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TESTING THE APPLICABILITY OF THE BRW APPROACH AT EMERGING STOCK MARKETS

In this paper the authors examine the performance of the historical simulation (HS) and the Boudoukh, Richardson and Whitelaw (BRW) approaches to VaR estimation at the selected emerging markets of the EU candidate states and potential candidate states. The aim of this paper is to examine the performance of the BRW approach in real market conditions to answer the question whether the BRW approach represents a significant improvement of the HS approach, as expected on the basis of theoretical analysis.

Keywords: *value-at-risk, historical simulation, time weighted simulation, emerging markets.*

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ЗАСТОСУВАННЯ МОДЕЛІ БУДУХА-РІЧАРДСОНА-УАЙТЛОУ ДО ФОНДОВИХ РИНКІВ, ЩО РОЗВИВАЮТЬСЯ

У статті розглянуто ретроспективне моделювання (РМ) і модель Будуха-Річардсона-Уайтлоу (БРУ) як підходи до оцінювання ризикової вартості на ринках країн-кандидатів в ЄС і потенційних країн-кандидатів. Вивчено ефективність підходу БРУ в реальних ринкових умовах, доведено переваги цього підходу над РМ, виявлених на основі теоретичного аналізу.

Ключові слова: *ризикова вартість, ретроспективне моделювання, моделювання з часовою корекцією, ринки, що розвиваються.*
Таб. 5. Літ. 13.

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ПРИМЕНЕНИЕ МОДЕЛИ БУДУХА-РИЧАРДСОНА-УАЙТЛОУ К РАЗВИВАЮЩИМСЯ ФОНДОВЫМ РЫНКАМ

В статье рассмотрены рестроспективное моделирование (РМ) и модель Будуха-Ричардсона-Уайтлоу (БРУ) как подходы к оценке рисковой стоимости на развивающихся рынках стран-кандидатов в ЕС и потенциальных стран-кандидатов. Изучено эффективность подхода БРУ в реальных рыночных условиях, выявлены преимущества подхода БРУ над РМ, обнаруженных на основе теоретического анализа.
Ключевые слова: *рисковая стоимость, ретроспективное моделирование, моделирование со временной коррекцией, развивающиеся рынки.*

Introduction. Over the last 2 decades, the concept "value-at-risk" has become a widely accepted instrument of risk management in banks and other financial institutions. Within the concept numerous methods are developed, but of all them, historical simulation (HS) is singled out by its popularity. The basic idea behind HS is that the movement of risk factors in previous periods contains all necessary information to estimate the value at risk. This method to estimate VaR is extremely convenient for markets, where is observed the occurrence of fat tails and the matrix of correlations between assets are unstable and subject to rapid change, such as emerging markets.

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Despite the advantages over the parametric methods and Monte-Carlo simulation approach, the HS approach is not an ideal solution for measuring market risk at emerging markets characterized by time varying volatility. Many empirical researches show that the stock market volatility of emerging markets changes in time. Large changes, tend to be followed by large changes and small changes tend to be followed by small changes. These circumstances are troubling for all VaR approaches based on IID assumption, such as the HS approach.

In order to eliminate the shortcomings of the HS approach, to capture time-varying volatility and retained its advantages in terms of fat tails, the BRW approach was developed by Boudoukh, Richardson and Whitelaw (1998). This approach represents a combination of two most widespread approaches to VaR estimation: the HS approach and the exponential smoothing approach to VaR estimation. In theory, the BRW approach eliminates the listed shortcomings of the HS approach. However, the empirical simulations do not show significant improvement as conducted by Pritsker (2001). Therefore, the aim of this paper is to examine the performance of the BRW approach under real market conditions, on the example of emerging markets that are characterized by high volatility and time-varying volatility.

The paper is organized as follows: The first section contains the introduction. The following section gives an overview of the most significant recent empirical research in the area of VaR models. Section 3 presents the theoretical background of the BRW approach. Section 4 provides a brief description of the analyzed data, methodology used and descriptive statistics of the selected emerging markets. In section 5 the backtesting results for tested models are presented, their performances are analyzed and the implications are discussed. The final section summarizes the conclusions.

Literature review. There is an abundance of studies testing various model based on the HS approach to VaR estimation, that can be classified in 2 groups: the first group consists of the studies examining the performance of various models of HS approach to VaR estimation, and the second group includes the studies that provide comparative analysis of the performances of the HS models with parametric methods to VaR estimation and Monte Carlo simulation.

