Measuring Market Risk in EU New Member States

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Abstract

The author in this paper examines different ways of calculating VaR in transitional economies of EU new member states. Majority of the EU new member states are all exposed to very similar processes of strong inflow of foreign direct and portfolio investments, and offer possibilities of huge profits for investors. These countries represent a very interesting opportunity for foreign and domestic banks, investment funds, pension funds, insurance companies and other investors. Banks and investment funds when investing in these financial markets employ the same risk measurement models for measuring market risk and forming of provision as they do in the developed markets. This means that risk managers in banks operating in EU new member states de facto presume similar or even equal characteristics and behaviour in these markets, as they would expect in developed markets. Using the VaR models, that are created and suited for developed and liquid markets, in developing markets raises a serious dilemma: Do the VaR models developed and tested in the developed and liquid financial markets apply to the volatile and shallow financial markets of EU new member states? Do the commonly used VaR models adequately capture market risk of these markets or are they only giving a false sense of security? In this paper the author also develops a new semi parametric VaR model that combines ARMA-GARCH volatility forecasting with bootstrapping, which should be more appropriate for turbulent transitional capital markets. Ten VaR models are tested on ten stock indexes from EU new member states. Performance of analysed VaR models is tested by Kupiec test, Christoffersen unconditional coverage test, Christoffersen independence test and Christoffersen conditional coverage test. To determine the models that are conditionally superior to the other tested models the following statistics are used: Lopez test, Blanco-Ihle test, Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The obtained results show that VaR models based on ARMA-GARCH volatility forecasts are superior to other tested types of VaR models. The findings show that common VaR models that are widely used in mature markets, such as historical simulation, variance-covariance model and RiskMetrics system are not well suited to transitional capital markets.

Key words: Market risk, VaR, GARCH, Bootstrapping, EU New Member States

1. Introduction

The aim of this paper is to discuss and compare different ways of calculating VaR in transitional economies of EU new member states. Majority of the EU new member states are all exposed to very similar processes of strong inflow of foreign direct and portfolio investments, and offer possibilities of huge profits for investors. These countries represent a very interesting opportunity for foreign and domestic banks, investment funds, pension funds, insurance companies and other investors. Banks and investment funds when investing in these financial markets employ the same risk measurement models for measuring market risk and forming of provision as they do in the developed markets. This means that risk managers in banks operating in EU new member states de facto presume similar or even equal characteristics and behaviour in these markets, as they would expect in developed markets. This is a dangerous assumption, which is not founded on empirical research.

Using the VaR models, that are created and suited for developed and liquid markets, in these, developing markets raises a dilemma: Do the VaR models developed and tested in the developed and liquid financial markets apply to the volatile and shallow financial markets of EU new member states? Do the commonly used VaR models adequately capture market risk of these markets or are they only giving a false sense of security. Employing VaR models in forming of bank's provisions that are not suited to developing markets can have serious consequences, resulting in big losses in banks' portfolio that could be undetected by the employed risk measurement models, leaving the banks unprepared for such events. Banks could also be penalized by the regulators, via higher scaling factor when forming their market risk provisions, due to the use of a faulty risk measurement model.

Although there is an abundance of articles concerning VaR and market risk measurement and management all of the existing models are developed and tested on mature, developed and liquid markets (Harvey, Whaley, 1992, Boudoukh, Richardson, Whitelaw, 1998, Brooks, Clare, Persand, 2000, Alexander, 2001 etc).

Testing of the VaR models in other, less developed or developing financial market is at best scarce (e.g. Parrondo, 1997, Hagerud, 1997, Santoso, 2000, Magnusson, Andonov, 2002, Valentinyi-Endrész, 2004, Žiković, 2005, 2006, Žiković, Bezić, 2006). Except for a few papers, research of VaR estimation and volatility forecasting in the financial markets of EU new member states or candidate states is non-existent.

To answer which VaR models adequately capture the market risk in the stock markets of the EU new member states ten VaR models will be tested on the stock indexes of EU new member states. VaR models will be calculated for a one-day holding period and 95% and 99% coverage of the market risk.

The VaR models analysed in this paper will be tested on ten national indexes: Slovenia - SBI20 index, Poland – WIG20 index, Czech Republic - PX50 index, Slovakia - SKSM index, Hungary - BUX index, Estonia - TALSE index, Lithuania - VILSE index, Latvia - RIGSE index, Cyprus – CYSMGENL and Malta - MALTEX. To secure the same out-of-the-sample VaR backtesting period for all of the tested indexes, the out-of-the-sample data sets are formed by taking out 500 of the latest observations from each index. The rest of the observations are used as presample observations needed for VaR starting values and volatility model calibration.

This paper is organized as follows: Section 2 reviews previous work on VaR comparison in the developed and emerging markets. In section 3 the state of risk measurement and management in EU new member states is analysed and discussed, and the statistical characteristics of stock market indexes of EU new member states are analysed. In section 4 a new semi-parametric approach to forecasting VaR model is developed. In section 5 the data that will be used in the analysis and the used methodology is explained. In section 6 ten VaR models are tested, ranked and compared. Conclusions are then drawn in the final section.

2. Summary of empirical research

According to empirical literature VaR models based on moving average volatility models seem to perform the worst. Otherwise, there is no straightforward result, and it is impossible to establish a ranking among the models. The results are very sensitive to the type of loss functions used, the chosen probability level of VaR, the period being turbulent or normal etc. Some researchers also find a trade-off between model sophistication and uncertainty. Although there is an abundance of research papers dealing with VaR and market risk measurement and management all of the existing VaR models are developed and tested on mature, developed and liquid markets (e.g.: Harvey, Whaley, 1992, Boudoukh, Richardson, Whitelaw, 1998, Hull, White, 1998a,b, Engle, Manganelli, 1999 Brooks, Clare, Persand, 2000, Alexander, 2001 etc). Testing of VaR models in other, less developed or developing financial market is at best scarce (e.g. Parrondo, 1997, Hagerud, 1997, Santoso, 2000, Magnusson, Andonov, 2002, Valentinyi-Endrész, 2004, Žiković, 2005, 2006, 2006b, Žiković, Bezić, 2006).

Besides the study of Hungarian stock index (BUX) by Valentinyi-Endrész (2004) in the VaR literature I could not find any research papers dealing with VaR model comparison or volatility forecasting in the financial markets of EU new member states or candidate states besides my own.

3. Characteristics of risk measurement and management in EU new member states

On May 1, 2004, ten new Member States - eight CEECs, Malta and Cyprus joined the EU. This enlargement raised the EU population by 74 million inhabitants to 454 million. The large number of countries and the size of the population involved (20% of the EU-15) made it EU's biggest enlargement ever. The financial markets of EU new member states, but especially CEEC have been liberalized and there are an increasing number of foreign financial institutions now operating in them. All segments of the financial sector have undergone a process of consolidation, and just a few companies now control most of the total financial assets in majority of the countries. Similarities in their economic histories and experiences, as well as comparable methods applied to building the market economies, lead to creation of similar structures and institutions. Similarities extend to the financial sector. In all of the EU new member states, there is a clear domination of banks as financial intermediaries (in terms of asset size); their share in total assets of financial institutions exceeds eighty percent (in Slovakia even over ninety percent) (Golajewska, Wyczański, 2002). A limited role of the equity market and great importance of public debt financing needs undermine the role of intermediaries active on the market, mainly investment funds and brokerage houses. In some countries, there are a large number of institutions licensed, but assets under their management are disproportionally low (Golajewska, Wyczański, 2002). The depth of the financial markets is highly diversified across the countries, as measured by total assets to GDP ratio. It ranges from as low as 66 percent (Poland, Hungary), to well above 100 percent, which is comparable to the level in developed countries (the Czech Republic). In most countries banking sector is relatively strongly concentrated, as a result of traditionally dominant role of savings banks in planned economies, as well as due to the recent mergers and acquisitions within banking sectors (partly stemming from mergers of strategic investors abroad, mainly from Italy and Austria).

Role and size of the stock exchange in most countries is still relatively low as a source of capital, which is shown by the low ratio of stock market capitalization to GDP. In consequence, the banking sector plays the most important role in financial intermediation. Thus, robustness and stability of banks seem to be crucial for the further growth of the countries in question, in mobilizing savings and utilizing them for financing investment projects. Foreign participation in banking sector in most EU new member states is high; the highest proportion is in Czech Republic, Hungary and in Poland. Foreign ownership is very low in Slovenia but it is expected to increase; similar strategy of greater openness to foreign capital in banking is also implemented in Slovakia.

A common feature of EU new member states is the lack of serious research about the impact of changes in banking regulation of their national banking sectors and economies. Furthermore, in the European Union not even all the members of the EU-15 countries have systematically conducted research on the consequences and impact of regulation changes on their banking sectors. New EU member states are even further behind in these issues. EU new member states are all significantly lagging behind the most developed EU countries in many fields but especially in matters of: financial legislation, market discipline, insider trading, disclosure of information (financial and other), embezzlement, fraud and knowledge of financial instruments and markets as well as the associated risks. The past 10 to 15 years have been associated with significant changes in the reliance on risk management in a number of transitional markets. In the past, the extension of credit in many economies reflected government guidelines or existing banking relationships. Institutional conditions played a large role; many banks were state-owned or were subject to government guidelines. There was no culture of risk management, the government, other banks, or the profitable segments of the corporate networks (which were often relied upon to provide guarantees to their weaker partners) would provide support in case of financial difficulty. Supervisory oversight was formal and focused on compliance with rules rather than risk mitigation. The system was not transparent, and market discipline was absent or ineffective. The high costs of this system (financial crises, persistent losses among public banks) have led to significant changes. State-owned banks have been privatised in many countries. Competition has been encouraged by liberalising entry, notably by foreign banks. There has been more reliance on market discipline, requiring greater transparency in governance and accounting. Prudential oversight has shifted towards ensuring that financial institutions are run in a way that is conducive to financial stability, as opposed to ensuring compliance with rules. To varying degrees, these changes have increased the accountability of bank managers and their incentives to improve risk management. In the past 10 years, risk management units have been established in banks in transitional market economies or their role has been strengthened, and boards of directors of these banks now explicitly consider risk management issues. Ongoing technical improvements include changes in the approach to valuation, including marking to market or fair value assessments, and the quantification of various risks, including the use of VaR calculations and stress testing, focused on market risks and to some extent on credit risks; and the pricing and allocation of credit, as well as provisioning and the allocation of capital on the basis of risk assessment. There has been a shift towards marking to market and fair value accounting that in many cases is broadly consistent with international or developed country accounting standards. Implementation appears to be well advanced in some emerging markets while lagging in others. A lot of countries are taking steps to implement international accounting standards for fair value accounting (IAS 39). Transparent accounting is a prerequisite for effective risk management and the exercise of market discipline. In addition, it creates the right incentives for bank managers. For example, a number of CEEC markets have kept non-performing loans on their books for extended periods without recognising the losses. The implementation of IAS 39 requires banks to recognise these losses, creating a strong incentive to dispose of the loans.

To understand the importance of market risk in modern banking in the EU new member states it is important to determine the amount of securities that banks in these countries hold on their balance sheets. It is surprising that ECB or the BIS do not publish these figures, thus it is necessary to find these in figure in national banking statistics. Because it is impossible to consistently determine across all countries which securities are held by the banks in banking book, and which in the trading book, in this paper both books are considered. In the following table 1 and figure 1 the sum of debt securities, shares and derivatives from both books is presented to give a feel of the importance of securities in banks' total assets. In table 1 the share of securities and their average values during the five-year period, in the consolidated balance sheet of commercial banks in EU new member states (excluding Malta and Cyprus for which no information about the detailed composition of consolidated balance sheets is available) presented. For the purpose of comparison the data for three mature economies - EU member states, Austria, Germany and France is also presented.

