CHARLES UNIVERSITY IN PRAGUE

FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies

Oldřich Koza

Behaviour of Stocks on the Prague Stock Exchange During the Financial Crisis: Evidence from Empirical Research

Bachelor's Thesis

Prague 2011

Author: Oldřich Koza
Supervisor: PhDr. Petr Teplý Ph.D

Academic year: 2010/2011

Bibliografický záznam:
Koza, Oldřich. *Chování akcií na Pražské burze během finanční krize: empirická studie*, Praha, 2011. Bakalářská práce, Univerzita Karlova, Fakulta sociálních věd, Institut ekonomických studií. Vedoucí bakalářské práce: PhDr. Petr Teplý Ph.D.

Název práce: Chování akcií na Pražské burze během finanční krize: empirická studie
Autor: Oldřich Koza
Institut: Institut ekonomických studií
Vedoucí bakalářské práce: PhDr. Petr Teplý Ph.D.
Externí vedoucí bakalářské práce: Ing. Jan Novotný MA
E-mail vedoucího: teply@fsv.cuni.cz
E-mail externího vedoucího: jnovotny@cerge-ei.cz

Abstrakt: Tato práce studuje chování čtyř nejvíce obchodovaných akcií na Burze cenných papírů Praha od ledna 2007 do července 2010. Hlavním cílém této práce je zjistit, jak finanční krize ovlivnila Pražskou burzu. Za pomoci standardních statistických metod, ARMA, GARCH a VAR modelů zkoumám na denních datech tyto fenomény: volatilitu, cenové skoky, efekt dne v týdnu, platnost hypotézy efektivních trhů a tok informací mezi akciemi. Výsledky analýzy ukazují, že krizí byly více zasaženy akcie bankovního sektoru než ostatní akcie. Krize byla především charakterizována průdkým nárustem volatility a korelace mezi jednotlivými akciemi na trhu. Krize také ovlivnila tok informací mezi akciemi a efekt dne v týdnu. Avšak cenové skoky a informační efektivnost ovlivněny nebyly.

Klíčová slova: Burza cenných papírů Praha, finanční krize, ARMA, GARCH, VAR, hypotéza efektivních trhů, vliv dne v týdnu, Grangerova kauzalita, Boxova-Jenkinsonoca metodologie

Délka práce: 80 337 znaků

Bibliographic entry:
Koza, Oldřich. *Behaviour of stocks on the Prague Stock Exchange During the Financial Crisis: Evidence from Empirical Research*, Prague, 2011. Bachelor's thesis, Charles University, Faculty of Social Sciences, Institute of Economic Studies. Supervisor: PhDr. Petr Teplý Ph.D.

Title: Behaviour of Stocks on the Prague Stock Exchange During the Financial Crisis: Evidence from Empirical Research
Author: Oldřich Koza
Department: Institute of Economic Studies
Supervisor: PhDr. Petr Teplý Ph.D.
External Supervisor: Ing. Jan Novotný MA
Supervisor's email address: teply@fsv.cuni.cz,
External Supervisor's email address: jnovotny@cerge-ei.cz

Abstract: This work studies the behaviour of the four most traded stocks on the Prague Stock Exchange from January 2007 to July 2010. Its main goal is to describe how the financial crisis influenced the Prague Stock Exchange. Employing standard statistical methods, ARMA, GARCH, and VAR models I examine on daily data the following phenomena: volatility, price jumps, the day of the week effect, validity of the efficient market hypothesis, and information flow between the stocks. The results imply that the financial crisis had stronger impact on the banking sector stocks than on other stocks. The crisis was mainly characterized by rapid growth in volatility and correlation between the stocks. It also influenced the information flow and the day of the week effect. However, the crisis did not trigger growth in the number of extreme price movements, and it did not cause the market to be less information efficient.

Keywords: Prague Stock Exchange, financial crisis, ARMA, GARCH, VAR, efficient market hypothesis, day of the week effect, Granger causality, Box-Jenkins methodology

Length of the thesis: 80,377 characters

Declaration: I hereby declare, that I have elaborated the Bachelor's thesis on my own and I have used only listed sources and references. Furthemore, I have written this thesis only for the purpose of achieving the Bachelor's degree at IES FSV UK. I acknowledge and agree with lending and publishing of the thesis.

In Prague, 18^{th} May, 2011 Oldřich Koza

I would like to thank Petr Teplý and Jan Novotný for supervising this thesis and providing me with priceless suggestions concerning content as well as style. Apart from that I would like to thank Tomáš Křehlík, Jáchym Hercher, and David Kubásek for valuable comments.

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1 Introduction

If you had invested CZK 1,000 in a typical portfolio of stocks traded on the Prague Stock Exchange (expressed by the PX Index) at the beginning of 2000, on October 29, 2007, when the PX Index reached its top, you would have been able to sell it for CZK 3,996. This is the same appreciation as if your bank paid you 25.8% annual interest. On the other hand, if you had invested CZK 1,000 in similar portfolio on October 29, 2007, by February 18, 2009 it would have been worth no more then CZK 325. By the time this thesis was completed during April 2011, you would still not have been able to sell your portfolio for more than CZK 653, and it is reasonable to assume it will still take some time until the Prague Stock Exchange completely recovers and the PX Index again reaches its values from the end of 2007.

In the Czech Republic, we could witness turmoil not only on the Prague Stock Exchange, but also the main macroeconomic fundamentals indicated serious problems in the Czech economy during the years 2008 and 2009. Real GDP growth slumped from 6.1% in 2007 to 2.5% in 2008 and in 2009 there was even a decline in real GDP by 4.1% (www.czso.cz)[1]. Unemployment in the Czech Republic grew from 4.2% in the second quarter of 2008 to 8.0% in the first quarter of 2010 and since than it decreased only slightly to 6.9% in the last quarter of 2010. (www.czso.cz)[1]. This financial and economic collapse went in general knowledge as the financial crisis of 2008 and 2009.

The goal of this thesis is to examine behaviour of the four main stocks traded on the Prague Stock Exchange before, during and after the financial crisis and to answer following questions. Did the financial crisis influence behaviour of stocks on the Prague Stock Exchange? Was there a structural change in price generating processes of the stocks? Or was the crash we witnessed merely change in trend and other properties of the data remained the same? If the former is true and the structural change was present, I examine whether the change was persistent and the effect of the financial crisis remained also after the recovery or disappeared when the recovery came. Understanding the behaviour of stocks before, during, and after the crises could help avert huge losses as those that we have seen in the recent past by improving portfolio decisions and better hedging.

[1]The data were downloaded on April 5, 2011

The four studied stocks are ČEZ, Erste Group Bank, Komerční Banka, and Telefonica O2 Czech Republic. For describing and evaluating the behaviour of these stocks several statistical and time series analysis tools are employed including univariate time series tools such as Box-Jenkins methodology for estimating ARMA models and its extension for estimating GARCH models; VAR models and Granger Causality from the field of multivariate time series analysis; and variance, bi-power variance and correlation analysis from the field of descriptive statistics. I examine how the financial crisis affected the following phenomena: day of the week effect on returns and volatility, validity of the efficient market hypothesis, occurrence extreme price movements, and information flow between the studied companies. Additionally, since these four stocks are representatives of energetic, banking, and telecommunication sector, I infer from the data on different impacts of the crisis on these sectors.

This work is further divided into the following chapters. Chapter 2 reviews literature on stock markets in the Central Europe with emphasis on the works using the tools that I use for the analysis. Chapter 3 provides comprehensive review of the methodology. Chapter 4 describes the Prague Stock Exchange, studied companies and the data. The data sample decomposition in context of the financial crisis is also described in this chapter. Chapter 5 provides the empirical results. Those are divided in the description statistics results, univariate time series analysis results, and multivariate time series analysis results. Finally, I present the conclusion.

2 Literature Review

Literature on time series analysis of stock returns on developed markets is fairly voluminous, but there is still relatively small amount of applications on the Czech stock market since the Prague Stock Exchange has still quite short history compared to developed EU and US markets. Vošvrda and Žikeš (2004) applied variance ratio test developed by Lo and MacKinlay (1988) to test the random walk in the time series of weekly close values of WIG, BUX, PX-50 and DAX indices for the period from 1996 to 2002. They strongly rejected the random walk hypothesis for the Czech index and using the Box-Jenkins methodology they found that ARIMA (1,1,1)-GARCH (1,1) model describes the data generating process of the Czech index the best. However, standardized residuals from their estimation did not fulfil the *iid* condition for the Czech index and thus Vošvrda and Žikeš (2004) did not succeed in specifying the model correctly. The Czech index was the only one from their data sample they were not able to capture correctly by ARIMA(P, I, Q)-GARCH(p, q) and this is strong motivation for my work.

Hanousek et al. (2008) studied impact of macroeconomic news on Central European markets and also the spill-over effects of German, U. S., Polish, and Hungarian indices on the PX index. They used five-minute data starting in the beginning of 2003 and ending in the end of 2006. They measured effect of the macroeconomic news based on the deviations of the actual announcement values from what had been expected. They found that the returns on the Czech stock index PX were significantly affected by all four studied indices, but mostly by the German returns, the effect of which was three times higher than the effect of U.S. returns and approximately two times higher than the effect of Polish returns. The smallest effect was found in the Hungarian returns. Regarding the macroeconomic news announcements, they found significant effect in U. S. multiple announcements, but not in the single ones. They also found asymmetric impact of announcements, where the negative effect of the negative news was about 50% stronger than the positive effect of the positive news. Surprisingly, the strongest negative impact had news that was in line with the market expectations. As for the EU announcements, they found negative impact of single positive news and it was the only significant effect found. They explain this surprising result as possible evidence of the fact that positive news releases related to the old EU members might be perceived by the market as a signal to transfer funds from the new EU markets to the old EU market.

On the other hand, Balázs and Kočenda (2011) using the 5-minute data in the period from June 2003 to January 2006 found very little co movements between the Prague Stock Exchange and the Western European stock markets as well as between Central European markets among themselves and they suggested it may be of importance for international portfolio diversification into the CEE for that reason.

Novotný (2010b) used high frequency data of the main indices from Prague, Warsaw, Budapest and Frankfurt Stock Exchanges from June 2003 to December 2008 and this is to my best knowledge the most recent work studying the time series of the Prague Stock Exchange. He focuses on price jumps and found that in the Prague Stock Exchange, contrary to the other studied stock exchanges, the lower the frequency of data sampling is, the lower the number of extreme price jumps. He claims that such a behaviour of the PX index is completely different from what one would assume, based on theory. He argues that this may be caused by a relatively small number of trades with a few stocks. Finally, he shows that the beginning of the recent financial crisis caused an overall increase in volatility, but not increase in the total number of price jumps.

One of the goals of this thesis is to test the *day of the week effect* and its changes due to the financial crisis. To my knowledge there has not been any work testing this hypothesis on the Czech stocks. I refer to Choudhry (2000), who used GARCH model to test the day of the week effect in emerging Asian markets on daily data from June 1990 to December 1995. He found significant Monday effect on both stock returns and conditional variance. His findings are in accordance with several information theory studies, that claim that stock variance should be the highest on Mondays, when informed traders have the greatest information advantage. If, for example, information arrives at constant rate over time, the variance on Monday close should be three times higher than on other days close. See e.g. French and Roll (1986).

From the field of multivariate time series analysis I refer to Hanousek and Filer (1997), who using VAR models and Granger Causality investigated the possibility that newly emerging equity markets in Central Europe exhibit semi-strong form of the information efficiency, in other words that no relationship exists between lagged values of changes in economic variables and changes in current equity prices. From all the studied markets they found that such efficiency is characteristic for the Czech Republic only.

Information Efficiency of the Central European Stock Markets was also studied by Diviš and Teplý (2005), who used standard statistics tools on weekly and monthly data from 1991 to 2004. They found all the Central European markets to be information efficient in the weak form of the hypothesis and discovered that from 1998 to 2004 the markets came closer to the strong form of the efficient market hypothesis.