The earliest research on validity of the applicability of the HS approach was conducted by Allen (1994). Allen compared the performance of the HS and variance-covariance approaches. Similar research was conducted by Crnkovic and Drachman (1997). Beder (1995) examine the HS approach to VaR estimation and argued that estimates of VaR depend don the parameter under which the models are set up. To similar observations came Hendricks (1996). He found that confidence level has very important impact on the HS approch validity. Standard error of the HS models arises as increasing to the confidence level. Schinassi (1999) criticized all the approaches toVaR estimation noting that it depends on historical relationships between price movements at many markets and they tend to break down during times of stress and turbulence when there are structural breaks in relationships across markets. A similar point has been made by Danielsson (2000). Examining traditional approaches, such as risk metrics, HS and Monte-Carlo simulation and their variants which are integrated with various ARCH models and various distributions and VaR models based on extreme value theory (EVT), Lee and Saltoglu (2001) showed that the HS approach generated accurately VaR estimates than the models based on EVT at the selected emerging markets (Indonesia, Korea, Malaysia, Taiwan, and Thailand). Opposite findings were documented by Samanta et al. (2010). They found that various HS models produce better VaR estimates than VaR models based on the risk metrics methodology at selected emerging markets, but produce poorer VaR estimates than VaR models based on EVT.

Although there is an abundance of papers examining the performance of the HS approach, few of these papers deal with BRW approach, especially at emerging markets. The most important studies are conducted by Boudoukh, Richardson and Whitelaw (1998), Prikisten (2001) and Zikovic (2010). Boudoukh, Richardson and Whitelaw (1998) tested the performance of the BRW approach and found that it performs better than the two competing approaches, EXP and HS, and at the same time produces independent VaR errors. Zikovic (2007) found that BRW simulation with decay factor set to 0.99 is superior to HS for a range of confidence levels in small and illiquid markets of the EU candidate states. Pritsker showed that the BRW approach and the HS approach adjust slowly to changes in the true level of risk. He concluded that correlation of VaR estimates with the true VaR is fairly high for BRW simulation in contrast to historical simulation.

A theoretical background of the BRW approach. The principle feature of the HS approach is that it does not make any assumptions on the theoretical distribution of data, but is based on the view that the current distribution of portfolio's P&L can be simulated by making draws from the historical time series of past changes of risk factors that determine the value of current portfolio. Only assumption that should be made using the HS approach is that the distribution of returns in the observation period will be identical to the distribution of future returns. Hence, the use of the HS approach makes sense if it is expected that the near future will be similar to the recent past. In order to this assumption be satisfied, we needs to provide a sufficient amount of data (about 34 years of monthly data). The use of very long observation periods, not only that increases the risk of involvement of market events that are irrelevant to the current volatility clustering, but also reduces the value of recent information. This makes a problem of adequate capture of the current volatility. In addition, long observation periods potentially violate the assumption of IID observations.

The problem of adequate capture of the current volatility is hidden in the procedure of the HS approach. The empirical density building for the portfolio's P&L, the HS approach assigns equal probability weight of 1/N (N — number of observations) to each observation (day's return). In doing so we lose the insight that the informativeness of historical data regarding the conditional distribution of current returns diminishes in time, and we accept that any observation has a constant influence on VaR estimate during sampling period. This means that observation, which is only one day older than the VaR estimates, has the same influence on the VaR estimate as the observation from beginning of the observation period, while the observation, which is one day older than this (first) observation, has no influence on the VaR estimate. There is no theoretical explanation for this. Additional problem that arises on this way of weighting is "ghost effect". It is a phenomenon of extreme losses that occurred in the distant past, continuously influencing the VaR estimate because they are used long period of time in the historical simulation and then suddenly their influence fall out when they disappear from the observation period.

According to Pritsker (2001), this way of weighting is equivalent to assuming that risk factors, and hence the historically simulated returns are independently and identically distributed (IID) in time. The assumption, which is hidden behind the procedure of the HS approach, limits the applicability of the HS approach, because it is known that the volatility of asset returns tends to change through time, and that periods of high and low volatility tend to cluster together. Hence a more realistic setting, which violates the IID assumption, would be that returns from the recent past better represent today portfolio's risk than returns from more distant past. Based up on this setting new approach was developed by Boudoukh, Richardson, Whitelaw (1998), BRW hereafter, which assigns a relatively higher amount of probability to returns from more recent past. The BRW approach combines 2 approaches to VaR estimation: the HS approach and the exponential smoothing approach to VaR estimation, using exponentially declining probability weights to past returns of a portfolio. In another words, the BRW approach represents time weighted simulation approach.

