1, 39.

The Portmanteau test for white noise applied to returns series supports the conclusion about the presence of ARCH/GARCH process in the series (Q-statistic = 299.316 with p-value 0.00). So, we will use the GARCH-type model in our estimation of the stock returns volatility.

To capture the autoregressive and moving average components we introduce the AR(1), AR(2) and MA(1), MA(39) terms into the mean equation. This helps to completely eliminate any sign of conditional autoregression in our GARCH model, which suggests the quality of the model. Besides, we introduce two dummy variables for 6^{th} and 9^{th} March 1999 observations, i.e. for the largest swings in returns, into the mean equation to account for the outliers.

We tried different specifications but the best model appeared to be the **TGARCH(1,1)** model with **AR(1), AR(2), MA(1),** and **MA(39)** terms which gives all the significant coefficients and eliminates conditional autoregression. Then to examine the direct impact of the conditional variance on the return values we included the conditional variance into the mean equation, thus considering the **TGARCH(1,1)-M** model with **AR(1), AR(2), MA(1),** and **MA(39)** terms which also gives significant coefficients, and the coefficient of the conditional variance in the mean equation is highly statistically significant. The results of estimation are provided in the Table 6.1 below.

Table 6.1. TGARCH's estimation results.

	TGARCH(1,1) with **AR(1), AR(2), MA(1),** and **MA(39)** terms		**TGARCH(1,1)-M** with **AR(1), AR(2), MA(1),** and **MA(39)** terms	
	coefficients	***std. dev.***	***coefficients***	***std. dev.***
mean equation				
constant $=\mu$	.0087	.0036	.0086	.0036
$D_{6th\ March\ 1999}$	.9527	.0468	.9524	.0489
$D_{9th\ March\ 1999}$	– .9635	.0386	-.9637	.0400
h_t	—	—	–.0928	.4284
ARMA terms				
AR(1)	.8159	.0365	.8148	.0365
AR(2)	.1762	.0353	.1771	.0353
MA(1)	–.9422	.0068	– .9417	.0073
MA(39)	.0375	.0050	.0380	.0056
variance equation				
constant $=\omega$	.00002	2.70e-06	.00002	2.74e-06
ARCH(1) $=\alpha_1$	.5196	.0396	.5161	.0414
TARCH(1) $=\gamma_1$	–.2865	.0440	–.2845	.0447
GARCH(1) $=\beta_1$	.6939	.0136	.6956	.0141
AIC / ***SIC***	**-6467.36**	**-6410.304**	**-6465.416**	**-6403.173**
Log-likelihood	**3244.68**		**3244.708**	

In both models the non-negativity condition ($\alpha_1 + \gamma \geq 0$ and $\alpha_1 \geq 0$) is satisfied. Coefficients near the ***TARCH*** component are significant and negative.

This suggests the presence of leverage effects. This conclusion stems from the fact that the Stata package accounts for the positive residuals from the mean equation rather than for the negative ones as the "classical" model suggests. So, emerging stock market exhibit the evidence of the leverage effect. In our case, positive innovations cause the increase in conditional heteroscedasticity by 0.2331, and negative ones – by 0.5196. The coefficient near h_t in mean equation of **TGARCH(1,1)-M** model with **AR(1), AR(2), MA(1),** and **MA(39)** terms is equal to **–.0928** thus, having a negative effect, however not of high magnitude, on the expected returns. This means that investors are penalized for the risk bearing.

In the variance equation we have significant positive coefficients α_1, which indicate the significant magnitude of the effect of the lagged squared error ε^2_{t-1} on the conditional variance h_t and also the existence of the ARCH process in the variance equation.

Having estimated $\alpha_1 + \gamma = .2331$, $\beta_1 = .6939$, $w = .0000228$ from the **TGARCH(1,1)** model with **AR(1), AR(2), MA(1),** and **MA(39)** terms, and $\alpha_1 + \gamma = .2316$, $\beta_1 = .6956$, $w = .0000226$ from the **TGARCH(1,1)-M** model with **AR(1), AR(2), MA(1),** and **MA(39)** terms we can calculate the long-term variance V, which is squared volatility coefficient. As it was stated above,

$$V = \frac{\omega}{1-(\alpha_1+\gamma)-\beta_1} = \frac{.0000228}{1-.2331-.6939} = .0003123 \tag{9}$$

from the first model. Thus, ***volatility*** is approximately $\sqrt{V} = \sqrt{.0003123} = .017672$ or **1.7672%** per day.

And

$$V_M = \frac{\omega}{1-(\alpha_1+\gamma)-\beta_1} = \frac{.0000226}{1-.2316-.6956} = .0003104 \tag{10}$$

from the second model. Thus, ***volatility*** is approximately $\sqrt{V} = \sqrt{.0003104} = .017618$ or **1.7618%** per day.

