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AN EMPIRICAL ANALYSIS OF STOCK RETURNS AND VOLATILITY: THE CASE OF STOCK MARKETS FROM CENTRAL AND EASTERN EUROPE

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Abstract

The main goal of this paper is to investigate the behaviour of stock returns in the case of stock markets from Central and Eastern Europe (CEE), focusing on the relationship between returns and conditional volatility. Since there is relatively little empirical research on the volatility of stock returns in underdeveloped stock markets, with even fewer studies on markets in the transitional economies of the CEE region, this paper is designed to shed some light on the econometric modelling of the conditional mean and volatility of stock returns from this region. The results presented in this paper provide confirmatory evidence that ARIMA and GARCH processes provide parsimonious approximations of mean and volatility dynamics in the case of the selected stock markets. There is overwhelming evidence corroborating the existence of a leverage effect, meaning that negative shocks increase volatility more than positive shocks do. Since financial decisions are generally based upon the trade-off between risk and return, the results presented in this paper will provide valuable information in decision making for those who are planning to invest in stock markets from the CEE region.

Keywords: *stock returns, volatility, CEE region*

JEL classification: *G11, C58*

1. INTRODUCTION

There are several reasons to model and forecast return and volatility. First, one may need to analyze the risk of holding an asset. Second, forecast confidence intervals may be time-varying, so that more accurate intervals can be obtained by modelling the variance of the errors. Third, more efficient estimators can be obtained if heteroskedasticity in the errors is handled properly (IHS Global Inc, 2013, p. 224). As documented by Bollerslev, Engle and Nelson (1994), financial time series are generally characterized by the presence of fat-tails and volatility clustering. Therefore, the assumption of constant volatility is unsuitable and can drive high levels of inaccuracy. Linear time series models are therefore unable to explain a number of important features common to much financial data, including (Brooks, 2008, p. 380): (1) *Leptokurtosis* – that is, the tendency for financial asset returns to have distributions that exhibit fat tails and excess peakedness at the mean. (2) *Volatility clustering/pooling* – the tendency for volatility in financial markets to appear in bunches. Thus large returns (of either sign) are expected to follow large returns, and small returns (of either sign) to follow small returns. A plausible explanation for this phenomenon, which seems to be an almost

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universal feature of asset return series in finance, is that the information arrivals which drive price changes themselves occur in bunches rather than being evenly spaced over time. (3) *Leverage effects* – the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude.

The main goal of this paper is to explain the behaviour of financial time series, i.e. stock returns in the case of stock markets from the Central and Eastern Europe (CEE), focusing on the relationship between returns and conditional volatility. Empirical studies have shown that this relationship is important for several reasons. First, the nature of stock return behaviour is fundamental to the formulation of the concept of risk in various financial theories and models. Second, stock return volatility is central to finance, whether in asset pricing, portfolio selection, or risk management. There is relatively less empirical research on the volatility of stock returns in underdeveloped stock markets, with even fewer studies on the markets in the transition economies of the CEE region. Therefore, in this paper we will focus on the econometric modelling of the conditional mean and volatility of stock returns from the CEE region.

The research should result in responses to the following questions: What are the general specificities of the financial time series from the underdeveloped stock markets from the CEE region? Do ARIMA and GARCH processes provide parsimonious approximations to mean and volatility dynamics in the case of stock markets from the CEE region? Do financial time series from the CEE region have a significant leverage effect? Bearing in mind the above, the central research hypothesis shall be as follows: *ARIMA and GARCH processes provide parsimonious approximations to mean and volatility dynamics in the case of stock markets from the CEE region.* The main limitations of this study are to be found in the shorter available financial time series in the selected stock markets.

Since financial decisions are generally based upon the trade-off between risk and return, results presented in this paper could be a good starting point in decision making for those who are planning to invest in stock markets from the CEE region.

The paper is organized as follows. After the introduction, part one gives a short overview of some recent literature relevant to the main objective of the paper. Part two presents a fundamental theoretical background and the research methodology. Part three brings a description of our data and research design. Part four is the main section of the paper and contains an analysis of the original empirical results. The last part contains some final remarks and conclusions.