The implementation of the BRW approach is very simple, similar to the implementation of the HS approach. To each of the most recent (k) returns of the portfolio: R(N), R(N-1),..., R(N-k.+1), assign a weight $[(1-\lambda)/(1-\lambda^k)]$,... $[(1-\lambda)/(1-\lambda^k)]$ λ^k-1, respectively, where λ is decay the factor. Note that the constant $[(1-\lambda)/(1-\lambda^k)]$ simply ensures that the weights sum to be one. After the probability weights are assigned, VaR is calculated from the empirical cumulative distribution function weighted of returns whit modified probability weights. Precisely, approximation of the VaR at the specific confidence level is made from empirical cumulative distribution function of (R) based on the return observations $R_{t-1},...,R_{t-N}$.

The HS approach is a special case of the BRW approach in which the decay factor (λ) is set equal to one. The main difference between these 2 approaches is the specification of the quantile process. Under the HS, each return is given the same weight, while in the BRW approach assigns different weights to the returns depending on the date of their occurrence. Hence, the HS estimate of VaR at a specific confidence level (cl) corresponds to the N(1-cl) lowest observation (return) in the N period rolling sample, an example at the 1% confidence level VAR using 250 daily returns (N = 250) corresponds to the third lowest observation, while in the BRW the exact observation depends on whether the extreme low returns were observed recently or further in the past.

In theory, although it is a slight improvement, combination of the HS approach with the EXP approach solves the HS problem of slow respond to new extreme low returns (crash). The reason why the HS approach to VaR estimate has almost no response to the crash is in the process of equal probability weight of 1/N. Recall, the HS estimate of VaR at a specific confidence level (cl) corresponds to the N(1-cl) lowest return in the N period rolling sample. Because a crash is the lowest return in the N period sample, the N(1-cl) lowest return after the crash, turns out to be the (N(1-cl)-1) lowest return before the crash. If those two lowest returns happen to be very close in magnitude, the crash actually has almost no impact on the HS estimate of VaR. Thanks to using exponentially declining probability weights to past returns of the portfolio, the BRW approach should respond immediately to crash. On the day after crash, the VaR estimate for the BRW approach should increase very substantially, in fact, VaR rises in magnitude to the size of the crash itself. The reason that this occurs is simple. In the BRW approach, the most recent observation receives probability weights of just over 1% for decay factor of 0.99 and of just over 3% for the decay factor of 0.97, (this values are taken as standards for the decay factor), under the condition that (the most recent observation) it is the lowest return in the N period sample, in both cases, it automatically becomes the VaR estimate at the 99% confidence level. Hence, the BRW approach appears to remedy one of the main problem of the HS approach, since very large losses are immediately reflected in VaR forecasts. In theory, the proposed solution is a reasonable trade off between statistical precision and adaptiveness to recent news.

The question that arises is the extent to which estimates of VaR, based on the BRW approach, respond to changes in the underlying riskness of the environment, or what is the probability that a VaR estimate, which is correct today, will increase tomorrow. According to proposition suggested by Pritsker (2001), under the assumption that today's VaR estimate for tomorrow's return is conditionally correct, but that risk changes with returns, so that tomorrow's return will influence risk for the day after tomorrow, the answer is that tomorrow's VaR estimate will not increase with probability (*1-cl*). This means if the confidence level is 1%, then a VaR estimate that is correct today will not increase tomorrow with the probability of 99%. Generally speaking, the procedure shows that when losses at time (t) are bounded below by the BRW VaR estimate at time t, then the BRW VaR estimate for time t+1 will indicate that risk at time t+1 is no greater than it was at time (t).