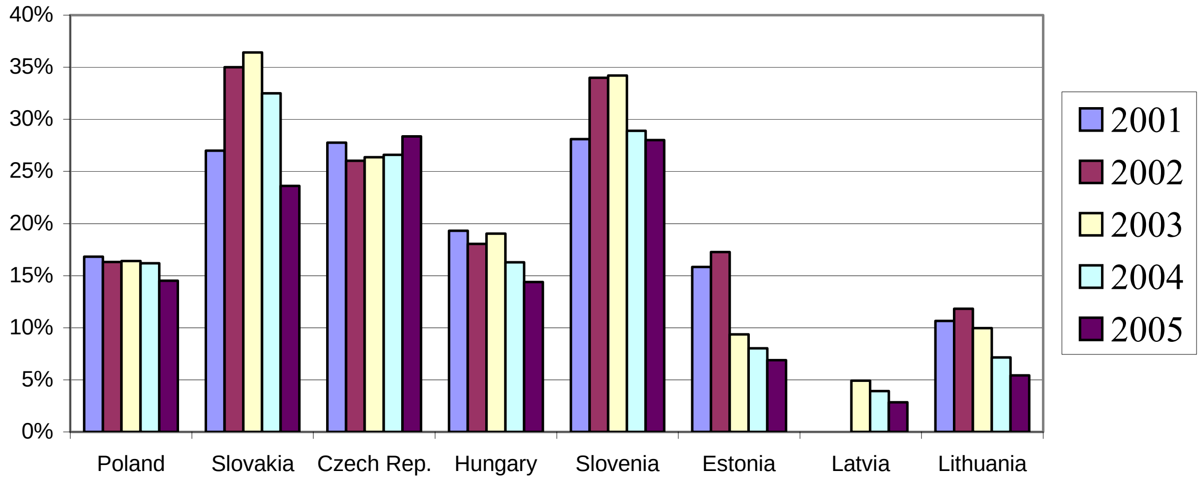
Table 1 - Share of securities in the consolidated balance sheet of commercial banks in national economies, in the period 2001- 2005

Year	Poland	Slovakia	Czech R.	Hungary	Slovenia	Estonia	Latvia	Lithuania	Avg
2001	16.8%	27.0%	27.8%	19.3%	28.1%	15.8%	N/A	10.6%	20.8%
2002	16.3%	35.0%	26.0%	18.0%	34.0%	17.3%	N/A	11.8%	22.6%
2003	16.4%	36.4%	26.4%	19.0%	34.2%	9.4%	4.9%	10.0%	19.6%
2004	16.2%	32.5%	26.6%	16.3%	28.9%	8.0%	3.9%	7.2%	17.4%
2005	14.5%	23.6%	28.3%	14.4%	28.0%	6.9%	2.9%	5.4%	15.5%
Average	16.0%	30.9%	27.0%	17.4%	30.6%	11.5%	3.9%	9.0%	19.2%

Year	Austria	Germany	France	Average
2001	9.8%	18.5%	39.1%	22.5%
2002	14.3%	18.0%	37.7%	23.4%
2003	14.2%	18.5%	41.2%	24.6%
2004	14.3%	19.9%	42.2%	25.5%
2005	N/A	20.7%	43.9%	32.3%
Average	13.2%	19.1%	40.8%	25.6%

Source: National central banks

Figure 1 - Share of securities in the consolidated balance sheet of commercial banks in EU new member states (excluding Malta and Cyprus), in the period 2001- 2005



Source: Table 1

The data from the table 1 shows that in the EU new member states (excluding Malta and Cyprus) there is a clear trend of decreasing share of assets held in securities. In the EU new member states in 2001 securities formed 20,5% of total banking assets, and this share fell to 15,2% in 2005. The country with the lowest share of securities in total banking assets (excluding Latvia, for which data for 2001 and 2002 is not available) is Lithuania, where in period 2001-2005, securities on average formed only 9,0% of total banking assets. In the same period the country with the highest share of securities in total banking assets was Slovakia with on average 30,9%. On the other hand, in the developed European countries there is a clear trend of growth in the share of securities in the total banking assets. The average value of securities in total assets for Austria, Germany and France grew from 22,5% in 2001 to 32.3% in 2005. In this group of countries, the country with the lowest share of securities in total banking assets was Austria, where in period 2001-2005, securities on average formed 13,2% of total banking assets. In the same period the country with the highest share of securities in total banking assets was France with on average 40,8%. The opposite trends between the EU new member states and EU old member states can be at least partially explained by the cleaning of banks' balance sheets in EU new member states from state issued securities and sale of interest in the companies that banks in the EU new member states obtained as collateral for bad debts during the privatisation and restructuring process. After this process is brought to the end it can be expected that EU new member states will follow the same trend that is present in the developed EU member states. Given the level of securities in total banking assets in both the developed economies and transitional economies it is clear that market risk management has a very important role in modern banking in Europe, and its importance is expected to grow.

In August of 2006 BIS published a study "The banking system in emerging economies: how much progress has been made?" covering risk management practices in emerging economies that is very indicative of the current situation, since it also includes some of the EU new member states. Especially interesting is the paper by Ramon Moreno "The changing nature of risks facing banks" where a survey of central banks regarding risk management practices in their countries is analysed. In this study a number of questionnaire respondents noted that the growth in bank trading books has increased exposure to market risk in a number of economies; such risk was generally not considered significant and was not analysed ten years ago.

All of the EU new member states adopted the directive for measuring market risk and backtesting internal models published by Basel Committee for Banking Supervision in Amendments from 1996. Conducted surveys show similar characteristics among EU new member states. Based on the overall results it can be concluded that:

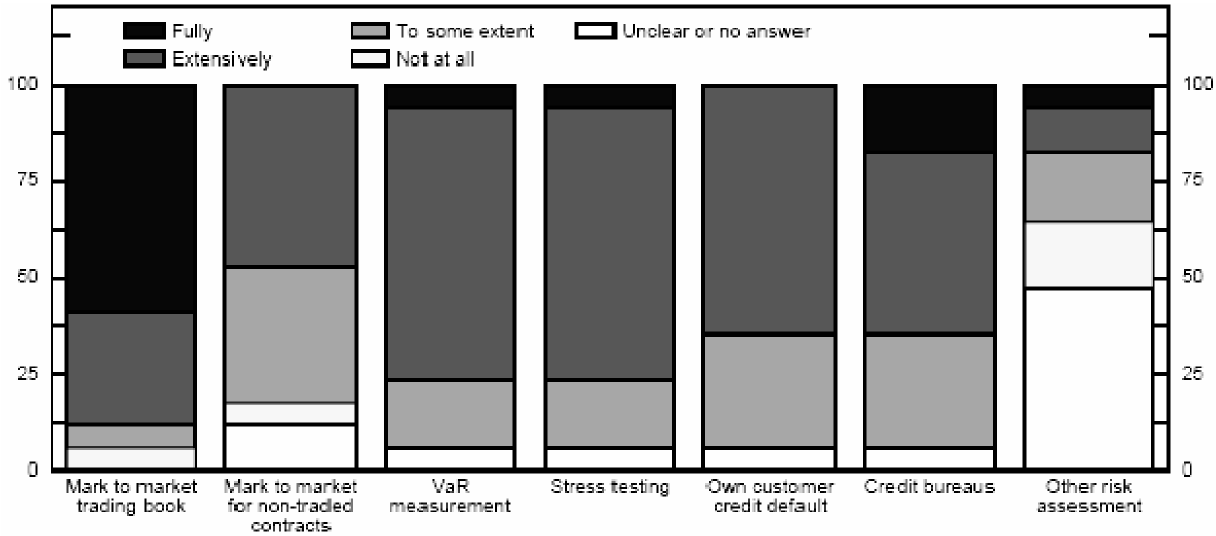
1) There are huge differences inside the national economies regarding the level of knowledge about risk management and Basel II standards for measuring and managing risks. Foreign owned banks are best versed in this subject compared to domestic banks that are significantly lagging.
2) Same differences can be seen in the actual preparation for the full implementation of the Basel guidelines. Foreign owned banks – under the pressure from their headquarters have started adopting the internal models for measurement of financial risks provided by their centrals. Smaller, domestic banks rely on the standardized approach prescribed by the national central banks.
3) The largest banks are preparing for the adoption of the most advanced – internal models of measuring all financial risks, probably because of already developed methodology for implementing risk measurement and management systems.

The surveys reveal that most of the middle and smaller size banks do not even have a risk management department. It is worrisome that even larger banks have understaffed risk management departments and there does not exist a manager in charge of every aspect of the financial risk. Besides the problem of understaffed risk management department, another serious problem is the quality and lack of knowledge and skill of the current employees.

As expected, only the largest banks provided data concerning market risk measurement. Most of these banks calculate the daily and monthly VaR figures, and only a smaller part of these banks already use VaR forecasts to set limits to trading desks. But even in these banks VaR is not calculated for all market risks, usually it is only FX and equity risk. For most banks, using VaR estimates to calculate economic capital and capital requirements is in the medium term plans. Despite the positive attitude of the banks towards VaR as a measure of risk, when considering the number of banks that actually calculate VaR and those that plan to use it as means to calculating capital requirement, this seams more like a reflection of the bank management's desire than the actual plan.

While the extent to which more market-oriented or sophisticated risk management tools have been adopted varies considerably, the good news is that the use of such tools now appears to be a more common part of banking practice in emerging markets, at least for bigger banks. Risk management techniques used by the banks in the emerging economies are illustrated in figure 2.

Figure 2 - Risk management techniques used by the banks in the emerging economies



Respondents comprise Chile, China, Colombia, the Czech Republic, Hong Kong SAR, Hungary, Indonesia, Korea, Malaysia, Mexico, the Philippines, Poland, Russia, Saudi Arabia, Singapore, Thailand and Turkey.

Source: Moreno Ramon: “The changing nature of risks facing banks”. in “The banking system in emerging economies: how much progress has been made?”. BIS papers No. 28, Aug 2006. 75 p.

In about 40% of responding countries there has been full or extensive adoption of marking to market, VaR (typically of market risks), stress testing, and reliance on credit default information or credit bureaus. An interesting indicator of the establishment of VaR as a risk measurement standard and the preparedness of the banks to fully implement Basel II capital accord is the fact that only a small fraction of the banks have gained approval from the national regulator to use the internal approach to calculate capital requirements. It is clear that banks in transitional markets are adopting more advanced techniques for risk assessment, such as VaR, stress testing and credit scoring. Underlying this have been sustained efforts by financial institutions in many emerging market economies to introduce functional risk management groups as well as the large improvements in IT infrastructure needed to handle up-to-date valuation and risk measurement requirements. In a number of economies, risk assessment is now used as the basis for daily transactions, and to improve such risk management practices as limits to different positions.

Overall basic statistics and normality test for daily log returns of all tested indexes in period 01.1.2000 - 31.12.2005 are presented in table 7. Financial markets of the EU new member states are experiencing a boom due to the catching up of these economies to the European standards and strong inflow of foreign direct and portfolio investments. Furthermore, securities from these markets are trading at a discount compared to securities from old EU member states. The only indexes that diverge from a strong positive trend present in CEE countries and Baltic states, in the analysed period, are CYSMGENL, WIG20 and MALTEX index. The CYSMGENL index shows virtually no common features with any of the other analysed indexes, which may indicate that investors did not perceive this stock market as potentially prosperous and benefiting from joining into EU. MALTEX and WIG20 index do not show a positive trend throughout the entire analysed period, from 2000 to 2006, but after a sharp decline in the value of their indexes they also experienced a strong positive trend in the second half of the observation period. It is visible from table 7 that all of the analysed indexes are characterised by fat tail and asymmetry, with six indexes having negative skewness and four indexes having positive skewness. Lilliefors and Jarque-Bera tests of normality for the tested stock indexes of EU new member states confirm the conclusion drawn from findings of skewness and kurtosis, that there is close to zero probability of empirical distributions of these returns being normally distributed.

The index with the highest daily mean return in the analysed period is RIGSE index (0,12%), and the index with the lowest mean value is CYSMGENL index (- 0,12%). CYSMGENL is the only index that has negative mean value in the analysed period. Investing long-term in RIGSE index yielded the highest gains, and investing in CYSMGENL yielded the highest losses. The most volatile index in the analysed period is RIGSE index with standard deviation of 1,63%. The least volatile index in the same period is SBI20 index with standard deviation of 0,69%. In the analysed period the largest daily gain of 9,46% is again recorded for RIGSE index. In the same period, RIGSE index experienced also the highest daily loss of 14,71%. In the analysed period RIGSE index has the highest value of negative asymmetry (- 1,278), and SBI20 index has the highest value of positive asymmetry (1,119). This means, that among the tested stock indexes, SBI20 index has the highest probability of experiencing positive returns, and RIGSE index has the highest probability of experiencing negative returns. Highest value of excess kurtosis is found for RIGSE index (23,6), and lowest value is found for PX50 index (4,36). Consequently, investing in RIGSE index means that one has to be prepared for extreme positive and negative returns. Average excess kurtosis across the stock indexes of EU new member countries equals 11.2, which is a very high value compared to stock indexes from developed countries or FX market.

According to Lilliefors test of normality among the tested stock indexes, BUX index is closes to being normally distributed. According to Jarque-Bera test of normality WIG20 index can be considered as being closest to normality. It is worth noting that both of these indexes have an insignificant probability of being normally distributed. Both normality tests identify the RIGSE index as being the farthest from normality.

According to the sample autocorrelation functions and sample partial autocorrelation functions of mean adjusted returns and the Ljung-Box Q-statistics for mean adjusted returns, it can be concluded that in seven out of ten tested stock indexes autocorrelation in the returns of stock indexes was detected. Sample autocorrelation functions and sample partial autocorrelation functions of squared mean adjusted returns and Ljung-Box Q-statistics for squared mean adjusted returns all detected significant heteroskedasticity in all of the tested stock indexes. Based on the performed tests for presence of autocorrelation and heteroskedasticity it can be concluded that daily log returns of stock indexes in the EU new member states exhibit a significant degree of autocorrelation and heteroskedasticity, making them unsuitable for proper implementation of many Value-at-Risk models. Since autocorrelation in returns was detected for most of the stock indexes from EU new member states, and presence of heteroskedasticity was discovered in all of the indexes, the return and volatility process of tested indexes was modelled as an ARMA-GARCH process. After estimating the parameters of ARMA-GARCH process and fitting the model, the innovations (residuals) from the process were obtained. Through analysis of sample autocorrelation functions and sample partial autocorrelation functions of standardised innovations and calculating the Ljung-Box Q-statistics for standardised innovations it was concluded that the conditional mean process used (ARMA), captured the autocorrelation present in the mean adjusted returns of the analysed stock indexes. Likewise, by using a GARCH process as a conditional volatility process sample autocorrelation functions and sample partial autocorrelation functions of squared standardised innovations as well as Ljung-Box Q-statistics and ARCH tests confirm that GARCH conditional volatility process captured the heteroskedasticity present in the mean adjusted returns of the analysed stock indexes. This means that after fitting an ARMA-GARCH model to stock indexes from EU new member states, which are not identically and independently distributed, obtained standardised innovations are identically and independently distributed. Estimated ARMA-GARCH parameters for stock indexes of EU new member states are presented in table 8.