2. LITERATURE REVIEW

ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986). These models are widely used in various branches of econometrics, especially in financial time series analysis. Since most of the empirical research on return and volatility comes from the developed stock markets, in this section we will only present some recent results of the econometric modelling of the conditional mean and volatility of stock returns from underdeveloped (emerging and frontier) stock markets.

Murinde and Poshakwale (2001) investigated volatility in the emerging stock markets in the CEE region, i.e. Croatia, the Czech Republic, Hungary, Poland, Russia and Slovakia. Although GARCH seemed to be the most appropriate process in characterizing volatility in these markets, the explanation provided by symmetric and asymmetric GARCH models was not significant enough for predicting future volatility.

Alberg, Shalit and Yosef (2008) gave a comprehensive empirical analysis of the mean return and conditional variance of the Tel Aviv Stock Exchange (TASE) indices by using various GARCH models. They found that the asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. The EGARCH model using a skewed Student-t distribution was the most successful for forecasting TASE indices.

Gokcan (2000) compared the linear (GARCH(1,1)) and non-linear (EGARCH) versions of the GARCH model by using the monthly stock market returns of seven emerging countries from February 1988 to December 1996. He found that for emerging stock markets the GARCH(1,1) model performed better than the EGARCH model, even if the stock market return series displayed skewed distributions.

Sandoval (2006) applied asymmetric GARCH models on exchange rate volatilities in emerging markets. The set of emerging market exchange rates did not show generalized asymmetric evidence. Bhaskar (2012) documented that the EGARCH model successfully models the Sensitive Index or Sensex related to Bombay Stock Exchange (BSE) data, whereas GJR-GARCH was able to explain conditional variance in the returns from Nifty associated with the National Stock Exchange (NSE). Worthington and Higgs (2004) examined the transmission of equity returns and volatility among Asian equity markets and investigates the differences that exist in this regard between the developed and emerging markets. Three developed markets (Hong Kong, Japan and Singapore) and six emerging markets (Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand) were included in the analysis. The results generally indicated the presence of large and predominantly positive mean and volatility spillovers.

Kovačić (2007) investigated the behaviour of stock returns in an emerging stock market, namely, the Macedonian Stock Exchange, focusing on the relationship between returns and conditional volatility. The results indicated that the Macedonian stock return time series display stylized facts such as volatility clustering, high kurtosis, and a low starting and slow-decaying autocorrelation function of squared returns, and that the asymmetric models show little evidence on the existence of leverage effect.

Égert and Koubaa (2004) investigated conditional variance patterns in daily return series of stock market indices in the G-7 (Canada, France, Germany, Italy, Japan, the UK and the US) and 6 selected economies of Central and Eastern Europe (the Czech Republic, Hungary, Poland, Russia, Slovakia and Slovenia). For this purpose, various linear and asymmetric GARCH models were employed. The estimation results revealed that the selected stock returns for the G-7 could be reasonably well modelled using linear specifications, whereas the overwhelming majority of the stock indices from the CEE region could be much better characterized using asymmetric models. In their research Kasch-Haroutounian and Price (2001) econometrically modelled returns from four emerging equity markets of CEE (Czech Republic, Hungary, Poland and Slovakia). The estimates of asymmetric models of conditional volatility showed rather weak evidence of asymmetries in the selected markets. Patev and Kanaryan (2003) investigate the nature of the Central European stock market volatility before, during and after major emerging market crises. Their results led to the conclusion that following a financial crisis, the negative return shocks had higher volatility than positive return shocks. Also, they found that an asymmetric GARCH model with non-normal distributed residuals captured most of the Central European stock market's volatility characteristics.

Shields (1997) investigated whether an analogous asymmetric characteristic is reflected in two emerging Eastern European Markets. No evidence of asymmetry was found. Shin (2005) examined the relationship between expected stock returns and conditional volatility in 14 emerging international stock markets. Using both a parametric and a flexible semi-parametric GARCH in mean model, he found that a positive relationship prevailed for the majority of the emerging markets. Also, the results lent little support to the asymmetric volatility argument that stock return volatility should be negatively correlated with stock returns.

