VOLATILITY AND KURTOSIS AT EMERGING MARKETS: COMPARATIVE ANALYSIS OF MACEDONIAN STOCK EXCHANGE AND SIX STOCK MARKETS FROM CENTRAL AND EASTERN EUROPE

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Abstract

This paper investigates volatility of the Macedonian Stock Exchange (MSE), analyzing ten years daily data movements of MSE index (MBI-10) and ten random chosen stocks and compare results with other six stock markets (Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia). We find that MSE volatility is close to Czech, Poland and Croatia markets. Regression analysis provides evidences for strong correlation between MSE stocks which significantly influence volatility of MBI-10 index.

Key words: *volatility, skewness, kurtosis, equity, RWMA, EWMA*

1. INTRODUCTION

The emerging stock markets in the transition economies of Central and Eastern Europe have been revitalized mostly through the process of privatization of public enterprises, but some like the Republic of Macedonia has recently established equity market at the end of last century. Most of them have attracted attention of investors in recent years. Investors have significant experience and knowledge about behavior of the developed markets, but similar experiences for emerging markets missed.

There is difference between returns in emerging capital markets from returns in developed markets (Geert Bekaert, 1995): average returns are higher, correlations with developed market returns are low, returns are more predictable and volatility is higher. Volatility has been studied mainly with respect to the developed stock markets in industrial countries (Fama, 1965), (French, 1987), (C.Mills, 1995), (Arnold, 1995) (Green, 2000). On the other side, there are limited number of studies for emerging markets (Shiller, 1990), (Bolt, 1994), (Flores, 1997).

MSE was not previously considered in the volatility literature until 2007 (Zlatko, 2007), where using GARCH-type models were derived conclusions that MSE returns series are characterized with volatility clustering.

2. LITERATURE REVIEW

Risk-return models are widely employed in financial modeling to provide a measure of risk that could be employed in portfolio selection, risk management, and derivatives pricing. A risk model is typically a combination of a probability distribution model and a risk measure. A successful univariate probability distribution model provide following: first, calculate returns' temporal dynamics, such as autocorrelations, volatility clustering, and long memory, second, employs a distributional assumption flexible enough to accommodate various degrees of skewness and heavy-tailedness, third, is scalable and practical and can be extended to a multivariate model covering a large number of assets.

The underlying dynamic of returns is either given exogenously or is based on the assumption that returns have independent and identical distributions. However, such characteristics do not fit adequately with the empirically-observed features of financial returns and investor choice.

Long ago in empirical studies it was noticed that returns of stocks (indexes, funds) are badly fitted by Gaussian distribution because of heavy tails and strong asymmetry (B.Mandelbrot, 1960) (B.Mandelbrot, 1963). Benoit Mandelbrot (Mandelbrot & Hudson, 2006) elaborates that random walk and Gaussian daily returns simply do not correspond to reality, and grossly underestimates the risk of huge market swings.

Fama (Fama, 1965) reported that daily returns of stocks on the Dow Jones Industrial Average (DJIA) display more kurtosis than permitted under the normality hypothesis. Since that early work of Fama, it has typically been found that daily returns display more kurtosis than that permitted under the assumptions of normality, while skewness has also been prevalent (C.Mills, 1995).

Risk in finance refers to the likelihood that investor will receive a return on an investment that is different from the return he expected to make. Investors who buy assets expect to earn returns over the time horizon that they hold the asset. Their actual returns over holding period may be different from the expected returns and this difference is source of risk. Risk is defined in statistical terms as variance in actual return around an expected return, the greater this variance, the more risky an investment is perceived to be. The spread of the actual returns around the expected return is measured by the variance or standard deviation of the distribution; the greater the deviation of the actual returns from expected returns, the greater the variance (Damodaran, 2006).

The expected returns and variances are almost always estimated using past returns rather than future returns. The assumption that all risk-returns models use when they use historical variances is that past return distributions are good indicators of future return distributions. When this assumption is violated, as is the case when the asset's characteristics have changed significantly over time, the historical estimates may not be good measures of risk.

The bias towards positive or negative returns is represented by the skewness of the distribution. If distribution is positively skewed, there is higher probability of large positive returns than negative returns. The shape of the tails of the distribution is measured by the kurtosis of the distribution; fatter tails lead to higher kurtosis. In investment terms, this represent the tendency of the price of this investment to jump (up or down from current levels) in either direction (Damodaran, 2006).