We see that the TGARCH model with AR and MA terms predicts a little higher long-term volatility than the TGARCH-in-mean model with AR and MA terms. This could happen due to the fact that it just accounts for the absence of the leverage effect and not accounts for the impact of the conditional variance on the expected return. The TGARCH-in-mean model with AR and MA terms accounts for the conditional variance in the mean equation, thus giving different residuals comparing to the first model. This, in turn, explains much larger impact of the lagged conditional variance on the current period conditional variance, which results in higher predicted value for the long-term volatility. However, if to look at the Akaike and Schwarz statistics presented in Table 6.1 above, we see that the first model, i.e. the model not including the conditional variance in the mean equation, is better performed. The ***LR*** test supports this conclusion (result (due to the test statistic ***LR*** = **0.06** with ***p***-value **81.32%** we cannot reject the hypothesis that the restricted model is a better performed one) Hence, we take the higher value, namely **1.7672%** per day, for the long-term volatility as an estimate.

However, let us look at the model. Mainstream researches argue that high-lag moving average terms, as MA(39) in our case, included in the model are typically an artifact caused by the outlying observations. So, let us try to introduce dummy variables for the rest four extreme values of returns, namely those for the 13th January 1999 and 30th and 31st January 2000, at the same time dropping the MA(39) term from the model. Actually, we obtain significant models, which are even better performed (according to the AIC and SIC statistics and the values of ML function) than previous ones. The results of the estimation of **TGARCH(1,1)** and **TGARCH(1,1)-in-Mean** with **AR(1), AR(2), MA(1)** terms**,** and six dummies capturing the effects of the outliers in the data, and respective statistics are presented in Table 6.2 below.

Table 6.2. Results of the estimation of TGARCH's without MA(39) term.

		TGARCH(1,1) with **AR(1), AR(2), MA(1)** terms**,** and **six dummy**		**TGARCH(1,1)-M** with **AR(1), AR(2), MA(1)** terms**,** and **six dummy**	
		coefficients	***std. dev.***	***coefficients***	***std. dev.***
mean equation					
constant $=\mu$		.0008	.0008	.0009	.0009
$D_{13th\ January\ 1999}$		.2326	.1420	.2326	.1465
$D_{13th\ January\ 1999}$		– .2849	.1594	-.2853	.1553
$D_{6th\ March\ 1999}$		.9676	.1605	.9675	.1691
$D_{9th\ March\ 1999}$		– .9618	.1146	-.9618	.1198
$D_{30th\ January\ 2000}$		.2638	.0136	.2639	.0135
$D_{31st\ January\ 2000}$		– .2820	.0065	-.2819	.0064
h_t		—	—	–.6571	2.2585
ARMA terms					
AR(1)		.7665	.0571	.7595	.0601
AR(2)		.1488	.0293	.1498	.0297
MA(1)		–.8473	.0511	– .8407	.0547
variance equation					
constant $=\omega$		7.85e-06	1.38e-06	7.78e-06	1.41e-06
ARCH(1) $=\alpha_1$		.1772	.0189	.1767	.0189
TARCH(1) $=\gamma_1$		–.0535	.0240	–.0535	.0239
GARCH(1) $=\beta_1$		.8468	.0097	.8474	.0100
AIC	***SIC***	**-6797.22**	**-6724.6031**	**-6795.287**	**-6717.484**
Log-likelihood		**3412.61**		**3412.644**	

As it can be seen from the table, models again indicate the presence of leverage effects on the market (the coefficient near ***TARCH*** term is negative), which means that negative innovations have larger impact on the stock return volatility than positive innovations. The negativity constraints to the models are satisfied, and we can calculate the long-term volatility for both models. However, according to the AIC and SIC statistics, again the first model, i.e. the model not including the conditional variance in the mean equation is better performed. ***LR*** test applied to the models considering TGARCH(1,1) as a restricted one supports this result (due to the test statistic ***LR*** = **0.07** with ***p***-value **79.47%** we cannot reject the hypothesis that the restricted model is a better one).

Hence, having estimated $\boldsymbol{\alpha_1} + \boldsymbol{\gamma_1} = .1237$, $\boldsymbol{\beta_1} = .8468$, $\boldsymbol{w} = .00000785$ from the **TGARCH(1,1)** model with **AR(1), AR(2), MA(1)** terms, and six dummies we use these figures to calculate the long-term volatility. It appears to be as follows:

$$V = \frac{\omega}{1-(\alpha_1+\gamma)-\beta_1} = \frac{.00000785}{1-.1237-.8468} = .0002661 \tag{11}$$

from the first model. Thus, ***volatility*** is approximately $\sqrt{V} = \sqrt{.000266102} = .016313$ or **1.6313%** per day.