3. THEORETICAL BACKGROUND AND METHODOLOGY

3.1 Theoretical background

As discussed by Engle (2001) the basic version of the least squares model assumes that the expected value of all error terms, when squared, is the same at any given point. This assumption is called homoskedasticity, and it is this assumption that is the focus of GARCH models. Data in which the variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of data than for others, are said to suffer from heteroskedasticity. Therefore, and as pointed out by Engle (2001), the standard warning is that in the presence of heteroskedasticity, the regression coefficients for an ordinary least squares regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision. Instead of considering this a problem to be corrected, ARCH and GARCH models treat heteroskedasticity as a variance to be modelled. As a result, not only are the deficiencies of least squares corrected, but a prediction is computed for the variance of each error term.

GARCH models are specifically designed to model and forecast conditional variances. They consist of two equations, i.e. the conditional variance equation and the conditional mean equation. In this research, for the second equation we will use the autoregressive moving average (ARIMA) model. There is a huge variety of ARIMA models. The general non-seasonal model is known as ARIMA(p,d,q) where p denotes the order of the autoregressive (AR) part, d stands for the degree of first differencing involved and q denotes the order of the moving average part (MA). The representation for the conditional mean of the ARIMA model is given by (IHS Global Inc, 2013, p. 94):

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \ldots + \varphi_p r_{t-p} + \varepsilon_t + \eta_1 \varepsilon_{t-1} + \ldots + \eta_q \varepsilon_{t-q}, \quad (1)$$

where r_t denotes the dependent variable at time t, φ_0 is the constant term, φ_j is the j-th autoregressive parameter, η_j is the j-th moving average parameter and ε_{t-k} is the error term at time t-k. Residuals of the estimated mean equation have to be tested for ARCH effects. It is standard procedure to use an ARCH LM test (H_0: *there is no ARCH effect in residuals*) which is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity in the residuals. A rejection of the null implies the existence of significant ARCH effects. The variance of the dependent variable is modelled as a function of the past values of the dependent variable and independent or exogenous variables.

The GARCH models allow variance not only to be dependent on past shocks but also to be dependent on the most recent variance of itself. The representation for the conditional variance of GARCH(q,p) is given as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 , \qquad 2)$$

where, ω, α_i and β_j are parameters.

The conditional variance equation specified in (2) is a function of three terms: (1) a constant term: ω, (2) news about volatility from the previous period, measured as the lag of the squared residual from the mean equation: ε_{t-i}^2 (the ARCH term) and (3) the last period's forecast variance: σ_{t-j}^2 (the GARCH term). If one restricts the parameters of the GARCH model to sum to one and drops the constant term:

$$\sigma_t^2 = \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \qquad (3)$$

such that

$$\sum_{j=1}^{q} \beta_j + \sum_{i=1}^{p} \alpha_i = 1 \qquad (4)$$

then we have an integrated GARCH model (IGARCH).

Although the standard GARCH process captures several important phenomena regarding financial time series, it fails to model the leverage effect. In a seminal paper, Black (1976) provided a compelling explanation for this effect in terms of the firm's financial leverage: a negative return implies a drop in the value of the firm's equity, increasing its leverage which, in turn, leads to higher equity-return volatility. The standard GARCH model assumes that the effects of different shocks on volatility depend only on size, regardless of sign. The model depends on summation of square shocks (ε_{t-i}), but it is well known that *volatility is higher after negative shocks* (bad news) than after positive shocks (good news). According to the ability to capture a stylized fact of asymmetry, GARCH family models can be divided into symmetric and asymmetric models[1].

Models (2) and (3) are typical symmetric GARCH models. An asymmetric model allows the possibility that the unexpected arrival of "bad news" has a larger impact on future volatility than an unexpected arrival of "good news" of similar magnitude.

To address this problem, many nonlinear extensions of GARCH have been proposed, such as the exponential GARCH (EGARCH), the threshold GARCH (TARCH), power ARCH (PARCH), etc. The representation for the conditional variance of the EGARCH model is given as follows (IHS Global Inc., 2013, p. 221):

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad (5)$$

where γ_k denotes the leverage effect.

The EGARCH model differs from the standard GARCH models in two main respects (Engle and Ng, 1993, p. 1753): (1) the EGARCH model allows good news and bad news to have a different impact on volatility, while the standard GARCH model does not, and (2) the EGARCH model allows big news to have a greater impact on volatility than the standard GARCH model.

The generalized specification for the conditional variance for the TARCH model is given by (IHS Global Inc, 2013, p. 220):

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- , \qquad (6)$$

where $I_{t-k}^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In this model, good news ($\varepsilon_{t-i}^2 > 0$) and bad news ($\varepsilon_{t-i} < 0$) differently affect conditional variance.