In case where distribution of returns is normal, investors do not have to worry about skewness and kurtosis. Normal distributions are symmetric (no skewness) and defined to have a kurtosis of zero.

When return distributions take this form, the characteristics of any investment can be measured with two variables - the expected return, which represents the opportunity in the investment, and the standard deviation or variance, which represents the danger.

Investors prefer positive skewed distributions to negatively skewed ones, and distributions with a lower likelihood of jumps (lower kurtosis) to those with a higher likelihood of jumps (higher kurtosis). Investors, as predominantly risk averse will appreciate good investments (with higher expected returns and more positive skewness), while risk-preference will make trade off with bad (higher variance and higher kurtosis) in making investments.

The coefficient of skewness gives information on the distribution of the returns of each stock. When the distribution is positively skewed, it means that returns are greater than the expected. Most of the models have assumption that investors are aiming for stocks for which the return distribution will be characterized rather by positive than negative skewness.

Kurtosis can be described as the degree to which, for a given variance, a distribution is weighted toward its tails. Kurtosis measures the bimodality of the distribution of the distribution, or the probability mass in the tails of the distribution. Thus, we can distinguish from the variance, which measures the dispersion of observations from the mean, in that it captures the probability of outcomes that are highly divergent from the mean: that is extreme outcomes. Random variables may also exhibit cokurtosis.

Kurtosis measures the degree of a distribution expressed as fat tails. Most of the investors are risk-averse which means that they prefer a distribution with low kurtosis, or we can explain differently as returns that are not far away from the mean.

For normal distribution an excess kurtosis has to be equal to 0. When we have a case of a positive skewness, it means to become possible to have a high excess kurtosis and not to have extreme negative returns in the future as well as that the extreme returns will only be positive. This can happen when the skewness is positive. When we have negative skewness, investors can face the extreme negative returns due to the impact of a high excess kurtosis.

When we have a case of return distribution that has a skewness lower than -1 and an excess kurtosis higher than 1, there is high probability to face sudden high negative returns increases. For a distribution with a skewness of -1 and an excess kurtosis of 5 (for example, technology stocks, media stocks, telecom stocks or hedge funds in arbitrage strategies), a classical approach will conclude that the investor will not lose more than -3.5% in the next 1 day with 99% probability. An approach, accounting for skewness and kurtosis, shows a -7.4% loss in the next 1 day with 99% probability. This is exactly what one observes on the equity market. The difference is large: an underestimation of 111% of the downside risks (i.e. 7.4%/3.5%-1=111%) when using volatility only to measure the risk.

As already mentioned, historical data from many markets indicate that the daily changes in stock prices do not follow Gaussian distribution. Huge changes in market prices occur much more frequently than predicted by the Gaussian distribution, popularly known as "heavy tails". Finance literature provides evidence that returns on capital markets are not normally distributed. Moreover return on equity markets shows large swings from the mean far more frequently than it can be predict by the assumption of normal distribution (Chamberlain, 1983) (Owen & Rabinovitch, 1983).

Financial market volatility is central to the theory and practice of asset pricing, asset allocation, and risk management. There are three ways to calculate volatility: using high-frequency data, implied volatility of options data and by econometric modeling. Although most textbook models assume volatilities and correlations to be constant, it is widely recognized among both finance academics and practitioners that they vary importantly over time. This recognition has spurred an extensive and vibrant research program into the distributional and dynamic properties of stock market volatility. Most of what we have learned from this burgeoning literature is based on the estimation of parametric ARCH or stochastic volatility models for the underlying returns, or on the analysis of implied volatilities from options or other derivatives prices. However, the validity of such volatility measures generally depends upon specific distributional assumptions, and in the case of implied volatilities, further assumptions concerning the market price of volatility risk (Torben G.Andersen, 2000).

Volatility, however, is only one of the distributional moments that can provide a stylized representation of returns. Empirical evidence has shown that the empirical distribution of financial series is likely to be skewed and fat-tailed (see Mandlebrot 1963, Bollerslev, 1987, Campbell and Siddique, 1999 and 2000, Alizadeh and Gabrielsen, 2011, among others).