In my thesis I continue with analysis of behaviour of the Prague Stock Exchange employing the time series instruments. My contribution is as follows. First, I use the recent data capturing the financial crisis. Second, I focus on particular stocks traded on the Prague Stock Exchange and not merely on the PX Index as a whole like the previous studies. I analyze the intra-market relations, which affect the behaviour of the PX index as a whole. And finally, I test hypotheses that to my best knowledge have not been tested on Prague Stock Exchange data yet, e. g. the day of the week effect.

3 Methodology

3.1 General Statistical Methodology

3.1.1 Sample Mean

The first basic indicator of the financial time series is its sample mean. Sample mean can be used to evaluate performance of the stock in the different time periods or to compare performance of several different stocks. In our case positive mean of the returns means increase in price of stock. Sample mean is defined as:

$$\hat{\mu} = \frac{\sum_{i=1}^{n} x_i}{n}. \tag{3.1}$$

3.1.2 Sample Variance

The second basic indicator used to evaluate the performance of the stock is its variance. The meaning of variance can be translated in several phenomena such as volatility, risk, nervousness, or uncertainty on the markets etc. Variance plays a key role in the capital assets pricing model introduced by Jack Treynor in 1961 (for more details on CAPM see e. g. Perold, 2004) and also in the GARCH model described later in this thesis. From the investor's point of view the lower the variance, the better. Sample variance is written as:

$$\hat{\sigma^2} = \frac{\sum_{i=1}^{n} (x_i - \hat{\mu})^2}{n-1}. \tag{3.2}$$

3.1.3 Sample Skewness

In statistical theory skewness is used as a measure of symmetry of the probability function of a random variable. If the probability function is symmetric, then skewness is equal to zero. Sample skewness serves as an estimation of the theoretical one assuming unknown data generating process behind our observed data. In finance, sample skewness tells us if more positive or negative abnormal returns are present. If, on the one hand, small or moderate returns higher than mean are obtained rather than the ones lower then mean, but on the other hand, extreme negative returns are more probable than the positive ones, the skewness of such a financial series would be negative. Sample skewness is defined as:

$$\hat{S} = \frac{\hat{\mu}_3}{\hat{\sigma}^3}, \tag{3.3}$$

where $\hat{\mu}_k = \sum_{i=1}^{n}(x_i - \hat{\mu})^k$.

3.1.4 Sample Kurtosis

Sample kurtosis is used to measure how much the data is clustered around its mean and it is very important indicator in finance. Normal distribution has kurtosis equal to 3. However, the financial time series are typically *leptokurtostic*. This means that most of the time returns are clustered around its mean and probability that the return will be very close to its mean is greater than in the normal distribution. However, also probability of extreme returns, either positive or negative, is significantly higher than in the normal distribution. Leptokurtostic data sample will have kurtosis higher than 3. In finance, instruments with such properties are also said to have *fat tails*. Fat-tailed property of returns is usually attributed to *conditional heteroskedasticity*, which will be described below in context of time series analysis. Sample Kurtosis is defined as:

$$\hat{K} = \frac{\hat{\mu}_4}{\hat{\sigma}^4}. \tag{3.4}$$

3.1.5 Bipower Variance

More advanced indicator of the volatility and its composition is bipower variance introduced by Barndorff-Nielsen (2004). Sample bipower variance from sample of n observations is defined as:

$$\hat{\sigma^2_{bi}} = \frac{\sum_{i=2}^{n} |x_i - \hat{\mu}||x_{i-1} - \hat{\mu}|}{n-2}. \tag{3.5}$$

The difference between interpretation of standard variance and bipower variance is that standard variance is more influenced by extreme price movements since it uses the squares of deviations of observations from their mean, while bipower variance is less sensitive to extreme price movements. Extreme price movements as well as application of bipower variance are in literature connected with price jumps. Although analysis and rigorous definition of price jumps are beyond the scope of this thesis (for more information on this topic see e. g. Novotný, 2010a), we can utilize from intuitive interpretation of the difference between standard variance and bipower variance and define their ratio for the last T observations at time t as:

$$R_t^{S/BP} = \frac{\hat{\sigma_t^2}}{\hat{\sigma_{bi}^2}} = \frac{\frac{\sum_{i=t-T+1}^{t}(x_i - \hat{\mu_t})^2}{T-1}}{\frac{\sum_{i=t-T+2}^{t}|x_i - \hat{\mu_t}||x_{i-1} - \hat{\mu_t}|}{T-2}}, \tag{3.6}$$

where $\hat{\mu_t} = \frac{\sum_{i=\text{t-T+1}}^{t} x_i}{T}$. This ratio satisfies by definition $R_t^{S/BP} > 1$. The higher the ratio, the more extreme movements are contained in the past T observations and the bigger portion of the volatility is due to extreme price movements. In this thesis I let period with T observations move by one step at each time and analyze how the number of extreme price movement changes during the time span of our data sample.

3.1.6 Sample Correlation

Correlation is another basic, but very useful tool for describing stocks behaviour. It is the most familiar measure of relationship or relationship between two sets of realizations of two distinct random variables. It cannot exceed 1 in absolute value. Correlation coefficient equal to 1 means perfect positive linear relationship, correlation coefficient equal to -1 means perfect negative linear relationship, and correlation coefficient equal to 0 means no linear relationship. Note that correlation measures only linear relationship and it is not able to capture some other dependencies. Also correlation cannot be translated as dependency. In Finance, it is particularly used as a basic indicator when studying market or stock co movements. It also plays an important role in CAPM. Sample correlation coefficient is defined as:

$$r_{xy} = \frac{Cov\hat{(x,y)}}{\hat{\sigma_x}\hat{\sigma_y}} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}, \tag{3.7}$$

where $\bar{x}$ and $\bar{y}$ are sample means.

3.2 Statistical Tests

The initial results from descriptive statistics indicators may suggest certain data properties. However, to be able to verify the initial suppositions, we have to employ statistical tests. This section summarizes the tests used in this thesis and explains their relation to the topic. Some other tests directly related to time series methodology are described in the context of time series analysis.

3.2.1 Welch's t-test

In statistics, Welch's t test is an adaptation of Student's t-test used to test the null hypothesis of equality of means of two samples. It is used when the two samples have possibly unequal variances. The statistic t for two samples with N_1 and N_2 observations is defined by the following formula:

$$t = \frac{\hat{\mu_1} - \hat{\mu_2}}{\sqrt{\frac{\hat{\sigma_1^2}}{N_1} + \frac{\hat{\sigma_2^2}}{N_2}}}. \tag{3.8}$$

Under the null hypothesis this statistic has students-t distribution with ν degrees of freedom with ν defined as next smaller integer of the value obtained from the following equation:

$$\nu = \frac{(\frac{\hat{\sigma_1^2}}{N_1} + \frac{\hat{\sigma_2^2}}{N_2})^2}{\frac{\hat{\sigma_1^4}}{N_1^2(N_1-1)} + \frac{\hat{\sigma_2^4}}{N_2^2(N_2-1)}}. \tag{3.9}$$

3.2.2 Variance F-test

As already mentioned, variance can be used as a measure of volatility on markets. To be able to test for a statistical significant difference in variance across two different periods or two differerent stocks, standard F-test can be used.

Given two different data samples we can test the null hypothesis that they come from populations with the same variance against the alternative that the variances differ. The test statistic is defined as follows:

$$F = \frac{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n-1}}{\frac{\sum_{i=1}^{m}(x_i - \bar{x})^2}{m-1}}, \tag{3.10}$$

where $(y_1, \ldots, y_n)$ and $(x_1, \ldots, x_n)$ are the two samples we test. Under the null hypothesis the F statistic has $F_{n-1,m-1}$ distribution and we reject the null hypothesis if F is too small all to big. The concrete values of bounds of the critical region depend on the significance level α we choose.

3.2.3 Normality Tests

Before we can start with time-series tools application, we have to ensure that the data given contains any information. The extreme case, where no information is hidden in the data, is normality of the data. However, the leptokurtostic properties of financial data suggest that normality conditions should not be fulfilled. In theory, normality conditions can also be imposed on the residuals from the estimated models as described below. However, in order not to overestimate volatility and because the leptokurtostic properties of financial time-series may be present also in the residuals from well estimated model, we will not impose normality condition on residuals in this thesis and we will rather use weaker condition of no serial correlation between residuals. The test for detecting serial correlation is introduced below in the time-series section.

For normality testing, the following two tests are used in this thesis.

3.2.3.1 Jarque Bera Test

The normal distribution is symmetric and has a bell shape with peakiness and tail thickness leading to a kurtosis of 3. Thus we can test the normality by checking the skewness and kurtosis from a sample of data. Comprehensive test considering these two properties was first introduced by Jarque and Bera (1980). If skewness is not close to zero, and if kurtosis is not close to 3, then we reject the normality of the population. We have already developed the sample measures of skewness and kurtosis. The Jarque Bera test statistic allows a joint test of these two properties.

$$JB = \frac{N}{6}\left(\hat{S}^2 + \frac{(K-3)^2}{4}\right). \tag{3.11}$$

If the true distribution is symmetric and has kurtosis 3, which includes the normal distribution, the JB statistic has asymptotically a χ^2 distribution with two degrees of freedom.

3.2.3.2 Shapiro-Wilk Test

The Shapiro-Wilk test was first presented by Shapiro and Wilk (1965). It tests the null hypothesis that a sample $x_1, \ldots, x_n$ comes from a normally distributed population. The test statistic is:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_i\right)^2}{\sum_{i=1}^{n} (x_i - \hat{\mu})^2}, \tag{3.12}$$

where x_i is the ith order statistics, i. e. the ith smallest number in the sample and the constants a_i are given by:

$$(a_1, \ldots, a_n) = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{\frac{1}{2}}}, \tag{3.13}$$

where $m = (m_1, \ldots, m_n)^T$ and $m_1, \ldots, m_n$ are the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution, and V is the covariance matrix of those order statistics. It can also be shown that W is bounded by 0 and 1. Under the null hypothesis W statistic is equal to 1. One can reject the null hypothesis if W is too small.

3.3 Time Series Methodology

Analysis in this thesis builds primarily on the time series theory and this section will serve as a recapitulation of the time series methodology used. I draw the following time-series methodology overview mainly from Kočenda and Černý (2007), but I describe and illustrate the methodology in the context of stock prices analysis.

When we use the term *time series* we mean a set of data ordered by time $\{y_t\}_{t=1}^{T}$, where each element of the set is a realization of certain random variable at some point of a time t. To make it possible to employ time series tools for estimating the generating process of the time series (e. g. Box-Jenkins methodology), we need the series to be *covariance stationary.* Further, covariance stationarity will be denoted simply as *stationarity.*

The properties *mean, variance,* and *covariance* are used to give a basic description of time series on the one hand and to define the *stationarity* on the other hand .
Mean is defined as $\mu_t = E(y_t)$. Mean is defined for each element of the time series, so that with T observations there are T means defined
Variance is defined as $var(y_t) = E[(y_t - \mu_t)^2]$. Variance is, similarly to mean, defined for each element of the time series
Covariance is defined as $cov(y_t, y_{t-s}) = E[(y_t - \mu_t)(y_{t-s} - \mu_{t-s})]$. Covariance is defined for each time t and for each time difference s.

We say that time series is *covariance stationary* if and only if:

1. $\mu_t = \mu_{t-s} = \mu < \infty$ for all t, s.

2. $var(y_t) = var(y_{t-s}) = \sigma^2 < \infty$ for all t, s.

3. $cov(y_t, y_{t-s}) = cov(y_{t-j}, y_{t-j-s}) < \infty$ for all t, s and j.

Since it is obvious that time series of stock prices contain a trend and thus are not stationary, it is not suitable to analyze the initial series P_t of stock prices. Simple transformation of the initial time series comes to mind. We could express the pricing process of each stock as $P_t = P_{t-1} + y_t$, where P_t would be price of a stock at time t and y_t would be change of price between time $t-1$ and t, and try to analyze the time series of absolute changes in the price $\{y_t\}_{t=1}^{T}$. This transformation of the time series is called *differencing*, because $y_t = P_t - P_{t-1} = \Delta y_t$. By this transformation we remove any linear trend in the time series and thus we may achieve a stationarity. Since we could be more interested in percentage changes than in the absolute ones we could obtain them by formulating $y_{t(\%)} = \frac{P_t - P_{t-1}}{P_t} \cdot 100\%$.