Basically, good news has an impact of α_i and bad news an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, then bad news increases volatility, and we say that there is a leverage effect for the *i*-th order. The representation for the conditional variance of the PARCH model is given as follows (IHS Global Inc., 2013, p. 222):

$$\sigma_t^\delta = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta + \sum_{i=1}^{p} \alpha_i \left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^\delta , \qquad (7)$$

where δ denotes the power parameter, and $\delta > 0$, $|\gamma_i| \le 1$ for $i = 1,..., r$, $\gamma_i = 0$ for all $i>r$, and $r \le p$. Following any modelling procedure, it is a good idea to assess the validity of the model.

Residuals and diagnostic statistics allow us to identify patterns that are either poorly fit by the model, have a strong influence upon the estimated parameters, or which have a high leverage.

This diagnostic check consists of: (1) testing serial correlation in residuals (H_0*: there is no serial correlation in the residuals*); (2) examining the existence of ARCH effects in residuals (H_0*: there is no ARCH effect in the residuals*) and finally (3) examining the normality of the residuals (H_0*: the residuals are normally distributed*).

3.2. Methodology and data

As a representative of the CEE region, we used the following stock traded indices from the CEE region: SASX-10 and BIRS (Bosnia and Herzegovina), SOFIX (Bulgaria), CROBEX (Croatia), PX (Czech Republic), BUX (Hungary), MBI10 (FYR Macedonia), MONEX20 (Montenegro), WIG20 (Poland), BET (Romania), BELEX15 (Serbia), SAX (Slovakia) and SBITOP (Slovenia).

According to MSCI[2] Inc. (2013), the capital markets of Bulgaria, Croatia, Serbia, Slovenia and Romania are classified as *frontier* markets. The Czech Republic, Hungary and Poland are included in *emerging* markets. According to this source, Bosnia and Herzegovina is included among the so called *standalone* markets. FYR Macedonia, Slovakia and Montenegro are not classified by the MSCI.

Furthermore, FTSE[3] Int. (2014) classifies the capital markets of Bulgaria, Croatia, Romania, Serbia, Slovak Republic and Slovenia as frontier markets. According to FTSE quality[4] of markets criteria, the capital markets of Czech Republic, Hungary and Poland are classified as emerging markets. Bosnia and Herzegovina, FYR Macedonia, Slovakia and Montenegro are not classified by the FTSE Int.

It is now well-known that emerging and frontier capital markets have vastly different characteristics than developed capital markets. According to Geert and Campbell (1997) there are at least four distinguishing features of emerging and frontier market returns: average returns are higher, correlations with developed market returns are low, returns are more predictable and volatility is higher.

When it comes to our research design, first, we will have to transform price series into return series. So, if we denote successive index value observations made at time t and $t+1$ as I_t and I_{t+1}, respectively, then continuous compounding transforms a price series $\{I_t\}$ into a return series $\{r_t\}$ as:

$$r_t = \ln \frac{I_t}{I_{t-1}} \quad (8)$$

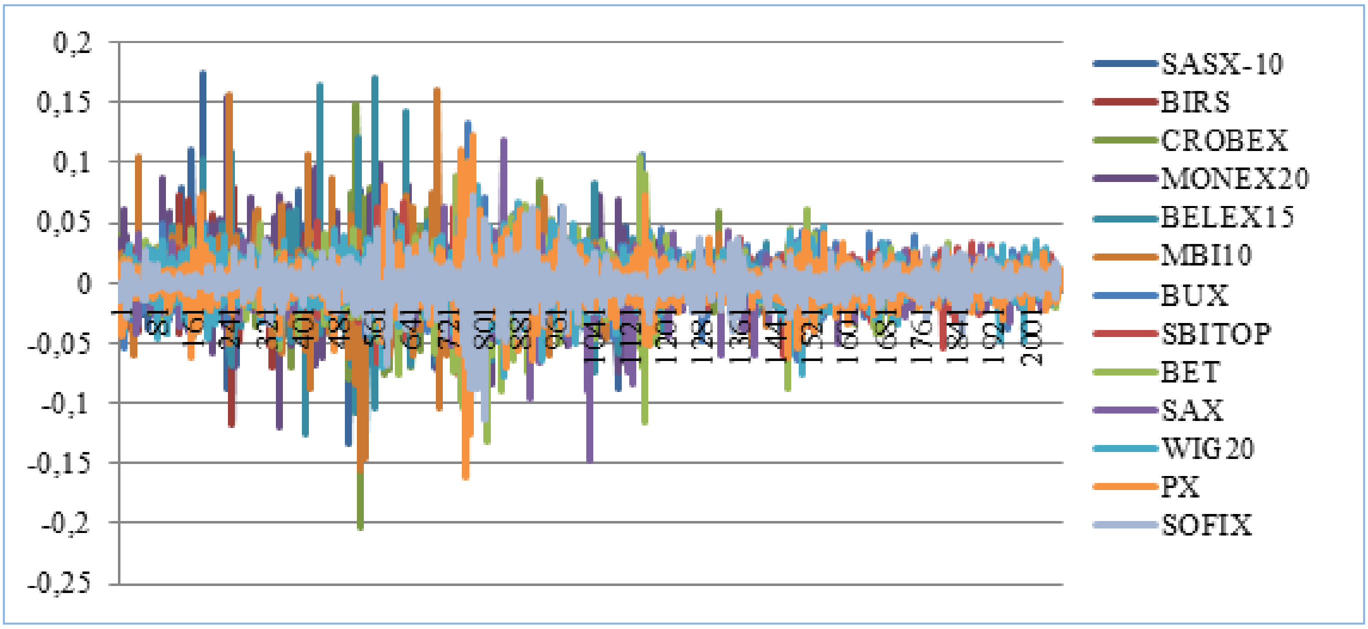
After this, research shall be conducted in the following four stages: (1) identifying and estimating an econometric ARIMA model for a mean equation; (2) using the residuals of the mean equation to test for ARCH effects; (3) specifying and estimating a volatility model (if ARCH effects are statistically significant) and (4) performing residual diagnostics.

4. EMPIRICAL RESULTS AND DISCUSSION

According to the previously explained research design, in this section we will present relevant results. First we will give a comparative illustration of daily index returns (Figure 1). Real financial time series for all stocks observed in this paper were retrieved from Yahoo! Finance Worldwide (2014). The period is from October 2005[5] to December 2013.

Preliminary investigation identified the following mean equation models as appropriate models to start with: ARIMA(1,1,1) for BELEX15, ARIMA(0,0,1) for BET, ARIMA(1,1,1) for BIRS, ARIMA(2,2,1) for BUX,

Figure 1 A comparative illustration of daily index returns



Source: Author's illustration

ARIMA(1,0,0) for CROBEX,ARIMA(2,2,1) for MBI10, ARIMA(1,0,0) for MONEX20, ARIMA(2,0,0) for PX, ARIMA(1,0,0) for SASX-10, ARIMA(1,0,0) for SAX, ARIMA(1,0,0) for SBITOP, ARIMA(2,0,0) for SOFIX, and ARIMA(0,0,1) for WIG20.

This investigation and lag length selection was based on the Akaike information criteria (*AIC*), significance of the model parameters and post-estimation tests such as Ljung-Box test for model residuals and squared residuals.

The Ljung-Box statistics LB(36) and $LB^2(36)$ for the returns and squared returns series respectively, are highly significant. Therefore, we reject the hypothesis that there is no autocorrelation in the level of returns and squared returns. The LB(36) test result could be interpreted as an indicator of market efficiency. According to Brigham (1992), a body of efficient market hypotheses (EMH) holds: (1) that stocks are always in equilibrium and (2) that it is impossible for an investor to consistently beat the market. According to the EMH, fair price is represented by current market price. EMH also represents a way of evaluating market (in) efficiency, meaning that an investor in an efficient market should not expect earnings above the market return while using technical analysis or fundamental analysis. EMH is a very attractive approach in that it gives a kind of guarantee that trading will be done at the price that is considered to be fair. Depending on the information set involved there are three forms of the EMH: (1) weak-form efficiency, (2) semi strong-form efficiency, (3) strong-form efficiency. Weak-form efficiency assumes that all historical information is incorporated into the market stock price. Semi strong-form efficiency assumes that, beside all historical information, stock market price also reflects expectations about a company. Strong-form efficiency is based on the assumption that market stock prices reflect not only historical and expected, but also insider information. What this means is that in an efficient market excess return will equal zero even with insider information.