As can be seen from table 8 ARMA-GARCH model successfully captured the dynamics of stock indexes from EU new member states and produced standardised innovations that under various tests proved to be independently and identically distributed. In modelling conditional volatility basic GARCH (1,1) model was sufficient for all but one stock index. In modelling conditional volatility for RIGSE index it was necessary to include a leverage term in the conditional mean equation. The most parsimonious asymmetric GARCH model that captured the leverage effect in the RIGSE index returns was the GJR-GARCH (1,1) model. Some of the tested indexes like SBI20, VILSE, MALTEX and CYSMGENL show unusually low persistence in volatility but are very reactive to volatility, which will make VaR forecasts based on GARCH volatility very spiky. Majority of stock indexes is not even closely integrated as is presumed by EWMA volatility modelling that is underlying the RiskMetrics model. VILSE index is farthest from being integrated with $\alpha + \beta$ being only 0,8167. All of the indexes from EU new member countries, except CYSMGENL index mean revert, i.e. there is convergence in term structure forecasts to the long-term average volatility level. CYSMGENL index distinctly differs from other tested stock indexes and could be modelled by an IGARCH model or a simple EWMA model because it is close to being fully integrated. Being integrated means that the volatility of CYSMGENL is itself a random walk process that has undefined unconditional variance and term structure. The estimated GARCH parameters of stock indexes from EU new member states point to the conclusion that VaR models based on simpler conditional volatility models, such as MA or EWMA will be underestimating or overestimating the true level of risk.

The results show that VaR models based on normality assumption, as well as for the nonparametric and semi-parametric approaches that are based on the assumption of independently and identically distributed observations, such as historical simulation and BRW approach are based on faulty premises when it comes to measuring and managing risk in EU new member states' capital markets. Daily log returns of stock indexes in the EU new member states exhibit a significant degree of autocorrelation and heteroskedasticity, which presents one of the most common obstacles to proper implementation of many VaR models. This is very indicative for risk managers, because this means that the elementary assumption of many VaR models is not satisfied, and that the VaR figures obtained from them cannot be trusted and at best, provide only unconditional coverage. It is necessary to implement a more sophisticated conditional volatility models to adequately capture the dynamics of these markets. VaR models that assume constant volatility or VaR models that take a more simplictic view of volaitlity modelling, will not perform satisfactory in these conditions.

4. Hybrid Historical simulation

In this section of the paper the author develops a new semi-parametric approach to forecasting VaR. The new model, which will hereafter be called "Hybrid historical simulation" (HHS), is based on the combination of nonparametric bootstrapping of standardized residuals and parametric GARCH volatility forecasting. The HHS model developed in this paper is designed to combine the best features of nonparametric and parametric approaches, but it is designed to do so in a simple and straightforward way. The HHS model successfully captures the two most conspicuous characteristics of financial asset returns, namely strong time varying volatility and excess kurtosis relative to the normal distribution. In the HHS model leptokurtosis and asymmetry are accounted for by the nonparametric part of the model, while the parametric – GARCH part of the model is suggested for removing heteroskedasticity from the data. While successfully dealing with leptokurtosis, asymmetry, autocorrelation and heteroskedasticity in the data, the HHS model is not as computationally intensive as some other approaches that are based on extreme value theory, mixtures of distributions or stable Paretian distributions. Furthermore, HHS model is far easier to understand and implement in practice. The number of parameters that have to be estimated in HHS model is small, and its' number is determined by the GARCH specification structure. The authors' suggestion is to use the simplest GARCH specification possible to keep the model as robust as possible to misspecification and model risk.

While greatly differing in approaches, some of the models are able to account for strong time varying volatility and excess kurtosis relative to the normal distribution. Simplistic methods, such as historical simulation and normal parametric variance-covariance approach, cannot adequately account for the volatility clustering and usually perform poorly in practice (Manganelli, Engle, 2001, Balaban, Bayar, Faff, 2004). The least sophisticated parametric method, which can still capture the volatility clustering and leptokurtosis in the data, is the basic GARCH model. There now exist a wide variety of generalizations of the functional form of volatility, and a large number of candidate distributions for the innovation sequence, several combinations of which have been shown to be very capable of capturing most of the various empirical features of the returns and also for delivering reasonably accurate out of the sample predictions of the entire distribution of a future return or just particular quantiles, as is needed for VaR forecasting (see Alexander, 2001, Ch. 9 and 10; Bao, Lee, Saltoglu, 2003). Unfortunately, these approaches have the drawbacks of requiring a relatively large number of parameters that cannot be solved in a closed, analytical form, and can result in negative scale parameters, both of which exacerbate the numeric computation of the maximum likelihood estimate, and bars use of less sophisticated software. Furthermore, the more volatility models get complex, estimated parameters can become unstable making such models vulnerable to parameter misspecification and model risk. Similarly, the EGARCH model introduced by Nelson (1991), which possesses some theoretical advantages over the GARCH model, is known to be very problematic in practice, with the choice of starting values being extremely critical for successful likelihood maximization (Frachot, 1995, Franses, van Dijk, 1996).

A similar critique that applies to more complex volatility models also applies to the distributional assumption of the VaR model, in that the density (required for the likelihood function) and distribution function (for computing the VaR) may not be expressible in closed analytical form. Examples include the hyperbolic distribution and Gauss-Laplace mixtures (Haas, Mittnik, Paolella, 2005), non-central Student's t (Campbell, Siddique, 1999, Broda, Paolella, 2006), geometric stable and stable Paretian distributions. These distributions require complex numeric procedures such as numeric integration, special function libraries, fast Fourier transform methods, multivariate root finding, etc., which cannot be found in many software packages and require considerable intellectual effort. Needles to say that the increase in number of parameters inevitably leads to parameter instability and estimation problems.

Nonparametric approaches require less effort and can easily account for leptokurtosis and to some extent even volatility clustering in the financial data. On the negative side, nonparametric approaches depend too much on the historical data set, they react slowly to changes in the market and are subject to predictable jumps in their forecasts of volatility. The simplest nonparametric approach, historical simulation provides a flexible and intuitive framework for risk analysis, but its basic version uses only the realized path of returns and therefore produces risk indicators with high variance. When the goal is to model returns for a horizon longer than data frequency, simulation approaches, such as, Monte Carlo simulation or bootstrapping techniques can be seen as sensible choices. Usually, the approach based on Monte Carlo simulation uses a set of stochastic differential equations for generating returns over the time horizon. Monte Carlo simulation uses arbitrary distributional assumptions, imposing the structure of risk that it is supposed to investigate. Unlike Monte Carlo simulation, the bootstrapping approach can be seen as a variation of the historical simulation approach, where it resamples from the empirical distribution of portfolio returns. Bootstrapping can be viewed as mixing Monte Carlo and historical simulation. This method guarantees that the multivariate properties of original data are preserved and is flexible enough to incorporate an update of both mean and volatility. Unfortunately, bootstrapping is based on a rather strict assumption that excess returns are identically and independently distributed. If returns are not IID, they are unsuitable for bootstrapping and can lead to biased results, because, for example, the eventual presence of autocorrelation and volatility clusters is ignored. To avoid this problem, it is possible to modify the basic bootstrapping scheme by weighting the realized observations. As Boudoukh, Richardson, and Whitelaw show, weighting of historical observations can be performed by exponentially decreasing the impact of past observations. The second, more appealing way is by incorporating volatility updating in future scenarios, and here there are several options. Hull and White (1998) show how to take into account volatility clusters into the basic historical simulation method (without bootstrapping), by scaling observations by the ratio of current over past conditional EWMA volatility forecasts. McNeil and Frey (2000) propose a bootstrapping approach, where the residuals of the ARMA-GARCH model follow an Extreme value (EV) distribution. Of course, instead of using an ARMA model, mean updating can be incorporated in future scenarios using different models, ranging from simple EWMA techniques to structural models.

The HHS approach developed by the author in this paper is based on the modification of recursive bootstrap procedure developed by Freedman and Peters (1984). This means that the proposed HHS model does not impose any theoretical distribution on the data since it uses empirical (historical) distribution of the return series. Two main problems with empirical data are the heteroskedasticity and presence of autocorrelation. In order to successfully implement bootstrapping the returns should not have any of these characteristics, meaning that they should be identically and independently distributed (IID). In the HHS model autocorrelations can be removed by modelling the conditional mean as an ARMA process. Heteroskedasticity can be removed by modelling returns as a GARCH process.

In modeling of residuals the proposed HHS approach uses the general specification of the form:

$r_t = \varphi(x) + \varepsilon_t$, $\varepsilon_t \sim (0, \sigma_t)$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{1}$$

$z_t = \varepsilon_t / \sigma_t$

where φ is some functional form, x is a vector of explanatory variables (observed at time t or lagged), ε_t is the disturbance term with zero mean and standard deviation σ_t, which follows a GARCH(p, q) process. Because of its simplicity and a good track record, HHS model uses the ARMA process as the functional form of φ.

The HHS model developed in this paper can be implemented in practice by applying the following steps:

1) Any autocorrelation in the returns is removed by fitting an ARMA(p,q) model to the historical observations, making the residuals identically and independently distributed:

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$$

$$\varepsilon_t = \eta_t \sqrt{\sigma_t^2} \qquad \eta_t \sim IID\ N(0,1) \tag{2}$$

2) GARCH(p,q) model is fitted to the obtained residuals:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{3}$$

3) To obtain standardized residuals $\{z_t\}$, residuals obtained from ARMA(p,q) fitting $\{\varepsilon_t\}$ are divided by conditional GARCH(p,q) volatility forecasts that where calculated for the same point in time:

$$z_t = \frac{\varepsilon_t}{\sigma_t} \tag{4}$$

Under the GARCH hypothesis the set of standardized residuals are independently and identically distributed and therefore suitable for bootstrapping. To ensure that the standardized residuals are truly IID, diagnostic tests, specifically Ljung-Box Q test for standardized residuals and squared standardized residuals, and Engle's ARCH test are applied. The p-statistics of model parameters indicate whether the GARCH model is well specified. If the obtained standardized residuals are not IID, some other autoregressive conditional heteroskedasticity model should be applied (i.e. IGARCH, GJR-GARCH, EGARCH, APARCH, FIGARCH or higher order GARCH model).

4) Identically and independently distributed standardized residual returns $\{z_t\}$ are bootstrapped for a large number of times, e.g. 10,000 times, to obtain a standardized historical time series Θ. Because bootstrapping is applied to IID residuals the results are unbiased

$$z = \{z_1, z_2, \ldots, z_t\} \quad z_i \in \Theta \tag{5}$$

5) After obtaining the bootstrapped standardized residuals the calculation of VaR is straightforward. The HHS model uses the Hull-White idea of volatility updating the standardized residuals $\{z_t\}$ and scales them by the latest GARCH volatility forecast ($\hat{\sigma}_{t+1}$) to obtained a series of historical residuals that have been updated by forecasted volatility to reflect the current market conditions $\{\hat{z}_{t+1}\}$.

$$\hat{z}_{t+1} = z_t \times \hat{\sigma}_{t+1}^2 \tag{6}$$

6) The simulated returns $\hat{r}_{t+1}$ are obtained by using updated historical residuals $\{\hat{z}_{t+1}\}$, into Equation (2):

$$\hat{r}_{t+1} = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i+1} + \sum_{i=1}^{q} \theta_i \hat{z}_{t-i+1} + \hat{z}_{t+1} \tag{7}$$

HHS model allows for the VaR at the arbitrary confidence levels *cl* to be obtained in several ways. HHS VaR can be approximated from $G(.;\ t;N)$, the empirical cumulative distribution function of $\{\hat{r}_t\}$ based on return observations $\hat{r}_{t-1},\ldots,\hat{r}_{t-N}$, and the procedure is the same as the one used for obtaining BRW VaR forecasts. HHS VaR can also be calculated by applying a smooth density estimator such as kernel. Following the results obtained by Silverman (1986) and Butler and Schachter (1998) the best choice would be the adaptive Gaussian or adaptive Epanechnikov kernel.

HHS model has another attractive characteristic; the observation period from which the standardized residuals are obtained can be modeled in two ways. The first option is to let observation period freely grow with the passing of time, resulting in slightly more conservative VaR estimates, but which are extremely resilient to extreme events. The second option is to arbitrary set the length of the observation period, allowing the VaR estimates to be less conservative but also less appropriate for capturing extreme events. The choice of length of the observation period is purely arbitrary but in author's opinion should in no case be shorter than one year of daily data.

5. Data and methodology

Data used in the analyses of performance of VaR models is the daily log returns from analysed indexes of EU new member states. The returns are collected from Bloomberg web site for the period 01.01.2000 - 31.12.2005. The calculated VaR figures are for a one-day ahead horizon and a 95 and 99 percent confidence level for losses, i.e., the five and one percent lower tail of the return distribution. Because of different holidays in analysed countries the data set ranges from minimum of 1414 observations for Slovakian SKSM index to maximum of 1554 observations for Latvian RIGSE index. To secure the same out-of-the-sample VaR backtesting period for all of the tested indexes, the out-of-the-sample data sets are formed by taking out 500 of the latest observations from each index. The rest of the observations (ranging from 914 observations for SKSM index to 1054 observations for RIGSE index) are used as presample observations needed for VaR starting values and volatility model calibration.