The volatility value is not very high comparing to the long-term volatilities calculated for other emerging financial markets where it reaches 10-12% per day over the period under investigation.

Now we can switch to the second part of the estimation.

6.2. WHAT DETERMINES VOLATILITY

First, we examine the monthly return series for the period from January 1998 till December 2002, thus, having 60 observations. In Table 6.3 the summary statistics for the underlying series is provided. Figure 6.5 shows the monthly returns dynamics over the entire sample period.

Table 6.3. Summary statistics for the monthly return series.

Variable	***Obs***	***Mean***	***Std. Dev.***	***Variance***	***Min***	***Max***
Rm	60	-.003356	.1208455	.0146036	-.403304	.27998

We see that unlike the daily data, monthly returns have negative mean value, however very close to zero. The range is rather high due to very low return value in August 1998 and high value in April 2002. After a big fall in August 1998 monthly returns started to grow resulting in the period of positive returns (except two falls in February-March and September 1999). Then the period of negative returns started. The only exception is the mentioned above April 2002.

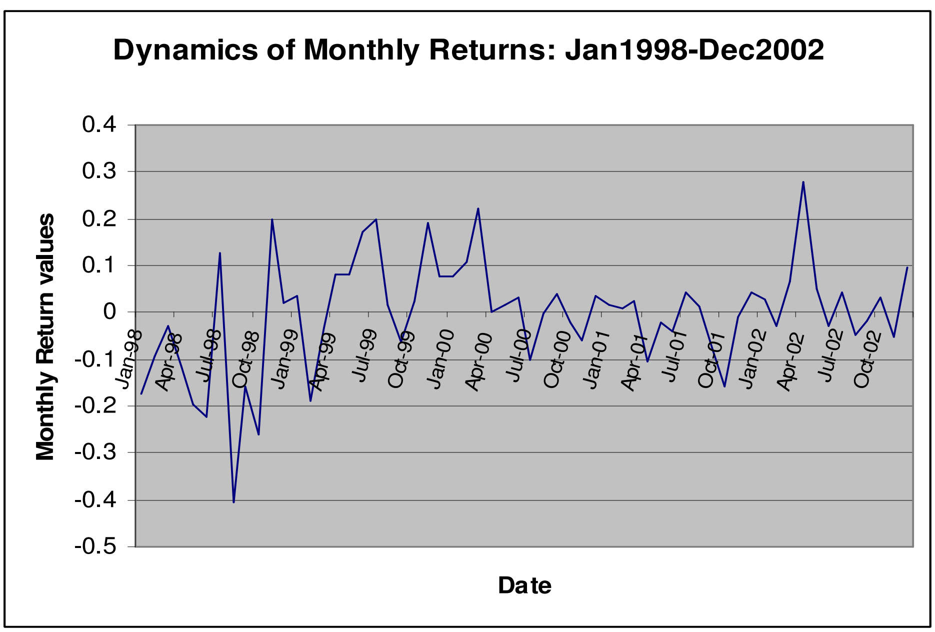

Figure 6.5. Monthly returns dynamics.

Then checking for normality we consider a histogram presented on the Figure 6.6. According to Jargue-Bera statistics (***JB*** = **6.485** with ***p***-value **0.039%**) the monthly PFTS returns are not normally distributed, the distribution is skewed to the left (negative skewness ***S*** = **- 0.49** < 0). High kurtosis value (***K*** = **4.27** > 3), however much lower than that for the daily returns series (which is consistent with the theory), suggests that the series distribution is fat-tailed, which most likely reflects the presence of autoregressive conditional heteroscedasticity (ARCH/GARCH) in the monthly returns series.

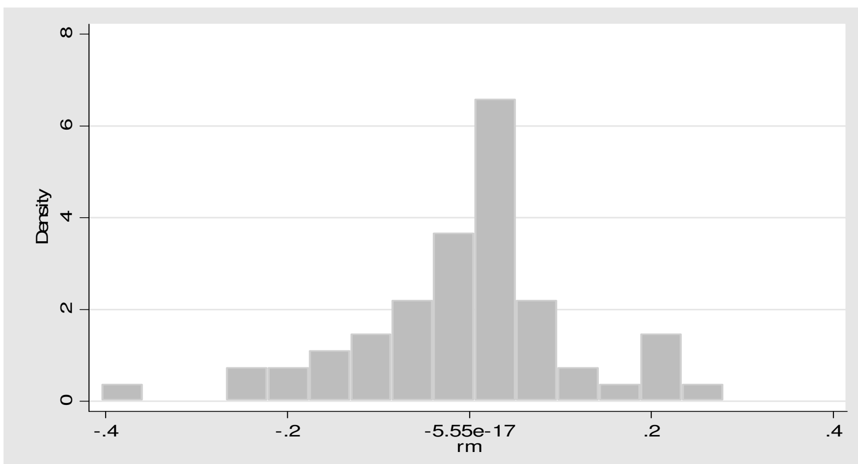

Figure 6.6. Histogram for the monthly returns: Jan 1998 – Dec 2002.

