

# Impact of the global financial crisis on stock market volatility: Evidence from Central European stock market

Petr Sed'a<sup>1</sup>

**Abstract.** Volatility measuring is an important task in financial markets, and it has held the attention of academics and practitioners over the last two decades. This paper deals with the impact of the global financial crisis on Central European stock market volatility represented by the Czech and Polish stock markets. Therefore, fluctuations and volatility in these markets before, during and after the crisis were analyzed. This paper tries to identify the length of the global financial crisis, estimate the potential risk in the stock market during financial turmoil and analyze the characteristics of the risk. For a comprehensive analysis, several sophisticated models of quantitative financial analysis were adopted. We especially worked with Jump-Diffusion GARCH model considering heteroskedasticity which allow greater accuracy than simple GARCH type volatility models.

**Keywords:** Global Financial Crisis, Central European Stock Market, Heteroskedasticity, Annualized Return, Volatility, Jump-Diffusion GARCH model.

**JEL Classification:** C 32, C 52, C 58, E 32

## 1 Introduction

Financial markets, due to their key role in the economic positions of countries, have been studied from different points of view. In this regard, one key aspect of the stock markets that has attracted much attention in financial literature is the analysis of the stock returns and its volatility. Ups and downs in prices are quite natural in stock market. Volatility is a symptom of a highly liquid stock market. Investors interpret a raise in stock market volatility as an increase in the risk of investment and consequently they shift their funds to less risky assets.

Volatility modeling and especially volatility dynamics are central to many issues in financial markets including derivative prices, leverage ratios, credit spreads, and portfolio decisions. In times of low market volatility it is relatively straightforward to measure volatility and understand volatility dynamics. At other times, financial markets are affected by severe disruptions which may be largely isolated events like the market crash of 1987, may be a series of events such as the Russian default and Long Term Capital Management Fund Crisis of 1998 or the global financial crisis in 2008-2009. During such periods, apparent spikes in volatility and large movements in asset prices complicate estimation of volatility and volatility dynamics. These crises dramatically influenced the market volatility and diversification opportunities for foreign investors.

The global financial crisis that still affects countless countries originated in the USA as a financial meltdown that materialized as the housing market bubble burst. Various financial institutions were hit by the crisis, which by then was no longer merely a problem of the USA. Among the top five global investment banks of the US, Merrill Lynch was sold to Bank of America, and Lehman Brothers filed for bankruptcy. The crisis began to affect the real economy. Czech Republic, an export-oriented economy with high liquidity and substantial reliance on foreign capital, was no exception. The fund withdrawal led by foreign investors in the Czech securities market exacerbated volatility in the securities market. Polish stock market can be described in a similar way.

Recently, several authors have investigated the volatility of Central and Eastern European stock markets; see Baruník et al. [2], Popelka [12] and Sed'a [12] found that significant autocorrelation, high volatility persistence, significant asymmetry, lack of relationship between the stock market volatility and the expected return and non-normality of the return distribution are basic characteristics of the stock market volatility in transition countries. Nevertheless, we can identify dealing with the influence of market crises over Central European stock market volatility in the literature quite rarely.

This paper deals with the impact of the subprime mortgage meltdown born in USA on the volatility of Czech and Polish security market as it spiraled into a global financial crisis. Policy makers and economic players are interested in whether the state and length of the global financial crisis could be measured accurately in stochastic terms. Moreover, the structural characteristics of risk to stock prices fluctuation are analyzed. For a comprehensive analysis, some sophisticated models of quantitative financial analysis were adopted. To identify the impact

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<sup>1</sup> VŠB-Technical University of Ostrava/Faculty of Economics, Department of Mathematical Methods in Economics, Sokolská třída 33, 701 21 Ostrava 1, petr.seda@vsb.cz.

of the global financial crisis on Central European stock markets, rapid fluctuations and volatility in these markets during the crisis were analysed.

The studies conducted in this paper can be summarized as follows: First, descriptive statistics of Czech and Polish stock markets and time series features will be computed. Second, annualized conditional volatility of mentioned returns will be estimated by the standard AR (1) - GARCH (1, 1) - GED model. Last, time-varying volatility of stock price indexes was analyzed in the pre-crisis, crisis and post-crisis periods using Jump-Diffusion GARCH model to identify jump risk in volatility.