According to the obtained results of the LB(36) test, selected stock markets from the CEE region are weak-form inefficient, since there is a strong chance that investors could use historical data to beat the market, i.e. earn above average gains.

Furthermore, the $LB^2(36)$ test result suggests significant autocorrelation in the squared returns series. In other words, the GARCH effect, i.e. time-varying second moment has been detected in returns series. Thus the use of GARCH-type models for the conditional variance is justified. Since we found statistically significant ARCH effects we performed a joint estimation of the mean and volatility equations.

In the preliminary analysis, for each index, we estimated symmetric and asymmetric GARCH models, i.e.: GARCH, IGARCH, EGARCH, GJR and PGARCH.

Preliminary investigation identified the following volatility equation models as appropriate models to start with: PARCH(1,1) for BELEX15, TARCH(1,1) for BET, EGARCH(1,1) for BIRS, PARCH(1,1) for BUX, PARCH(1,1) for CROBEX, GARCH(1,1) for MBI10, EGARCH(1,1) for MONEX20, TARCH(1,1) for PX, EGARCH(1,1) for SASX-10, PARCH(1,1) for SAX, TARCH(1,1) for SBITOP, TARCH(1,1) for SOFIX and EGARCH(1,1) for WIG20. This investigation was based on the *AIC*, the significance of the model parameters and the diagnostic check which consisted of: testing serial correlation in residuals, examining the existence of ARCH effects in residuals and finally examining the normality of the residuals. Table 1 presents the estimation results for the mean and variance equations.

Furthermore, we estimated the parameters and test their significance in the case of the mean and volatility equation as well. In the variance equation the first three coefficients: ω, α and β are highly significant at the conventional significance level. There is a high persistence of shocks in the volatility. This persistence is measured in the GARCH case by the sum α of β and is in each case close to 1. The coefficient γ is significant at the 5% level in all models, which means that a leverage effect does exist (negative shocks increase the volatility more than positive shocks).

However, in contrast to the results found for most other markets, the leverage effect term has an unexpected negative sign the in cases of BIRS, MONEX20, SASX-10 and WIG20. For stock returns, the parameter is usually estimated to be positive; in this case, it reflects the leverage effect, signifying that negative returns increase future volatility by a larger amount than positive returns of the same magnitude.

The present findings seem to be consistent with the research conducted by Kovačić (2007). Furthermore, a Ljung-Box test was used to check for any remaining autocorrelations in standardized and squared standardized residuals from the estimated variance equation. Since these two statistics were not significant, we conclude that the variance equation is specified correctly. Remaining ARCH effects were not detected in the standardized residuals. Table 2 presents the results of the ARCH test.

Finally, when it comes to examining the normality of the residuals, we rejected the null hypothesis of normally distributed errors. This isn't something that is desirable when it comes to the diagnostic check of the model, but the model has no serial correlation, and no ARCH effect. This is an important issue for future research.

Table 1 Estimation results for the mean and variance equations

Indices	Parameters								
	Mean equation				Variance equation				
	φ_0	φ_1	φ_2	η_1	ω	α	β	γ	δ
BELEX15	1,40E-05**	2,20E-01**	-	-9,80E-01**	0,009**	0,158**	0,848**	0,069**	0,253**
BET	4,20E-04	-	-	8,60E-02**	0,000**	0,194**	0,763**	0,074*	-
BIRS	2,80E-06	9,60E-02**	-	-9,80E-01**	-0,235**	0,167**	0,987**	-0,014*	-
BUX	-2,10E-07	-6,30E-01**	-3,40E-01**	-1,00E+06**	0	0,121**	0,875**	0,408**	1,363**
CROBEX	4,00E-05	1,30E-01**	-	-	0	0,136**	0,884**	0,168**	1,589**
MBI10	-2,80E-07	-4,30E-01**	-2,20E-01**	-1,00E+00**	0,000**	0,284**	0,651**	-	-
MONEX20	-1,20E-04	1,70E-01**	-	-	-0,312**	0,228**	0,981**	-0,026**	-
PX	9,20E-05	3,80E-02	-4,60E-02	-	0,000**	0,088**	0,836**	0,099**	-
SASX-10	-3,80E-04	1,50E-01**	-	-	-0,240**	0,192**	0,987**	-0,025**	-
SAX	-2,60E-04	-1,20E-01**	-	-	0,000*	0,017**	0,969**	0,126**	2,364**
SBITOP	3,90E-05	1,90E-01**	-	-	0,000**	0,199**	0,697**	0,097**	-
SOFIX	1,70E-04	1,10E-01**	5,70E-02*	-	0,000**	0,243**	0,696**	0,096**	-
WIG20	4,00E-05	-	-	2,40E-02	-0,217**	0,133**	0,987**	-0,068**	-

Notes: ** denotes statistical significance at 1% level; * denotes statistical significance at 5% level. Estimations are carried out by EViews econometric software

Table 2 Heteroskedasticity Test: ARCH

Index	F-statistic	R-squared	Prob. F	Prob. Chi-Square
BELEX15	2,472	2,471	0,116	0,116
BET	3,594	3,591	0,058	0,058
BIRS	3,366	3,363	0,067	0,067
BUX	0,036	0,036	0,849	0,849
CROBEX	0,652	0,653	0,419	0,419
MBI10	1,537	1,537	0,215	0,215
MONEX20	2,575	2,574	0,109	0,109
PX	0,467	0,467	0,494	0,494
SASX-10	0,044	0,044	0,833	0,833
SAX	0,023	0,023	0,879	0,879
SBITOP	0,201	0,201	0,654	0,654
SOFIX	0,020	0,020	0,887	0,887
WIG20	2,375	2,374	0,124	0,123

Contrary to the findings of Shin (2005), Shields (1997), Murinde and Poshakwale (2001) and Kasch-Haroutounian and Price (2001) the estimation results revealed that the selected returns of the stock indices from Central and Eastern Europe could be much better characterized using asymmetric models. The present findings seem to be consistent with the research conducted by Alberg, Shalit and Yosef (2008), Égert and Koubaa (2004), Patev and Kanaryan (2003) and Bhaskar (2012).

In other words, the selected stock markets of transition economies exhibit asymmetry because negative shocks hit these markets much harder than positive news. As Égert and Koubaa (2004) have already pointed out, this corroborates the usual observation that emerging stock markets may collapse much more suddenly and recover more slowly than developed stock markets.

5. CONCLUSION

On the basis of the theoretical inferences and empirical evidence presented in this paper, it seems fair to suggest that ARIMA and GARCH processes provide parsimonious approximations of mean and volatility dynamics in the case of stock markets from the CEE region. The findings of this study suggest the existence of a leverage effect, meaning that in the case of stock markets from the CEE region negative shocks increase the volatility more than positive shocks.

Furthermore, we found evidence of stock market information inefficiency, since there is a strong chance that investors could use historical data to earn above average gains. Although further work is required to gain a more complete understanding of the relationship between stock returns and volatility in the CEE region, the main practical consequence of the results presented in this paper is that they could be a good starting point in decision making for those who are planning to invest in stock markets from the CEE region.

Since the nature of the return-volatility relationship is fundamental to the formulation of the concept of risk in various financial models, further research should shed some more light on the contemporary theoretical, methodological and applicative approaches for using these models when shaping investment strategy.

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(Endnotes)

[1] This common property refers to the fact that volatility of returns has various effects on positive and negative shocks.

[2] The MSCI market classification framework consists of following three criteria: economic development, size and liquidity as well as market accessibility. The MSCI Inc. (2013) provides an evaluation of the four market accessibility criteria, which are: (1) openness to foreign ownership; (2) ease of capital inflows/outflows; (3) efficiency of the operational framework and (4) stability of the institutional framework.

[3] FTSE Group (FTSE) is a global leader in indexing and analytic solutions. FTSE calculates thousands of unique indices that measure and benchmark markets and asset classes in more than 80 countries around the world. FTSE is wholly owned by London Stock Exchange Group.

[4] According to the FTSE Int. (2014) criteria for evaluating quality of market are: (1) the quality of regulation; (2) the dealing landscape; (3) custody and settlement procedures, and (4) the presence of a derivatives market would all be taken into account.

[5] In order to keep the data consistency we used October 2005 as a starting point while the base date for BELEX-15 was 1st October, 2005.