The correlogram for the monthly return series with 28 lags is presented in the Table A2 (see Appendix A). It shows significant autocorrelation and partial autocorrelation coefficients suggesting that the autocorrelation in the series is highly likely to be present. In order to check our expectations about the presence of the ARCH/GARCH process in the series we consider the Ljung-Box ***Q***-statistics, which follows the $\chi^2(n)$ distribution with ***n*** degrees of freedom, where ***n*** = number of lags. All the ***p***-values except that of the 12th lag do not exceed 10%. Thus, we check the most suspicious ***Q***-values in the table of the $\chi^2(n)$ distribution. Only for lags 1 and 10 – 16 we cannot reject the null hypothesis of no autocorrelation in the series. However, the values of the ***Q***-statistics for all other lags are greater than the respective critical value of $\chi^2(n)$ at 5% level of significance. Therefore, the series is indeed autocorrelated, suggesting that the AR and MA terms should be introduced to our model for volatility estimation.

We need to construct a new model in order to make predicted conditional volatility series consistent with the monthly data for the macroeconomic indicators. This will allow estimation of the impact of the main macro variables on the stock returns movements over time and indication of their determinants. To start we estimate the ARMA model AR term of lags 2, 4, 17 and MA term of lags 2, 4. The results of model estimation with different specifications suggest insignificance of AR(2) and both MA(2) and MA(4) terms. The estimated parameters of the models are summarized in Table 6.4 below.

Table 6.4. Summary of the ARMA specifications.

variable	Model				
	1		2		3	
rm	***Coef Std.dev***	***P>|z|***	***Coef Std.dev***	***P>|z|***	***Coef Std.dev***	***P>|z|***
cons	.0006 .0157	.969	.0013 .0158	.935	.0011 .0181	.952
ARMA						
AR(2)	.7738 .1644	.000			.1136 .1161	.328
AR(4)	-.4883 .1246	.000	.2440 .1137	.032	.2277 .1122	.042
AR(17)	-.3585 .1011	.000	-.3481 .1542	.024	-.3284 .1606	.041
MA(2)	-.836 .1319	.000				
MA(4)	1.0 .	.000				
ML value	52.80055		47.4653		47.95569	

The first model seems to be the best from the given three, since it gives the highest value of the likelihood function, and all the coefficients near AR and MA components are highly significant. The second model is much more parsimonious.

In order to check whether the autocorrelation was captured by the model, we consider the Ljung-Box ***Q***-statistics for the residual series calculated from the two models. This is shown in Table A3 and A4 (see Appendix A). The ***Q***-statistics and its ***p***-values indicate the absence of the autocorrelation in the residual series, predicted from both ARMA models. Thus, constructed models capture all the autocorrelation presented in the monthly return series.

Now we can determine our GARCH model specification. It appears that all the three AR terms of lags 2, 4, 17, and both MA terms of lags 2, 4 are highly significant when introduced to the GARCH model. The final specification of the model appers to be as follows:

mean equation: $$rm_t = a_0 + d402 + \gamma h_t + \varepsilon_t \qquad (12a)$$

including ***AR(2)***, ***AR(4)***, ***AR(17)*** and ***MA(2)***, ***MA(4)*** terms,

where $$\varepsilon_t / \Omega_{t-1} \sim N(0, h_t)$$

variance equation: $$h_t = \omega + \alpha\varepsilon_{t-2}^2 + \beta h_{t-2} + \delta\varepsilon_{t-2} I_{t-2} \qquad (12b)$$

where $\boldsymbol{rm}_t$ is an expected monthly return, $\boldsymbol{h}_t$ is a conditional variance, $\boldsymbol{I_{t-2}} = 1$ if $\boldsymbol{\varepsilon_{t-2}} < 0$, i.e. it accounts for all the negative errors with lag 2. Ω_{t-1} is an information matrix containing all the information available at the previous period. The non-negativity constraints are the following: $\boldsymbol{\alpha} + \boldsymbol{\delta} \geq 0$ and $\boldsymbol{\alpha} \geq 0$. Here positive $\boldsymbol{\delta}$ coefficient suggests the presence of the leverage effects on the market, i.e. the negative returns have greater impact on the conditional variance than the positive returns.

Here should be noticed that due to the Stata estimation procedure we expect positive coefficient $\boldsymbol{\delta}$, since Stata accounts for positive errors, i.e. $\boldsymbol{I_{t-2}} = 1$ if $\boldsymbol{\varepsilon_{t-2}} > 0$. In such a notation positive $\boldsymbol{\delta}$ will again suggest asymmetry in a sense that negative returns affect the conditional volatility more significantly than the positive returns.