The tested VaR models are: Normal variance-covariance VaR, RiskMetrics system, Historical simulation, Age-weighted (BRW) Historical simulation, RiskMetrics system augmented with GARCH type volatility forecasting and Hybrid Historical simulation developed by the author in this paper. The first three of these eight models are standard VaR models that are usually available in market risk measurement software packages offered to banks. Historical simulation is tested with different rolling window periods of 50, 100, 250 and 500 days. Age-weighted Historical simulation is a hybrid VaR model developed by Boudoukh, Richardson, Whitelaw in their paper “The Best of Both Worlds: A hybrid Approach to Calculating Value at Risk” from 1998. Age-weighted Historical simulation is tested with two decay factors of 0.97 and 0.99. RiskMetrics system augmented with GARCH type volatility forecasting is a modification of the famous RiskMetrics system where the volatility forecasting used in RiskMetrics system – exponentially weighted moving average model, will is replaced by GARCH type volatility forecasting.

Regarding the volatility modelling, the data shows that GARCH representation will be necessary to adequately capture the dynamics of data generating processes of analysed indexes. The dynamics of the data generating processes are complex because changes in the efficiency of the market alter the long-run level and persistence of volatility. Furthermore, there is ample of empirical evidence on a positive relationship between trading volume and volatility. Thus, the rapid expansion of stock markets in EU new member states might have contradictory impacts on volatility: supposing that some predictability (significant AR term) is present in the series, increasing efficiency tends to lower the level and persistence of volatility, but larger volume might push its level up. Volatility can be raised due to other reasons too, for example when news in the return series arrive more often and are of larger magnitude than usual (shift in the volatility of error term). The increasing integration of the local stock markets into international capital markets may only further amplify that effect.

The return data is tested for autocorrelation both in log returns as well as squared log returns. Autocorrelation in log returns is tested by ACF, PACF and mean adjusted Ljung-Box Q-statistic. Autocorrelation in squared log returns is tested by ACF, PACF, Ljung-Box Q-statistic and Engle’s ARCH test. When autocorrelation is detected in the log returns the most parsimonious ARMA(p, q) model adequate to remove autocorrelation is fitted to the data. When autocorrelation is detected in the squared log returns the most parsimonious GARCH model is fitted to the ARMA filtered (if necessary) data to remove heteroskedasticity from the series.

The log return series $r_t=100*ln(P_t/P_{t-1})$ in this paper is specified as an ARMA-GARCH process and is estimated by maximum likelihood estimation (MLE):

$$
\begin{aligned}
r_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \\
\varepsilon_t &= \eta_t \sqrt{\sigma_t^2} \\
\sigma_t^2 &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2
\end{aligned}
\tag{8}
$$

where $\eta_t \sim IID\ N(0,1)$

After ARMA-GARCH filtering the obtained innovation series is scaled by GARCH conditional variance to obtain standardized innovations. If the employed ARMA-GARCH model successfully captures the dynamic of the data generating process of the return series standardised innovations should be independently and identically distributed. Presumption of IID in standardised innovations is tested by ACF, PACF and Ljung-Box Q-statistic. If the tests do not discover autocorrelation in the standardized innovations employed ARMA can be considered adequate. Squared standardised innovations are tested for autocorrelation and ARCH effects through ACF, PACF, Ljung-Box Q-statistic and ARCH test. The most parsimonious GARCH model that passes the tests of autocorrelation or ARCH effects in the squared standardized innovations is chosen to describe the volatility dynamics of the return series.

In the following analysis VaR models based on historical simulation are calculated as quantiles of empirical distribution with an equally weighted moving observations window. Normal variance-covariance VaR is calculated as equally weighted moving average with observation window length of 250 returns (approximately one year). RiskMetrics model is calculated as described in the RiskMetrics Technical document, with lambda set at 0.94. BRW VaR is calculated as described by Boudoukh, Richardson, Whitelaw (1998), with the same suggested decay factors of 0.97 and 0.99. GARCH-RiskMetrics is a parametric approach to VaR similar to RiskMetrics model but uses GARCH volatility forecasting instead of EWMA volatility forecasting. HHS model developed in this paper is calculated as described earlier, uses the same GARCH volatility forecasting as GARCH-RiskMetrics model, uses unbounded observation window length and calculates quantiles via order statistics.

All of the analysed VaR models are tested in several ways to determine their statistical characteristics and ability to adequately measure market risk in the countries analysed in this paper. First test is the Kupiec test, a simple expansion of the failure rate, which is also prescribed by Basel Committee on Banking Supervision. The set-up for this test is the classic framework for a sequence of successes and failures, also known as Bernoulli trials. Since a good risk measurement should secure that VaR exceedences are independent through time, as any clustering of VaR failures could easily force a bank into bankruptcy as the second test, the Christoffersen independence test is calculated. It tests whether VaR exceedences are IID. Results for Christoffersen unconditional test (UC) are also reported but in the author's opinion they provide a somewhat distorted image of the relative performance of VaR models. Since Christoffersen unconditional test is distributed as chi-square with one degree of freedom, deviations from the expected value of the test that occur on the conservative side (i.e. number of exceedences is lower than the excepted value) are treated more severely, a characteristic that is not compatible with regulators desire to increase the safety of the banking sector. From the regulatory standpoint Kupiec binomial test is preferred to Christoffersen unconditional test because it is more desirable to have positive than negative deviations. The same logic extends to the Christoffersen conditional coverage (CC) test, which also should be considered with a serious reserve since it automatically puts in a disadvantage VaR models that report a lower number of VaR exceedences per confidence level than expected. Furthermore, two forecast evaluation approaches are used to evaluate the relative performance of tested VaR models. This approach allows for ranking of different competing models, but does not give any formal statistical indication of model adequacy. In ranking them, it also allows to take account of any particular concerns one might have. For example, higher losses can be given greater weight because of concern about higher losses.

Furthermore, because they are not statistical tests, forecast evaluation approaches do not suffer from the low power of standard tests such as the Kupiec test. This makes forecast evaluation approach very attractive for backtesting with the small data sets typically available in practice. The first model is the Lopez size-adjusted loss function (1998). Second is the Blanco-Ihle loss function that gives each tail-loss observation a weight equal to the tail loss divided by the VaR. The loss function ensures that higher tail losses get awarded higher values. Blanco-Ihle is an excellent test for comparing competing VaR models that report the same frequency of tail losses, and whose tail losses are IID. Ranking VaR models by Blanco-Ihle approach is one of the best approaches to distinguish between such VaR tests. Forecasting performance of VaR models is evaluated by two statistical loss functions. First measure of forecasting performance of the tested VaR models is the root mean squared error (RMSE) measure which examines the degree to which the VaR forecasts tend to vary around the realized returns for a given date. Smaller deviations from the expected value indicate better VaR measure. Second measure of forecasting performance of the tested VaR models is the mean absolute percentage error measure (MAPE) for measuring bunching proposed by Boudoukh, Richardson, and Whitelaw (1998). MAPE is a combined measure of both bias and bunching. Smaller deviations from the expected value indicate better VaR measure. All the diagnostics, VaR calculations and backtesting in this paper are performed in MatLab and EViews software packages.

6. Findings

In this section the backtesting results for ten VaR models analysed in this are presented and their performance according to different criteria is analysed. Performance of each VaR model is evaluated for each individual index, based on every performance test. The summary of VaR model performance is given in backtesting tables 9 - 28 in Appendix. Significance level for VaR model acceptance is set at 10% to secure a more rigorous backtesting criterion.

Overall summary results are very useful to see how tested VaR model fare with regulatory backtesting framework based on the complete testing sample. Kupiec test and Christoffersen independence test are used to identifying VaR models that are acceptable to the regulator, and actually provide the desired level of safety to individual banks and, due to contagion effect, to the entire banking sector.

The results of the overall acceptance, according to Kupiec and Christoffersen independence test, of tested VaR models on the analysed market of EU new member states, at 95% confidence level are presented in table 2.

Table 2 - Number of VaR model failures according to Kupiec and Christoffersen independence test, tested on EU new member states' stock indexes, 500 observations, at 95% confidence level

Model	**HS 50**	**HS 100**	**HS 250**	**HS 500**	**BRW λ=0,97**	**BRW λ=0,99**
Kupiec test	8	4	1	1	0	0
Christoffersen IND test	6	5	5	5	5	5

Model	**Normal VCV**	**Risk Metrics**	**GARCH RM**	**HHS**
Kupiec test	1	1	0	0
Christoffersen IND test	4	4	2	2

Source: Tables 9-28

From the data in table 2 it is clear that at 95% confidence level, tested VaR models perform very differently with a majority of VaR models failing Kupiec test for at least one stock index. The results of Christoffersen independence test cause even greater concern because all of the tested VaR models failed the tested for more than one stock index.

The only VaR models that passed the Kupiec test across all the analysed stock indexes are the HHS model, GARCH-RiskMetrics model and both BRW models with λ = 0.97 and 0.99. The worst performer according to Kupiec test, out of the tested VaR model was the HS 50 model, which failed the Kupiec test for eight out of ten stock indexes. HS 50 model is followed by HS 100. It is surprising that even RiskMetrics model that is famous for its good track record at 95% confidence level failed the Kupiec test for one stock index (Slovenian - SBI20 index).

None of the ten tested VaR models satisfied the Christoffersen independence test across all the analysed stock indexes, but the two models with the best performance are the HHS model and GARCH-RiskMetrics model that failed the test only for two indexes out of the sample of ten. Both model failed the Christoffersen independence test for MALTEX and VILSE index. The worst performers are historical simulation models, together with BRW models. Overall, the best performers according to Kupiec and Christoffersen independence test at 95% confidence level across stock indexes of EU new member states are the HHS model and the GARCH-RiskMetrics model. The worst performer is the HS 50 model.

Although it is very informative to look at VaR model performance at different confidence levels, the true test of VaR model acceptability to the regulators is its performance at 99% confidence level, as prescribed by the Basel Committee. The results of the overall acceptance, according to Kupiec and Christoffersen independence test, of tested VaR models on the analysed market of EU new member states, at 99% confidence level are presented in table 3.

Table 3 - Number of VaR model failures according to Kupiec and Christoffersen independence test, tested on EU new member states' stock indexes, 500 observations, at 99% confidence level

Model	**HS 50**	**HS 100**	**HS 250**	**HS 500**	**BRW λ=0,97**	**BRW λ=0,99**
Kupiec test	10	10	3	1	9	1
Christoffersen IND test	3	3	3	2	3	3

Model	**Normal VCV**	**Risk Metrics**	**GARCH RM**	**HHS**
Kupiec test	7	4	3	0
Christoffersen IND test	1	2	0	0

Source: Tables 9-28

The data from table 3 shows a very distributing fact that should serve as a great warning to all regulators. At 99% confidence level, almost all of tested VaR models perform very poorly. In the analysed period, only one tested VaR model – the HHS model developed by the author, satisfied the Kupiec test at 99% confidence level across all of the analysed stock indexes from EU new member states. The results of Christoffersen independence test are equally alarming because only two VaR models (HHS model and GARCH-RiskMetrics model) passed the test.

The HHS model that is the only VaR model that passed the Kupiec test for all of the analysed stock indexes at 99% confidence level is followed by HS 500 model and BRW model with λ = 0.99, which failed the Kupiec test for one index. HS 500 model failed the Kupiec test for BUX index, and BRW model with λ = 0.99 failed the Kupiec test for MALTEX index. The GARCH-RiskMetrics models that shared the first place with HHS model at 95% confidence level failed the Kupiec test at 99% confidence level for three out of ten analysed stock indexes (SBI20 index, PX50 index and SKSM index).

The worst performers according to Kupiec test, out of the tested VaR model, at 99% confidence level, were the HS 50 and HS 100 models, which failed the Kupiec test for all of the ten tested stock indexes. HS 50 and HS 100 models are followed by BRW model with λ = 0.97 (nine failures) and Normal variance-covariance (seven failures). The drastic difference in the performance of the two BRW models at 99% confidence level can be attributed to the fact that volatility in the capital markets of EU new member states is very persistent and in such circumstances fast decaying volatility models perform very poorly.

Two out of the ten tested VaR models satisfied the Christoffersen independence test across all the analysed stock indexes. Equal to the results obtained for 95% confidence level HHS model and GARCH-RiskMetrics are the best performers even at 99% confidence level. The worst performers according to Christoffersen independence test are again the historical simulation models, together with BRW models.

Overall, the best performer according to both the Kupiec and Christoffersen independence test at 99% confidence level across stock indexes of EU new member states is the HHS model. The worst performers are the HS 50 and HS 100 models.

Performed backtesting at both at 95% and 99% confidence level clearly point to the conclusion that widespread models of calculating Value at Risk, such as Historical simulation, Normal variance-covariance approach and RiskMetrics system do not capture the dynamics of data generating processes of stock indexes from EU new member states.

Due to different assumptions and volatility prediction techniques, different VaR models provided forecasts for tested stock indexes that differed significantly. For example, at 95% confidence level TALSE index recorded the greatest difference between the highest average VaR forecasted by GARCH-RiskMetrics model and lowest average VaR forecasted by HS 50 model, which was 77,94%. TALSE index, at 99% confidence level also recorder the greatest difference between the highest average VaR forecasted by HHS model and lowest average VaR forecasted by HS 50 model, which was 77,89%.