One of the early models employed in capturing volatility is the equally weighted moving average model. This framework assumes that the *N*-period historic estimate of variance is based on an equally weighted moving average of the *N*-past one-period squared returns. However, under this formulation all past squared returns that enter the moving average are equally weighted and this may lead to unrealistic estimates of volatility. In this respect the exponentially weighted moving average (EWMA) framework proposed by J.P Morgan's Risk Metrics TM assigns geometrically declining weights on past observations with the highest weight been attributed to the latest (i.e. more resent) observation. By assigning the highest weight to the latest observations and the least to the oldest the model is able to capture the dynamic features of volatility.

In their paper (Chris Brooks, 2002) several authors proposes a new model for autoregressive conditional heteroscedasticity and kurtosis. Via a time-varying degrees of freedom parameter, the conditional variance and conditional kurtosis are permitted to evolve separately. The model uses only the standard Student's t density and consequently can be estimated simply using maximum likelihood. The method is applied to a set of four daily financial asset return series comprising US and UK stocks and bonds, and significant evidence in favor of the presence of autoregressive conditional kurtosis is observed. They argue that conditional kurtosis appears to be positively but not significantly related to returns and that the response of kurtosis to good and bad news is not significantly asymmetric.

Several authors argue (M.Angeles Carnero, n.d.) that the relationship between kurtosis, persistence of schocks to volatility, and first –order autocorrelation of squares is different in GARCH and ARSV models. This difference can explain why, when these models are fitted to the same series, the persistence estimated is usually higher in GARCH than in ARSV models, and why Gaussian models seem to be adequate, whereas GARCH models often require leptokurtic conditional distributions.

In his paper (J.Kon, 1984) proposed a discrete mixture of normal distributions to explain the observed significant kurtosis (fat tails) and significant positive skewness in the distribution of daily rates of returns for a sample of common stocks and indexes. Stationarity tests on the parameter estimates of this discrete mixture of normal distributions model revealed significant differences in the mean estimates that can explain the observed skewness and significant differences in the variance estimates that can explain the observed kurtosis. An alternative explanation for the observed fat tails is the symmetric student model. The result of a comparison between the models is that the discrete mixture of normal distributions model has substantially more descriptive validity than the student model.

Several authors (Alexandros Gabrielsen, 2012) paper provides an insight to the time-varying dynamics of the shape of the distribution of financial return series by proposing an exponential weighted moving average model that jointly estimates volatility, skewness and kurtosis over time using a modified form of the Gram-Charlier density in which skewness and kurtosis appear directly in the functional form of this density.

In their study for the dynamics of expected stock returns and volatility in emerging financial markets, (Giorgio De Santis, 2009) found that clustering, predictability and persistence in conditional volatility, as others have documented for mature markets. However, emerging markets exhibit higher conditional volatility and conditional probability of large price changes than mature markets. Exposure to high country-specific risk does not appear to be rewarded with higher expected returns. They detect a risk-reward relation in Latin America but not in Asia when we assume some level of international integration. They did not find support for the claim that market liberalization increases price volatility.

3. METHODOLOGY

We determine the character of volatility of daily stock returns and daily index values, and calculate skewness and kurtosis. First, for each day, we take the natural log of the ratio of stock prices.

$$\mu_i = \ln\left(\frac{S_i}{S_{i-1}}\right)$$

Then we calculate the skewness and kurtosis for the whole measurement period.

Kurtosis (Kenney & Keeping, 1951) characterizes the relative peakedness or flatness of a distribution compared with the normal distribution and is calculated as:

$$\mathrm{Kurt}[x] = \frac{E\left[(x-\bar{x})^4\right]}{\sigma^4} - 3$$

where $E\left[(x-\bar{x})^4\right]$ is the fourth moment around the mean, and σ is the standard deviation of x.

Distributions with zero kurtosis are called *mesokurtic*. Normal distribution has zero kurtosis. Distributions with high kurtosis distribution are called leptokurtic, and tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Distributions with negative kurtosis (*platykurtic*) have a flat top near the mean and shorter, thinner tails.

The historical or *n*-period Rolling Window Moving Average (RWMA) estimator of the volatility corresponds to the standard deviation and it is given by the following expression:

$$\hat{\sigma}_{t+1} = \sqrt{\frac{1}{n}\sum_{s=t-n+1}^{t}(\mu_s - \mu)^2}$$

where r_s is the return of the asset at period s and m is the mean return of the asset.

The size n is critical when one considers the effect of an extremely high or low observation in the sense that the smaller the size of the window, the bigger the effect on volatility. The weakness of this approach is that all returns earn the same weight. Yesterday's (very recent) return has no more influence on the variance than last month's return.