Unfortunately, many empirical simulations show that the BRW approach does not behave as expected based on the procedure behind (basically) the BRW approach. The empirical simulations show that the BRW model is slow to respond changes in risk. The consequences of this are that VaR estimates are not very accurate. In addition, in the case of short portfolio BRW does not respond to the crash despite the fact there was a significant increase in risk. The reason for this is that the BRW based on nonparametrically estimating the left tail of the P&L distribution and implicitly assume that whatever happens in the right tail of the distribution contains no information on the left tail of P&L. That is why the BRW approach is enable to associate increases in returns with increases in total risk in case of a short portfolio. Since the updates are risk based on movement in the portfolio's P&L and not on the price of financial instruments, the BRW approach can respond to asymmetry between conditional volatility and portfolio returns in a wrong way.

Data analysis. The data used in the performance analyses of the HS and the BRW approaches are the daily returns of stock indices of the EU candidate states and potential candidate states, i.e. Croatia, Serbia, Bosnia and Herzegovina, Montenegro, Macedonia, and Turkey. The tested stock indices are BIRS, MBI10, MONEX20, BELEXline, CROBEX and UX100. For emerging markets, such as those of the EU candidates and potential candidate, a significant problem for a serious and statistically significant analysis is the short histories of their market economies and active trading at stock markets. The short time series of returns of individual stocks and their highly variable liquidity are the reasons for analyses of the stock indices of these countries. The returns are collected from each official stock exchange web site for the period 2.2.2009 - 2.2.2012. with the total number of observations of 753. The data covers the periods of varying volatility patterns observed in the EU.

The calculated VaR figures are for a one-day ahead horizon and 95 and 99% confidence levels. The confidence levels of 95 and 99% have been selected, having in mind the basic characteristics of the VaR calculation, that the 95% confidence level is appropriate for application in stable market conditions, while the 99% confidence level is appropriate for application in volatile market conditions. As the representative of the HS approach, HS500 model has been used, while for the BRW approach, BRW500 models with decay factors of 0.97 and 0.99 has been applied. To secure the same out-of-the-sample VaR back testing period for all the tested stock indices, the out-of-the-sample data sets were formed by taking out 253 of the latest observations for each stock indices. The rest of the observations were used as resample observations needed for the VaR starting values.

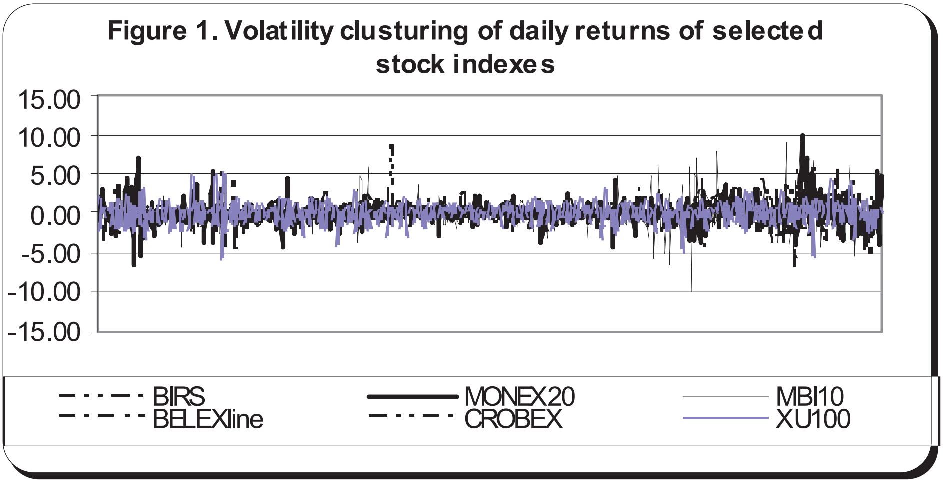
At the beginning of the analysis, we have analyzed the characteristics of the selected markets in the entire period of observation, in order to convince ourselves that these markets represent a good basis for testing the BRW approach to answer the question whether BRW approach represents a significant improvement of HS approach, as can be expected from the theoretical analysis. The HS approach provides reasonable VaR estimates at developed markets. However, emerging markets have their own peculiarities that need to be taken into account. Analysis of characteristics of the selected market is done based on the selected stock indices, because they represent the best approximation of the market portfolio in these countries. As it is known, the degree of development and characteristics of the market are represented by market portfolio. Since it is possible to construct a market portfolio, the analysis was based on these selected stock indices.