Innumerable expert studies have been provided to identify the volatility of stock prices, and the structural characteristics of risk. The adoption of stochastic volatility to let volatility change stochastically and the inclusion of jump risk to reflect the risk of rapid fluctuation in the market in a model can be seen in Merton [11], Hull and White [10], Heston [9], and Chang [6]. Papers that have dealt with the characteristics of basic time series such as heteroscedasticity of daily financial time series and jump are the ARCH model by Engle [8], Ball and Torous [1] and the Jump-Diffusion model of Chang and Kim [4]. The aim of this paper is to identify and estimate the potential jump risk in the stock market volatility comparing financial crisis period with the time of normalcy and using data from Czech and Polish stock markets.

## 2 Jump-diffusion GARCH model

The seminal papers of Engle [8] and Bollerslev [3] GARCH or generalized autoregressive conditional heteroskedasticity models have become a standard tool in modeling the conditional variances of the returns from financial time series data. The popularity of these models lies in their compatibility with major stylized facts for asset returns, the existence of efficient statistical methods for estimating model parameters, and the availability of useful volatility forecasts.

The stock index returns may have jump risk at the same time which is caused mainly by heteroskedasticity and rapid market fluctuation. In this chapter we will take a look on how to consider heteroskedasticity and jump risk term in the model in order to identify the process of forming appropriate return and risk premium in such case. Normally, the jump risk model taking the form of discrete data and considering heteroskedasticity in GARCH (1, 1) may be according to Chang et al. [7] defined as follows:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + k\sigma_t + \varepsilon_t + \sum_{j=0}^{q_t} v_{jt}, \quad (1)$$

$$\varepsilon_t = \xi_t \sigma_t, \quad (2)$$

$$\xi_t \sim N(0,1), \quad (3)$$

$$q_t \sim e^{-\lambda} \frac{\lambda^j}{j!}, \quad (4)$$

$$v_t \sim N(0, v^2), \quad (5)$$

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2, \quad (6)$$

where  $r_t$  is the return of stock index estimated here, which shows the volume of information inflow in the market. It is determined by the independently and log-normally distributed jump  $v_{jt}$  and the Poisson distributed random variable  $q_t$ . The mean of  $q_t$  is recognized as  $\lambda$  the intensity of jump. The Poisson event causes a heteroskedastic jump with each jump size of  $\exp(v_j)$ ,  $j = 1, 2, \dots, q_t$  in stock prices return. Therefore,  $v_{jt}$  is assumed as a random variable with a mean of 0, variance of  $v^2$ , as an *i.i.d.* normal distribution. Parameter  $k$  represents time-varying risk premium.

The GARCH heteroskedasticity is defined by equation (6).  $\beta_0, \beta_1, \beta_2$  are constants satisfying the conditions of  $\beta_0 > 0, \beta_1 + \beta_2 < 1$ . If  $\sum_{j=0}^{q_t} v_{jt}$ , the Poisson jump risk term, is insignificant, the model will be equal to the

GARCH model of Bollerslev [3]. Equations (1) to (6) that include unobserved state variable can be gained by using the Kalman filter model after converting into state-space models. Detailed estimation can be according Kim and Chang [5] referred as follows:

$$r_t = r(g_t) + G(g_t)\alpha_t + \varepsilon_t, \tag{7}$$

$$\alpha_t = F_t\alpha_{t-1} + R\eta_t. \tag{8}$$

In the diffusion-jump model that considers GARCH volatility, the return volatility of index is  $h_t$  which can be calculated as the weighted average of the diffusion and jump parts:

$$h_t = \sum_{j=0}^J (\sigma_t^2 + q_t \cdot v^2) Pr[q_t = j | \psi_t]. \tag{9}$$

The GARCH conditional volatility  $\sigma_{t+k,t}^2$  of point  $t+k$  considered at point  $t$  of the diffusion part in equation (9) can be denoted for repetitive calculation:

$$\sigma_{t+k,t}^2 = \beta_0 + \beta_1 \left( \sum_{j=0}^J (\sigma_{t+k-1,t}^2 + q_t \cdot v^2) \varpi_j^{k-1} Pr[q_t = j | \psi_t] \right) + \sigma_{t+k-1,t}^2. \tag{10}$$

### 3 Empirical application

In this chapter a data description and estimation results will be presented. The studies will be summarized as described in the Introduction section.