The highest frequency of failures at 95% confidence level was recorder in VILSE index by HS 50 model and it amounted to 8,6%, which is 72% more than the expected frequency of failures. At 99% confidence level the highest frequencies of failure were recorded in VILSE index, again by HS50 model (3,6%) and in SBI20 index by RiskMetrics model (3,6%) which is 3,6 times more than the expected frequency of failures.

To investigate the main characteristics of each tested VaR model in these turbulent markets, and check the validity of the findings it is necessary to evaluate the performance of each tested VaR model across all of the analysed stock indexes. To accomplish this it is necessary to rank the competing VaR models by their ability to provide satisfactory conditional coverage for market risk in the analysed stock indexes. Ranking of the analysed VaR models in this paper is primarily performed by separating the VaR models between the ones that satisfy the Kupiec test and those that fail the test. VaR models that satisfy the Kupiec test are tested by Christoffersen independence test. Models that pass the Christoffersen independence test are than ranked according to their Blanco-Ihle score and by their MAPE and RMSE measures. VaR models that fail the Kupiec test are ranked by their frequency of failures, giving better ranking to models with lower frequency. Further ranking for VaR models that failed the Kupiec test follows the same procedure that applies to VaR models that satisfied the Kupiec test. Based on their performance VaR models are given points from 1 to 10, giving the best VaR model for a particular stock index 1 point, and giving the worst performing VaR model 10 points. Rankings obtained by following the outlined procedure are presented in table 4.

Table 4 - Ranking of VaR models across analysed stock indexes by backtesting performance at 99% confidence level

	SBI20	BUX	WIG20	PX50	SKSM
HS 50	9	10	10	10	10
HS 100	6	9	9	8	8
HS 250	4	5	5	5	4
HS 500	3	7	3	2	2
BRW λ=0,97	8	8	7	7	6
BRW λ=0,99	1	4	4	3	3
Normal VCV	7	6	6	9	7
Risk Metrics	10	3	8	6	9
GARCH RM	5	2	1	4	5
HHS	2	1	2	1	1
	TALSE	RIGSE	VILSE	CYSMGENL	MALTEX
HS 50	10	10	10	10	10
HS 100	9	8	9	9	9
HS 250	6	4	7	5	8
HS 500	3	3	3	4	4
BRW λ=0,97	8	9	8	8	7
BRW λ=0,99	4	5	5	6	5
Normal VCV	5	7	4	7	6
Risk Metrics	7	6	6	3	3
GARCH RM	2	1	1	2	2
HHS	1	2	2	1	1

Source: Tables 9-28

From the scoring in table 4 it can be concluded that for SBI20 index the best performer is the BRW model with $\lambda = 0.99$, followed by the HHS model. The worst performer for SBI20 index is the RiskMetrics model. Such result for RiskMetrics model come as no surprise knowing that the volatility process of SBI20 index is not close to being integrated and has very different volatility parameters than assumed under EWMA volatility model used by RiskMetrics. Historical simulation models had mixed results, with HS models with longer rolling windows being far superior to models with shorter rolling windows. GARCH-RiskMetrics model although far better than the basic RiskMetrics model was ranked fifth, which can be explained by low volatility persistence in SBI20 index which clearly creates problems for purely parametric approaches of measuring market risk. The best performer for the BUX index is the HHS model followed by GARCH-RiskMetrics model. RiskMetrics model placed also very high at third place. The worst performers for BUX index are the HS50 and HS100 models. BRW models are not ranked high, but are far better ranked than most of historical simulation models. The best performer for the WIG20 index is the GARCH-RiskMetrics model followed by HHS model. The worst performers for WIG20 index are the HS50 and HS100 models. Historical simulation models with longer rolling windows performed very good with HS 500 model taking the third place. RiskMetrics model was ranked very low, lower than the Normal variance-covariance model. BRW models gave mixed results, with BRW model with $\lambda = 0.99$ being ranked better than most of the historical simulation models. The best performer for the PX50 index is the HHS model followed by HS 500 model. The worst performers for PX50 index are the HS50 and Normal variance-covariance model. BRW model with $\lambda = 0.99$ took the third place. GARCH-RiskMetrics and RiskMetrics models did not perform very well, with GARCH-RiskMetrics model being again significantly better than RiskMetrics model. The best performer for the SKSM index is the HHS model followed by HS 500 model. The worst performer for SKSM index is the HS50 model. BRW model with λ = 0.99 took the third place. GARCH-RiskMetrics and RiskMetrics models did not perform very well, with RiskMetrics model being among the worst performers for this index, even worse than the Normal variance-covariance model. The best performer for the TALSE index is the HHS model followed by GARCH-RiskMetrics model. The worst performers for TALSE index are the HS50 and HS100 models. HS 500 model was ranked third. BRW models are not ranked high, but are far better ranked than historical simulation models, with the exception of HS 500 model. RiskMetrics is among the worst performers for this index, even worse than the Normal variance-covariance model. The best performer for the RIGSE index is the GARCH-RiskMetrics model followed by HHS model. HS 500 model was ranked third. BRW models are not ranked high, but are far better ranked than historical simulation models, with the exception of HS 500 model. The worst performers for RIGSE index are the HS50 model and BRW model with λ = 0.97. The best performer for the VILSE index is the GARCH-RiskMetrics model followed by HHS model. HS 500 model was ranked third. BRW model are not ranked high, but BRW models with λ = 0.99 is far better ranked than majority of historical simulation models. The worst performers for VILSE index are the HS50 model and BRW model with λ = 0.97. RiskMetrics is not among the worst performers for this index, but is worse than the Normal variance-covariance model. The best performer for the CYSMGENL index is the HHS model followed by GARCH-RiskMetrics model. RiskMetrics model is placed also very high at third place. The worst performers for CYSMGENL index are the HS50 and HS100 models. BRW models did not perform very well with HS 250 and HS 500 models being better ranked. The best performer for the MALTEX index is the HHS model followed by GARCH-RiskMetrics model. The worst performers for MALTEX index are the HS50 and HS100 models. RiskMetrics is not among the best performers for this index, but is better than the Normal variance-covariance.

According to the performed tests and ranking, HHS VaR model developed by the author in this paper performed extremely well. HHS model is ranked as best performer for six out of ten indexes and for the remaining four indexes it is ranked as second. GARCH-RiskMetrics model as the closes competitor to HHS model, was ranked as the best VaR model only for three indexes, but on two occasions was ranked as low as fifth. Overall ranking results for analysed VaR models by their backtesting performance are given in table 5.

Table 5 - Overall ranking scores of VaR models by backtesting performance at 99% confidence level

Model	Score	Place
HHS	14	**1**
GARCH RM	25	**2**
HS 500	34	**3**
BRW λ=0,99	40	**4**
HS 250	53	**5**
Risk Metrics	61	**6**
Normal VCV	64	**7**
BRW λ=0,97	76	**10**
HS 100	84	**11**
HS 50	99	**12**

Source: Table 4

Overall the HHS model is the best performing tested VaR model across the stock indexes from EU new member states. In the second places lagging behind the HHS model by almost double the points is the modification of RiskMetrics model, the GARCH-RiskMetrics model. HS 500 model performed surprisingly well on the tested sample of stock indexes and although it is very simple, proved to be an acceptably good VaR estimator. The worst performing VaR models are the HS 50 and HS 100 models. Classical parametric VaR models, the RiskMetrics model and Normal variance-covariance model are not placed very high in the overall ranking (sixth and seventh place) indicating that they are not very well suited to forecasting VaR in the EU new member states. The obtained results, summarised in table 5 confirm that the widespread models of calculating Value at Risk, such as Historical simulation, Normal variance-covariance model and RiskMetrics system do not capture the dynamics of data generating processes of stock indexes from EU new member states.

HS 500 model performed surprisingly well although the basic prerequisites for its proper implementation, such as IID of returns, are not satisfied in the testing sample. This interesting phenomenon has a very simple explanation. Due to the extreme losses that occurred prior to and during the testing period HS 500 VaR model set its forecasts very high automatically achieved unconditional coverage without taking into consideration the actual level of risk. Because it reacts very slowly to changes in volatility, its average VaR is among the highest of all the tested VaR models. Although HS 500 model provides correct unconditional coverage for all but one tested stock indexes it would prove very costly for a bank implementing it, because in times of low volatility it signals the need for high provisions, which would create high opportunity costs. On the other hand, due to its very low reactivity and high persistence, HS 500 model hides a very serious danger of underestimating the true level of risk for longer periods if the market enters a volatile period after a longer period of low volatility. BRW model with $\lambda = 0.99$ is placed fourth in the overall ranking, being superior to all historical simulation models except the historical simulation model with longest rolling window – HS 500. RiskMetrics is ranked sixth making it superior to the basic parametric approaches - Normal variance-covariance model. Based on the performed analysis it is safe to say that in the capital markets of EU new member states BRW model is very sensitive to the choice of decay factor. The proof of this can be seen from ranking of the same model but with slightly different decay factors. BRW model with decay factor of 0.99 is ranked as fourth, but BRW model with decay factor of 0.97 is among the worst ranked VaR models. Since it is obvious that ad hoc setting of decay factor does not function in the capital markets of EU new member states some formal procedure should be developed to estimate the optimal value of decay factor. With the optimal decay factor for each market it is very possible that BRW model would perform much better.

These findings point to the conclusion that extensions of basic Value at Risk models, such as age-weighted Historical simulation and RiskMetrics system show improvement in measuring market risk over the basic models. Based on the ranking it can also be concluded that modifying the RiskMetrics model with GARCH based volatility forecasting brought significant improvements to basic RiskMetrics model, making it a very good risk measure for tested stock indexes second only to HHS VaR model. Along with the analysis of backtesting results the qualitative characteristics of tested VaR models should also be taken into consideration to provide a complete picture. Qualitative characteristics of each of the tested VaR models are presented in table 6.

Table 6 - Characteristics of tested VaR models

Characteristics	Normal VCV	RiskMetrics	GARCH-RiskMetrics	Historical simulation	BRW	HHS
Distribution	normal	normal	normal	actual	quasi-actual	quasi-actual
Tails	normal	normal	fat	actual	quasi-actual	quasi-actual
Reaction speed	slow	fast	fast	slow	medium	fast
Intellectual effort	low	moderate	moderate	very low	moderate	moderate
Model risk	huge	huge	moderate	moderate	low	low
Computation time	low	low	moderate	low	moderate	high
Communicability	easy	easy	moderate	easy	moderate	moderate

Source: Author

Table 6 shows that HHS model has a lot of advantages over most of the other tested VaR models. HHS model uses a quasi-actual distribution of empirical returns, since GARCH volatility updating modifies the empirical distribution. The same applies to the treatment of tails. Reaction speed of the HHS model is fast, reacting to every change in level of volatility regardless of the sign of the returns, through GARCH volatility estimation. Model risk associated with HHS model is quite low because the only parameters that have to be estimated for the model are GARCH model parameters, besides which no other assumptions are made. Unfortunately, intellectual effort in implementing HHS model is quite high as well as the computational time, but with the development of faster computer processors and greater investment in education, this should present a minor problem. Based on analysed statistical properties of stock indexes from EU new member states as well as the VaR backtesting results and rankings it is safe to say that Value at Risk models that are commonly used in developed financial market are not suited for measuring market risk in EU new member states. Presented findings bear very important implications that have to be addressed by regulators and risk practitioners operating in EU new member states. Risk managers have to start thinking outside the frames set by their parent companies or else their banks investing in these markets may find themselves in serious trouble, faced with losses that they were not expecting. Contrary to the widespread opinion it is not enough to simply implement VaR models being offered by various software companies. Every VaR software package that a bank is thinking about implementing should be rigorously tested and analysed to see if it really provides a correct estimate of the true level of risk a bank is exposed to. National regulators have to take into consideration that simplistic VaR models that are widely used in some countries are not well suited for these illiquid and developing financial markets. Before allowance is given to banks on using internal VaR models that are either purchased or developed in-house national regulators should rigorously checks and analyse the backtesting performance as well as the theoretical framework of such model for any inconsistencies or unwanted simplifications. As the results obtained in this paper show returns on indexes from EU new member states are characterised by fat tails, asymmetry, autocorrelation and heteroskedasticity, all of which considerably complicate VaR estimation and require more complex and computationally and intellectually demanding VaR models.

The obtained results also indicate that it may be highly misleading to compare VaR numbers across financial institutions if the reported numbers are based on different VaR models. As was shown VaR estimates for the same stock index according to two different VaR models differed by more than 77%. However, it has to be pointed out that the Value at Risk concept itself is an extremely useful tool for financial institutions with regard to their in-house risk management.

7. Conclusion

This paper examines the characteristics of stock indexes from EU new member states, and tests the validity of common VaR models in adequately capturing market risk in these markets. The author in this paper also developed and tested a new semi-parametric approach to forecasting VaR. Performed tests indicate that volatility clustering and occurrence of extreme positive and negative returns characterise the returns of stock indexes from EU new member states. From statistical analysis of stock indexes from EU new member states performed in the paper, it was determined that all of the indexes are characterised by fat tail and asymmetry. These characteristics of analysed stock indexes of EU new member states have serious consequences for the performance of VaR models. Even more troubling for the VaR models based on normality assumption, as well as for the nonparametric and semi-parametric approaches that are based on the assumption of independently and identically distributed observations, such as historical simulation and BRW approach is the finding that daily log returns of stock indexes in the EU new member states exhibit a significant degree of autocorrelation and heteroskedasticity. This proves that the elementary assumption of many VaR models is not satisfied, and that the VaR figures obtained from them cannot be trusted and at best, provide only unconditional coverage. Since autocorrelation and heteroskedasticity automatically exclude the possibility of observations being independently and identically distributed it is necessary to capture the structure in the analysed data and obtain independently and identically distributed. As was shown in the paper ARMA-GARCH model successfully captured the dynamics of stock indexes from EU new member states and produced standardised innovations that under various tests proved to be independently and identically distributed. VaR models that assume constant volatility or VaR models that take a more simplistic view of volatility modelling will not perform satisfactory in these conditions. It is necessary to implement a more sophisticated conditional volatility models to adequately capture the dynamics of these markets.

