Abstract: - The main aim of this paper is to investigate the possibility of precise volatility modeling in the case of the regional emerging markets after the financial crisis. Focus is on the regions of the Eastern Europe, Balkans excluding Greece and Turkey, and Serbia. The research is conducted on Stoxx total benchmark indices: Stoxx Eastern Europe TMI, Stoxx Balkan TMI ex Greece & Turkey, as well as Belgrade stock exchange index Belexline.

Time series cover the period from the beginning of the 2010, until the end of March 2012. The conditional mean in the research follows simple ARMA models, while the conditional variance is modeled by several GARCH type models, where Gaussian and Student-t error distributions are assumed.

The purpose of the research is to examine if the stylized facts still can be identified in the observed time series after the period of the financial crisis. Also, the paper aims to test if the financial series possess the existence of leverage effect, as well as to test if the past price movements of observed financial series can be used for prediction of future movements by using look-forward neural network.

Key-Words: - Volatility modeling, GARCH models, neural network, Eastern Europe, Balkan, Serbia

1 Introduction


2 Problem Formulation

2.1 Observed data

The focus of the research is on the regions of the Eastern Europe, Balkans excluding Greece and Turkey, and Serbia. The research is conducted on Stoxx total benchmark indices: Stoxx Eastern Europe TMI (Stoxx E. Europe), Stoxx Balkan TMI ex Greece & Turkey (Stoxx Balkan), as well as Belgrade stock exchange index Belexline. The STOXX Eastern Europe Total Market Index (TMI) represents the Eastern European region as a whole, which covers approximately 95 percent of the free float market capitalisation of 18 Eastern European countries: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Macedonia (FYROM), Poland, Romania, Russia, Serbia, Slovak Republic, Slovenia, Turkey and Ukraine. The STOXX Balkan Total Market Index (TMI) ex Greece & Turkey Index is a regional subset of the Stoxx E. EuropeIndex, which covers approximately 95 percent of the free float market capitalisation of 18 Eastern European countries: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Macedonia (FYROM), Poland, Romania, Russia, Serbia, Slovak Republic, Slovenia, Turkey and Ukraine. The STOXX Balkan Total Market Index (TMI) ex Greece & Turkey Index is a regional subset of the Stoxx E. EuropeIndex, which covers Bulgaria, Croatia, Macedonia (FYROM), Romania, Serbia and Slovenia. Belexline is free float market capitalization positioned on the Belgrade Stock Exchange (BELEX), with a purpose to closely describe movements of the broad market. This index is not adjusted for paid dividends, and it is composed of shares traded on the BELEX markets.
Time series cover the period from the January 01. 2010 until the March 31. 2012. It represents approximately 600 observations per series.

2.2 Stylized facts and basic characteristics

The main aim of the first part of the paper is to examine the basic characteristics of observed financial time series. Empirically documented regularities of financial time series are the following:

- Volatility of the financial time series tends to cluster, which means that usually periods of low volatility are followed by periods of low volatility, and periods of high volatility are followed by periods of high volatility. This characteristic of the financial time series has its practical value in building models for volatility prediction.

- Mean reverting characteristic of volatility implies that financial time series have their own normal level of volatility, and it is expected that volatility will tend to return to that level.

- Heavy tails are well known characteristic, which implies that we can expect extreme values more frequently than we would expect if the financial time series followed normal distribution. Also, the distributions of these series are characterized by narrower and higher peaks.

- Asymmetric reaction to “good” and “bad” news implies that volatility of financial time series tend to react differently on positive and negative innovations. Usually, bad news generates greater volatility than good news, which is a phenomenon known in finance as “leverage effect”.

For the purpose of examining the stylized facts, we observed some basic statistics of the financial series, such as sample mean, standard deviation, skewness and excess kurtosis. Also we applied t-test in order to check if the mean returns are significantly different from zero, as well as Jarque-Bera [7] normality test:

\[ JB = \frac{\hat{S}^2(r)}{6/T} + \frac{[\hat{K} - 3]^2}{24/T} \]

The indicators \( \hat{S} \) and \( \hat{K} \) represent the sample skewness and excess kurtosis. H0 of normality should be rejected if the p-value of the JB statistic is lesser than the significance level.