Unfortunately, none of these two transformations of time series $\{P\}_{t=1}^{T}$can serve for our purposes. Series $\{y_t\}_{t=1}^{T}$ or $\left\{y_{t(\%)}\right\}_{t=1}^{T}$ can be simulated in such a way that causes the original time series $\{P_t\}_{t=1}^{T}$to have possibly negative values at some points of time t. For that reason, differences neither percentage changes are not suitable transformations for the purpose of modelling the right generating process behind the data observed.

The price generating process providing that each element P_t of the time series $\{P_t\}_{t=1}^T$ of some stock price remains positive can be much easier formulated as $P_t = P_{t-1}\exp(y_t)$. We can further express y_t as $y_t = \log(\frac{P_t}{P_{t-1}})$ and denote it as *logarithmic return*. Throughout the further text logarithmic returns will be used for the analysis and they will be denoted as y_t .

3.3.1 White Noise

White noise is a term frequently used in time series econometrics and I will use it further in this thesis. White noise is a time series that does not contain any information that. It will be further denoted as $\{\varepsilon_t\}_{t=1}^T$. For example a series of identically and independently distributed (*iid*) random variables with 0 mean is white noise. When we estimate a time series using a correct model as described further in section 3.3, than the residuals from this estimation must be white noise.

3.3.2 ARMA Models

Autoregressive moving average process of the orders p and q , $ARMA(p,q)$, is defined as

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}, \tag{3.14}$$

where $\{\varepsilon_t\}_{t=1}^T$ is *white noise*, $a_0 + \sum_{i=1}^p a_i y_{t-i}$ is *autoregressive* part of the process, and $\sum_{i=1}^q \beta_i \varepsilon_{t-i}$ is *moving average* part of the process.

For determining a suitable number of lags in AR and MA processes the *Box-Jenkins methodology* is used. The Box-Jenkins methodology, however, can be used only for stationary time series, so I will present here the conditions for time series generated by $ARMA$ process to be stationary and tools how to test the stationarity.

The sufficient condition for $ARMA(p,q)$ process to be stationary is:
a)$\sum_{i=1}^p |a_i| < 1$ & b) The sums $(\beta_s + \beta_1\beta_{s+1} + \beta_2\beta_{s+2} + \ldots)$ must be finite for all s. Obviously, when q is finite, the condition b) always holds.
The necessary condition for $ARMA(p,q)$ process to be stationary is:
a)$\sum_{i=1}^p a_i < 1$ & b) The sums $(\beta_s + \beta_1\beta_{s+1} + \beta_2\beta_{s+2} + \ldots)$ must be finite for all s. In reality, we do not know the true process and we cannot utilize these conditions. Thus, we need some tests to decide if the studied time series is stationary.

3.3.3 Stationarity Tests

3.3.3.1 Dickey-Fuller Tests

There are two similarly named tests widely used for testing the presence of unit root in time series assumed to be generated with $AR(p)$ processes. The first one was developed by Dickey and Fuller (1979) and can be applied only for data assumed to be generated with an $AR(1)$ process. The augmented version of this test, *augmented Dickey-Fuller test*, is its extension for a general $AR(p)$ process. The augmented Dickey-Fuller test is based on testing the null hypothesis $\sum_{i=1}^{p} a_i = 1$, i. e. the time series contains a unit root, against the alternative $\sum_{i=1}^{p} a_i < 1$, which is a necessary condition for the stationarity of the generated time series. According to Kočenda and Černý (2007) the shortcoming of this test is its low power. This means that the test has a high chance of an error of the second type, in other words, the probability of not rejecting the false H_0 is hugh. That is why it is of use to employ another test to determine the stationarity correctly.

3.3.3.2 KPSS Test

This test owes its name to Kwiatkowski et al. (1992). In contrast with the Dickey-Fuller the null hypothesis of th KPSS tests claims that the time series is stationary. Because of the different null hypotheses of both tests it is ideal to combine them when testing for stationarity. For detailed description of the test see again e.g. Kočenda and Černý (2007).

3.3.4 Estimation of ARMA Processes

In this section, I introduce tools that can help us determine the right ARMA(p,q) process lying behind our observed data and further I present how to apply them in the Box-Jenkins methodology. Note that the results of Box-Jenkins methodology and its parts hold only if the time series is stationary. Throughout the rest of this section we will assume this condition to hold.

3.3.4.1 Autocorrelation and Partial Autocorrelation Function - ACF and PACF

ACF for any general lag s is defined as

$$\rho_s = \frac{cov(y_t, y_{t-s})}{var(y_t)}. \tag{3.15}$$

$PACF$ for any general lag s is defined as:

$$\phi_{11} = \rho_1, \tag{3.16}$$

$$\phi_{22} = (\rho_2 - \rho_1^2)/(1 - \rho_1^2), \tag{3.17}$$

$$\phi_{ss} = \frac{\rho_s - \sum_{j=1}^{s-1} \phi_{s-1,j}\rho_{s-j}}{1 - \sum_{j=1}^{s-1} \phi_{s-1,j}\rho_j} \text{ for } s > 2, \tag{3.18}$$

where $\phi_{sj} = \phi_{s-1,j} - \phi_{ss}\phi_{s-1,s-j}$.

ACF and $PACF$ are useful tools for determining the right number of lags p and q in $ARMA$ processes. The above defined ACF and $PACF$ are the theoretical ones and are computed directly from the formula for known $ARMA(p, q)$ process. These theoretical functions have important properties. For given $ARMA(p, q)$ process ACF shows direct or oscillating decay beginning at lag q and PACF shows direct or oscillating decay beginning at lag p.

However, in reality the situation is quite the opposite. We do not know the true data generating process and we attempt to find it. For this purpose serve the sample ACF and $PACF$. Having observations $\{y_t\}_{t=1}^{T}$the sample ACF is defined as follows:

$$\hat{\rho_s} = \frac{\sum_{t=s+1}^{T} (y_t - \bar{y})(y_{t-s} - \bar{y})}{\sum_{t=1}^{T} (y_t - \bar{y})^2}, \tag{3.19}$$

where $\bar{y}$ is the sample mean. Regarding the sample $PACF$, we obtain it, if we replace the theoretical ρ_s in the formulas for $PACF$ by its estimation $\hat{\rho_s}$. After computing the sample ACF and $PACF$ we compare them with the theoretical ones and thus try to find the suitable number of lags p and q.

3.3.4.2 Ljung-Box Q-test

The Ljung-Box Q-test attributed to Ljung and Box (1978) is used to find autocorrelations in the first k lags, where k is arbitrary stated. The test is based on the Ljung-Box Q-statistic defined as:

$$Q = T(T + 2) \sum_{i=1}^{k} \frac{\hat{\rho_i}^2}{T - i}, \tag{3.20}$$

where $\hat{\rho_i}$ are elements of the sample ACF. Under the null hypothesis that all autocorrelations up to lag k are zero, the Q-statistic is χ^2 distributed with k degrees of freedom. This test is in *Box-Jenkins methodology* used for analyzing the residuals that should not contain autocorrelations, if p and q were estimated correctly. This test is also often used to indirectly test, whether residuals from the estimated model are *iid*.

Obviously, when there is autocorrelation between residuals, they cannot be *iid*.

3.3.4.3 Information Criteria

It can also happen that several different $ARMA(p, q)$ models seem to be appropriate for our data and the residuals from all the models are diagnosed to be white noise. In such case we should use information criteria to select the model that is the most parsimonious and satisfactorily captures the dynamics of the data. Over-parameterized models are not favourable and should be excluded. For this purpose the *Akaike information criterion (AIC)* and the *Schwarz Bayes information criterion (SBIC)* are most often used.

$$AIC = T \log SSR + 2n, \tag{3.21}$$

$$SBIC = T \log SSR + n \log T, \tag{3.22}$$

where SSR is the *sum of squared residuals,* n is the number of explanatory variables, and T is the number of usable observations. Note that by adding more explanatory variables we lose usable observations, so to compare two models with different number of explanatory variables we have to adjust the overall number of observations we use. To select the best model, the value of information criteria is to be minimized. $SBIC$ will compared to AIC usually select more parsimonious model.

3.3.4.4 Box-Jenkins Methodology

The Box-Jenkins methodology is a sequence of steps that are used to find and determine the right $ARMA(p, q)$ process, which is supposed to lie behind our observed data. The methodology employs above described tools and the steps are following:

1. Plot the sample ACF and $PACF$ up to lag $s = T/4$ in order to determine the appropriate number of lags p and q.

2. Estimate $ARMA(p, q)$ with the chosen lags p and q. To estimate AR model without any MA terms an OLS can be used. But to estimate $ARMA$ model we have to use *non-linear least squares* or the *maximum likelihood estimator* due to the MA term.

3. Plot the sample ACF and $PACF$ for the series of residuals up to lag $s = T/4$, compute the Q-statistics and perform the Q-test for residuals for lags up to $T/4$. If all the sample autocorrelations and partial autocorrelations are close to zero and if all the Q-tests do not reject the null hypothesis, then the estimated model might be the correct one.

4. If we got to this point with several possibly correct $ARMA(p, q)$ models, then we should choose the one that minimizes the information criteria.

3.3.5 GARCH Models

Generalized autoregressive conditional heteroskedasticity ($GARCH$) model was first introduced by Bollerslev (1986) and since then it became very popular and widely used tool, particularly in the field of finance. Financial time series are prone to exhibit periods of high and low volatility. This property of financial time series was empirically shown already by Mandelbrot (1963), who wrote: "Large price changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes of either sign". This property is known as volatility clustering. And exactly the volatility clustering can be modelled using *conditionally heteroskedastic disturbances.* As already stated, variance plays a key role for example in *Capital Asset Pricing model* (CAPM) and thus the ability of $GARCH$ models to model and predict the changing variance of financial time series is of great importance.

A general $ARMA(P, Q) - GARCH(p, q)$ process can be written as:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=1}^{q} b_i \varepsilon_{t-i} + \varepsilon_t, \tag{3.23}$$

$$\varepsilon_t = \nu_t \sqrt{\alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}}, \tag{3.24}$$

where $\nu_t \sim iid\, N(0,1),\ \alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_i \geq 0$, for all i: $\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1$, and

$$h_t = E_{t-1}(\varepsilon_t^2) = E_{t-1}\left[\nu_t^2(\alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i})\right] = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}. \tag{3.25}$$

The restrictions $\alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_i \geq 0$ ensure that the variance is always greater than zero and the restriction $\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1$ is necessary and sufficient condition for the stability of the conditional variance equation.

The above specified term α_0 is generally interpreted as a long term volatility to which the system converges. On the other hand, the $ARCH$ term $\alpha_i \varepsilon_{t-i}^2$ reflects the effect of lagged shocks or surprises on the volatility at time t. And the $GARCH$ term $\beta_i h_{t-i}$ measures the effect of past expected variance on the current volatility. High (but lower than 1) β_i indicates high persistence in volatility and thus high probability of volatility clustering. The term $\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i$ indicate the speed of convergence of the forecast of variance to a steady state. The closer to one it is, the slower the convergence.

3.3.5.1 GARCH Models Estimation

Similarly to the *Box-Jenkins methodology,* there is a standard sequence of steps to estimate the right $ARMA(P,Q) - GARCH(p,q)$ model.

1. We estimate the most appropriate $ARMA(P,Q)$ model using the *Box-Jenkins methodology.*

2. Then we test the squared residuals e_t^2 of the estimated model for the presence of conditional heteroskedasticity. To execute this test, we apply the *Ljung-Box Q-test.* Rejecting the null hypothesis means that the errors follow an ARCH or GARCH process.