#### 3.1 Data

Empirical analysis is performed on daily data of PX and WIG20 indexes in period from 2004 till 2012, it includes total of 2225 observations. This period was chosen purposely, to investigate changes of the Czech and Polish equity markets volatility during time with a special emphasis on the resolution of behavior in the time before, during and after the global financial crisis in 2008-2009. We have more than 8 years long time series of the closing rates of PX and WIG20 indexes. Those time series were obtained from www.pse.cz and www.wse.com.pl.

The returns  $r_t$  at time  $t$  were defined as the logarithm of PX and WIG20 indices  $p$ , that is,  $r_t = \log(p_t - p_{t-1})$ . Visual inspection of the plot of daily values and returns series of both indices proved very useful, for details see Figure 1 and Figure 2. As it has been already empirically confirmed, crises are not devoted to developed markets only. Emerging markets includes Czech Republic and Poland isn't excluded from this rule and may face such instability sometime. Following the spread of bad news about U.S financial crisis the Central European equity markets, Czech and Polish ones included, we have seen a more than 60 percent decline of both selected indexes in 2008, see Figure 1. This happened primarily due to the withdrawal by foreign portfolio investors between September and December 2008 and its psychological impact on national investors.

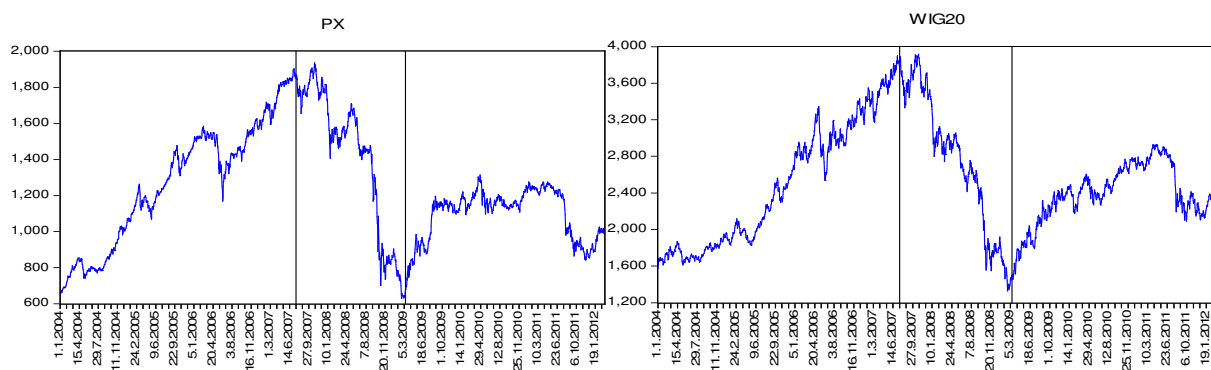


Figure 1 PX and WIG20 values (2004-2012)

It can be seen that from Figure 2 that return fluctuates around mean value that is close to zero. Volatility is low for certain time periods and high for other periods. The movements are in the positive and negative territory and larger fluctuations tend to cluster together separated by periods of relative calm. From 2004 to early 2007, the financial markets had been very calm in general. The volatility of PX and WIG20 indexes was highest in 2008. Thus Figure 2 show volatility clustering where large returns tend to be followed by small returns leading to continuous periods of volatility and stability. The market volatility, as measured by the PX and WIG20 volatility have been below long-term averages. However, the global financial crisis of 2008 changed this: most asset

classes experienced significant pullbacks, the correlation between asset classes increased significantly and the markets have become extremely volatile.