Table 1 gives a summary of the descriptive statistics and normality test for the entire analyzed sample for all the stock indices. Descriptive statistics of selected stock indices confirm the results of recent studies. The stock indices have a large difference between theirs maximum and minimum returns. The standard deviations are also high, indicating a high level of fluctuations of daily returns. The analysis of the distribution of selected stock indices returns show that stock indices have far fatter tails than assumed under normality ranging from 2.4 (XU100) index to 9.3 (in case of the MBI 10). In other words, all the analyzed stock indices show significant leptokurtosis. Skewness of all the stock indices is significantly different from zero, which indicates that the stock indices have asymmetric returns.There is also evidence of negative skewness in case of the XU100, which means that the left tail is particularly extreme. In order to formally examine whether returns follow normal distribution, we employed the Jarque-Bera test. The value of this test indicates that we should reject the null hypothesis of normality providing the evidence that the return series are not normally distributed.

Table 1. **Descriptive statistics of the selected emerging markets**

	BIRS	MONEX20	MBI10	BELEX*line*	CROBEX	XU100
Mean	-0.01595	0.00081	-0.00800	0.00313	0.00734	0.01181
Standard Dev.	0.74925	1.43753	1.54785	1.05578	1.32456	1.18405
Sample Variance	0.56138	2.06650	2.39584	1.11466	1.75446	1.40196
Kurtosis	5.24368	7.62009	9.28806	3.78256	6.77766	2.47085
Skewness	0.10091	1.14415	0.77569	0.42647	0.48361	-0.18281
Jerque-Bera test	159.22	834.00	1312.57	42.04	477.10	12.98
P – value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00152

Source: Authors' calculations.



Source: Authors' calculations

Figure 1 exhibits clustering and time varying volatility at these markets. Statistically, volatility clustering implies a strong autocorrelation in returns. These findings are confirmed by ACF, PACF and Ljung Box Q-statistics. To test the presence of the ARCH effects, we used a Lagrange multiplier for ARCH(1) model. The results of these tests, for each of the selected stock indices, are presented in Tables 2 and 3 in Appendix.

Given the theoretical basis of both HS and BRW approaches, as well as characteristics of the selected markets, we can conclude that the selected markets are a good basis for testing the BRW approach.

For each analyzed stock index, VaR estimates were performed on the following way: First, we estimated the one-day aheaded horizon VaR using the returns from the first 500 days. In that way we obtained VaR estimate for day 03.02.2011 (estimate VaR for the 501st day in the observed period). Then, for the next day, 04.02.2011, we used the returns for past 500 days (covering the period from the 2nd to the 501st days). Actually, in that way we got estimate VaR for the 502nd day in the observed period. The process is repeated for all 253 days and obtained 253 VaR estimates for period 28.01.2011 to 02.02.2012.

Backtesting results. In this section the back testing results for the tested models are presented, analyzed and discussed. Tested VaR models were evaluated in terms of their accuracy in estimating VaR over last 253 days in the observed period. We called this period the backtesting period. Each model was tested as follows: first, the daily

VaR estimates were compared with the actual losses that occurred in the backtesting period. In the case where actual loss on a particular day exceeds VaR estimate for that day, we conclude that VaR break occurred. Then, count the number/percentage of VaR breaks over the back testing period of 253 days. According to Jorionu (2001), for good model percentage of VaR breaks should be equal to the same as one minus the level of confidence. In our case, this means that we should expect that the number of VaR breaks not to be more than 3 at the 99% confidence level (1% of the total number VaR estimates), or not more than 13 VaR breaks at the 95% confidence level (5% of the total number of VaR estimates).

The number/percentage of VaR breaks over the backtesting period, separately for each of the tested VaR models, for each of the selected stock indices, is given in Table 4. As can be seen in it, percentages of VaR breaks of the tested models are higher than the theoretical values. The exceptions are in the case of the HS500 model at the confidence level of 99% in case the MBI10 stock index, the HS500 model at the confidence level of 95% in the cases of the MBI10 stock index and the BELEXline stock index and the BRW500 model with the decay factor of 97% at the confidence level of 95% in the cases of the MBI10 stock index, the BELEXline stock index and the CROBEX stock index and the BRW500 model with the decay factor of 99% at the confidence level of 95% in the case MBI10 stock index. These higher than expected frequencies of VaR breaks mean that both HS and BRW approaches underestimate VaR figures and they are slow to respond to changes in the underlying riskiness of the environment. The worst performers are the BRW500 model with decay factor of 99% and the BRW500 model with the decay factor of 99%, at a confidence level of 99%. According to Jorion's criteria, every tested VaR model was successful in predicting risk at least one stock index, except the BRW500 model with the decay factor of 99% and the BRW500 model with the decay factor of 99% at the confidence level of 99% BRW500 model showed best performances, with the decay factor of 97% at the confidence level of 95%, which proved successful in predicting risk in cases of 3 of the 6 selected emerging markets, and in the cases of the BELEXline, the CROBEX and the MBI10.