The problem of RWMA Estimator is fixed by using the Exponential Weighted Moving Averages Estimator (EWMA) in which more recent returns have greater weight on the variance. EWMA is more commonly used in risk management calculations and is given by the square root of

$$\hat{\sigma}_{t+1}^2 = \lambda\hat{\sigma}_t^2 + (1-\lambda)(\mu_t - \mu)^2$$

where λ is the decay factor, also known as the smoothing constant. In this method, the weights are geometrically declining, so the most recent observation has more weight compared to older ones. This weighting scheme helps to capture the dynamic properties of the data. Commonly, the smoothing constants are 0.94 for daily data and 0.97 for monthly data (Suganuma, n.d.).

4. COMPARATIVE ANALYSIS OF MSE VOLATILITY AND OTHER SIX CENTRAL AND EASTERN EUROPE STOCK-EXCHANGES

We analyzed the daily closing data for MBI-10 index for the period 30 December 2004 to 31 December 2014. The base data for MBI-10 is 30 December 2004 = 1000. We also observed daily time-series for MSE several stocks' closing prices: ALK, BESK, GRNT, KMB, MPT, REPL, SBT, STIL, MTUR, TPFL for period 01 January 2003 – 31 December 2012. We restricted our research to determine skewness, kurtosis and volatility for MSE and to compare with results of other six emerging markets from Central and Eastern Europe (Poshakwale, 2001).

Descriptive statistics provide results for mean, median, standard deviation, skewness and kurtosis based on daily logarithmic returns and squared returns. We compare our findings with the results for six stock markets (Poshakwale, 2001) as reported in Tables 1 and 5, respectively. The results of calculation of aforementioned values for MSE are provided in Tables 2 and 6. We use RWMA and EWMA to determine volatility.

Table 1. Descriptive Statistics for Daily Logarithmic Returns on six markets

	Croatia	**Czech**	**Poland**	**Hungary**	**Slovakia**	**Russia**
Mean	0.00	–0.02	0.05	0.11	–0.07	0.31
Median	0.00	0.00	0.00	0.00	0.00	0.00
Std. Deviation	2.41	1.17	2.25	1.90	1.66	4.11
Skewness	0.36	–0.23	–0.09	–0.52	–3.11	12.26
Kurtosis	10.89	7.34	5.84	17.30	64.25	306.15

Derivative reproduction (Poshakwale, 2001)

The returns of six emerging stock markets exhibit skewness and significant kurtosis. The analyzed stock markets volatility clustering characterized with high kurtosis and variance and confirmed the findings of Diebold (Diebold, 1986).

Table 2. Descriptive Statistics for Daily Logarithmic Returns on MSE

	Macedonia
Mean	0,000243
Median	-0,00014
Std. Deviation	0,014255
Skewness	-0,12546
Kurtosis	8,047635

Comparative analysis of skewness and kurtosis of daily logarithmic returns of MBI-10 and other six markets confirm significant correlation with Croatia, Czech, Poland and Hungary markets, as well as notable differences compared with Slovakia and Russia. MBI-10 skewness is negative like Czech, Poland, Hungary and Slovakia stock-markets.

Beside aforementioned we provide accurate calculations of skewness and kurtosis for ten MSE stocks from our sample on following table:

Table 3. Descriptive Statistics for Daily Logarithmic Returns for MSE stocks

	SKEWNESS	**KURTOSIS**
ALK	-0,08	5,77
GRNT	0,41	4,26
KMB	0,17	5,57
MPT	0,25	7,90
REPL	0,42	32,26
SBT	-0,51	8,61
STIL	-5,99	121,15
MTUR	0,23	10,67
TPLF	0,22	5,56
BESK	0,16	8,55

Table 3: Column 1: Stock ISIN code. Column 2: skewness. Column 3: kurtosis.