In order to account for the high positive return in April 2002 (while all the figures around are negative) we impose the dummy variable ***d***402 for this month. This should significantly improve the predictive power of the model.

The estimated model appears to be as follows:

mean equation: $\boldsymbol{rm}_t = .03295 + .2655\boldsymbol{d}402 - 2.307\boldsymbol{h}_t$ (13)

variance equation: $\boldsymbol{h}_t = .00022 + 3.4454\varepsilon^2_{t-2} + .0669\boldsymbol{h}_{t-2} - 2.4685\varepsilon_{t-2}\boldsymbol{I}_{t-2}$ (14)

with the coefficients near AR and MA components summarized in Table 6.5:

Table 6.5 Coefficients of AR and MA components.

	AR(2)	AR(4)	AR(17)	MA(2)	MA(4)
Coefficient	.6877	.0240	-.2863	-1.2751	.6201
Std. dev.	.0682	.1021	.0402	.1031	.1202

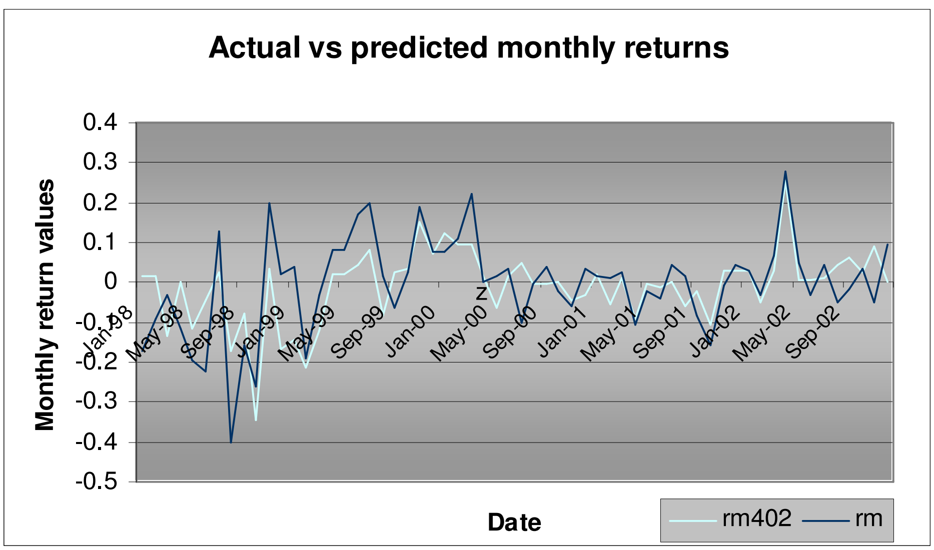

Figure 6.7. Comparing the actual and predicted monthly returns.

From the Figure 6.7 we see that the predicted series follow all the fluctuations in the actual monthly return series. Thus, we can suggest the high predictive power of our model, since it captures all the peculiarities of the data over the period under consideration. So, predicted from the model conditional variance series for the entire sample period would be highly reliable.

Having constructed the model for the monthly returns we now turn to our goal in this part of the research – examining the relationship between the volatility of the stock returns and the main macroeconomic indicators, namely, GDP, export and import, and their growth.

In the Table 6.6 below we present the estimation results of the models containing the macroeconomic indicators as explanatory variables in the variance equation. We are interested now in the impact that the macroeconomic variables can have on the stock return volatility. Therefore, the main attention is paid to the significance, sign and the magnitude of this impact.

Here ***GDP, %yoy*** is a change in real GDP comparing to the same period of the previous year; ***EX*** and ***IM*** denote exports and imports measured in $mln.; ***XMG*** is an index of market openness which is calculated as a ratio of the trade balance to the real GDP.

In all the reported models the coefficients of macroeconomic variables are highly significant. This indicates the fact that the fundamentals affect a conditional variance, thus, a stock return volatility, to a certain degree. What should be mentioned here is that the impact of all the macroeconomic indicators except the imports is negative. Besides, combined in a certain way some variables make the impact of others negligible and insignificant. This happens in case of real GDP lowering the impact of exports or imports, and in case of real GDP changes neglecting the impact of changes in exports and imports. The coefficient near the degree of the market openness appears to be significant in both models, it is included in.

Table 6.6. Estimation results of the models with macro components.