Based on analysed statistical properties of stock indexes from EU new member states as well as the VaR backtesting results and rankings it is safe to say that Value at Risk models that are commonly used in developed financial market are not suited for measuring market risk in EU new member states. Presented findings bear very important implications that have to be addressed by regulators and risk practitioners operating in EU new member states. Contrary to the widespread opinion it is not enough to blindly implement the VaR models that are being offered by various software companies. Every VaR software package that a bank is thinking about implementing should be rigorously tested and analysed to see if it really provides a correct estimate of the true level of risk a bank is exposed to. National regulators have to take into consideration that simplistic VaR models that are widely used in some countries are not well suited for these illiquid and developing financial markets. Before allowance is given to banks on using internal VaR models that are either purchased or developed in-house national regulators should rigorously checks and analyse the backtesting performance as well as the theoretical framework of such model for any inconsistencies or unwanted simplifications. As the results obtained in this paper show returns on indexes from EU new member states are characterised by fat tails, asymmetry, autocorrelation and heteroskedasticity, all of which considerably complicate VaR estimation and require more complex and computationally and intellectually demanding VaR models.

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Appendix

Table 7 - Basic statistics and normality tests for daily log returns of stock indexes from EU new member states, period 01.1.2000 - 31.12.2005.

	SBI20	BUX	WIG20	PX50	SKSM	TALSE	RIGSE	VILSE	CYSMGE
Sample size	1461	1501	1505	1502	1414	1521	1554	1503	15
Mean	0.000644	0.000579	0.000239	0.00074	0.001184	0.001016	0.001202	0.000993	-0.0012
Median	0.0005	0.00051	0.00019	0.000961	0.0003	0.000965	0.000608	0.000814	-0.0010
Minimum	-0.047674	-0.068735	-0.077057	-0.062054	-0.088167	-0.058741	-0.14705	-0.10216	-0.098
Maximum	0.083109	0.060043	0.062461	0.041785	0.059591	0.073425	0.094609	0.053092	0.074
Standard deviation	0.006888	0.013921	0.01561	0.012581	0.013255	0.010472	0.016286	0.008965	0.015
Skewness	1.119	-0.117	0.069	-0.267	-0.114	0.225	-1.278	-0.649	-0.
Kurtosis	21.647	4.6873	4.4498	4.3604	7.4742	9.0341	23.563	17.469	7.8
Jarque-Bera test	21,404	180.16	131.94	132.67	1,176.90	2,311.20	27,721	13,174	1,483
(p value)	0	0	0	0	0	0	0	0	
Lilliefors test	0.077501	0.031092	0.053572	0.040504	0.094636	0.079737	0.15709	0.083442	0.084
(p value)	0	0	0	0	0	0	0	0	

Source: Author

Table 8 - Estimated ARMA-GARCH parameters for stock indexes of EU new member states

	Mean			Volatility			
	C	AR	MA	K	GARCH	ARCH	Leverage
SBI20	0.000514	0.42607 -0.14067		6.69E-06	0.50069	0.39003	
BUX	0			8.59E-06	0.89067	0.066215	
WIG20	0			5.6E-06	0.93292	0.047987	
PX50	0.000755			4.69E-06	0.90381	0.069603	
SKSM	0.000689		-0.05749	1.27E-05	0.85016	0.07733	
TALSE	0.00096		0.21580 0.09233	6.76E-06	0.84035	0.10469	
VILSE	0	1.08050 -0.08366	-0.96844	1.31E-05	0.55848	0.25825	
RIGSE	0.000755		-0.13221	4.69E-06	0.90381	0.069603	-0.39327
CYSMGENL	-0.00135	0.13036		6.04E-06	0.79835	0.19802	
MALTEX	-0.00054	0.27526		6.71E-06	0.64587	0.18561	

Source: Author

Table 9 - Backtesting results and diagnostics of 500 VaR forecasts for SBI20 index daily log returns, 95% confidence level, period 03.12.2003 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	35	33	29	21	29	26	31	33	25	28
Frequency of failures	0.07	0.066	0.058	0.042	0.058	0.052	0.062	0.066	0.05	0.056
Kupiec test (p value)	0.019643	0.045412	0.17647	0.75905	0.17647	0.36861	0.09445	0.045412	0.44706	0.23168
Christoffersen UC test (p value)	0.052333	0.11684	0.42294	0.3992	0.42294	0.83842	0.23456	0.11684	1	0.54553
Christoffersen IND test (p value)	0.001662	0.003907	0.004448	0.058758	0.004448	0.046153	0.001687	0.000668	0.51405	0.7268
Christoffersen CC test (p value)	0.001084	0.004549	0.012694	0.11749	0.012694	0.13415	0.003562	0.000896	0.80823	0.7837
Lopez test	10.165	8.1521	4.1267	-3.9049	4.1364	1.1193	6.1315	8.1599	0.087587	3.1102
Blanco-Ihle test	28.035	23.843	15.928	10.322	20.364	15.269	17.138	30.033	10.905	14.873
RMSE	0.007954	0.007795	0.008109	0.009046	0.008717	0.00844	0.00776	0.007906	0.009329	0.008447
MAPE	2.2718	1.8404	1.389	1.3042	1.3741	1.3242	1.6434	2.2219	1.8304	2.0673
Average VaR	-0.007631	-0.007843	-0.00835	-0.009502	-0.008609	-0.00875	-0.008025	-0.007725	-0.009209	-0.008285
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	YES	YES	**NO**	**NO**	YES	YES
Christoffersen IND test	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	YES	YES

Source: Author

Table 10 - Backtesting results and diagnostics of 500 VaR forecasts for SBI20 index daily log returns, 99% confidence level, period 03.12.2003 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	15	9	7	5	10	7	10	18	8	7
Frequency of failures	0.03	0.018	0.014	0.01	0.02	0.014	0.02	0.036	0.016	0.014
Kupiec test (p value)	6.15E-05	0.031102	0.13232	0.38404	0.013244	0.13232	0.013244	1.16E-06	0.06711	0.13232
Christoffersen UC test (p value)	0.000286	0.10602	0.39657	1	0.047896	0.39657	0.047896	6.10E-06	0.21487	0.39657
Christoffersen IND test (p value)	0.007142	0.14477	0.078954	0.034295	0.52246	0.65537	0.18573	0.023097	0.60964	0.65537
Christoffersen CC test (p value)	3.72E-05	0.093525	0.1492	0.10646	0.11517	0.63195	0.058871	2.73E-06	0.40678	0.63195
Lopez test	10.067	4.045	2.0447	0.01972	5.0421	2.0273	5.0646	13.085	3.0313	2.0276
Blanco-Ihle test	9.0629	3.6694	3.5894	1.2881	3.816	2.0738	6.0303	12.174	3.0783	2.5829
RMSE	0.013481	0.014417	0.014085	0.016685	0.015729	0.016029	0.011075	0.011344	0.01329	0.013854
MAPE	1.9576	1.0474	1.0449	0.85037	0.88279	0.88529	1.5137	2.7955	0.8803	0.90274
Average VaR	-0.013248	-0.014728	-0.014543	-0.017157	-0.015591	-0.016409	-0.011633	-0.011289	-0.013024	-0.013495
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	**NO**	YES	**NO**	**NO**	**NO**	YES
Christoffersen IND test	**NO**	YES	**NO**	**NO**	YES	YES	YES	**NO**	YES	YES

Source: Author

Table 11 - Backtesting results and diagnostics of 500 VaR forecasts for BUX index daily log returns, 95% confidence level, period 13.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	30	35	32	29	24	28	25	24	13	20
Frequency of failures	0.06	0.07	0.064	0.058	0.048	0.056	0.05	0.048	0.026	0.04
Kupiec test (p value)	0.13085	0.019643	0.066371	0.17647	0.52865	0.23168	0.44706	0.52865	0.99449	0.82115
Christoffersen UC test (p value)	0.31923	0.052333	0.16777	0.42294	0.83639	0.54553	1	0.83639	0.006901	0.28848
Christoffersen IND test (p value)	0.38133	0.74804	0.50453	0.80199	0.11931	0.7268	0.51405	0.44939	0.40428	0.8236
Christoffersen CC test (p value)	0.41509	0.14455	0.30911	0.70292	0.29099	0.7837	0.80823	0.73535	0.01837	0.55533
Lopez test	5.2759	10.275	7.2889	4.2652	-0.78307	3.2533	0.23754	-0.82547	-11.878	-4.8435
Blanco-Ihle test	19.888	17.421	17.581	15.349	13.365	15.136	13.125	8.6934	4.8039	6.8498
RMSE	0.017181	0.016047	0.015485	0.016156	0.017665	0.016195	0.016353	0.018	0.019635	0.017916
MAPE	1.7132	2.4489	3.3566	2.7132	1.2244	2.0948	2.399	1.8279	2.788	2.7207
Average VaR	-0.017613	-0.017203	-0.016699	-0.017617	-0.018508	-0.017606	-0.018009	-0.01939	-0.021785	-0.019935
Acceptance (Kupiec test)	YES	**NO**	**NO**	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 12 - Backtesting results and diagnostics of 500 VaR forecasts for BUX index daily log returns, 99% confidence level, period 13.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	15	12	9	10	12	6	10	5	3	3
Frequency of failures	0.03	0.024	0.018	0.02	0.024	0.012	0.02	0.01	0.006	0.006
Kupiec test (p value)	6.15E-05	0.001901	0.031102	0.013244	0.001901	0.23708	0.013244	0.38404	0.73638	0.73638
Christoffersen UC test (p value)	0.000286	0.007663	0.10602	0.047896	0.007663	0.66302	0.047896	1	0.33148	0.33148
Christoffersen IND test (p value)	0.33489	0.44186	0.56529	0.18573	0.44186	0.70234	0.18573	0.75037	0.84892	0.84892
Christoffersen CC test (p value)	0.000871	0.021257	0.22956	0.058871	0.021257	0.84538	0.058871	0.95065	0.61281	0.61281
Lopez test	10.14	7.1458	4.1033	5.1092	7.116	1.0945	5.1087	0.062911	-1.9531	-1.9587
Blanco-Ihle test	7.1688	7.0205	4.1127	4.2704	5.5231	3.6922	4.1703	2.0634	1.2737	1.0693
RMSE	0.026958	0.028692	0.025458	0.025101	0.027397	0.029133	0.023905	0.026593	0.028905	0.030469
MAPE	2.0249	1.4963	1.0524	1.1845	1.596	0.53865	1.1845	0.41646	0.82544	0.82544
Average VaR	-0.025895	-0.027832	-0.026848	-0.027295	-0.027718	-0.029934	-0.026144	-0.027923	-0.030811	-0.03229
Acceptance (Kupiec test)	**NO**	**NO**	**NO**	**NO**	**NO**	YES	**NO**	YES	YES	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 13 - Backtesting results and diagnostics of 500 VaR forecasts for WIG20 index daily log returns, 95% confidence level, period 09.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	27	25	20	14	24	16	19	24	12	12
Frequency of failures	0.054	0.05	0.04	0.028	0.048	0.032	0.038	0.048	0.024	0.024
Kupiec test (p value)	0.29612	0.44706	0.82115	0.98919	0.52865	0.96571	0.87277	0.52865	0.99739	0.99739
Christoffersen UC test (p value)	0.6852	1	0.28848	0.014162	0.83639	0.048624	0.19939	0.83639	0.003118	0.003118
Christoffersen IND test (p value)	0.70388	0.48092	0.8236	0.36861	0.4182	0.53106	0.74834	0.91433	0.44186	0.44186
Christoffersen CC test (p value)	0.85693	0.78005	0.55533	0.032938	0.70539	0.11762	0.4169	0.97325	0.009425	0.009425
Lopez test	2.2228	0.19328	-4.8406	-10.891	-0.81766	-8.8517	-5.8471	-0.83096	-12.903	-12.887
Blanco-Ihle test	17	14	10	5	13	9	9	10.586	4.5414	5.6689
RMSE	0.015101	0.016021	0.017438	0.018652	0.016576	0.01722	0.016947	0.015295	0.019303	0.017948
MAPE	1.005	1.803	2.0449	2.4938	1.7307	2.0998	1.9551	0.73815	2.7232	2.7232
Average VaR	-0.015961	-0.017153	-0.018792	-0.020642	-0.017523	-0.018759	-0.018536	-0.016665	-0.021238	-0.019842
Acceptance (Kupiec test)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 14 - Backtesting results and diagnostics of 500 VaR forecasts for WIG20 index daily log returns, 99% confidence level, period 09.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	14	10	5	4	9	4	6	10	5	6
Frequency of failures	0.028	0.02	0.01	0.008	0.018	0.008	0.012	0.02	0.01	0.012
Kupiec test (p value)	0.000206	0.013244	0.38404	0.56039	0.031102	0.56039	0.23708	0.013244	0.38404	0.23708
Christoffersen UC test (p value)	0.000914	0.047896	1	0.64143	0.10602	0.64143	0.66302	0.047896	1	0.66302
Christoffersen IND test (p value)	0.39933	0.18573	0.75037	0.7993	0.14477	0.7993	0.70234	0.52246	0.75037	0.70234
Christoffersen CC test (p value)	0.002874	0.058871	0.95065	0.8687	0.093525	0.8687	0.84538	0.11517	0.95065	0.84538
Lopez test	9.0919	5.0863	0.038835	-0.97314	4.0622	-0.97341	1.0504	5.0646	0.020414	1.022
Blanco-Ihle test	5.0301	4.9045	1.4832	0.91814	3.1877	1.0352	2.201	2.8371	0.65868	0.71743
RMSE	0.023573	0.025369	0.027317	0.028519	0.026224	0.028731	0.025029	0.02245	0.028329	0.027947
MAPE	1.8703	1.2294	0.59102	0.70574	0.99002	0.70574	1	1.2369	0.46135	0.34663
Average VaR	-0.024292	-0.026287	-0.029079	-0.03032	-0.027273	-0.030297	-0.026618	-0.023982	-0.030037	-0.029671
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	**NO**	YES	YES	**NO**	YES	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 15 - Backtesting results and diagnostics of 500 VaR forecasts for PX50 index daily log returns, 95% confidence level, period 09.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	32	25	26	21	22	21	20	20	13	13
Frequency of failures	0.064	0.05	0.052	0.042	0.044	0.042	0.04	0.04	0.026	0.026
Kupiec test (p value)	0.066371	0.44706	0.36861	0.75905	0.6879	0.75905	0.82115	0.82115	0.99449	0.99449
Christoffersen UC test (p value)	0.16777	1	0.83842	0.3992	0.53008	0.3992	0.28848	0.28848	0.006901	0.006901
Christoffersen IND test (p value)	0.056742	0.51405	0.046153	0.058758	0.33241	0.28078	0.23401	0.23401	0.33905	0.33905
Christoffersen CC test (p value)	0.062886	0.80823	0.13415	0.11749	0.51332	0.39179	0.28041	0.28041	0.016469	0.016469
Lopez test	7.3137	0.32282	1.2847	-3.7566	-2.7728	-3.7368	-4.7609	-4.7898	-11.838	-11.823
Blanco-Ihle test	33.235	30.34	21.409	17.267	20.267	19.712	15.661	13.426	8.4172	9.8957
RMSE	0.015802	0.014549	0.013307	0.015149	0.015772	0.014311	0.014661	0.01515	0.017261	0.016152
MAPE	1.9751	1.995	2.6509	1.9352	1.1995	2.0524	2.182	1.5885	2.3591	2.3591
Average VaR	-0.014415	-0.014413	-0.013662	-0.015611	-0.015256	-0.014706	-0.0154	-0.015471	-0.018231	-0.017064
Acceptance (Kupiec test)	**NO**	YES	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	**NO**	YES	**NO**	**NO**	YES	YES	YES	YES	YES	YES