Using regression analysis we have determined strong positive correlation between stocks prices at MSE (most of the values oscillate around 0,90), as shown on following table:

Table 4. Correlation Coefficients at MSE

	ALK	BESK	GRNT	KMB	MPT	REPL	SBT	STIL	MTUR	TPFL
ALK	1									
BESK	0,95	1,00								
GRNT	0,97	0,97	1,00							
KMB	0,89	0,79	0,82	1,00						
MPT	0,96	0,97	0,97	0,84	1,00					
REPL	0,88	0,89	0,91	0,81	0,86	1,00				
SBT	0,73	0,62	0,62	0,84	0,73	0,51	1,00			
STIL	0,87	0,92	0,94	0,63	0,91	0,83	0,43	1,00		
MTUR	0,96	0,95	0,98	0,83	0,95	0,91	0,65	0,90	1,00	
TPFL	0,96	0,97	0,96	0,79	0,96	0,84	0,66	0,91	0,94	1,00

The difference of MBI-10 kurtosis compared with stocks kurtosis suggest that MBI-10 changes are not immediately followed by the other stocks on MSE, which results in reduced overall impact on MBI-10 changes.

Results of calculation of the mean, median, standard deviation, skewness and kurtosis of daily squared returns for six stock-markets and MSE are on following tables (5 and 6):

Table 5. Descriptive Statistics of Squared Returns on six-markets

	Croatia	**Czech**	**Poland**	**Hungary**	**Slovakia**	**Russia**
Mean	5.82	1.37	5.06	3.63	2.75	17.00
Median	0.43	0.22	1.25	0.32	0.13	0.62
Std. Deviation	18.33	3.44	11.12	14.56	21.94	297.28
Skewness	9.59	5.90	5.39	10.95	30.90	34.30
Kurtosis	134.57	52.97	43.99	175.20	1087.75	1196.68

Derivative reproduction **(Poshakwale, 2001)**

Table 6. Descriptive Statistics of Squared Returns for MBI-10

	Macedonia
Mean	0,000203
Median	-0,000284
Std. Deviation	0,000643
Skewness	7,409521
Kurtosis	73,6557

Comparative analysis shows high MBI-10 correlation with Czech and Poland stock markets indexes (PX-50 and WIG-20), lower values than CROBEX and BUX as well as significant deviation compared with SAX and ASPG.

Results for skewness and kurtosis of squared returns for MSE stocks are on following table:

Table 7. Descriptive Statistics of Squared Returns of MSE stocks

	SKEWNESS	**KURTOSIS**
ALK	4,97	28,69
GRNT	3,74	14,43
KMB	4,61	23,90
MPT	10,48	199,98
REPL	12,60	210,86
SBT	8,89	125,61
STIL	36,03	1451,90
MTUR	6,27	50,31
TPLF	4,87	29,21
BESK	8,94	163,26

Using RWMA and EWMA we determine volatility of MSE as presented on following table:

Table 8. MSE Volatility data

	σ	σ_σ MA	σ_σ EWMA
ALK	0.0232	0.00856	0.00791
BESK	0.0270	0.01265	0.00903
GRNT	0.0271	0.01070	0.00825
KMB	0.0227	0.00875	0.00770
MPT	0.0256	0.00777	0.00806
REPL	0.0213	0.00937	0.00785
SBT	0.0210	0.00615	0.00684
STIL	0.0342	0.01907	0.01361
MTUR	0.0190	0.00551	0.00521
TPFL	0.0242	0.00874	0.00806
MBI-10	0.0167	0.00548	0.00636
MSE	0.0238	0.00934	0.00808

Table 8: Column 1: Stock code. Column 2: volatility of the daily return series. Column 3: volatility of the volatility sequence calculated using rolling window moving average. Column 4: volatility of the volatility sequence calculated using exponentially weighted moving average.

CONCLUSION

We find that the MSE values for volatility of the volatility sequence are very similar when calculated using RWMA and EWMA methods. The MSE stock returns time series display stylized facts such as volatility clustering and high kurtosis. We provide evidence of similarity or difference in volatility across emerging markets.

Kurtosis of daily logarithmic returns of MBI-10 takes almost same values like kurtosis of PX-50 and WIG-20 and small deviation compared with CROBEX and BSE BUX. We have found evidences that MBI-10 signalize significant stock price changes (2006-2008, MSE have bullish and 2010-2012 bearish trend), when high drops or peaks of stock prices in fact happened what confirm our findings. We find that large daily changes i.e. heavy tails occur significantly less frequently on individual stocks from MSE compared with SAX and ASPG as indexes of Slovakia and Russia stock markets.

Kurtosis of MBI-10 squared returns takes larger values for MSE stocks than for PX-50 and WIG-20 stocks and lower than CROBEX and BAS BUX. Finally, we find that changes of MBI-10 are not immediately followed in the other stocks on MSE, which results in reduced overall impact on MBI-10 changes.

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