Model containing…	**GDP, %yoy**	**EX & IM**	**XMG, $\frac{(EX-IM)}{RGDP}$**	**XMG & GDP%yoy**
Variable	***Coeffic (st.dev)***	***Coeffic (st.dev)***	***Coeffic (st.dev)***	***Coeffic (st.dev)***
Mean eq.				
_cons	-.0004 (.0233)	-.0126 (.0146)	.0313 (.0123)	.0139 (.0429)
d402	.2821 (.8506)	.3030 (.4506)		
γ	-.3024 (2.4567)	.11054 (1.5985)	-4.1436 (2.233)	2.0728 (4.8052)
AR(2)	1.0275 (.1497)	-1.5331 (.1223)	.5996 (.1868)	.6354 (.4106)
AR(4)	-.8052 (.1662)	-.8071 (.1078)	-.2166 (.2465)	-.2166 (.2465)
AR(17)	-.1481 (.0777)	.03745 (.0441)	-.3059 (.1088)	-.1763 (.1835)
MA(2)	-.9757 (.1125)	1.6905 (.0887)	-.6684 (.1704)	-.8694 (.3132)
MA(4)	.8732 (.1281)	.9189 (.0969)	.8090 (.0845)	.5789 (.2480)
Variance eq.				
_cons	-5.3561 (.1959)	-3.9522 (.6235)	-8.3076 (2.2856)	-4.4790 (.0110)
α	.2349 (.2766)	.1751 (.3047)	.9330 (.4980)	.5731 (.4729)
β	-.5577 (.2884)	.5726 (.2242)	.1714 (.0914)	-.0632 (.2348)
δ	.6535 (.1853)	-.3988 (.2317)	.1811 (.7710)	-.8595 (.6205)
GDP, %yoy	-.1602 (.0494)	—	—	-.0984 (.0143)
EX	—	-.00725 (.00065)	—	—
IM	—	.0056 (.0001)	—	—
XMG	—	—	-.0005 (.0003)	-.00003 2.37e-06
ML value	59.54542	65.03385	55.5274	50.89173

All the specifications including month over month changes in exports and imports fail, i.e. the coefficients are insignificant or the maximization of the maximum likelihood function is simply impossible to complete. Hence, if we want to investigate the relationship between the fundamental economic factors and the stock return volatility, it is possible to make inferences about the impact of the fundamental economic factors but not their growth on the volatility of the stock returns. The only exception is GDP, which absolute values insignificantly relate to the volatility of the stock returns. However, its growth appears to have a very significant impact on the volatility.

The magnitude of the underlying impact is not low as it may seem at first sight when just looking at figures in Table 6.5. We see that 1% change in real GDP growth will cause the volatility to change by 0.16 which is not a small number regarding the fact that the mean value of the predicted conditional variance is 0.016. Thus, a 1% change in real GDP growth causes volatility to change by the amount which 10 times exceeds its mean. The magnitude of the impact of the openness of the market is actually low. A 1% change in the ratio XMG causes volatility to change by .0005 which is not much comparing to its mean value. As for the exports and imports, their impact is 10 times greater than that of the market openness, but still low comparing to the volatility mean value.

The signs of the coefficients are as they were expected. An increase in GDP growth, in exports and in the degree of market openness make the economy stronger lowering the investment risks, thus, the volatility also decreases. On the contrary, the increase in imports lowers the state revenue, thus, increasing risks of the sustainability of own economy, which causes a stock return volatility to increase.

So, we can say that there is a significant impact of the certain macroeconomic indicators on the volatility of the stock return on the market. However, this does not suggest that the fundamentals are the only possible explanations for the high volatility of the stock markets. There are certainly other factors determining the fact that the stock returns appear to be highly volatile.

The vivid example in the Ukrainian financial market is the mentioned above the largest spike in the market when in the March 1999 stock prices sharply increased and momentarily fall to almost the previous level. We cannot explain this fact by the fundamentals. Hence, they could be explained from the point of view of the theory of the feedback trading, the presence of the so called "noise traders" in the market, etc.

Unfortunately, the Ukrainian statistics does not provide enough data for the investigations of the non-fundamental phenomena on the financial markets. What is more, the financial market in Ukraine could be called newly created, since it exists for only about 7 years, and the number of possible gathered observations is not enough to make very reliable inferences about what is actually happening in the market.

Chapter 7

CONCLUSIONS

We have estimated the two models, namely TGARCH(1,1) and TGARCH(1,1)–in-Mean models with AR(1), AR(2), MA(1), and MA(39) terms. Estimation results suggest the presence of leverage effects on the Ukrainian financial market. Hence, the market is asymmetric, i.e. the impact of innovations on the stock returns volatility is different in magnitude for negative and positive innovations, in particular, providing larger impact for the negative innovations. The calculated value of the long-term volatility suggests that the volatility is rather high; however relatively to the data for other emerging financial markets (which suggests 10-12% long-term volatility), Ukrainian financial market is much less volatile. The coefficient values obtained from the estimation are not very different for two models, however according to the Akaike and Schwarz criterion, the model not including conditional variance into mean equation performs better. Moreover, both models satisfy the non-negativity conditions and provide the signs and magnitude of the estimated coefficients consistent with our expectations. The leverage effects in the returns series are indicated as expected to appear on the emerging financial market.