Source: Author

Table 16 - Backtesting results and diagnostics of 500 VaR forecasts for PX50 index daily log returns, 99% confidence level, period 09.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	14	9	8	7	9	6	10	8	8	7
Frequency of failures	0.028	0.018	0.016	0.014	0.018	0.012	0.02	0.016	0.016	0.014
Kupiec test (p value)	0.000206	0.031102	0.06711	0.13232	0.031102	0.23708	0.013244	0.06711	0.06711	0.13232
Christoffersen UC test (p value)	0.000914	0.10602	0.21487	0.39657	0.10602	0.66302	0.047896	0.21487	0.21487	0.39657
Christoffersen IND test (p value)	0.39933	0.56529	0.60964	0.65537	0.56529	0.70234	0.18573	0.60964	0.60964	0.65537
Christoffersen CC test (p value)	0.002874	0.22956	0.40678	0.63195	0.22956	0.84538	0.058871	0.40678	0.40678	0.63195
Lopez test	9.1682	4.1618	3.0849	2.0791	4.1205	1.0862	5.134	3.1149	3.0823	2.0611
Blanco-Ihle test	11.536	9.9184	3.1027	2.7535	7.0154	3.3922	6.0369	5.1612	3.0785	2.0755
RMSE	0.025003	0.024644	0.02696	0.027823	0.026294	0.029557	0.021107	0.021945	0.024848	0.027341
MAPE	1.7905	1.1596	1.0125	0.81546	1.1521	0.75312	1.3117	1.0549	1.0549	0.88778
Average VaR	-0.023011	-0.024503	-0.028144	-0.029201	-0.025858	-0.030363	-0.022449	-0.02243	-0.025785	-0.028168
Acceptance (Kupiec test)	**NO**	**NO**	**NO**	YES	**NO**	YES	**NO**	**NO**	**NO**	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 17 - Backtesting results and diagnostics of 500 VaR forecasts for SKSM index daily log returns, 95% confidence level, period 10.10.2003 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	37	29	29	25	28	24	21	24	16	22
Frequency of failures	0.074	0.058	0.058	0.05	0.056	0.048	0.042	0.048	0.032	0.044
Kupiec test (p value)	0.007661	0.17647	0.17647	0.44706	0.23168	0.52865	0.75905	0.52865	0.96571	0.6879
Christoffersen UC test (p value)	0.02112	0.42294	0.42294	1	0.54553	0.83639	0.3992	0.83639	0.048624	0.53008
Christoffersen IND test (p value)	0.43839	0.80199	0.54743	0.80616	0.067983	0.87753	0.89924	0.44939	0.30316	0.15421
Christoffersen CC test (p value)	0.051887	0.70292	0.60529	0.97034	0.15752	0.96735	0.69532	0.73535	0.084226	0.29756
Lopez test	12.362	4.3648	4.3368	0.32085	3.3136	-0.69014	-3.7182	-0.70877	-8.8052	-2.7396
Blanco-Ihle test	32.462	30.93	22.868	20.569	25.843	21.288	16.828	24.047	9.7456	15.288
RMSE	0.0162	0.016772	0.015581	0.01598	0.017609	0.016813	0.017435	0.01737	0.019772	0.016895
MAPE	2.4988	2.5062	1.9352	2.5436	1.0075	1.5511	2.3591	1.813	2.02	1.9177
Average VaR	-0.014295	-0.015258	-0.015254	-0.015886	-0.016192	-0.016445	-0.017629	-0.017316	-0.020881	-0.017428
Acceptance (Kupiec test)	**NO**	YES	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	YES	YES	YES	YES	**NO**	YES	YES	YES	YES	YES

Source: Author

Table 18 - Backtesting results and diagnostics of 500 VaR forecasts for SKSM index daily log returns, 99% confidence level, period 10.10.2003 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	16	13	7	7	9	5	12	15	8	6
Frequency of failures	0.032	0.026	0.014	0.014	0.018	0.01	0.024	0.03	0.016	0.012
Kupiec test (p value)	1.73E-05	0.000646	0.13232	0.13232	0.031102	0.38404	0.001901	6.15E-05	0.06711	0.23708
Christoffersen UC test (p value)	8.40E-05	0.00274	0.39657	0.39657	0.10602	1	0.007663	0.000286	0.21487	0.66302
Christoffersen IND test (p value)	0.30316	0.40428	0.65537	0.65537	0.56529	0.75037	0.44186	0.33489	0.60964	0.70234
Christoffersen CC test (p value)	0.000258	0.007951	0.63195	0.63195	0.22956	0.95065	0.021257	0.000871	0.40678	0.84538
Lopez test	11.183	8.191	2.0911	2.0785	4.1269	0.07547	7.1608	10.173	3.1078	1.0709
Blanco-Ihle test	10.404	9.9805	2.9491	2.4079	5.9708	2.5385	6.5735	10.357	3.9468	2.2656
RMSE	0.028019	0.029633	0.032989	0.032981	0.034227	0.03787	0.024553	0.024769	0.028172	0.033007
MAPE	1.7731	1.182	0.798	0.798	0.67581	0.32918	1.6185	1.4738	0.83791	0.53865
Average VaR	-0.026811	-0.028625	-0.034518	-0.034636	-0.033225	-0.038751	-0.025799	-0.025112	-0.029532	-0.034199
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	**NO**	YES	**NO**	**NO**	**NO**	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 19 - Backtesting results and diagnostics of 500 VaR forecasts for TALSE index daily log returns, 95% confidence level, period 16.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	34	28	16	12	25	19	10	21	7	9
Frequency of failures	0.068	0.056	0.032	0.024	0.05	0.038	0.02	0.042	0.014	0.018
Kupiec test (p value)	0.03026	0.23168	0.96571	0.99739	0.44706	0.87277	0.99954	0.75905	0.99998	0.99983
Christoffersen UC test (p value)	0.079233	0.54553	0.048624	0.003118	1	0.19939	0.000493	0.3992	1.41E-05	0.000169
Christoffersen IND test (p value)	0.005762	0.017199	0.010905	0.28312	0.03444	0.032264	0.52246	0.058758	0.65537	0.56529
Christoffersen CC test (p value)	0.004739	0.048769	0.005603	0.007121	0.10685	0.04435	0.001881	0.11749	7.30E-05	0.00072
Lopez test	9.1711	3.1586	-8.8873	-12.909	0.12809	-5.887	-14.924	-3.9028	-17.962	-15.948
Blanco-Ihle test	26.382	21.514	11.746	7.053	16.11	11.148	5.3851	13.346	2.2999	3.5721
RMSE	0.010627	0.010744	0.01182	0.012556	0.011145	0.011463	0.013587	0.01302	0.015362	0.013803
MAPE	2.1895	2.5212	3.2643	3.4638	1.9027	2.4788	3.2793	2.7531	3.9327	3.4763
Average VaR	-0.008432	-0.009014	-0.011033	-0.012488	-0.009476	-0.010634	-0.013561	-0.011337	-0.014998	-0.0133
Acceptance (Kupiec test)	**NO**	YES	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	**NO**	**NO**	**NO**	YES	**NO**	**NO**	YES	**NO**	YES	YES

Source: Author

Table 20 - Backtesting results and diagnostics of 500 VaR forecasts for TALSE index daily log returns, 99% confidence level, period 16.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	11	9	6	2	6	5	2	6	1	1
Frequency of failures	0.022	0.018	0.012	0.004	0.012	0.01	0.004	0.012	0.002	0.002
Kupiec test (p value)	0.005208	0.031102	0.23708	0.87661	0.23708	0.38404	0.87661	0.23708	0.96025	0.96025
Christoffersen UC test (p value)	0.019918	0.10602	0.66302	0.12504	0.66302	1	0.12504	0.66302	0.02824	0.02824
Christoffersen IND test (p value)	0.23191	0.56529	0.70234	0.89904	0.70234	0.75037	0.89904	0.70234	0.94947	0.94947
Christoffersen CC test (p value)	0.032579	0.22956	0.84538	0.30589	0.84538	0.95065	0.30589	0.84538	0.089933	0.089933
Lopez test	6.0801	4.064	1.0349	-2.9751	1.063	0.028851	-2.9646	1.0492	-3.9826	-3.988
Blanco-Ihle test	8.1953	5.48	1.7801	0.93433	5.2915	1.2642	1.6517	4.1732	0.84619	0.45831
RMSE	0.016023	0.018176	0.020874	0.024226	0.017741	0.021049	0.019621	0.018381	0.021677	0.025894
MAPE	1.2768	1.0025	0.86035	0.85287	0.58105	0.73067	0.85287	0.90274	0.96509	0.96509
Average VaR	-0.014105	-0.016086	-0.02031	-0.024507	-0.016394	-0.020452	-0.01991	-0.016709	-0.021213	-0.025102
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 21 - Backtesting results and diagnostics of 500 VaR forecasts for RIGSE index daily log returns, 95% confidence level, period 16.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	34	28	29	31	29	25	18	20	8	20
Frequency of failures	0.068	0.056	0.058	0.062	0.058	0.05	0.036	0.04	0.016	0.04
Kupiec test (p value)	0.03026	0.23168	0.17647	0.09445	0.17647	0.44706	0.91354	0.82115	0.99994	0.82115
Christoffersen UC test (p value)	0.079233	0.54553	0.42294	0.23456	0.42294	1	0.13135	0.28848	5.21E-05	0.28848
Christoffersen IND test (p value)	0.81973	0.60744	0.54743	0.042634	0.54743	0.80616	0.24571	0.8236	0.60964	0.19617
Christoffersen CC test (p value)	0.20883	0.73004	0.60529	0.063201	0.60529	0.97034	0.16333	0.55533	0.000245	0.24693
Lopez test	9.1564	3.1278	4.1272	6.1376	4.1184	0.11691	-6.912	-4.9139	-16.976	-4.9344
Blanco-Ihle test	17.852	12.865	12.027	13.151	11.767	10.833	7.046	7.5287	1.4951	5.0509
RMSE	0.011239	0.011055	0.010752	0.01104	0.012071	0.011201	0.012159	0.012568	0.015685	0.012558
MAPE	1.9401	2.3067	2.1845	2.9102	1.6958	1.8329	1.5387	1.3965	3.0599	1.5985
Average VaR	-0.010932	-0.011253	-0.011	-0.011242	-0.012175	-0.011563	-0.012877	-0.012913	-0.016513	-0.013069
Acceptance (Kupiec test)	**NO**	YES	YES	**NO**	YES	YES	YES	YES	YES	YES
Christoffersen IND test	YES	YES	YES	**NO**	YES	YES	YES	YES	YES	YES