Table 4. **The number/percentage of VaR breaks over the backtesting period**

	HS500 99%VaR		**HS500 95%VaR**		**BRW500 with decay factor 99% 99%VaR**		**BRW500 with decay factor 97% 99%VaR**		**BRW500 with decay factor 99% 95%VaR**		**BRW500 with decay factor 97% 95%VaR**	
Stock index	No. of breaks	%	No. of breaks	%	No. of breaks	%	No. of breaks	%	No. of breaks	%	No. of breaks	%
BIRS	11	4.35	28	11.07	6	2.37	6	2.37	20	7.91	18	7.11
MONEX 20	6	2.37	15	5.93	6	2.37	8	3.16	18	7.11	17	6.72
MBI10	1	0.40	8	3.16	3	1.19	4	1.58	12	4.74	11	4.35
BELE-Xline	4	1.58	12	4.74	3	1.19	6	2.37	16	6.32	12	4.74
CRO-BEX	4	1.58	16	6.32	4	1.58	3	1.19	13	5.14	12	4.74
XU100	3	1.19	21	8.30	3	1.19	4	1.58	16	6.32	16	6.32

Source: Authors' calculations.

In order to see whether the % of VaR breaks associated with tested VaR models can be considered as equal to the theoretical values, we employ the Kupiec's test. This test is usually used to identify VaR models acceptable to the regulators, and provide the desired level of safety to individual banks and, due to contagion effect, to the entire banking sector (Zikovic, 2010). The idea behind this test is that frequency of VaR breaks should be statistically consistent with the probability level for which VaR is estimated. We use the Kupiec's test at 5% significance level for the tested VaR models, because the significance level of this magnitude gives the model a certain benefit of doubt, and implies that we would reject the model only if the evidence against is reasonably strong.

The Kupiec test backtesting results, at the 5% significance level, for the tested VaR models at the 95 and 99% confidence levels are presented in Table 5. As can be seen there, the hypothesis that the percentage of VaR breaks is equal to the theoretical value could not be accepted in the cases of the HS500 model at the confidence levels of 95 and 99% in the case of the BIRS stock index, the model HS500 at the confidence level of 95% in the case of XU100 stock index, the BRW500 model with the decay factor of 97% at the confidence level of 99% in the case of the MONEX20 stock index and BRW500 model with the decay factor of 99% at the confidence level of 95% in the case of the BIRS. The worst performers according to the Kupiec test, out of the tested VaR models, are the HS500 model at the confidence level of 95%, followed by HS500 at the confidence level of 99%, BRW500 model with the decay factor of 97% at the confidence level of 99% and BRW500 model with the decay factor of 99% at the confidence level of 95%, all of which failed the test for one out of 6 tested indices, except the HS500 model at the confidence level of 95% failed the Kupiec test for 2 of 6 tested indices. The best performer according to the test at the confidence level of 99% across the stock indices of the EU candidates and potential candidates is BRW500 model with the decay factor of 99%. It was successful in all of the selected stock indices. The best performer according to the Kupiec test at the confidence level of 95% across the stock indices of the EU candidate states and potential states is BRW500 model with the decay factor of 97%. Also, this model satisfies the Kupiec's test in all the tested stock indices.