Models including dummy variables to capture effects of all the six outliers allow excluding of an MA(39) term which is considered as artefact and appears to be a subject to the impact of the outliers. According to the Akaike and Schwarz criterion and the LR test results, models without MA(39) term perform better. According to this model, the long-tem volatility is not very high in Ukraine, which is consistent with previous findings on the other emerging financial markets. The market appear to be asymmetric, suggesting the presence of leverage effects on the market.

The estimation of the relationship between the volatility, i.e. the conditional variance of the monthly returns and the macroeconomic variables provides with the results consistent with our expectations. Namely, the impact of the change in GDP growth, exports and the openness of the market on the volatility is negative, and the impact of the imports changes is positive. The magnitude of the underlying impact is not large for all but the GDP growth indicators. Changes in the GDP growth have an impact which is ten times bigger than the mean value of the conditional variance.

However, we can say that the fundamental factors cannot be considered as the only possible explanation for the volatility of stock returns. The impact of the non-fundamental factor should also be taken into account. Hence, there is still much room for further investigation of the stock market in Ukraine, and in particular the volatility of the stock returns and its determinants. However, for the moment there exist certain problems with the data available on the Ukrainian stock market. First of all, the Ukrainian financial market is operating not for a long period, thus, even for the data which is available the time horizon is short, and in the majority of times the relevant data is simply do not exist.

Taking into account the importance of the financial markets investigation for the economy in transition, the further research is highly encouraged.

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APPENDIX A

Table A1. Correlogram for returns series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| |	***| |	1	-0.409	-0.409	221.75	0.000
| |	*| |	2	0.012	-0.186	221.95	0.000
| |	| |	3	0.031	-0.048	223.26	0.000
| |	| |	4	0.004	0.003	223.29	0.000
| |	| |	5	-0.007	0.004	223.36	0.000
| |	| |	6	0.009	0.012	223.47	0.000
| |	| |	7	-0.003	0.006	223.48	0.000
| |	| |	8	0.026	0.035	224.39	0.000
| |	| |	9	-0.030	-0.005	225.59	0.000
| |	| |	10	0.034	0.027	227.16	0.000
| |	| |	11	0.014	0.044	227.40	0.000
| |	| |	12	-0.019	0.013	227.86	0.000
| |	| |	13	0.028	0.033	228.88	0.000
| |	| |	14	-0.001	0.025	228.88	0.000
| |	| |	15	0.008	0.026	228.97	0.000
| |	| |	16	0.010	0.028	229.09	0.000
| |	| |	17	0.001	0.020	229.09	0.000
| |	| |	18	-0.006	0.002	229.14	0.000
| |	| |	19	-0.012	-0.020	229.33	0.000
| |	| |	20	-0.007	-0.030	229.39	0.000
| |	| |	21	0.012	-0.012	229.59	0.000
| |	| |	22	-0.024	-0.031	230.39	0.000
| |	| |	23	0.022	-0.003	231.03	0.000
| |	| |	24	0.011	0.018	231.20	0.000
| |	| |	25	-0.028	-0.016	232.29	0.000
| |	| |	26	0.061	0.052	237.24	0.000
| |	| |	27	-0.036	0.010	239.03	0.000
| |	| |	28	-0.006	-0.012	239.07	0.000
| |	| |	29	0.036	0.028	240.79	0.000
| |	| |	30	-0.006	0.027	240.84	0.000
| |	| |	31	0.005	0.025	240.87	0.000
| |	| |	32	-0.001	0.015	240.88	0.000
| |	| |	33	-0.013	-0.008	241.11	0.000
| |	| |	34	0.003	-0.013	241.13	0.000
| |	| |	35	0.011	0.009	241.29	0.000
| |	|* |	36	0.059	0.083	246.04	0.000
| |	| |	37	-0.054	0.008	249.99	0.000
*| |	*| |	38	-0.070	-0.105	256.61	0.000
|* |	|* |	39	0.169	0.098	295.72	0.000