3. Third, we identify the orders of GARCH(p, q) process. We can use visual inspection of the sample ACF and PACF of the squared residuals e_t^2. Indication of $ARMA(m,q)$ process means that the residuals follow $GARCH(p,q)$ process with $m = max(p,q)$

4. After detection of GARCH process and selection of the orders p and q, we estimate the whole ARMA(P, Q) - GARCH(p, q) model. This cannot be done by simple OLS due to nonlinearity. Instead, *maximum likelihood estimator* must be used. We must check the significance of all the estimated coefficients and assure all the restrictions on coefficients are fulfiled, because inclusion of a GARCH process can make some of the original ARMA(P, Q) model insignificant.

5. The last step is to diagnose the standardized residuals u_t, defined as $u_t = e_t/\sqrt{h_t}$. If the estimated model is the correct one, standardized residuals should be *white noise.* To test for *iid*, we can apply the *Ljung-Box Q-test.* After completing this step, if there are more candidate models, we can again select the best model using the *information criteria.*

3.3.5.2 Modelling the Day of the Week Effect Using GARCH Models

In this thesis, I use the standard GARCH model with Monday and Friday dummy variables added into the mean equation and conditional variance to test also for the day of the week effect. I use similarly specified model as Choudhry (2000), but in order not to overparameterize the model and not to lose degrees of freedom, especially during the financial crisis period, when only 135 observations are present, I add only Friday and Monday dummies, in which it is assumed some effect can be found. Equations including dummy variables that I work with can be written as:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=1}^{q} b_i \varepsilon_{t-i} + \gamma_m D_m + \gamma_f D_f + \varepsilon_t, \tag{3.26}$$

$$\varepsilon_t = \nu_t \sqrt{\alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} + \delta_m D_m + \delta_f D_f}. \tag{3.27}$$

where all the restrictions from equations (24) and (25) hold, and D_m and D_f are dummy variables having value of 1 if the day at time t is Monday or Friday respectively and value of zero otherwise.

3.3.6 VAR Models and Granger Causality

Vector Autoregression (VAR) model and its dominance in multivariate time series econometrics is mainly due to Sims (1980). VAR is often used, when we analyze two or more variables and we do not know ex-ante which of them is exogenous. We will use this approach only for the case of two variables and we will use the reduced form of VAR (1) defined as:

$$y_{1t} = a_1 + b_{11} y_{1,t-1} + b_{12} y_{2,t-1} + \varepsilon_{1t}, \tag{3.28}$$

$$y_{2t} = a_2 + b_{21} y_{2,t-1} + b_{22} y_{1,t-1} + \varepsilon_{2t}. \tag{3.29}$$

To estimate the coefficients, simple OLS can be used.

In our case, we are rather than in the exact values of the coefficients interested in causality or in information flow between the stocks. To investigate the information flows, the concept of *Granger causality* introduced by Granger (1969) will be used. The idea of the concept is very simple, we say that y_{2t} Granger causes y_{1t}, if lagged values of y_{2t} (in our case $y_{2,t-1}$) have any explanatory power on the current values of y_{1t}. To test the null hypothesis of y_{2t} not Granger causing y_{1t} (i.e. in our case b_{12}= 0), we can use simple *t-test* and its *p-value*, which is displayed always when we estimate the equation. When the coefficient is significant, we reject the null hypothesis of no *Granger Causality*. Note that if we used more lagged values of y_{2t}, instead of simple t-test we would have to use F-test to test the joint hypothesis of no explanatory power of none of them. Note also that similarly to correlation, the concept of *Granger causality* represents only statistical causality and does not tell us anything about the underlying structure of the investigated linkages.

4 Data

4.1 Prague Stock Exchange

The Prague Stock Exchange is the biggest organiser of the securities market in the Czech Republic. It is based on a membership principle and thus only licensed securities dealers are entitled to trade. By law it is a joint stock company. The Prague Stock Exchange is a member of the Federation of the European Securities Exchanges. U.S. Securities and Exchange Commission gave it the status of a "designated offshore securities market" and thus included it into the list of reliable offshore exchanges for U.S. investors (www.bcpp.cz)[1]. The majority shareholder of the Prague Stock Exchange is Wiener Börse AG. Compared to the world major stock exchanges, the Prague Stock Exchange is very small exchange and is strongly influenced by NYSE and the Frankfurt Stock Exchange as was shown e. g. by Hanousek et al. (2008).

4.1.1 History

The Prague Stock Exchange was established for the first time in 1871 and both securities and commodities were traded. In the interwar period the importance of the Prague Stock Exchange grew and it even suppressed the Vienna Stock Exchange. However, the arrival of World War II meant the end of trading at the Prague Stock Exchange for more than 60 years. The Prague Stock exchange was not re-established until November 24, 1992 and the first trades on the Prague Stock Exchange were made on April 6, 1993. In 1993 995 securities issues from the 1st wave of voucher privatisation were launched on the market. In 1994 the new official PX 50 index began to be calculated. In 1995 674 securities issues from the 2nd wave of voucher privatisation were launched on the market, but in 1997 1301 illiquid shares issues were withdrawn from the free market. On January 4, 1999 a new continuously calculated PX index was introduced. On October 1, 2002 trading of the first foreign share issue of ERSTE BANK was initiated and on June 28, 2004 the first IPO (Zentiva) was conducted on the Prague Stock Exchange. Finally, on December 8, 2008 Wiener Börse AG became the majority shareholder of the Prague Stock Exchange, holding a share

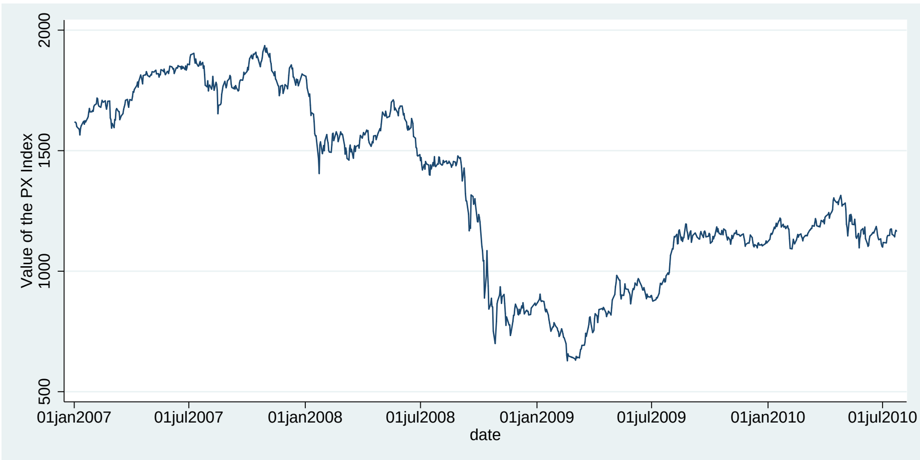
[1]The information was taken from the website on May 3, 2011

of 92.739% in the Exchange's registered capital (www.bcpp.cz)[2].

4.1.2 PX index

The PX index serves as an indicator of the Prague Stock Exchange's overall performance. Its value is calculated as a weighted average of prices of stocks on the Prague Stock Exchange based on their market capitalization. The PX index replaced PX-50 index in 1999. Current form of the index is recounted every 15 seconds from 9:11 a.m. to 4:08 p.m. Only stocks with market capitalization higher than 0.5 billion and with average daily trading volume during six months prior to the decisive date are included in the index. Composition of the PX Index is updated quarterly (en.wienerborse.at)[2]. The four studied companies ČEZ, Erste Bank Group, Komerční Banka, and Telefonica O2 Czech Republic were chosen, because they form the biggest portion of the PX Index and their stocks together form currently 77.2 % of the PX Index (www.bcpp.cz)[2].

Figure 4.1: Graph of the PX index from 1/2/2007 to 7/23/2010



4.2 ČEZ

ČEZ, a. s. is the corporate parent of ČEZ Group. According to its market capitalization, ČEZ is the biggest share emission on the Prague Stock Exchange. Its market capitalization is currently 178,786.2 million CZK. It forms 22.66 % of Index PX and it has 190,502,130 released securities. The core business of ČEZ a.s. is the sale and production of electricity. ČEZ Group is also player in wholesale and retail electricity market. The other businesses include power system services, production, distribution, and sale of heat energy, telecommunication, nuclear research, and mining of raw materials, among others (www.bcpp.cz)[2].

[2]The information was taken from the website on May 3, 2011

4.3 ERSTE Bank Group

Erste Group Bank AG is the first foreign share issue on the Prague Stock Exchange. Trading was initiated on October 1, 2002. It forms with its market capitalization of 135,417.4 million CZK 17.16 % of the PX Index, thus, after ČEZ and KB it forms the third biggest part of the index. Amount of its securities traded on the Prague Stock Exchange is 322,089,890 (www.bcpp.cz)[3].

Erste BankGroup AG was founded in 1819 as the first Austrian savings bank. In 1997, Erste Group announces a strategy to expand its retail business into Central and Eastern Europe. Accomplished this strategy, number of its customers grew through numerous acquisitons from 600,000 to 16.6 million, of which 15.5 million clients live in Central and Eastern Europe. Česká Spořitelna a.s. became a member of Erste Group in 2000. Strategic objectives of Erste Group AG are retail banking and its targeting on Central and Eastern Europe (en.wienerborse.at)[3]. For the sake of brevity, throughout the text Erste Bank Group stocks will be denoted simply as ERSTE.

4.4 Komerční Banka

Komerční banka is a part of the Société Générale Group. It is the second biggest emission on the Prague Stock Exchange measured by its market capitalization, which is currently 156,122.1 million CZK. Amount of Komerční Banka securities released on the Prague Stock Exchange is 36,307,464. Its weight in the PX Index is 19.78 %. Komerční banka group provides complex services for clients in retail, investment, and corporate banking. In retail banking, Komercni banka offers its clients deposit and credit products and payment services. Corporate and investing banking includes services for corporations, medium-sized companies, and municipalities. Concrete services are trade finance, loans, leasing, factoring, asset management, financial advisory, and other services (www.bcpp.cz)[3]. Throughout the text Komerční banka stocks will be denoted as KB.

4.5 Telefonica O2 Czech Republic

Telefonica O2 Czech Republic, a.s. was formed on July 1, 2006 by the merger of ČESKÝ TELECOM, a.s. and Eurotel Praha, spol. s.r.o. The merger of both companies integrated fixed telecommunication services formerly provided by ČESKÝ TELECOM, a.s. and mobile services formerly provided by Eurotel Praha, spol. s.r.o. Telefonica O2 Czech Republic is currently the fourth biggest emission on the Prague Stock Exchange

[3] The information was taken from the website on May 3, 2011

with market capitalization equal to 133,667.3 million CZK and with 322,089,890 securities issued. Today it forms 16.94 % of the PX Index (www.bcpp.cz)[4]

Telefonica O2 Czech Republic provides comprehensive offer of voice, data, and internet services including offers to use its network infrastructure for other providers of these services. The sell of services aims on two basic customer segments: the consumer segment and the business segment, including corporate clients and state administration. Telefonica O2 Czech Republic belongs to the group of companies operating under O2 (www.bcpp.cz)[4]. Telefonica O2 Czech Republic stocks will be futher denoted as TELEFONICA or only TELEF.

4.6 Determination of the Financial Crisis

Although nervousness on the markets grew already from 2007 and deciding when the financial crisis started is not clear, the generally accepted beginning of the financial crisis based on the main event - the fall of Lehman Brothers - is September of 2009. See e. g. Novotný (2010a). More specifically, I define September 15, 2009 as the beginning of the financial crisis, when the Bankruptcy of Lehman Brothers was announced. I define the financial crisis in the same way Novotný (2010a) does as a structural break in the behaviour of financial markets. I assume the crisis on the Prague Stock Exchange lasted until the end of the first quarter of 2009. Reasons for this selection are following. First, the reasons for recovery from financial crises usually are rather psychological than fundamental. Mood on the markets plays an important role and it is not usually possible to determine the particular event that would trigger the recovery. At least I was not able assign to the beginning of the recovery to any particular news. Second, since many economic indicators are published quarterly, it is reasonable to use the end of quarter, when there does not exist any clearer date. Third, on the Prague Stock Exchange the bottom was reached in the middle of the first quarter of 2009. And finally, it was shown on the long-run data from the USA that there exists Granger-Causality between the stock market and the macroeconomic development up to lag of three quarters (see Comincioli, 1995). And since the macroeconomic data from the Czech Republic indicates the recovery started on the break of 2009 and 2010, it is in accordance with this study to assume the end of the crisis on the Czech stock market on the end of the first and the second quarter of 2009 - three quarters earlier.

[4]The information was taken from the website on May 3, 2011

4.7 Data Sample and its Decomposition

Our data sample comprises daily market data from the four main stocks on the Prague Stock Exchange from the beginning of 2007 to July 23, 2010. The studied stocks are ČEZ, ERSTE, KB, and TELFONICA. The data was taken from public database at www.akcie.cz[5]. The data sample consists of 894 observations of each stock except for KB, where one observation from May 13, 2008 is missing. For the purpose of analysis of the financial crisis effect, the sample is divided. The pre-crisis period sample includes 430 observations (except for KB, where it is 429 observations) from the beginning of 2007 to Friday September 12, 2008. The crisis sample comprises 135 observations from Monday September 15, 2008 to March 31, 2009. And finally, the post-crisis sample includes 329 observations from April 1, 2009 to July 23, 2010. For analysis in this thesis, in accordance with most of the financial econometric and time series studies, the logarithmic daily returns are used. The logarithmic return is defined as: $y_t = \log(\frac{P_{s,t}}{P_{s,t-1}})$, where $P_{s,t}$ and $P_{s,t-1}$ are close prices of stock s at day t and $t-1$ respectively. Note that by using logarithmic returns we lose the first observation in our sample and thus we utilize only 893 observations.

[5]The data were downloaded from the website on July 25, 2010

5 Empirical Results

5.1 Descriptive Statistics

Descriptive statistics provides the first valuable information about behaviour of the stocks before, during, and after the financial crisis. Table 5.1 summarizes the basic statistical indicators divided for each stock in the above defined periods

Table 5.1: Descriptive Statistics

	crisis	N	μ	σ^2	S	K	MIN	MAX	JB	Q-stat.
ČEZ	before	429	0.0253	0.0003	-0.086	6.523	-0.077	0.108	33.42	39.52
	during	135	-0.0028	0.0022	-0.062	6.281	-0.165	0.198	13.29	32.33
	after	329	0.0005	0.0002	-0.102	4.471	-0.059	O.053	12.10	45.81
ERSTE	before	429	-0.0013	0.0005	0.352	5.113	-0.087	0.103	27.35	38.98
	during	135	-0.0076	0.0045	-0.140	4.629	-0.251	0.178	7.53	27.68
	after	329	0.0024	0.0010	0.214	5.810	-0.136	0.136	23.8	44.47
KB	before	427	0.0004	0.0004	0.223	4.889	-0.070	0.088	21.23	50.26
	durinf	135	-0.0041	0.0025	-0.491	4.552	-0.189	0.142	10.96	40.57
	after	329	0.0018	0.0006	0.145	6.033	-0.124	0.104	24.27	31.64
TELEF	before	427	-0.0001	0.0002	-0.164	12.225	-0.082	0.097	65.61	38.98
	during	135	-0.0007	0.0011	0.105	8.701	-0.142	0.146	19.97	32.24
	after	329	0.0002	0.0002	-0.625	7.835	-0.082	0.042	47.90	52.42

Notes: N - number of observations, μ - sample mean, σ^2 - sample variance, S - sample skewness, K - sample kurtosis, JB - Jarque-Bera statistic, MIN - minimal return in given period, MAX - maximal return in given period, Q stat. - Ljung-Box Q-statistic of the returns for 40 lags.

5.1.1 Trend

All the stocks had negative mean returns during the crisis and positive after the crisis. However, before the crisis ČEZ and KB grew, while ERSTE and TELEFONICA already declined. We can also see that during the crisis ERSTE and KB fell more than ČEZ and TELEFONICA. On the other hand in the period after the crisis banking sector stocks grew remarkably faster. Furthermore, when one looks on Figure 5.1, another difference between banking sector stocks and other sector stocks is noticeable. While ČEZ and

Figure 5.1: Close price graphs

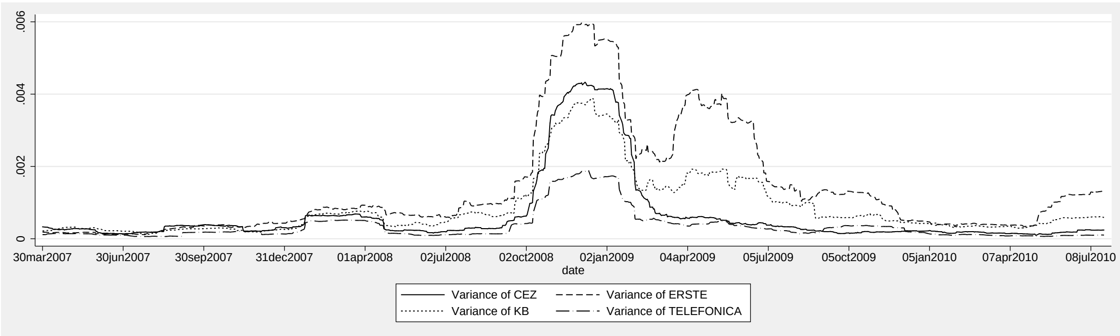
TELEFONICA reached the bottom already in the end of October 2008, ERSTE and KB did not reach their minimum until the end of February 2009. These findings are in accordance with generally agreed notion that the crisis affected mainly banking sector and lasted longer in the banking sector. On the other hand, recovery was faster in the banking sector as it became obvious that ERSTE and KB would not have problems with their capital structure after all.

5.1.2 Volatility

Volatility on markets is most often measured by variance of returns. Table 5.1 shows very significant growth of variance during the crisis. For more formal analysis of variance I applied the variance F-test. Results of this test confirm for all the studied stocks the intuitive notion that variance significantly rose during the crisis and then declined back after the crisis. However, for all the stocks except for TELEFONICA this test rejects also the hypothesis that variance of the returns was the same before and after the crisis. More specifically, we can conclude that for KB and ERSTE variance after the crisis remained higher than before the crisis, however for ČEZ variance was lower after the crisis than before the crisis and for TELEFONICA it remained the same. Graphics can again give us more information about development of volatility.

Figure 5.2 contains quarterly moving variances of returns of all the measured stocks. On figure 5.2 we can see the upsurge in volatility starting in September 2008. We can

Figure 5.2: Quarterly moving variance of returns



Notes: The moving variances were computed from day-by-day moving samples of 63 subsequent observations. The 63-day period was chosen, because it approximately represents the number of trading days in one quarter. The dates on the time axis represent date of the most recent observation in the sample, in other words the end of the particular moving quarter.

also see that in the last quarter of 2008 investors were nervous mostly about ERSTE, followed by ČEZ, KB, and TELEFONICA. We can again recognize that while in the case of ČEZ and TELEFONICA the moving variance significantly declines as values form break of 2008 and 2009 are added to it, for KB, and particularly for ERSTE, volatility remains high also for the whole first quarter of 2009 and after a slight decline on break of 2008 and 2009 there is second, but lower peak of the volatility in the first quarter of 2009. We can see the same patterns, when we take a look on Figure A.1 in the Appendix. These findings are in accordance with the conclusion from section 5.1.1 suggesting that the crisis lasted longer in the banking sector.

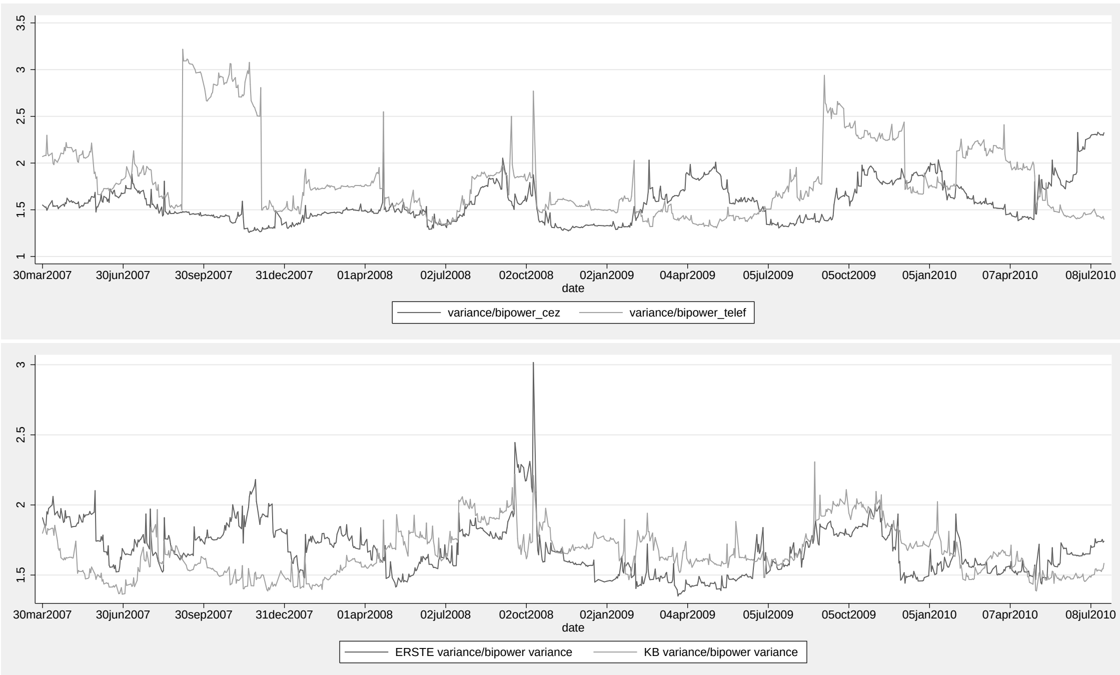
5.1.3 Extreme Price Movements (Price Jumps)

Novotný (2010b) studied price jumps on high frequency data and did not find any evidence of growth neither in the total number of price jumps nor in their absolute values during the last quarter of 2008. Thus, the hypothesis I test in this section is following: Despite overall growth in volatility, the financial crisis did not cause growth neither in total number of price jumps nor in their absolute values also when daily data are tested.

As stated in methodology, kurtosis and ratio of variance and bipower variance can be used to measure to what extent was volatility caused rather by extreme price movements than the moderate ones. Skewness, on the other hand, gives us hint, whether negative or positive price movements prevailed. Kurtosis higher than 3 is typical for financial markets and our data are not an exception. We can see that all the studied stocks have Kurtosis higher than 4 and thus we can conclude that they were more jumpy than normal Gaussian distribution is. Over all, the highest Kurtosis can be seen in TELEFONICA returns. However, Table 5.1 does not suggest that the financial crisis caused increase in kurtosis and thus in price jumps. More to the contrary, kurtosis of the stocks during the crisis was lower than before the crisis and in the case of ERSTE and KB even the lowest from all the studied periods.

Bipower variance analysis gives us similar results. Moving ratios of variance and bipower variance computed according to Formula 3.6 can be seen on Figure 5.3. The

Figure 5.3: Quarterly moving ratio of variance and bipower variance



Notes: The quarterly moving ratio of variance and bipower variance was computed from day-by-day moving samples of 63 subsequent observations. The 63-day period was chosen, because it approximately represents the number of trading days in one quarter. The dates on time axis represent date of the most recent observation in the sample, in other words the end of the particular moving quarter.

figure shows for all the four stocks growth of the ratio as observations from break of September and October 2008 were added. However, the ratio quickly declines and no other significant rise can be found until the end of the crisis. Moreover, when mean of the ratio before, during, and after the crisis is computed and we use the *Welch's t-test* to test the change in mean of the ratio, we see that in the case of ČEZ and TELEFONICA the mean of the ratio was the lowest during the crisis. ERSTE had the mean of the ratio the highest before the crisis and difference between periods during and after the crisis is statistically insignificant. Only for KB we can confirm statistically significant rise in the ratio during the crisis.

Regarding skewness of the returns, the results differ across the stocks. ČEZ has longer negative tails in all the three periods. TELEFONICA is negatively skewed before and after the crisis, but positively during the crisis. And finally banking sector stocks have positive skewness before and after the crisis, but negative during the crisis.

Results from this section can be interpreted as follows. Although the financial crisis had very strong impact on volatility of all studied stocks, it was not translated in rise of extreme price movements and thus we cannot reject our initial hypothesis. This conclusion is confirmed by both indicators, kurtosis and bipower variance for ČEZ, ERSTE, and TELEFONICA. In the case of KB kurtosis and bipower variance disagree.

Skewness indicates that the crisis caused rise in negative extreme price movements compared to the positive ones for banking sector stocks, but this effect disappeared after the crisis. However, this does not hold for ČEZ and TELEFONICA. This result supports findings from previous sections. Behaviour of the banking sector stocks was more influenced by the crisis than behaviour of the telecommunication and energetic sector stocks.

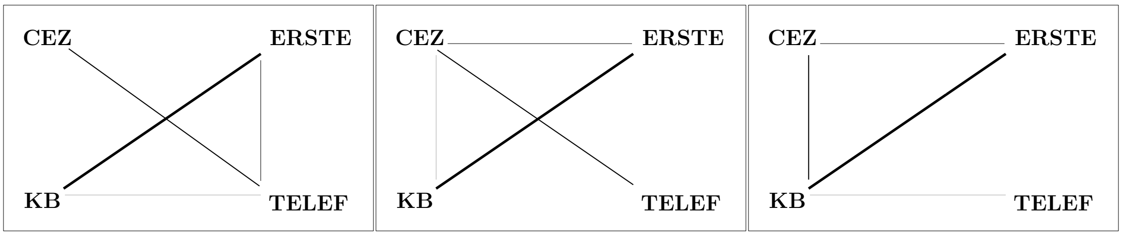
5.1.4 Normality

To test normality of the data I used the *Jarque-Bera test* and *Shapiro-Wilk test*. As can be seen in Table 5.1, *Jarque-Bera test* strongly rejects normality of all the stocks in all the three periods. The *Shapiro-Wilk test* confirms these results. This is not surprising conclusion given the sample kurtosis estimates.

5.1.5 Correlation Analysis

Starting with this analysis, I have three initial hypotheses. First, I expect higher correlation between stocks from the same sector, which is KB and ERSTE, because they will likely react similarly on given information. Second, I expect lower correlation between ČEZ and other stocks since ČEZ is generally perceived as defensive stock that usually behaves unlike the rest of the market. And finally, I expect correlation to be higher between all the stocks during the crisis than during other periods, because there was a panic on the market and information usually had the same negative impact on all the stocks. The correlation matrices of the ČEZ, ERSTE, KB, and TELEFONICA returns before, during, and after the crisis are presented in Table A.1 in the Appendix. The graphical reults of the correlation analysis are presented below. All the computed correlations are positive and Figure 5.4 present the four strongest correlations before, during, and after the crisis respectively. The thicker the line connecting the particular stocks is, the stronger the correlation. Given the correlation coefficients, we can see that in all the three periods the highest correlation is between KB and ERSTE and also that all the correlations grew during the crisis. Both results were expected. On the other hand, we cannot confirm the hypothesis of ČEZ being a defensive stock since all the correlation are positive and those with ČEZ are not the lowest. The results also imply that as the correlation during the crisis grew, diversification of stocks portfolio played a less role. If we assume these results would be similar generaly during any crisis, we can conclude that even with “well” diversified portfolio of stocks, investors cannot be protected during economic crises.

Figure 5.4: Correlations before, during, and after the crisis



Notes: All the correlations are positive. The thickness of the line connecting the particular stocks indicates the rank of the value of the correlation coefficient among all the possible combinations. The two lowest correlations were ommited.

5.2 Time Series Results

5.2.1 Stationarity

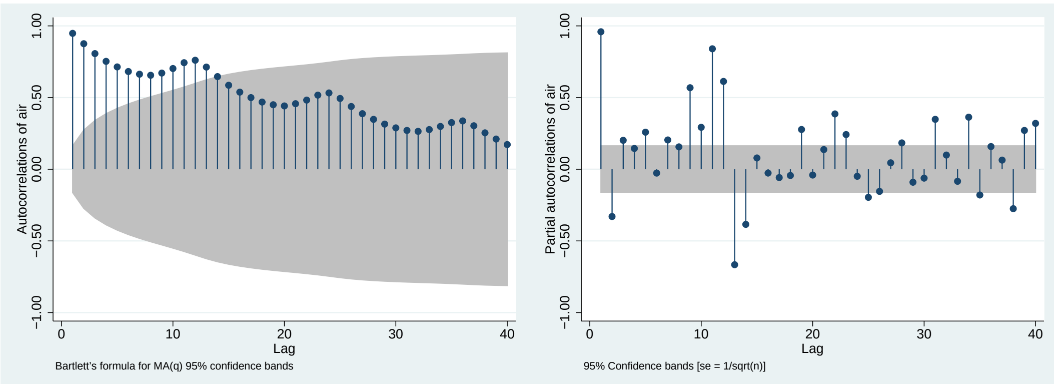
Before we can start with estimation of ARMA - GACH models, we have to make sure that we can use the tools of the *Box-Jenkins methodology* and its extension for estimation of GARCH models. Namely, we have to test whether the time series we work with is stationary. For testing the stationarity I employed the *Dickey - Fuller test* and the *KPSS test*. Both tests are described in the methodology. *Dickey-Fuller test* strongly rejects the presence of unit root in returns of all the studied stocks in all the three periods. Accordingly, *KPSS test* cannot reject stationarity for any stock in any period. I am aware of the fact that both tests have relatively low power and cannot capture all kinds of non-stationarity. That is why I use both together and I assume their joint result to be strong enough to allow me to apply the *Box-Jenkins methodology*.

5.2.2 ARMA Models

The goal of this part was to estimate the most appropriate ARMA(p, q) model for each stock (ČEZ, ERSTE, KB and TELEFONICA) in each period (before, during, and after the crisis). However, the efficient market hypothesis, claims that on information efficient market it holds that $E_{t-1}(P_t \mid \Theta_{t-1}) = P_{t-1}$, where P_t is price of a stock at time t and Θ_t is a set of all available information at time t. This implies that on information efficient market the conditional expected return of a stock at each time t is equal to zero. It is clear that the conditional expectations of returns generated by ARMA process are not zero and thus finding a significant ARMA process in the returns would reject the EMH. Moreover, Hanousek and Filer (1997) found the Prague Stock Exchange information efficient, when testing the past macroeconomic announcements effect on current returns. It is clear that if the past information does not influence current returns, then the past returns should not have explanatory power for current returns either. Thus, my initial hypothesis here is that no ARMA process should be found. Question is whether during the financial crisis the same efficiency holds or whether overall panic on the market can cause violation of the EMH.

I used the standard Box-Jenkins methodology steps for each stock before, during, and after the crisis. However, already at the first step when plotting the sample ACF and PACF of each time series, it became apparent ARMA would probably not be the right generating process of the returns of any stock in any period. For ARMA generated time series the sample ACF and PACF show either direct or oscillating decaying trend after a certain lag, which is not the case of any time series from our sample. Moreover, the sample ACF and PACF indicated for all the time series from our sample that the data generating process would probably not include any AR or MA process. None of the first five lags was significant on the sample ACF and PACF in any time series from our sample. For illustration I introduce the following figures. Figure 5.5 presents the sample ACF and PACF of ARMA simulated time series and Figure 5.6 presents the sample ACF and PACF for ERSTE returns in the period before the crisis. This example was chosen as illustrative. Other time series of our sample have very similar properties. All the sample ACF and PACF are available upon request and are not included in the thesis for the sake of brevity. Given all the sample ACF and PACF

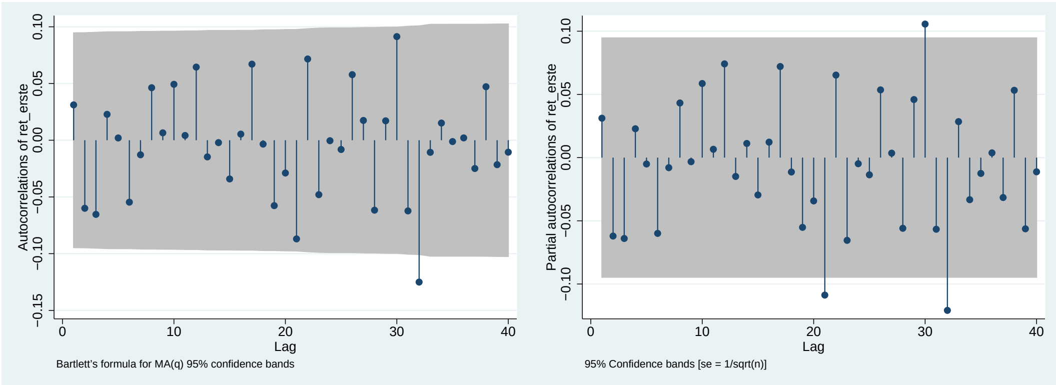
Figure 5.5: Sample ACF and PACF for ARMA simulated time series



Notes: The grey area indicates the 95% confidence interval for the null hypothesis that the (partial) autocorrelation for the particular lag is equal to zero.

I used the Ljung-Box Q-test to test the hypothesis that no autocorrelation is present in any of the time series. Values of the Q-statistic are presented in Table 5.1. The test confirmed the results from the sample ACF and PACF and did not reject the

Figure 5.6: Sample ACF and PACF for ERSTE returns in the period before the financial crisis



Notes: The grey area indicates the 95% confidence interval for the null hypothesis that the (partial) autocorrelation for the particular lag is equal to zero.

null hypothesis of no autocorrelation in any the time series. These results are not surprising and are in accordance with my initial hypothesis based on the EMH and Hanousek and Filer (1997). Hence, from the ARMA models point of view we cannot reject the hypothesis that the Prague Stock Exchange was information efficient in any of the studied periods and thus we can conclude that the crisis did not influence the information efficiency of the Prague Stock Exchange.

5.2.3 GARCH Models

Due to the fact that no ARMA term was found in the returns, the mean equation for GARCH will be specified without the AR and MA terms. As stated in methodology, I include in both equations also dummy variables for Monday and Friday to test effect of these days on both, returns and volatility. Similarly to ARMA estimation, I estimate the GARCH model for ČEZ, ERSTE, KB, and TELEFONICA returns in all the three periods. Using the standard methodology for GARCH estimation and diagnosing the standardized residuals, I found GARCH(1,1) to be sufficient for all the stocks and periods. No serial correlation was found in the standardized residuals $\frac{\varepsilon_t}{\sqrt{h_t}}$ or in their squared values $\frac{\varepsilon_t^2}{h_t}$. P-values of the Ljung-Box Q-test for $\frac{\varepsilon_t}{\sqrt{h_t}}$ and $\frac{\varepsilon_t^2}{h_t}$ are presented in Table A.2 in the Appendix. Absence of serial correlation in the standardized residuals implies the lack of need to employ higher order ARCH process.

For the sake of further comparison of the coefficients I present all the coefficient in Table 5.2 even if GARCH or ARCH term was not significant and thus is probably not present in the real data generating process in some of the cases. In order to make it easier for the reader to recall the meaning of the coefficients presented in Table 5.2 I once more (now without the ARMA terms) present the mean and conditional variance equations here. The restrictions on the coefficients are equal to the ones from equations

(3.23) and (3.24).

$$y_t = a_0 + \gamma_m D_m + \gamma_f D_f, \tag{5.1}$$

$$\varepsilon_t = \nu_t \sqrt{\alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} + \delta_m D_m + \delta_f D_f}. \tag{5.2}$$

Table 5.2: GARCH model and the day of the week effect coefficients

		a_0	γ_m	γ_f	α_0	α_1	β_1	δ_m	δ_f
ČEZ	BEF.	0.0008	-0.0009	0.0006	$9.34 \cdot 10^{-5a}$	0.2200^a	0.6448^a	-0.0002^a	$-6.08 \cdot 10^{-5}$
		(0.0010)	(0.0017)	(0.0021)	$(3.07 \cdot 10^{-5})$	(0.0778)	(0.1144)	$(5.25 \cdot 10^{-5})$	$(7.55 \cdot 10^{-5})$
	DUR.	-0.0011	0.0065	$3.82 \cdot 10^{-5}$	$-8.71 \cdot 10^{-5}$	0.2223^b	0.7608^a	0.0004	0.0003
		(0.0032)	(0.0073)	(0.0070)	(0.0001)	(0.1160)	(0.1039)	(0.0005)	(0.0005)
	AFT.	-0.0001	0.0039^b	0.0006	$1.16 \cdot 10^{-5}$	–	0.9709^a	$5.00 \cdot 10^{-5}$	$-1.38 \cdot 10^{-5}$
		(0.0009)	(0.0018)	(0.0017)	$(1.88 \cdot 10^{-5})$		(0.0129)	$(5.00 \cdot 10^{-5})$	$(5.72 \cdot 10^{-5})$
ERSTE	BEF.	-0.0006	-0.0003	-0.0006	$3.14 \cdot 10^{-5}$	0.0228^b	0.9816^a	$-5.69 \cdot 10^{-5}$	$-9.94 \cdot 10^{-5c}$
		(0.0011)	(0.0021)	(0.0022)	$(2.16 \cdot 10^{-5})$	(0.0122)	(0.0136)	$(7.79 \cdot 10^{-5})$	$(5.87 \cdot 10^{-5})$
	DUR.	-0.0070	0.0031	-0.0020	0.0013	0.4813^c	0.1448	0.0007	0.0033^b
		(0.0052)	(0.0111)	(0.0144)	(0.0010)	(0.2678)	(0.2976)	(0.0019)	(0.0017)
	AFT.	$3.70 \cdot 10^{-5}$	0.0073^b	-0.0003	0.0001^b	0.104^a	0.086^a	-0.0003^c	-0.0002
		(0.0018)	(0.0031)	(0.0036)	$(5.46 \cdot 10^{-5})$	(0.022)	(0.0297)	(0.0002)	(0.0002)
KB	BEF.	0.0012	0.0002	0.0010	$4.83 \cdot 10^{-5c}$	0.1088^a	0.8529^a	$8.77 \cdot 10^{-5}$	-0.0002^b
		(0.0011)	(0.0021)	(0.0017)	$(2.85 \cdot 10^{-5})$	(0.0329)	(0.0400)	$(6.84 \cdot 10^{-5})$	$(7.06 \cdot 10^{-5})$
	DUR.	-0.0052	0.0056	0.0004	0.0009	0.2093	0.2983	0.0009	0.0014
		(0.0039)	(0.0092)	(0.0093)	(0.0012)	(0.2387)	(0.6054)	(0.0019)	(0.0011)
	AFT.	-0.0002	0.0054^c	0.0006	$4.73 \cdot 10^{-5}$	0.1067^c	0.7342^a	$-2.36 \cdot 10^{-5}$	0.0002
		(0.0014)	(0.0032)	(0.0033)	$(7.51 \cdot 10^{-5})$	(0.0563)	(0.1169)	(0.0002)	(0.0001)
TELEF	BEF.	0.0001	0.0018	$8.34 \cdot 10^{-5}$	$5.81 \cdot 10^{-5}$	0.1386^b	0.6682^a	$-5.86 \cdot 10^{-5b}$	$-6.62 \cdot 10^{-5c}$
		(0.0007)	(0.0012)	(0.0013)	$(1.73 \cdot 10^{-5})$	(0.0655)	(0.1453)	$(2.97 \cdot 10^{-5})$	$(3.73 \cdot 10^{-5})$
	DUR.	$-7.43 \cdot 10^{-5}$	0.0022	-0.0025	$9.63 \cdot 10^{-5}$	0.3149^b	0.4238^b	$-6.18 \cdot 10^{-5}$	0.0007^b
		(0.0022)	(0.0060)	(0.0072)	(0.0001)	(0.1421)	(0.1665)	(0.0004)	(0.0003)
	AFT	$-1.22 \cdot 10^{-5}$	0.0025^b	-0.0015	$1.49 \cdot 10^{-5}$	–	0.9905^a	$-7.38 \cdot 10^{-5a}$	$8.53 \cdot 10^{-5}$
		(0.0007)	(0.0012)	(0.0015)	$(1.02 \cdot 10^{-5})$		(0.0028)	$(2.34 \cdot 10^{-5})$	$(3.50 \cdot 10^{-5})$

Notes: ^{a},^{b},^{c} represent significance level of 1, 5, and 10% respectively. Standard error in parenthesis, Q-statistics of the standardized residuals and their squares are presented in Table A.2 in the Appendix.

5.2.3.1 GARCH and ARCH Effect

In the case of ČEZ and TELEFONICA after the crisis, the ARCH term did not fulfil the restriction $\alpha_1 > 0$ and thus was removed from the estimated equation. In all other cases except for KB during the crisis, the ARCH term was significant and less than 1 and thus the impact of previous day shock on current volatility was present, but not destabilizing.

Regarding the GARCH term, it was significant in all the cases except for ERSTE and KB during the crisis. This can indicate again on different impact of the crisis on the banking sector stocks, where previous day volatility prediction was not significant for explaining current volatility. Moreover, in the case of KB during the crisis, the GARCH process was probably not present in the data generating process at all since neither the ARCH term was significant. For both, ERSTE and KB, this insignificancy of the GARCH term is caused by rapid growth in standard error of the coefficients. Possible explanation for this is that there was a complete structural break of the data generating process in case of the banking sector stocks during the crisis that caused that the volatility was not predictable by the GARCH model during the crisis. However, this break was not present in the case of ČEZ and TELEFONICA.

Another structural break of the data generating process can be found in the case of ČEZ and TELEFONICA after the crisis, where ARCH term did not meet the positivity condition and had to be removed from the equations. Nevertheless, GARCH term alone was sufficient to specify the conditional volatility equation and the standardized residuals fulfilled the *iid* condition. Furthermore, in the case of ČEZ and ERSTE after the crisis the GARCH term had the strongest effect on volatility from all the analyzed time series. This is not surprising since the ARCH term was removed from the equation and all the explanatory power remained for the GARCH term. Value of the GARCH term for ČEZ and ERSTE after the crisis close to 1 means slow convergence of volatility to a steady state and high persistence in volatility.

In the case of ERSTE before the crisis, the sum of ARCH and GARCH term was higher than one. This means the volatility was explosive. Slow convergence of volatility to a steady state (sum of GARCH and ARCH term higher than 0.9) was also found in the case of ČEZ during the crisis and in the case KB before the crisis. Except for KB and ERSTE during the crisis, and for the cases, where the ARCH term is not defined, the ARCH term is always considerably lower than the GARCH term. This result implies that the previous day volatility prediction had higher effect on the current observed volatility than the previous day shocks and news. This also implies that all the time series except for KB and ERSTE during the crisis were prone to volatility clustering.

None of the constant terms in the mean equation was significant and thus we do not assume any long term trend in the prices of stocks in any of the periods. The constant term in the conditional variance equation was found to be significant only in case of ČEZ before the crisis, ERSTE after the crisis, and KB before the crisis. These results do not indicate any pattern in the volatility.

5.2.3.2 Day of the Week Effect

Regarding the returns, there is a strong pattern in the behaviour all the stocks. In the period before and during the crisis nor Monday, neither Friday effect was significant, but in the period after the crisis Monday effect was positive and significant. in the case ČEZ, ERSTE, and TELEFONICA there was a positive Monday effect on returns at 5% significance level, for KB the effect was significant at 10% level. Thus, the studied stocks on the Prague Stock Exchange behave after the crisis in line with the calendar time hypothesis (French (1980)) that claims that the stocks should rise higher on Mondays than on the other week days as the time between the close of trading day on Friday and close of trading day on Monday is three times longer than it is on other weekdays. As this hypothesis is only valid during the recovery from the crisis, when there prevailed optimism on markets, we can explain this result in the way that after weekends the traders are more eager to invest their money as their optimism has longer time to escalate. However, from our data it seems that the calendar time hypothesis does not hold during the bad times on the market.

Regarding the volatility, Table 5.2 shows a significant negative effect of Monday on volatility in the case of ČEZ and TELEFONICA before the crisis and in the case of KB and TELEFONICA after the crisis. No positive Monday effect on volatility was found. Thus, our findings dispute the theory of availability of information. See e. g. French and Roll (1986). Friday had, according to Table 5.2, positive significant effect on volatility of ERSTE and TELEFONICA during the crisis and negative significant effect on volatility of ERSTE, KB, and TELEFONICA before the crisis. These results do not indicate any clear effect of the financial crisis on the day of the week effect on volatility.

5.3 Multivariate Time Series Results

The objective of this section is to examine the direction of information flows between the stocks and the changes in the structure of information flows before, during, and after the crisis. For this purpose I use the concept of Granger causality applied on VAR models with two variables and one lag. Thus, I test the explanatory power of yesterday's return of stock A on today's return of stock B.

One would expect the information to flow from ČEZ to other stocks as ČEZ has the biggest market capitalization from all the stocks on the Prague Stocks Exchange and thus can push other stocks. This can be explained as follows. When price of ČEZ rises, the PX Index is significantly influenced. The growth of the PX Index can attract more investors who might buy also other stocks than ČEZ, and vice versa. I expect ČEZ to have higher effect on TELEFONICA than on the banking sector stocks.

I also assume this effect not to be valid during the crisis, when on the other hand panic came from the banking sector and I expect banks to drag the whole market down. Hence, the information during the crisis is expected to flow from ERSTE and KB to ČEZ and TELEFONICA.

One would also expect certain information flow between the two banking sector stocks, ERSTE and KB. However, it is difficult to predict the direction of this flow. To formulate the hypothesis about the direction of the information flow between ERSTE and KB I used values of their capital adequacy according to BASEL II standards and I expect the one with lower capital adequacy to be more dynamic, to react faster on information issuance, and to influence the one with higher capital adequacy. The idea behind this hypothesis is straightforward. The bank with lower capital adequacy can make higher profits based on positive news and on the other hand is more exposed to impacts of negative news. Thus, investors react and trade stocks of this bank in a larger scale. The bank with higher capital adequacy does not react immediately on the information, but is rather affected with some time lag by overall mood in the whole banking sector. The levels of capital adequacy of ERSTE and KB for the years 2007, 2008, 2009, and 2010 are listed in the following table:

Table 5.3: Capital Adequacy of ERSTE and KB according to BASEL II

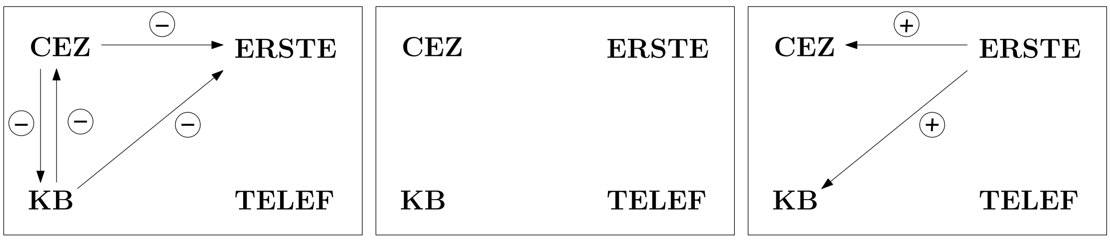
	2007	2008	2009	2010
ERSTE	7.0 %	7.2 %	10.8 %	11.8 %
KB	10.1 %	12.1%	14.1%	15.3 %

Notes: The values of capital adequacy are downloaded from the official websites of the banks www.erstegroup.com and www.kb.cz on May 5, 2011.

Given these levels of capital adequacy, I assume ERSTE to be more dynamic, to react on news in a larger scale and to drag KB. Thus, I expect the information to flow from ERSTE to KB in all the three periods.

The results of Granger Causality tests are listed in Table A.3 in the Appendix. However, the graphical results may be more intuitive. The following figure presents all the information flows, where the evidence of Granger Causality at 10% significance level was found.

Figure 5.7: Granger causality before, during, and after the crisis



Notes: The arrows represent the direction of the information flow, signs show whether the effect of the information was positive or negative.

From these results, we can recognize that there was an information flow from ČEZ to ERSTE and KB before the crisis. But the effect of the information is unlike I expected negative. The same negative information flow lead from KB to ČEZ and to ERSTE before the crisis. This can be explained as follows. Investors that have their stakes in more companies recognize growth in price of ČEZ or KB one day and next day they withdraw their money from other companies and buy yesterday growing ČEZ or KB and thus cause negative change in price of the other stocks.

Further, we see that the financial crisis interrupted all the information linkages and the initial hypothesis about information flow during the crisis does not hold here. After the financial crisis completely new relationships emerged. The information flow went from ERSTE to KB as anticipated. My initial hypothesis can provide sufficient explanation for this result, because ERSTE's capital adequacy ratio was smaller than the KB's one. Furthermore, we can see also the information flow leading from ERSTE to ČEZ. I explain this result in the following way. Since ERSTE was from all the four stocks most affected by the financial crisis, its recovery after the crisis could have higher effect on the overall mood on the market an thus it could have had an effect also on ČEZ, not only on KB.

6 Conclusion

This work studies behaviour of the four main stocks traded on the Prague Stock Exchange before, during, and after the financial crisis of 2008 and 2009. The financial crisis is defined as a structural break in the behaviour of the financial markets. As the beginning of the crisis I use September 15, 2008, when Lehman Brothers announced bankruptcy, and as the end of the crisis I use March 31, 2009. The financial crisis had substantial effect on prices of all the stocks traded on the Prague Stock Exchange. The index developed to measure overall performance of the Prague Stock Exchange, the PX Index, can best express the magnitude of the effect of the financial crisis on the stocks traded there. The PX slumped from 1936.1 points on October 29, 2007 to 628.5 points on February 18, 2009, which is a decline of more than 67 %. The main goal of this work was to answer the question whether the financial crisis influenced behaviour of the stocks traded on the Prague Stock Exchange, whether there was a structural change in price generating processes of the stocks, or whether the crash we witnessed was merely a change in trend and other properties of the data remained the same. The four studied companies are: ČEZ, Erste Group Bank, Komerční Banka, and Telefonica O2 Czech Republic. The analysis is conducted using daily data from the January 2, 2007 to July 23, 2010.

The results of the analysis show that the crisis had different and stronger impact on the banking sector than on ČEZ and TELEFONICA. This is not surprising given the fact that the crisis was triggered by the problems in the US banking sector. The crisis was mainly characterized by rapid growth in volatility on the market. The volatility was the highest during the last quarter of 2008. Then, in the case of ČEZ and TELEFONICA, it quickly declined in the beginning of 2009. However, in the case of ERSTE and KB it remained high during the whole first quarter of 2009. Despite the massive growth in volatility, the crisis did not trigger growth in the number of extreme price movements. This result is in accordance with Novotný (2010b), who reached the same conclusion employing high frequency data for his analysis. However, in the case of the banking sector stocks, the crisis caused relative growth in the number of negative extreme price movements to the positive ones. This effect disappeared after the crisis. The crisis also caused significant growth in all the correlations between the stocks. And thus even well diversified portfolio could not protect investor from losses.

I used the Box-Jenkins methodology to find whether any autoregressive or moving average process was present in the returns. I was not able to detect any ARMA process in the data. From this point of view I was not able to reject the efficient market hypothesis on the Prague Stock Exchange. I was also not able to find any evidence that the Prague Stock Exchange would have been less information efficient during the financial crisis than during the periods before or after the financial crisis. This result is in line with both studies - Diviš and Teplý (2005) and Hanousek and Filer (1997), which used older data and different approaches, but came to the same conclusion.

Using generalized autoregressive conditional heteroskedaticity model I found that GARCH (1,1) model sufficiently describes the data generating process of all the returns all the stocks, except for banking sector stocks during the crisis and for ČEZ and TELEFONICA after the crisis. The data generating process of ČEZ and TELEFONICA after the crisis can be described by a GARCH (0,1) process. For ERSTE during the crisis the GARCH(1,0) model was sufficient and for KB during the crisis no GARCH process was found. These results again illustrate the different behaviour of banking sector stocks during the crisis, which was the only period when it was not possible to predict their volatility. In all other cases volatility prediction was possible, and the predicted volatility had significantly stronger effect on the actual volatility than the previous day news or shocks. This result implies that all the stocks in all the studied periods except for KB and ERSTE during the crisis were prone to volatility clustering.

Regarding the effect of the day of the week, I found a very strong pattern in the period of recovery from the crisis, when Monday had significant positive effect on returns of all the studied stocks. I explain this result by prevailing optimism on the market. This result supports the calendar time hypothesis introduced by French (1980). However, similar effect was not found in any other period. On the other hand, I found no signifficant Monday effect on volatility in any of the periods. This result is in contradiction with the theory of availability of information and with findings of Choudhry (2000), who studied Asian stocks. The Granger causality results indicate that the financial crisis interrupted all the information flows between the stocks that existed before the crisis. After the crisis completely new relationships emerged and ERSTE as the worst affected stock by the crisis became the leader of the market in the period of the recovery. As its price was growing it pushed up also ČEZ and KB.

Understanding the behaviour of stocks during economic crises can help avert huge losses as those that we have seen in the recent past. The results indicate the need for more research of the stocks behaviour during economic crises in different time periods and different countries to decide whether the impact of the recent financial crisis on the Czech stock market was unique, or whether some patterns are generally common to economic crises and thus deeper theory can be built based on the empirical research.

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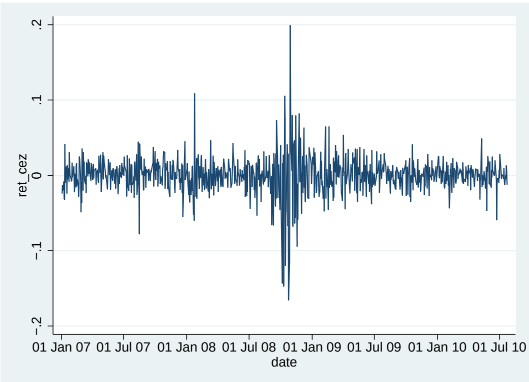
A Appendix

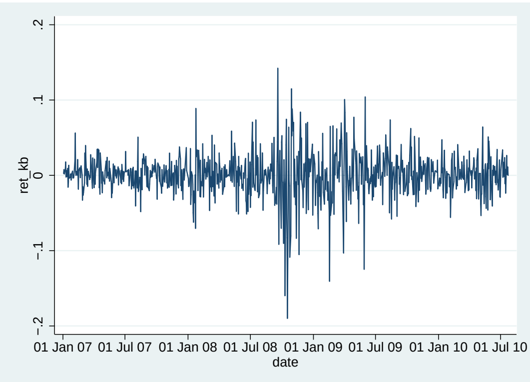
A.1 Figures

Figure A.1: Graphs of returns

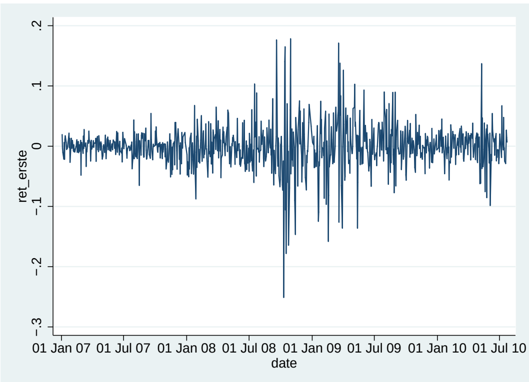
(a) ČEZ



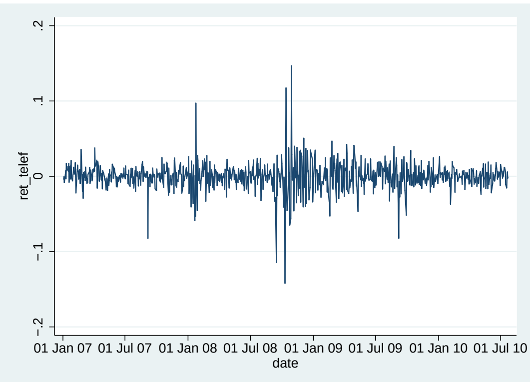
(b) ERSTE BANK



(c) KOMERČNÍ BANKA



(d) TELEFONICA O2



A.2 Tables

Table A.1: Correlation matrices

(a) Before the crisis

	ČEZ	ERSTE	KB	TELEF
ČEZ	1			
ERSTE	0.2894	1		
KB	0.3560	0.4951	1	
TELEF	0.4516	0.3885	0.3865	1

(b) During the crisis

	ČEZ	ERSTE	KB	TELEF
ČEZ	1			
ERSTE	0.6429	1		
KB	0.6722	0.6931	1	
TELEF	0.6800	0.4871	0.5293	1

(c) After the crisis

	ČEZ	ERSTE	KB	TELEF
ČEZ	1			
ERSTE	0.5155	1		
KB	0.5476	0.5849	1	
TELEF	0.3757	0.3164	0.4163	1

Notes: The correlation matrices are symmetric. That is why the cells upon the diagonal are blank.

Table A.2: Results of the Ljung-Box Q-test of the residuals from estimated GARCH model

	Q-test of standardized residuals				Q-test of squared standardized residuals			
	ČEZ	ERSTE	KB	TELEF	ČEZ	ERSTE	KB	TELEF
BEF.	0.345	0.495	0.260	0.923	0.959	0.815	0.932	1.000
DUR.	0.995	0.828	0.715	0.800	0.988	0.970	0.961	0.729
AFT.	0.259	0.668	0.926	0.47	0.834	0.902	0.283	0.96

Notes: The table presents p-values of the Ljung-Box Q-test for the null hypothesis that in the first 40 lags no autocorrelation is present.

Table A.3: Granger Causality - complete results

(a) ČEZ as dependent variable

	ČEZ	ERSTE	KB	TELEF
BEF.	-	-0.0583	-0.1257	0.0567
		(0.154)	(0.009)	(0.443)
DUR.	-	0.0065	0.0461	0.0495
		(0.934)	(0.671)	(0.768)
AFT.	-	0.0652	0.0167	-0.0482
		(0.031)	(0.668)	(0.459)

(b) ERSTE as a dependent variable

	ČEZ	ERSTE	KB	TELEF
BEF.	-0.1107	-	-0.2115	-0.0925
	(0.074)		(0.001)	(0.292)
DUR.	0.1407	-	0.1280	0.2240
	(0.372)		(0.417)	(0.261)
AFT.	-0.1954	-	0.0485	-0.0585
	(0.147)		(0.567)	(0.665)

(c) KB as a dependent variable

	ČEZ	ERSTE	KB	TELEF
BEF.	-0.1050	0.0030	-	0.0645
	(0.059)	(0.952)		(0.399)
DUR.	0.0428	0.0879	-	0.0565
	(0.725)	0.317)		(0.714)
AFT.	-0.0624	0.1010	-	-0.0826
	(0.574)	(0.061)		(0.463)

(d) TELEFONICA as a dependent variable

	ČEZ	ERSTE	KB	TELEF
BEF.	-0.0501	0.0217	-0.0244	-
	(0.212)	(0.491)	(0.501)	
DUR.	-0.1257	-0.0097	-0.0287	-
	(0.116)	(0.840)	(0.665)	
AFT.	0.0263	-0.0136	-0.0180	-
	(0.655)	(0.583)	(0.765)	

Notes: The tables contain estimated values of the coefficient b_{12} from equattion (3.28) and its significance in parentheses. All the combinations of the stocks being both, response and explanatory variables are presented. E. g. Table (a) contains coefficients b_{12} and their significance from 12 different equations, where response variable is always ČEZ and explanatory variables are ERSTE, KB, and TELEFONICA pectively for all 3 periods before, during, and after the crisis.

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