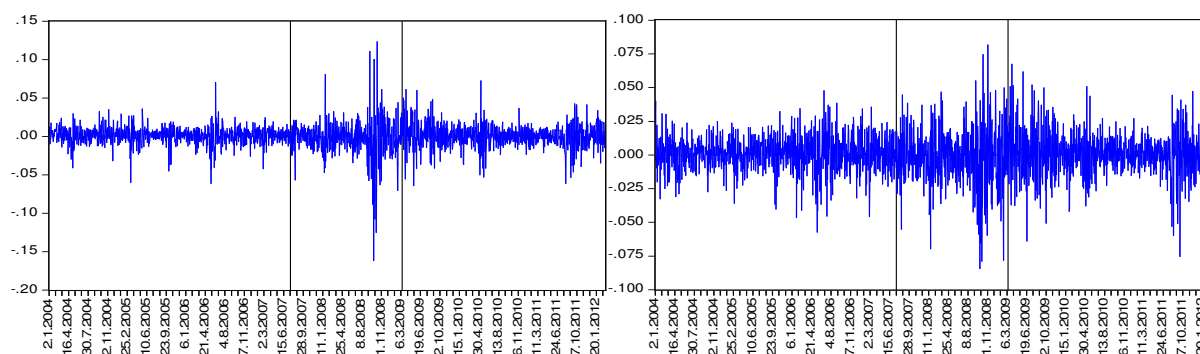


Figure 2 PX and WIG20 returns (2004-2012)

Volatility clustering implies a strong autocorrelation in squared return. Since the volatility was highest in 2008 when the values of both indexes reached the minimum values in investigated period we divided the basic period 2004-2012 into three testing periods. First, pre-crisis period, was defined from January 2004 to the end of June 2007, the second, crisis period, started at the beginning of July 2007 and finished by March 2009 and the last, post-crisis period, was defined from April 2009 to the middle of March 2012. Our goal is to investigate and compare the behaviour of volatility in all the periods.

### 3.2 Estimation results

Table 1 shows several descriptive statistics and time series features of the PX and WIG20 indexes returns of the normalcy, the financial crisis and post crisis periods.

	PX			WIG20		
	Pre-crisis	Crisis	Post-crisis	Pre-crisis	Crisis	Post-crisis
<b>Mean</b>	0,0011	-0,0025	0,0006	0,0009	-0,0022	0,0006
<b>Maximum</b>	0,0705	0,1236	0,0725	0,0475	0,0815	0,0672
<b>Minimum</b>	-0,0613	-0,1619	-0,0644	-0,0573	-0,0844	-0,0754
<b>St. Deviation</b>	0,0107	0,0251	0,0152	0,0127	0,0218	0,0158
<b>Skewness</b>	-0,5572	-0,3939	-0,0439	-0,3235	-0,2187	-0,0234
<b>Kurtosis</b>	8,6038	12,1049	5,7086	4,5116	4,7066	5,4142
<b>Jarque-Bera test</b>	1254,09	1492,78	239,91	103,86	55,48	190,48
<b>Probability</b>	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
<b>Observation</b>	922	429	784	922	429	784

Table 2 Descriptive statistics of PX and WIG20 indexes

According to Table 1, the daily PX and WIG20 returns show mostly leptokurtic distribution with a heavy tail, instead of normal distribution. The sample statistics of analysed time series data indicate that it is desirable to consider heteroscedasticity and jump risk when estimating the volatility of the Czech and Polish markets. As expected, the volatility of stock price is much larger during the financial crisis than in time of normalcy.