For testing individual autocorrelation functions, we used Q(m)statistic from the test defined by Ljung and Box [8]:

\[ Q(m) = T(T + 2) \sum_{i=1}^{m} \frac{\hat{\beta}_i^2}{T - i} \]

The decision rule is to reject H0 if the p-value is lesser than the significance level.

All the tests are conducted at 5% significance level.

2.3 Volatility models

The conditional mean in the research follows simple ARMA models, while the conditional variance is modeled by two GARCH type models with assumed Gaussian and Student-t error distributions. The basic model is AR(1)-GARCH(1,1). In the mentioned model, conditional mean is modeled by the following formula:

\[ r_t = \phi_0 + \sum_{i=1}^{n} \phi_i r_{t-i} + \sigma_t \epsilon_t \sim N(0,1) \]

\( r_t \) is the index return, and \( \epsilon_t \) is a Gaussian innovation with zero mean and a conditional variance \( \sigma_t^2 \).

Conditional variance follows the GARCH model, introduced by Bollerslev [9]:

\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{n} \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^{n} \beta_i \sigma_{t-i}^2 \]

The coefficients \( \alpha_i \) and \( \beta_i \) are non-negative constants which measure the reaction of the particular volatility on market movements, and the persistence of volatility.

The main disadvantage of the standard GARCH model is the fact that it is not able to capture different impacts which good and bad news have on the volatility. Asymmetric reaction to “good” and “bad” news is known in financial series analysis as the “leverage effect”. In order to measure the leverage effect on the financial series, we used Threshold GARCH, also known as GJR GARCH introduced by Glosten et al [10]:

\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{n} (\alpha_i + \gamma N_{t-i}) \sigma_{t-i}^2 + \sum_{i=1}^{n} \beta_i \sigma_{t-i}^2 \]

The \( N_{t-i} \) is a dummy variable which identifies the “bad” news by taking the value 1, and the “good” news by taking the value 0. The positive coefficient \( \gamma \) indicates that “bad” news have stronger impact on volatility than “good” news, and vice versa.

The empirical results show that most of the financial time series is characterized with “fat tails”, which implies that we can expect extreme values more frequently than we would expect if the financial time series followed normal distribution. Therefore, apart from standard Gaussian distribution, the above described models are also tested with the Student-t distribution, which has heavier tails than standard normal distribution.

Decision on the most appropriate model is made by the Akaike information criterion (AIC) introduced by Akaike [11], and defined as:
\[ AIC = -\frac{2}{T} \ln(\text{likelihood}) + \frac{2}{T} (\text{no. of parameters}) \]

The coefficient \( T \) is the sample size, and the maximum-likelihood estimates are used to evaluate the likelihood function.

Finally, the linear logistic regression model is fitted for \( P (M_t=1) \) using \( M_{t-1}; S_{t-1}; M_{t-2}; S_{t-2} \) as input. The direction of Belexline movements is defined by:

\[
M_t = \begin{cases} 
1 & \text{for } r > 0 \\
0 & \text{otherwise}
\end{cases}
\]

The same principle is used for defining the directions of Stoxx indices movements. The main idea is to examine if past volatility movements of either the Belexline or regional Stoxx indices can predict the future Belexline volatility movement, in order to build the look-forward neural networks.

3 Obtained results

3.1 The basic properties

The basic statistics of the observed series are shown in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Belex</th>
<th>Balkan</th>
<th>E.Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nobs</td>
<td>603</td>
<td>621</td>
<td>621</td>
</tr>
<tr>
<td>NAs</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Minimum</td>
<td>-62.42</td>
<td>-4.66</td>
<td>-17.04</td>
</tr>
<tr>
<td>Maximum</td>
<td>64.79</td>
<td>3.6</td>
<td>14.34</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.70375</td>
<td>-0.0605</td>
<td>-0.062287</td>
</tr>
<tr>
<td>Median</td>
<td>-0.54</td>
<td>-0.03</td>
<td>0.15</td>
</tr>
<tr>
<td>Variance</td>
<td>87.12207</td>
<td>0.48167</td>
<td>11.661387</td>
</tr>
<tr>
<td>Stddev</td>
<td>9.333921</td>
<td>0.694024</td>
<td>3.414877</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.2202</td>
<td>-0.62913</td>
<td>-0.616781</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>9.598208</td>
<td>6.582617</td>
<td>2.327249</td>
</tr>
</tbody>
</table>

Table 1: Basic statistics of Belexline, Stoxx Balkan and Stoxx E. Europe indices.