Table A2. Correlogram for the monthly returns.

```
                                                   -1   0   1     -1   0   1
LAG        AC        PAC        Q      Prob>Q      [AC]           [PAC]
------------------------------------------------------------------------------
1        0.2403    0.2435    3.6405   0.0564        |-             |-
2        0.2007    0.1559    6.2235   0.0445        |-             |-
3        0.0304   -0.0516    6.2837   0.0986        |              |
4        0.3169    0.3319    12.957   0.0115        |--            |--
5        0.1377    0.0317    14.239   0.0142        |-             |
6        0.1286    0.0269    15.379   0.0175        |-             |
7        0.0911    0.0918    15.961   0.0255        |              |
8        0.0840   -0.0125    16.466   0.0362        |              |
9       -0.0020   -0.0118    16.467   0.0578        |              |
10      -0.1167   -0.1673     17.48   0.0644        |             -|
11      -0.0572    0.0091    17.728   0.0881        |              |
12      -0.0664   -0.0876     18.07   0.1136        |              |
13      -0.1501   -0.2019    19.854   0.0989       -|             -|
14      -0.1262    0.0139    21.142   0.0981       -|              |
15      -0.1524   -0.1954    23.061   0.0828       -|             -|
16      -0.0433    0.1417     23.22   0.1080        |              |-
17      -0.2287   -0.3756    27.745   0.0480       -|           ---|
18      -0.2278   -0.1357     32.34   0.0200       -|             -|
19      -0.1750   -0.1452    35.117   0.0135       -|             -|
20      -0.0786   -0.1913    35.692   0.0167        |             -|
21      -0.1414   -0.1037    37.598   0.0144       -|              |
22      -0.1435   -0.2258    39.615   0.0120       -|             -|
23      -0.0823   -0.2349    40.296   0.0142        |             -|
24      -0.0638   -0.1950    40.716   0.0179        |             -|
25       0.0910    0.0044    41.596   0.0199        |              |
26       0.0553    0.1405    41.931   0.0250        |              |-
27      -0.0103   -0.0733    41.943   0.0333        |              |
28      -0.0127    0.0767    41.961   0.0437        |              |
```

Table A3. ***Q***-statistics for residuals from the ARMA model 1.

Model 1

LAG	AC	PAC	Q	Prob>Q
1	0.1721	0.1781	1.8685	0.1716
2	-0.0539	-0.0919	2.0551	0.3579
3	-0.1396	-0.1250	3.3264	0.3440
4	0.0271	0.0824	3.3753	0.4971
5	-0.0051	-0.0481	3.3771	0.6421
6	0.0165	0.0147	3.3958	0.7578
7	0.0536	0.0518	3.5972	0.8248
8	0.1432	0.1555	5.0641	0.7507
9	0.0129	0.0064	5.0763	0.8276
10	-0.1072	-0.0542	5.9315	0.8210
11	-0.0269	0.0731	5.9866	0.8743
12	0.0368	0.0563	6.0918	0.9114
13	0.0061	-0.0027	6.0948	0.9426
14	-0.0549	-0.0132	6.3388	0.9572
15	0.0219	0.0739	6.3786	0.9727
16	0.0814	0.1165	6.9384	0.9744
17	0.1271	0.2441	8.3351	0.9588
18	-0.1585	-0.1464	10.56	0.9121
19	0.0447	0.2786	10.741	0.9322
20	-0.0348	-0.1661	10.854	0.9499
21	-0.0878	0.0282	11.589	0.9501
22	-0.0890	-0.0830	12.365	0.9494
23	-0.0330	0.0316	12.474	0.9625
24	0.0544	0.1046	12.78	0.9696
25	0.1249	0.2592	14.438	0.9535
26	0.0965	0.1210	15.457	0.9484
27	-0.0698	0.1476	16.006	0.9528
28	-0.0865	-0.1115	16.876	0.9510

Table A4. ***Q***-statistics for residuals from the ARMA model 2.

Model 2

LAG	AC	PAC	Q	Prob>Q
1	0.1753	0.1799	1.9386	0.1638
2	0.0625	0.0342	2.189	0.3347
3	-0.1306	-0.1560	3.303	0.3472
4	0.0173	0.0778	3.3227	0.5053
5	0.0508	0.0630	3.4976	0.6238
6	0.1091	0.0821	4.3171	0.6338
7	0.0652	0.0359	4.6154	0.7068
8	0.0666	0.1040	4.9326	0.7648
9	0.0325	0.1024	5.0098	0.8335
10	-0.0986	-0.0813	5.7337	0.8371
11	-0.0044	0.1173	5.7352	0.8904
12	-0.0559	-0.0908	5.9774	0.9172
13	-0.0716	-0.0456	6.3833	0.9311
14	-0.0732	-0.0758	6.8171	0.9415
15	-0.0269	-0.0412	6.8768	0.9610
16	0.0937	0.1262	7.6187	0.9594
17	0.1043	0.0333	8.5606	0.9530
18	-0.1558	-0.2204	10.712	0.9062
19	-0.0650	0.0612	11.095	0.9206
20	-0.0508	-0.1469	11.336	0.9371
21	-0.0388	-0.0217	11.479	0.9526
22	-0.1022	-0.2681	12.502	0.9461
23	0.0373	-0.0223	12.642	0.9593
24	0.0291	-0.0615	12.73	0.9704
25	0.1640	0.2410	15.588	0.9266
26	0.0600	0.1775	15.982	0.9366
27	-0.0616	0.2210	16.41	0.9447
28	-0.0404	-0.1086	16.6	0.9561