Source: Author

Table 22 - Backtesting results and diagnostics of 500 VaR forecasts for RIGSE index daily log returns, 99% confidence level, period 16.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	17	11	4	2	11	4	8	6	1	1
Frequency of failures	0.034	0.022	0.008	0.004	0.022	0.008	0.016	0.012	0.002	0.002
Kupiec test (p value)	4.60E-06	0.005208	0.56039	0.87661	0.005208	0.56039	0.06711	0.23708	0.96025	0.96025
Christoffersen UC test (p value)	2.33E-05	0.019918	0.64143	0.12504	0.019918	0.64143	0.21487	0.66302	0.02824	0.02824
Christoffersen IND test (p value)	0.60145	0.48129	0.7993	0.89904	0.23191	0.7993	0.60964	0.70234	0.94947	0.94947
Christoffersen CC test (p value)	0.000113	0.051948	0.8687	0.30589	0.032579	0.8687	0.40678	0.84538	0.089933	0.089933
Lopez test	12.061	6.0342	-0.9927	-2.9961	6.035	-0.99064	3.0194	1.0201	-3.9983	-3.998
Blanco-Ihle test	4.8962	2.3797	0.38057	0.18473	2.4853	0.50577	1.0754	1.2635	0.080799	0.09282
RMSE	0.015468	0.017143	0.019708	0.021219	0.017556	0.01954	0.017499	0.018083	0.022678	0.022633
MAPE	2.2768	1.4439	0.56608	0.50125	1.3865	0.39152	1.0349	0.59601	0.75062	0.75062
Average VaR	-0.016021	-0.018241	-0.020951	-0.022318	-0.018448	-0.020865	-0.01878	-0.018776	-0.023354	-0.023326
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	**NO**	YES	**NO**	YES	YES	YES
Christoffersen IND test	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: Author

Table 23 - Backtesting results and diagnostics of 500 VaR forecasts for VILSE index daily log returns, 95% confidence level, period 30.12.2003 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	43	39	25	23	29	25	18	17	13	14
Frequency of failures	0.086	0.078	0.05	0.046	0.058	0.05	0.036	0.034	0.026	0.028
Kupiec test (p value)	0.000251	0.002701	0.44706	0.61007	0.17647	0.44706	0.91354	0.94408	0.99449	0.98919
Christoffersen UC test (p value)	0.000762	0.007699	1	0.67759	0.42294	1	0.13135	0.082169	0.006901	0.014162
Christoffersen IND test (p value)	0.029397	0.008042	0.000737	0.002456	0.32643	0.005742	0.023097	0.016105	0.039413	0.054505
Christoffersen CC test (p value)	0.000323	0.000856	0.003357	0.009344	0.44817	0.022044	0.024262	0.012199	0.003117	0.00777
Lopez test	18.184	14.175	0.14534	-1.8595	4.1354	0.14027	-6.9078	-7.9126	-11.934	-10.914
Blanco-Ihle test	30.204	22.116	16.314	15.316	16.824	15.491	7.8505	8.1307	5.1213	7.5836
RMSE	0.010079	0.010956	0.011019	0.010712	0.010556	0.010842	0.012348	0.012115	0.013243	0.011956
MAPE	4.0274	3.6608	2.6683	2.5162	1.6683	1.6035	2.4589	2.2095	3.0374	2.788
Average VaR	-0.00845	-0.009783	-0.010386	-0.010461	-0.00955	-0.010216	-0.012466	-0.0116	-0.013361	-0.011931
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	**NO**	**NO**	**NO**	**NO**	YES	**NO**	**NO**	**NO**	**NO**	**NO**

Source: Author

Table 24 - Backtesting results and diagnostics of 500 VaR forecasts for VILSE index daily log returns, 99% confidence level, period 30.12.2003 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	18	14	6	2	14	6	5	7	3	2
Frequency of failures	0.036	0.028	0.012	0.004	0.028	0.012	0.01	0.014	0.006	0.004
Kupiec test (p value)	1.16E-06	0.000206	0.23708	0.87661	0.000206	0.23708	0.38404	0.13232	0.73638	0.87661
Christoffersen UC test (p value)	6.10E-06	0.000914	0.66302	0.12504	0.000914	0.66302	1	0.39657	0.33148	0.12504
Christoffersen IND test (p value)	0.15539	0.054505	0.05405	0.89904	0.054505	0.05405	0.75037	0.002146	0.84892	0.89904
Christoffersen CC test (p value)	1.32E-05	0.000645	0.1422	0.30589	0.000645	0.1422	0.95065	0.006287	0.61281	0.30589
Lopez test	13.089	9.0837	1.051	-2.9686	9.0538	1.0378	0.036003	2.0388	-1.9749	-2.9748
Blanco-Ihle test	8.9673	7.4494	3.5403	1.8309	4.2634	2.2339	2.0295	2.3925	1.4887	1.4817
RMSE	0.014861	0.016259	0.018865	0.021069	0.017528	0.020536	0.017912	0.01732	0.018655	0.019146
MAPE	2.7955	1.9676	0.83541	0.92519	2.0349	0.83541	0.70075	0.61596	0.94763	0.92519
Average VaR	-0.013633	-0.015692	-0.018899	-0.021971	-0.017056	-0.020839	-0.018564	-0.017246	-0.018897	-0.019396
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	**NO**	YES	YES	YES	YES	YES
Christoffersen IND test	YES	**NO**	**NO**	YES	**NO**	**NO**	YES	**NO**	YES	YES

Source: Author

Table 25 - Backtesting results and diagnostics of 500 VaR forecasts for CYSMGENL index daily log returns, 95% confidence level, period 13.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	32	29	25	17	27	19	16	15	10	10
Frequency of failures	0.064	0.058	0.05	0.034	0.054	0.038	0.032	0.03	0.02	0.02
Kupiec test (p value)	0.066371	0.17647	0.44706	0.94408	0.29612	0.87277	0.96571	0.98014	0.99954	0.99954
Christoffersen UC test (p value)	0.16777	0.42294	1	0.082169	0.6852	0.19939	0.048624	0.027102	0.000493	0.000493
Christoffersen IND test (p value)	0.056742	0.0238	0.15562	0.12343	0.060759	0.032264	0.096153	0.33489	0.18573	0.18573
Christoffersen CC test (p value)	0.062886	0.05638	0.36489	0.067383	0.15875	0.04435	0.035856	0.054634	0.000961	0.000961
Lopez test	7.1875	4.2028	0.16105	-7.8844	2.1416	-5.853	-8.8818	-9.9302	-14.962	-14.97
Blanco-Ihle test	19.628	19.854	13.161	7.8048	11.947	11.905	8.1436	4.4086	2.0546	1.5497
RMSE	0.012454	0.012428	0.012518	0.014993	0.013395	0.012975	0.014343	0.014538	0.016829	0.017437
MAPE	1.8279	2.7805	2.818	3.3392	1.5162	2.4688	2.9875	2.0274	3.3815	3.3815
Average VaR	-0.012044	-0.012238	-0.012894	-0.015673	-0.013193	-0.013344	-0.015142	-0.014903	-0.017354	-0.017929
Acceptance (Kupiec test)	**NO**	YES	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	**NO**	**NO**	YES	YES	**NO**	**NO**	**NO**	YES	YES	YES

Source: Author

Table 26 - Backtesting results and diagnostics of 500 VaR forecasts for CYSMGENL index daily log returns, 99% confidence level, period 13.01.2004 -31.12.2005

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH RM	HHS
Number of failures	14	13	5	4	9	6	8	3	3	2
Frequency of failures	0.028	0.026	0.01	0.008	0.018	0.012	0.016	0.006	0.006	0.004
Kupiec test (p value)	0.000206	0.000646	0.38404	0.56039	0.031102	0.23708	0.06711	0.73638	0.99019	0.99741
Christoffersen UC test (p value)	0.000914	0.00274	1	0.64143	0.10602	0.66302	0.21487	0.33148	0.008738	0.001851
Christoffersen IND test (p value)	0.054505	0.039413	0.75037	0.7993	0.007289	0.05405	0.60964	0.84892	0.84892	0.89904
Christoffersen CC test (p value)	0.000645	0.001349	0.95065	0.8687	0.007399	0.1422	0.40678	0.61281	0.031556	0.007796
Lopez test	9.0806	8.0807	0.052169	-0.98404	4.0558	1.0302	3.0502	-1.9843	-6.9917	-7.9963
Blanco-Ihle test	5.963	5.5848	2.6515	0.68855	3.8444	1.5693	2.3528	0.75319	0.34632	0.12772
RMSE	0.019067	0.021875	0.021501	0.029459	0.021912	0.025138	0.020238	0.020776	0.021321	0.022937
MAPE	2.0524	1.6259	0.85786	0.7182	1.2244	1.202	1.2344	0.73815	1.4564	1.5985
Average VaR	-0.018143	-0.021179	-0.022584	-0.029743	-0.021239	-0.02554	-0.021454	-0.021023	-0.021668	-0.023171
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	**NO**	YES	**NO**	YES	YES	YES
Christoffersen IND test	**NO**	**NO**	YES	YES	**NO**	**NO**	YES	YES	YES	YES

Source: Author

Table 27 - Backtesting results and diagnostics of 500 VaR forecasts for MALTEX index daily log returns, 95% confidence level, period 19.12.2003 -31.12.2005

	HS 50	**HS 100**	**HS 250**	**HS 500**	**BRW λ=0,97**	**BRW λ=0,99**	**Normal VCV**	**Risk Metrics**	**GARCH RM**	**HHS**
Number of failures	38	32	29	29	29	25	23	15	22	18
Frequency of failures	0.076	0.064	0.058	0.058	0.058	0.05	0.046	0.03	0.044	0.036
Kupiec test (p value)	0.004606	0.066371	0.17647	0.17647	0.17647	0.44706	0.61007	0.98014	0.6879	0.91354
Christoffersen UC test (p value)	0.012912	0.16777	0.42294	0.42294	0.42294	1	0.67759	0.027102	0.53008	0.13135
Christoffersen IND test (p value)	0.000923	0.000409	0.000664	0.004448	0.0238	0.000737	0.000253	0.073289	0.012682	0.023097
Christoffersen CC test (p value)	0.000188	0.000749	0.002211	0.012694	0.05638	0.003357	0.001136	0.017492	0.036752	0.024262
Lopez test	13.185	7.1658	4.1659	4.1589	4.1476	0.14955	-1.8724	-9.9247	-2.912	-6.9333
Blanco-Ihle test	28.751	21.818	21.739	19.101	18.747	17.613	13.924	6.5804	7.4822	5.0329
RMSE	0.009685	0.009608	0.009283	0.009086	0.010274	0.009652	0.010206	0.011404	0.010616	0.011426
MAPE	2.8653	2.3317	2.596	2.606	1.3591	2.3815	2.611	1.7082	2.0549	1.8279
Average VaR	-0.008362	-0.00873	-0.008615	-0.008573	-0.009389	-0.009157	-0.0101	-0.01132	-0.010786	-0.011724
Acceptance (Kupiec test)	**NO**	**NO**	YES	YES	YES	YES	YES	YES	YES	YES
Christoffersen IND test	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**

Source: Author

Table 28 - Backtesting results and diagnostics of 500 VaR forecasts for MALTEX index daily log returns, 99% confidence level, period 19.12.2003 -31.12.2005

	HS 50	**HS 100**	**HS 250**	**HS 500**	**BRW λ=0,97**	**BRW λ=0,99**	**Normal VCV**	**Risk Metrics**	**GARCH RM**	**HHS**
Number of failures	14	14	11	7	11	8	11	7	5	1
Frequency of failures	0.028	0.028	0.022	0.014	0.022	0.016	0.022	0.014	0.01	0.002
Kupiec test (p value)	0.000206	0.000206	0.005208	0.13232	0.005208	0.06711	0.005208	0.13232	0.38404	0.96025
Christoffersen UC test (p value)	0.000914	0.000914	0.019918	0.39657	0.019918	0.21487	0.019918	0.39657	1	0.02824
Christoffersen IND test (p value)	0.00024	0.00024	0.01859	2.71E-05	2.28E-05	7.84E-05	0.01859	0.65537	0.75037	0.94947
Christoffersen CC test (p value)	4.83E-06	4.83E-06	0.004172	0.000105	8.47E-06	0.00019	0.004172	0.63195	0.95065	0.089933
Lopez test	9.0861	9.0755	6.0651	2.0506	6.0593	3.0523	6.0608	2.0311	0.021748	-3.9981
Blanco-Ihle test	8.0993	6.621	5.1271	3.2902	4.9743	3.9556	4.6325	1.8141	1.1596	0.054165
RMSE	0.015232	0.014296	0.014546	0.01483	0.016758	0.017363	0.014151	0.016222	0.014758	0.019224
MAPE	2.0449	1.9676	1.2519	0.98254	1.5162	0.92519	1.2519	0.5187	0.73815	0.75062
Average VaR	-0.014756	-0.014632	-0.015081	-0.015721	-0.016748	-0.017866	-0.0148	-0.016349	-0.015254	-0.019489
Acceptance (Kupiec test)	**NO**	**NO**	**NO**	YES	**NO**	**NO**	**NO**	YES	YES	YES
Christoffersen IND test	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	YES	YES	YES

Source: Author