All three series show some similar characteristics. The observed series are mean-reverting. The p-values of conducted t-tests shown in Table 2 indicate that the means of the observed series are significantly different from zero, except for the Stoxx Balkan.

The series are characterized with low excess kurtosis for Stoxx E. Europe index which is unusual for financial series, and very high kurtosis for Belexline and Stoxx Balkan indices. The results of Jarque-Bera normality tests from Table 2 confirm the above conclusion, rejecting the hypothesis of normality in series distributions. The leptokurtic distributions characterized by “fat tails”, very high kurtosis and narrower and higher peak comparing to normal distribution is also evident from the Figure 2.

Fig. 1: Distributions of Belexline, Stoxx Balkan and Stoxx E. Europe indices comparing to normal distribution.

All three series show the evidence of the existence of the autocorrelation. Conducted Ljung-Box tests imply that the \( H_0: \rho_1 = \rho_2 = \ldots = \rho_m = 0 \) has to be rejected at 5% confidence level (results in Table 2).

<table>
<thead>
<tr>
<th>Test</th>
<th>Test value</th>
<th>Belex</th>
<th>Balkan</th>
<th>E.Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-test</td>
<td>test statistic</td>
<td>-1.851</td>
<td>-2.172</td>
<td>-0.455</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.065</td>
<td>0.030</td>
<td>0.650</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>X-squared</td>
<td>2339.801</td>
<td>1172.914</td>
<td>181.784</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Ljung-Box</td>
<td>X-squared</td>
<td>33.720</td>
<td>4.828</td>
<td>8.562</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.000</td>
<td>0.028</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Table 2: Results and p-values of t-test, Jarque-Bera and Ljung-Box tests.
The results presented in the Table 3 indicate the much stronger correlation between Belexline and Stoxx Balkan indices, than the one between Belexline and Stoxx E. Europe indices, which is not a surprise. Also, data from the table indicate that Stoxx Balkan is more correlated to Stoxx Balkan, which can be indicator of market movements, but also could be due to similarity of the Stoxx Balkan and Stoxx E. Europe indices methodologies.

<table>
<thead>
<tr>
<th></th>
<th>Pearson</th>
<th>Kendall</th>
<th>Spearman</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belex/ Balkan</td>
<td>0.407</td>
<td>0.226</td>
<td>0.314</td>
</tr>
<tr>
<td>Belex/ E.Europe</td>
<td>0.214</td>
<td>0.090</td>
<td>0.133</td>
</tr>
<tr>
<td>Balkan/ E.Europe</td>
<td>0.562</td>
<td>0.326</td>
<td>0.461</td>
</tr>
</tbody>
</table>

Table 3: Correlation between Belexline, Stoxx Balkan and Stoxx E. Europe indices (calculated by Pearson, Kendall and Spearman methodology).

### 3.2 Fitted models

As it is mentioned before, the conditional mean in the research follows AR(1) model, while the conditional variance is modeled by GARCH(1,1) and TGARCH(1,1) models with assumed Gaussian errors distribution, as well as with Student-t distribution, since the observed series mainly showed the fat tails properties. The coefficients of the fitted models are shown in Table 5.

It is noticeable that the mean equation in all the series is fitted with AR(1) model, characterized with statistically significant but low $\phi_1$ coefficients. This implies that the series have weak, but statistically significant autocorrelation.

The Ljung-Box test conducted on squared AR(1) model residuals shows the evidence of heteroskedasticity. For that reason, GARCH and TGARCH models are fitted. All the models satisfy the stationarity constraints, since the sum of the coefficients $\alpha$ and $\beta$ is lesser than 1 in every observed model. The coefficient $\alpha$ measures the volatility reaction on market movements. Since $\alpha$ coefficient has relatively low and similar value in all three series, we do not expect "spiky" diagram of returns, and we can conclude that the conditional volatilities of observed series show similar reaction and persistence. The coefficient $\beta$ in the variance equation measures the persistence of volatility. Higher values for this coefficient in Stoxx Balkan and Stoxx E. Europe indices imply that innovations to conditional variance will take longer to die out. Belexline index shows the evidence of lesser persistence. The other necessary and sufficient conditions for the existence of the second moment of $\varepsilon_t$ for GARCH(1,1) model are satisfied for Belexline and Stoxx Balkan indices, but Stoxx E. Europe doesn’t have the required leptokurtic distribution.