Table 5. **Kupiec test backtesting results at the 5% significance level, period 28.01.2009 02.02.2012**

	HS500 99%VaR		**HS500 95%VaR**		**BRW500** whith decay factor of **99% 99%VaR**		**BRW500** whit decay factor of **97% 99%VaR**		**BRW500** whit decay factor of **99% 95%VaR**		**BRW500** whit decay factor of **97% 95%VaR**	
Stock index	critical value	p-value	critikal value	p value	Critical value	p-value	Critical value	p-value	Critical value	p-value	Critical value	p-value
BIRS	15.68258	0.00007	14.79654	0.00012	3.47077	0.06246	3.47077	0.062462	3.85009	0.04974	2.11770	0.14560
MONEX20	3.47078	0.06246	0.434841	0.50962	3.47077	0.06246	7.59989	0.00584	2.11770	0.14560	1.42811	0.23207
MBI10	1.21289	0.27076	2.057937	0.15141	0.08324	0.77295	0.73324	0.391833	0.03574	0.85004	0.23653	0.62671
BELEX line	0.73324	0.39183	0.03574	0.85004	0.08324	0.77295	3.47077	0.062462	0.86471	0.35242	0.03574	0.85004
CROBEX	0.73324	0.39183	0.864719	0.35242	0.73324	0.39183	0.08324	0.772953	0.01010	0.91992	0.03574	0.85004
XU100	0.08324	0.77295	4.881845	0.02714	0.08324	0.77295	0.73324	0.391833	0.86471	0.35242	0.86471	0.35242

Source: Authors' calculations

However, although it is very informative to look at VaR model performance at different confidence levels, the true test of VaR model acceptability to regulators is its' performance at the 99% confidence level, as prescribed by the Basel Committee (Zikovic, 2007). According to the Basel Committee's backtesting criteria, we can conclude that BRW approach provides better performances than the HS approach in the cases of emerging markets, but we can not argue that the BRW approach provides significant improvement of the HS approach.

Conclusion. By the given results of this research and the market characteristics in which the research was conducted, it can be concluded that the BRW represents the HS approach improvement to some degree. More precisely, we found small advantages of using the BRW approach with the standard decay factor values of 0.97 and 0.99 over the HS approach. This conclusion is confirmed by the results of the Kupiec's test. However, we need to be careful accepting this conclusion because of the limitations of the Kupiec's test. The test proposed by Kupiec provides only an unconditional assessment as it simply counts breaks over the entire backtesting period. In the presence of time varying volatility, the conditional accuracy of VaR estimates assumes importance. In such cases, the Kupiec's test has limited use as it may classify inaccurate VaR as acceptably accurate. Since the intent was to review the performance of the HS and the BRW approach in accordance with the Basel rules, other tests weren't used in this study for evaluation of the accuracy of VaR models, only Kupiec's test that complies with the requirements of Basel II.

Although the BRW approach suffers from the explained logical inconsistency, this approach still represents a significant improvement over the HS approach, since it drastically simplifies the assumptions needed in the parametric models and it incorporates a more flexible specification than the HS approach.

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Appendix:

Table 2. **AFC, PACF, Q-statistics for the seleted stock indices**

	MBI10 Index				CROBEX Index			
Lag	**ACF**	**PACF**	**Q-Stat**	**Prob**	**ACF**	**PACF**	**Q-Stat**	**Prob**
1	0.11701	0.11701	10.32272	0.00131	0.12141	0.12141	11.14453	0.00084
28	-0.05421	-0.05443	57.46837	0.00085	-0.01256	0.00282	44.49713	0.02479
	BIRSIndex				**MONEX20 Index**			
Lag	**ACF**	**PACF**	**Q-Stat**	**Prob**	**ACF**	**PACF**	**Q-Stat**	**Prob**
1	0.12966	0.12966	12.70902	0.00036	0.18431	0.18431	25.68277	0.00000
28	-0.02758	-0.02808	52.10121	0.00373	-0.04108	-0.04301	98.99281	0.00000
	XU100 Index				**BELEXline Index**			
	ACF	**PACF**	**Q-Stat**	**Prob**	**ACF**	**PACF**	**Q-Stat**	**Prob**
1	-0.11232	-0.11232	9.53692	0.00201	0.34403	0.34403	89.47562	0.00000
28	-0.04829	-0.05661	47.09518	0.01339	-0.11018	-0.06755	244.79192	0.00000

Source: Authors' calculations.

Table 3. **Lagrange Multiplier for ARCH(1) model for selected stock indices**

	BIRS	**MONEX20**	**MBI10**	**BELEX*line***	**CROBEX**	**XU100**
Lagrange Multiplier	752.772	74.9276	10.384	158.3463926	8.084225	26.0671571
p-value	1E-165	4.883E-18	0.00127	2.59988E-36	0.004465	3.2975E-07

Notice: 95% confidence level.
Source: Authors' calculations.

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