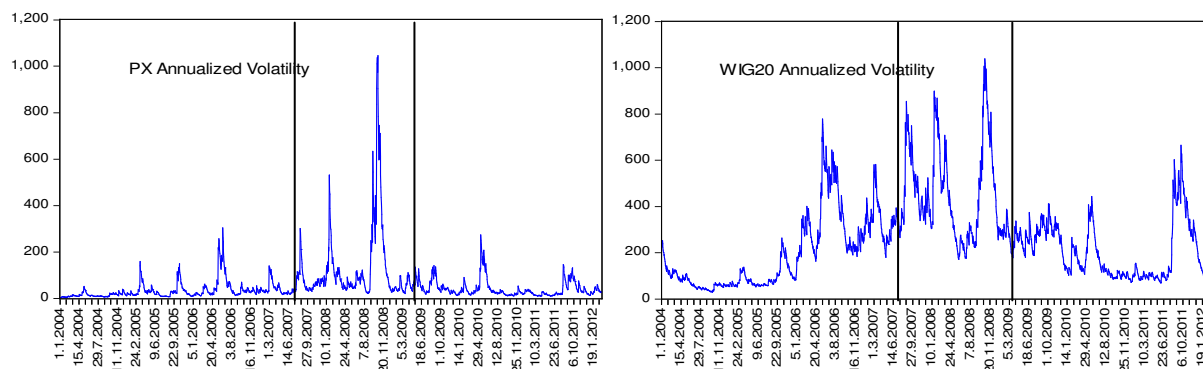


Figure 3 Conditional volatility of PX and WIG20 indexes (2004-2012)

Figure 3 shows annualized conditional volatility of PX and WIG20 indexes return estimated by the standard AR (1) -GARCH (1, 1) - GED model. Annualized conditional volatility can be calculated from the daily volatility multiplied by square root of trading days. According Figure 3, conditional volatility of WIG20 index is larger than PX index volatility in general. In particular, in the case of WIG20 return volatility, risk has doubled compared to PX return volatility on average. Conditional volatility of both indexes grows significantly during the global financial turmoil.

Parameter	Pre-crisis		Crisis		Post-crisis	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
$\alpha_0$	0,0016	5,49	-0,0005	-0,63	0,002	0,59
$\alpha_1$	0,0264	1,72	0,0140	0,26	0,0006	0,16
$\beta_0$	0,0001	2,64	0,0001	1,72	0,0003	2,11
$\beta_1$	0,1076	4,79	0,1856	3,38	0,1156	4,75
$\beta_2$	0,8341	21,74	0,8007	15,79	0,8697	36,13
$\lambda$	0,0005	1,15	0,2165	2,49	0,0451	1,87
$\nu$	0,0023	0,02	0,0466	1,24	0,0071	0,05
$k$	-0,0579	-1,41	0,0142	1,16	-0,0396	-1,29

**Table 2** Jump-Diffusion GARCH (1, 1) model with heteroskedasticity for PX index

Parameter	Pre-crisis		Crisis		Post-crisis	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
$\alpha_0$	0,0011	2,90	-0,0016	-1,79	0,0005	1,16
$\alpha_1$	0,0090	0,27	-0,0271	-0,51	-0,0205	-0,57
$\beta_0$	0,0000	1,68	0,0000	1,49	0,0000	1,55
$\beta_1$	0,0441	2,91	0,0913	2,94	0,0676	4,02
$\beta_2$	0,9371	43,95	0,8894	24,07	0,9236	51,30
$\lambda$	0,1314	1,56	0,2729	3,12	0,0981	2,06
$\nu$	0,0001	0,01	0,0006	0,47	0,0004	0,26
$k$	-0,0705	-1,13	0,0638	1,86	-0,0679	-1,11

**Table 3** Jump-Diffusion GARCH (1, 1) model with heteroskedasticity for WIG20 index

Table 2 and Table 3 show the estimations for PX and WIG20 indexes by period. There are the results of the Jump-Diffusion GARCH model with heteroscedasticity proposed by equations (1) to (6) and estimated using Maximum Likelihood method. According to the Jump-Diffusion GARCH model considering heteroscedasticity, no statistically significant jump behaviour was observed in the Czech and Polish stock market in the pre-crisis period, between January 2004 and July, 2007. On the other hand, during the global financial crisis, from July 2007 to March 2009, the jump risk with relatively high statistical significance occurred in both stock markets around every five days (Czech market) or three-four days (Polish market). Therefore, during the financial turmoil, jump has occurred more frequently in the Polish stock market than in the Czech market. In the post-crisis period the behaviour of the both investigated markets again tended to normalcy. In other words, there was observed statistically significant jumps in volatility only in Polish market around every 10 days.

According to the Jump-Diffusion GARCH model with heteroscedasticity projected during the study,  $\beta_1 + \beta_2$  that denote the persistence of variance process in the Czech stock market shows 0.9101 in pre-crisis period and surprisingly 0.9863 during the crisis. In addition, the ARCH factor was larger during the financial crisis than in time of normalcy. Meanwhile, the persistence parameter in the Polish market was 0.9812 during pre-crisis period but 0.9807 during the crisis. Also in the case of the Polish market, the ARCH factor was larger in crisis than in normalcy. Variance process was less persistent during the crisis than in normalcy. In addition, it is noteworthy that the time-varying risk premium in both markets was negative in normalcy but positive in the time of crisis.

It seems that conditional volatility estimated in the jump model shows that the size of volatility in stock price during the financial crisis differs from that projected through the AR (1) - GARCH (1, 1) - GED model. This may prove the necessity of using a more precise model in measuring risk during a crisis.

## 4 Summary and conclusions

The stock market in Central Europe shows relatively high dependence on foreign capital and various Polish and especially Czech conglomerates and small- and medium sized enterprises are export-oriented. The volatility of PX and WIG20 stock returns has been investigated and modelled using AR (1) – GARCH (1, 1) and Jump-Diffusion GARCH (1, 1) models. This study tried to identify an impact of the global financial crisis, estimate the risk in the stock markets during the financial turmoil, and comprehensively analyse the characteristics of the risk.

Based on results of the Jump-Diffusion GARCH model considering heteroscedasticity, no statistically significant jump behaviour was projected in both stock markets in normalcy, between January 4, 2004 and June 29, 2007. However, during the global financial crisis, from July 2, 2007 to March 31, 2010, jump risk with relatively high statistical significance occurred in both stock markets. In case of the Czech market jump risk appeared every five days, while on the Polish market around every three or four days. As for the post-crisis period, jump with statistical significance appeared around every 10 days on the Polish market only. In summary, jump risk has occurred more frequently in the Polish stock market than in the Czech market, and especially during the financial turmoil.

As a possible extension of this paper, the Markov Switching ARCH model or the SWARCH ( $k, q$ ) model can be adopted to clearly identify the state of the global financial crisis. Making a stochastic estimation on the point when risk state probability rises in the stock market could provide a stronger empirical result than the case in which the beginning of the crisis is randomly set.

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## References

- [1] Ball, C. A. and Torous, W. N.: On Jump in Common Stock Prices and Their Impact on Call Option Pricing. *Journal of Finance* **40** (1985), 155-173.
- [2] Baruník, J., Vácha, L. and Vošvrda, M: Tail Behavior of the Central European Stock Markets during the Financial Crisis, *AUCO Czech Economic Review* **4** (2010), 282-294.
- [3] Bollerslev, T.: Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* **31** (1986), 307-327.
- [4] Chang, K. H. and Kim, M. J.: Stress Testing of Financial Industries: A Simple New Approach to Joint Stress Testing of Korean Banking, Securities, and Non-Life Insurance Industries. *Asia-Pacific Journal of Financial Studies* **38** (2009), 521-543.
- [5] Chang, K. H. and Kim, M. J.: *Financial Econometrics*. Kyungmoonsa, 2002.
- [6] Chang, K. H.: Characteristics of Stochastic Volatility in Korean Stock Returns. *The Korean Journal of Financial Management* **20**, (2003), 213-231.
- [7] Chang, K. H., Cho, K. Y. and Hong, M. G.: Stock Volatility, Foreign Exchange Rate Volatility and the Global Financial Crisis, *Journal of Economic Research* **15** (2010), 249-272.
- [8] Engle, R. F.: Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica* **50** (1982), 987-1007.
- [9] Heston, S.: A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Option. *Review of Financial Studies* **6** (1993), 327-344.
- [10] Hull, J. and White, A.: The Pricing of Options on Assets with Stochastic Volatilities. *Journal of Finance* **42** (1987), 281-300.
- [11] Merton, R. C.: Theory of Rational Option Pricing, *Bell Journal of Economics and Management Science* **4** (1973), 141-183.
- [12] Popelka, J.: *Využití lineárních a nelineárních modelů volatility při analýze českých podílových fondů a akcií*. VŠE, Praha, 2007.
- [13] Sed'a, P.: Asymmetric Conditional Volatility Modelling: Evidence from Central European Stock Markets. In: *Proceedings of Finanční řízení podniků a finančních institucí 2011*. VŠB – Technical University of Ostrava, Ostrava, 2011, 375-383.