The coefficient $\gamma$ obtained form the TGARCH model didn’t show required statistical significance neither for Belexline nor Stoxx E. Europe indices, which implies that those indices do not show the proof of the “leverage effect”. That means that volatility of observed markets is not impacted by asymmetric information, which is not common for the financial markets. Examining the Stoxx Balkan index, we can find evidence of stronger influence of “bad” news at 5% significance level for GARCH, and 10% significance level for TGARCH model.

Models based on Student-t distribution usually better fit the data obtained from financial time series, since the extreme returns in those series occur more frequently than implied by a normal distribution. The AIC criteria showed that in our research, GARCH and TGARCH models based on Student-t distribution performed slightly better.

The table 4 shows the coefficients of the fitted logistic linear regressions.

<table>
<thead>
<tr>
<th></th>
<th>Belexline/Stoxx Balkan</th>
<th>Belexline/Stoxx E. Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-0.6206 ***</td>
<td>-0.56533 **</td>
</tr>
<tr>
<td>Mt[2:600]</td>
<td>0.2839</td>
<td>0.38692 *</td>
</tr>
<tr>
<td>St[2:600]</td>
<td>0.4616 **</td>
<td>0.23785</td>
</tr>
<tr>
<td>Mt[1:599]</td>
<td>0.2427</td>
<td>0.27463</td>
</tr>
<tr>
<td>St[1:599]</td>
<td>0.0916</td>
<td>0.03404</td>
</tr>
</tbody>
</table>

Table 4: The coefficients of the fitted logistic linear regresion, Belexline/Stoxx Balkan and Belexline/Stoxx E. Europe

Since both logistic linear regressions have statistically significant coefficients at 5% level, it is evident that direction of Belexline index is predictable by both Stoxx Balkan and Stoxx E. Europe indices. Therefore, we used the obtained coefficients to build a 4-2-1 look-forward network with direct link for $P(M_t=1)$:

$$M_t=1 \text{ if } -0.48-3.95h_1+1.63h_2+0.70M_{t-1}-0.18S_{t-1} - 0.47M_{t-2} - 0.69S_{t-2}. $$
Table 5: The coefficients of fitted AR(2)-GARCH(1,1) and AR(2)-TGARCH(1,1) models, with Gaussian and Student-t distributions

### 4 Conclusion

The main aim of this paper was to investigate the characteristics and possibilities of volatility modeling after the financial crisis in the case of Stoxx Eastern Europe TMI, Stoxx Balkan TMI ex Greece & Turkey and Belexline indices. The research covered the period from the beginning of the 2010 until the end of March 2012, using AR(1)-GARCH(1,1) and AR(1)-TGARCH(1,1) models, both with standard Gaussian and Student-t distributions. Finally, we examined the predictability of the Belexline movements based on both its own past movements, as well as past market movements. We came to the following conclusions:

- Belexline, Stoxx Balkan and Stoxx E. Europe complied with most of the stylized facts: all series are mean-reverting, with clustering volatility and heavy tails. Belexline and Stoxx Balkan also have the leptokurtic distributions. The evidence of the “leverage effect” is found only in Stoxx Balkan index.

- It is possible to model the volatility with simple AR(1)-GARCH(1,1) or AR(1)-TGARCH(1,1) models. The best results for the Belexline and Stoxx E. Europe indices are achieved by fitting AR(1)-GARCH(1,1) model with Student-t distribution. For Stoxx Balkan index the model AR(1)-TGARCH(1,1) with Student-t distribution is better suited, since there is the evidence of the “leverage effect”.

- The direction of Belexline index is predictable by both Stoxx Balkan and Stoxx E. Europe indices. For the purpose of prediction, a 4-2-1 look-forward network can be used.

For the future research, it would be interesting to test “day-of-the-week” as well as “month-of-the-year” effects. Some former researches showed that there is no evidence of these effects on the regional merkets, so we think that it would be interesting to check if those results still stand. Also, it would be interesting to test some other types of GARCH models, as well as to test their out-of-the-sample predictability.
References:


