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Modeling the Market Risk in the Context of the Basel III Acord

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Abstract. *Basel III revealed new aspects to be considered in terms of risk management and supervision of banking systems. Banks may use internal models to determine minimum capital requirements imposed by new regulations to be adopted gradually in the period 2013-2019. In this context, the implementation of internal models by banks, applying VaR or ES risk measures, is a challenge both in terms of continued growth in the number of methods used and the complexity of practical approaches. This study aims to estimate the market risk by VaR and ES risk measures using parametric methods, nonparametric and Monte Carlo simulations. There will also be implemented stress tests to assess the capital adequacy under stressed macroeconomic environment.*

Keywords: VaR; ES; Monte Carlo simulations; GARCH models; kernel smoothing.

JEL Codes: C14, C15, G21.
REL Codes: 11B, 10Z.

1. Introduction

The current global financial crisis has revealed some of the weakness of the banking systems. The globalization and the competition among banks have determined an excessive use of financial innovations and also an increase of the leverage in order to maintain their profitability. The banks' appetite for sophisticated derivatives, difficult to evaluate (such collateralized obligations, mortgaged backed securities and credit default swaps), led to the risks' undervaluation and concentration, subsequently materializing in capital erosion.

Many of the studies analyzing the current financial crisis emphasize as one of the major causes the weakness of the regulatory and supervision framework. Therefore, there is a consensus at the international level regarding the revision of the regulatory and supervision framework for banking activities as demonstrated by the Basel III that will be progressively implemented in the following years 2013-2019.

The document "*Revisions to the Basel II market risk framework"* issued by Basel Committee on Banking Supervision (BCBS) in February 2011 highlights the necessity of enhanced risk coverage, especially related to capital markets activities, and also an increase in the quality and quantity of the capital. Recent studies show that many banks recorded significant losses during 2007-2009, although they have comply with the minimum capital requirements as stated by Pillar I, Basel II. In the absence of an adequate capital and liquidity some banks have failed, while others have to reorganize their activity. In this context, the Basel III amendments for market risk address capital adequacy with respect to the liquidity of the financial instruments, especially for those with high maturities.

Another issue revealed by the current crisis is related to the procyclicality of the capital requirements that imply lower mandatory capital in periods of economic expansion and higher capital in recessions. According to the Minsky (1992) procyclicality is also the effect of the human behavior that amplifies the shocks affecting the financial institutions and markets and the economy as a whole.

Moreover the current crisis has demonstrated that the Basel II requirements lead to the risk sensitivity and coverage of the regulatory capital requirement, as the economic cycles have deteriorated the quality of assets and liabilities from the in and off-balance sheet of the bank. In order to reduce the procyclicality of the regulatory capital for market risk, the new proposals of BCBS include stress tests for one year time horizon in the measurement of the Value-at-Risk.

The implementation of internal models by banks, applying VaR or ES risk measures, is a challenge both in terms of continued growth in the number of methods used and the complexity of practical approaches such as: linear and non-linear parametric approaches (Alexander, 2008), historical simulation (Boudoukh, Richardson, Whitelaw, 1998, Barone-Adesi, Giannopoulos, Vosper, 1999), Extreme Value Theory (McNeil, Frey, 2002), Monte Carlo simulation (Glasserman, 2004), regression quantiles methods – CAViaR (Conditional Autoregressive Value at Risk, Engle, Manganelli, 2004), Markov Switching techniques (Gray, 1996, Klassen, 2002, Haas et al., 2004).

In practice, the complexity and difficulty of implementing VaR models consist in selecting the appropriate specification of the model, given that different methodologies lead to different capital requirements. Several studies on this topic were made by Berkowitz, Christoffersen and Pelletier (2011), Perignon and Smith (2010a, 2010b), Perignon, Deng and Wang (2008), Christoffersen (1998, 2001, 2004), Sarma et al. (2003), Lopez (1998).

In this context, market risk management represents a challenge for supervision and regulatory authorities, banks and also for the researchers.

Basel Committee on Banking Supervision addressed through *"Revisions to the Basel II market risk framework"* (2011) document new issues regarding the measurement of the market risk. In this way, the trading book capital requirements using the internal models approach will be the subject to the general and specific market risk capital charge measured using a 10-day VaR at the 99 percent confidence level and a stressed VaR. One of the most important revisions refers to the incremental risk capital charge, which includes default risk and migration risk for unsecuritised credit products.

A quantitative impact study regarding trading book conducted by Basel Committee on Banking Supervision in 2009 across a sample of 49 banks from 10 countries had as objective the capital requirements under the standardized measurement method for incremental risk exposure, securitization exposures, stressed VaR and the specific risk. The impact study shows an average increase of at least 11.5% of overall capital requirements and of 223.7% of market risk capital requirements. The increase in capital requirements for market risk breaks down as follows: 110.8% stresstesting VaR, 60.4% the incremental risk, 5.4% trading securitization and 0.2% the specific risk.

2. The data

The purpose of this study is to estimate the market risk from FX position and from equity position by using Value-at-Risk and Expected Shortfall as a measure of the risk. In this way, we consider one portfolio composed from four currencies (euro, US dollar, British pound and Swiss franc) and another portfolio composed from five most traded equities on Romanian capital market (SIF1, SIF2, SIF3, SIF4 and SIF5). Historical observations from each portfolio are used in order to determine the returns distribution and therefore to quantify market risk by the means of Value at Risk (VaR) and Expected Shortfall (ES). The data series used for the first portfolio were extracted from the database of National Bank of Romania, representing the exchange rate EUR/RON, USD/RON, GBP/RON and CHF/RON, with daily observations from January 8, 2002 – April 8, 2011 (2267 observations). For the second portfolio, data series were extracted from the Bucharest Stock Exchange database, also, daily observations which covered the same period as in the case of the first portfolio (2267 observations).

The returns of two portfolios considered were determined by using the following formula:

$$R_i = \ln \frac{S_t}{S_{t-1}} \tag{1}$$

where R_i represents the return of the asset *i*, S_t represents the exchange rate *i* between two currencies or the price of the stock *i* at the moment *t*. We assumed the following structure of the currency portfolio: a share of 70% for the euro, 10% for US dollar, 5% for the British pound and 15% for Swiss franc. In the case of the stock portfolio we assumed equally weights for the five stocks which we are selected.

To estimate de market risk we proceeded further to analyze the behavior of the data series used, i.e. the return of the currencies portfolio and the return of the stock portfolio. In Table 1 we present some descriptive statistics for the daily returns of both currency and stock portfolios. The two data series are leptokurtic as the Kurtosis is greater than 3. In addition, the Skewness indicates a right asymmetry for the return of the currency portfolio and a left asymmetry for the other one.

Table 1

Descriptive statistics for the returns of the portfolios

Indicators	Currency portfolio	Stock portfolio
Mean	0.0001	0.0010
Minimum	-0.0274	-0.1608
Maximum	0.0340	0.1382
Standard Dev.	0.0048	0.0275
Skewness	0.5337	-0.1108
Kurtosis	8.7594	7.7276

From the evolution of the returns for the selected portfolios depicted in Figure 1 we can draw some conclusions.

a. currency portfolio b. stock portfolio

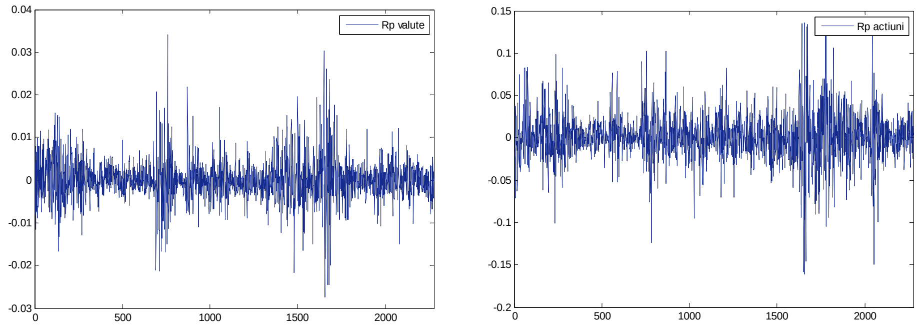


Figure 1. *The return of the currency and stock portfolio*

First, as expected the portfolios' returns are heteroskedastic, as a result of the volatility clustering: alternating periods of low volatility with those of high volatility. Second, the volatility of the stock portfolio returns is much higher than that of the currency portfolio, implying higher capital requirements for the market risk resulting from the exposure on equities. Thirdly, we noticed that in recent years (2008-2011) the volatility of analyzed returns increased drastically, this period capturing the global financial crisis. In the case of the stock portfolio composed by the SIF´s companies stocks the maximum return was 13.83% and the minimum return was reached -16.08%, while for the currency portfolio 3.4% and -2.74% respectively.

3. Modeling market risk

The estimation of the market risk by VaR and expected shortfall was realized through models which are established in risk management as parametric models, historical simulations and Monte Carlo simulations. More specifically, in this study we use the following models: a parametric model with a mixture of normal distributions, three nonparametric models based on historical simulation and a model based on Monte Carlo simulation. The computations were performed in Matlab.

3.1. The parametric model with mixture of normal distributions

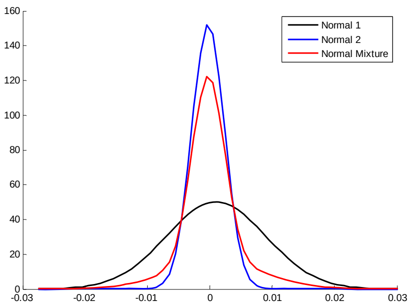
A useful statistical tool for capturing different states of the financial markets is the mixture of normal distributions. In this context, the portfolio returns are assumed to be generated by two market regimes: one with a moderate volatility and another with a higher volatility. Under each regime the returns are assumed normally distributed, where the more volatile regime has the mean μ_1 and the variance σ_1^2 , while the moderate regime with the mean μ_2 and the variance σ_2^2. Therefore, we can determine a mixture of the two normal distributions with the following distribution function:

$$G(x) = \pi\, F\left(x; \mu_1, \sigma_1^2\right) + (1-\pi) F\left(x; \mu_2, \sigma_2^2\right) \qquad (2)$$

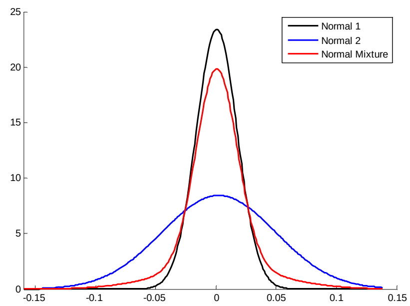
where π represents the probability of the highly volatile market regime, $F\left(x; \mu_t, \sigma_t^2\right)$ is the normal distribution function of the assets t with the mean μ_t and the variance σ_t^2 (for t = 1, 2).

Figure 2 presented below shows the distribution approximation of the returns by using a mixture of Normal distributions for the two portfolios. It appears that one of the normal distribution has a lower standard deviation corresponding to less volatile market regime and the other distribution has a much higher standard deviations associated to the volatile market regime.

a) currency portfolio



b) stock portfolio



Source: Authors´ calculations.

Figure 2. *Distribution approximation of the returns with a mixture of normal distributions*

The parameters estimation was performed by Expectation Maximization (EM) algorithm (Alexander, 2008). The EM algorithm introduces explicitly a latent variable in the maximization of the likelihood function. In order to compute the parameters of the mixture distribution, EM algorithm consists of iterating between two steps, the E-step and the M-step. The E-step implies the computation of the expected log-likelihood given the results obtained for the parameters of the function to be optimized and given the distribution of the latent variable. The M-step involves an optimization which is applied to find a new value of the parameters that maximize the likelihood function. The EM algorithm iterates the two steps successively until the convergence is reached. Table 2 presented the estimates obtained for the chosen model by applying the EM algorithm.

Table 2

Estimated parameters of the Normal mixture distributions

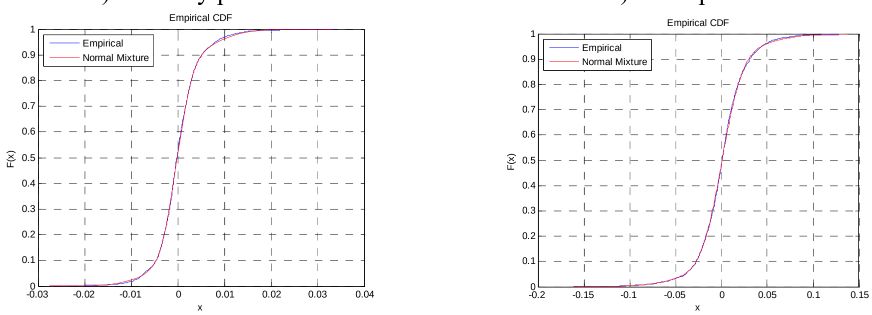
Variable	π	μ_1 %	μ_2 %	σ_1 %	σ_2 %
Currency portf.	0.2901	0.10	-0.02	0.79	0.26
Stock portf.	0.2382	0.23	0.06	4.69	1.70

Source: Authors´ calculations.

From Table 2 we observe that in the case of the currency portfolio the probability associated to the highly volatile regime is 29.01% (where the daily returns have a mean of 0.10% and a standard deviation of 0.79%) and the probability of the moderate volatility regime is 70.99% (the mean is -0.02% and the standard deviation is 1.70%). In other word, it was given a greater importance to the regime with moderate volatility. Similarly, for the stock portfolio two regimes were determined, where the more turbulent regime has an estimated volatility of 4.69% and an associated probability of 23.82%.

The estimation of the 1 day-VaR measures were realized in Matlab, determining the quantiles of the Normal mixture distribution corresponding to a 99% and 95% confidence levels. We have also calculated the ES indicator that represents the average level of loss, given that the VaR is exceeded.

a) currency portfolio b) stock portfolio



Source: Authors´ calculations.

Figure 3. *Empirical cumulative distribution function (99% confidence level)*

Figure 3 illustrates the empirical versus the theoretical cumulative distribution function for the mixture distributions. We observe that the two cumulative distribution functions almost overlap; therefore we conclude that the mixture distribution adequately captures the data series. The estimates of the VaR and ES are presented in Table 4 and will be discussed later in comparison with the results of the other methods.

3.2. The historical simulations models

The second category of models that we are using in this study refers to the historical simulations methods, i.e. simulations with equal weights assigned to the portfolio returns (HS), historical simulations with exponential weights (HS EW) and filtered historical simulation (FHS). VaR measures were estimated based on distributions determined through kernel smoothing techniques.

The estimation of kernel density represents a nonparametric method to determine the density function of a random variable. The aim of kernel fitting is to derive a smooth curve for a set of the discrete variables. Thus, using kernel fitting it can be inferred the population density from an empirical density function.

Given a random sample $\{x_1, x_2, ..., x_n\}$ on a random variable *X*, the kernel approximation to the density of *X* is defined by the following relation:

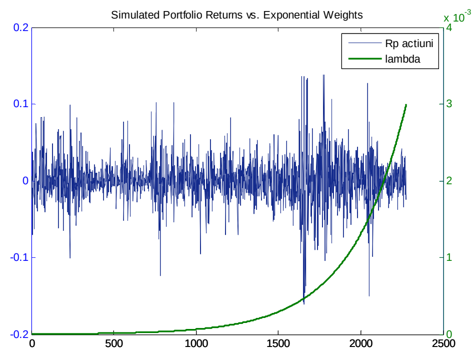
$$\hat{f}_h(x) = (nh)^{-1} \sum_{i=1}^{n} K(u) \tag{3}$$

where $u = \frac{x - x_i}{h}$, K is the kernel function and h is the smoothing parameter representing the bandwidth. The aim of kernel fitting algorithm is to find the optimal bandwidth. The kernel algorithm is of several types such as uniform, triangular, Gaussian, Epanechnikov etc. The algorithm used in this study, kernel Epanechnikov, can be determined using the formula:

$$K(u) = \begin{cases} \frac{3}{4}(1-u^2), & -1 \le u \le 1 \\ 0 & else\,where. \end{cases} \tag{4}$$

In the first historical simulation (HS) model implemented here, we assume that past and current returns are equally important in the construction of the distribution of the future returns. In other words, in our first HS specification far in the past observed returns are equally likely with recent realized returns to be observed in the near future.

In the second model (HS EW), the returns are assigned different weights. The methodology implemented is the one proposed by Boudoukh, Richardson and Whitelaw (1998). To estimate the final distribution we proceeded by giving lower weights to the past returns and higher weights to the recent returns. The historical simulation depends on the smoothing parameter, λ, which captures the behavior of the data series. Figure 4 shows the historical return of the stock portfolio and how we attribute their weights for the parameter $\lambda = 0.997$.



Source: Authors´ calculations.

Figure 4. *The historical return of stock portfolio and the assignment of weights (* $\lambda = 0.997$ *)*

In the third model we apply historical simulation based on the filtered returns (FHS) according to the methodology developed by Hull and White (1998) and Duffie and Pan (1997). In order to filter the returns, ARMAX-GARCH models were used. Such choice is motivated by the stylized facts discussed in the literature. The returns of both portfolios considered here are heteroskedastic and leptokurtic and present volatility clustering.

The filtered returns are determined as:

$$R_{t,T} = \left(\frac{\hat{\sigma}_T}{\hat{\sigma}_t} \right) R_t , \tag{5}$$

where R_t is the historical return at the moment *t*, $\hat{\sigma}_t$ represents the standard deviation at the moment *t* estimated by a GARCH model and *T* is fixed.

We introduced an AR(1) term in the mean equation of the GARCH model in order to solve the problem of the autocorrelation of the portfolio's returns.

We found relevant the following GARCH models: AR(1)-GJR and AR(1)-EGARCH with normal distribution for the currency portfolio and

AR(1)-GARCH with normal and t distribution for the stock portfolio. Table 3 illustrates the estimation of the GARCH models considered.

Table 3

The parameters estimated for the GARCH models

AR(1)-GJR(1,1,1) N		**AR(1)-EGARCH(1,1,1) N**		**AR(1)-GARCH(1,1) N**		**AR(1)-GARCH(1,1) T**	
Currency portfolio				**Stock portfolio**			
Mean equation		**Mean equation**		**Mean equation**		**Mean equation**	
Variable	Parameters	Variable	Parameters	Variable	Parameters	Variable	Parameters
C	0.0001	C	0.0001	C	0.0012	C	0.0009
	(0.0001)*		(0.0001)*		(0.0004)		0.0003
AR(1)	0.0722	AR(1)	0.0696	AR(1)	0.1094	AR(1)	0.0919
	(0.0212)		(0.0206)		(0.0214)		0.0216
Variance equation		Variance equation		Variance equation		Variance equation	
Variable	Parameters	Variable	Parameters	Variable	Parameters	Variable	Parameters
C	0.0000	C	-0.2123	C	0.0000	C	0.0000
	(0.0000)		(0.0408)		(0.0000)		0.0000
GARCH(1)	0.8754	GARCH(1)	0.9796	GARCH(1)	0.8220	GARCH(1)	0.8125
	(0.0089)		(0.0038)		(0.0112)		0.0189
ARCH(1)	0.0998	ARCH(1)	0.2475	ARCH(1)	0.1736	ARCH(1)	0.1853
	(0.0112)		(0.0161)		(0.0138)		0.0225
Leverage(1)	0.0347	Leverage(1)	-0.0264	Leverage(1)	-	Leverage(1)	-
	(0.0137)		(0.0084)				
Log likehood	9304.70	Log likehood	9297.60	Log likehood	5359.10	Log likehood	5397.7
Akaike criterion	-8.1728	Akaike criterion	-8.1665	Akaike criterion	-4.7046	Akaike criterion	-4.7373
Schwarz criterion	-8.1576	Schwarz criterion	-8.1513	Schwarz criterion	-4.692	Schwarz criterion	-4.7226

*The estimated parameter is not statistically significant.

Source: Authors´ calculations, the probability associated of the parameters is passed in the parenthesis.

It was found that the return of the currency portfolio responds asymmetrically to the shocks that appear on the market since the parameter of the leverage was statistically significant for a 1% confidence level. On the other hand, this was not the case for the returns of the stock portfolio. However, this is a common result in the empirical literature.

3.3. Monte Carlo simulation

In this study we used multivariate GARCH models in order to capture the temporal dependence in the second order moments of asset returns. We first estimate the parameters of a multivariate GARCH model and then we generate by Monte Carlo simulations possible futures evolutions of the returns for the currency portfolio and the stock portfolio.

The multivariate model used is CCC GARCH (Constant Conditional Correlation GARCH) introduced by Bolerslev (1990). The CCC GARCH model assumes that the variance-covariance matrix at time t is:

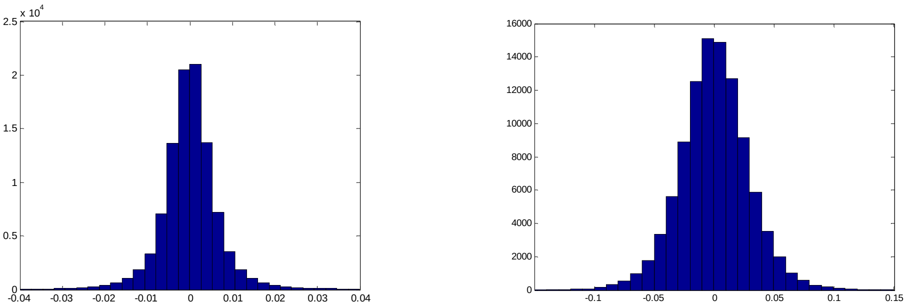
$$V_t = D_t C D_t \tag{6}$$

where D_t is a diagonal matrix of the time varying GARCH volatilities at the moment t, C is a correlation matrix that is constant over time. The variance-covariance matrix is positive defined if and only if the associated correlation matrix is positive definite. For example, the estimated correlation matrix for the portfolio of equities is as follows:

$$R = \begin{pmatrix} 1 & & & \\ 0.4413 & 1 & & \\ 0.6176 & 0.5116 & 1 & \\ 0.8156 & 0.4146 & 0.5572 & 1 \end{pmatrix}$$

Once the CCC GARCH model parameters were estimated, we have generated 10,000 possible paths for the next day in order to calculate VaR and ES risk measures. The estimates are presented in Table 4, while Figure 5 shows the distributions generated for the return of the two portfolios.

a. currency portfolio b. stock portfolio



Source: Authors' calculations.

Figure 5. *Return distributions estimated by Monte Carlo simulation*

3.4. Empirical results

Results obtained for the 1 day-VaR and 1 day-ES at the 99% and 95% confidence level are illustrated in Table 4. In the case of the currency portfolio, we observed that the highest values of VaR and ES at the 99% confidence level were determined under the Monte Carlo simulation approach, the parametric model and HS model. In the case of the stock portfolio, the highest level of VaR and ES (99% confidence level) was recorded by the parametric model followed by HS and the Monte Carlo simulation approach. Also, as expected, the VaR and ES measures are much higher for the stock portfolio than those obtained for the currency portfolio.

Table 4

Estimations for 1 day-VaR and 1 day-ES

Models	1-α	Parame-tric Model	HS	HS EW			FHS		Monte Carlo CCC GARH
				λ=0.95	λ=0.97	λ=0.99	AR(1)-GJR(1.1.1)	AR(1)-EGARCH(1.1.1)	
Currency portfolio									(%)
VaR	95	-0.69	-0.72	-0.63	-0.65	-0.57	-0.65	-0.73	-0.91
	99	-1.34	-1.21	-0.80	-0.80	-0.85	-1.07	-1.19	-2.00
ES	95	-1.01	-1.04	-1.01	-0.99	-0.92	-0.99	-1.05	-1.49
	99	-1.87	-1.73	-1.16	-1.16	-1.26	-1.52	-1.71	-2.98
Models	**1-α**	**Parametri c Model**	**HS**	**HS EW**			**FHS**		**Monte Carlo CCC GARH**
				λ=0.95	**λ=0.97**	**λ=0.99**	**AR(1)-GARCH(1.1)**	**AR(1)-GARCHt(1.1)**	
Stock portfolio									(%)
VaR	95	-4.03	-3.98	-2.50	-2.48	-3.01	-2.89	-2.87	-4.59
	99	-7.94	-7.86	-3.64	-3.74	-5.26	-4.60	-4.58	-7.44
ES	95	-6.73	-6.60	-4.47	-4.46	-5.23	-5.11	-5.10	-6.25
	99	-10.89	-10.76	-6.05	-6.18	-7.84	-7.22	-7.22	-9.26

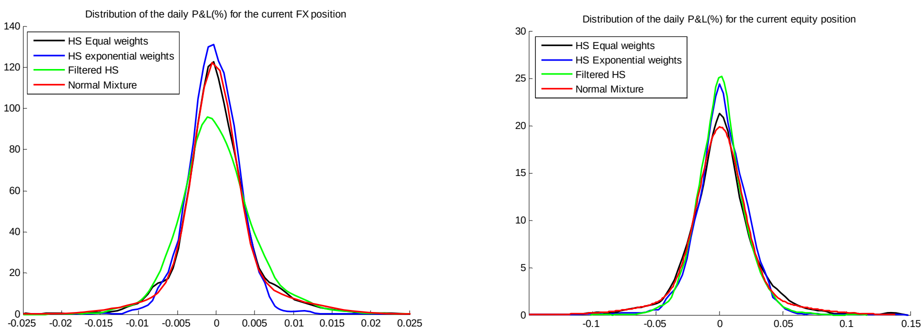
Source: Authors' calculations.

Analyzing HS EW models, we see that the VaR depends on λ and a low value of this parameter reveals a greater importance attributed of recent returns. Regarding FHS models, we observed that the lowest capital requirements were recorded by AR(1)-GJR model.

It is also important to highlight that in the case of the stock portfolio, for a 99% confidence level, values obtained for the ES measure are very high, reaching a maximum of 10.89% for the parametric model with a mixture distribution, implying higher capital requirements.

These results are closely related to the recent financial crises which has generated a very high volatility on the capital market in Romania especially in 2008, a fact confirmed by the Annual Report of the Bucharest Stock Exchange (2008) which reveal the following: "Against the background of the local stock market liquidity much lower than for other markets from US, Europe or Asia, the phenomenon of contagion that have been transformed correlations between BSE indices and those of international stock markets caused extremely high volatility. This situation made possible for some of the most important financial instruments traded on BSE to not be displayed purchase orders in a few trading sessions in recent months of 2008 (…). Therefore, the first time in over a decade of the history of BSE, in 8 October 2008 was necessary to suspend the trading session due to excessively high volatility."

Figure presented below shows the empirical distribution of the portfolio returns for each model that we implemented (HS, HS EW, FHS, parametric model) and on which we calculated VaR and ES. The distribution for CCC GARCH model was already presented in section 3.3.



Source: Authors' calculations.

Figure 7. *Estimated distributions for the currency / stock portfolio (λ=0,95)*

4. Stresstesting VaR

Basel III and the new regulation regarding market risk require to calculate a stressed VaR, which must supplement the VaR based on the most recent one-year observation period.

We chose two methods for implementing the stress tests: the FHS method and the parametric method with mixture distributions. In the first method, the parameter that we stress is the current volatility, σ_T. This parameter can be increased from the estimated value to higher values and adjusting all the past observation with the stressed value (according to relation 5), resulting a new return distribution with a higher standard deviation.

In the normal mixture method, the parameter stressed is the probability associated to the highly volatile regime, π. In this exercise we can determine the impact in VaR and therefore in the capital requirement of an increase of the probability, π, from the current estimated level.

Table 5 shows the results of the stress tests for different values from the interval 1% - 5% of the current volatility and for four different values of the probability of the highly volatile regime (0.4, 0.5, 0.6 and 0.95).

Table 5

Stress test VaR

Scenarios	σ_T (%)	VaR 99%, FHS (%)		π	VaR 99%, Parametric Model (%)	
		Currency portfolio	Stock portfolio		Currency portfolio	Stock portfolio
1	1	-2.42 (EGARCH)	-2.48 (GARCH t)	0.4	-1.,45	-9.04
2	2.5	-6.16 (GJR)	-6.23 (GARCH N)	0.5	-1.53	-9.48
3	3	-7.40 (GJR)	-7.47 (GARCH N)	0.6	-1.59	-9.83
4	5	-12.12 (EGARCH)	-12.44 (GARCH t)	0.95	-1.73	-10.68

Source: Authors' calculations.

5. Concluding remarks

"Basel III: A global regulatory framework for more resilient banks and banking systems" document highlights the need for more comprehensive treatment of risks, particularly those arising from capital market trading and an increase in the quality of the capital base.

In this paper, we highlight the usefulness of some models for measuring market risk such as parametric models, nonparametric models and Monte Carlo simulations. Estimations resulted indicate higher capital requirements in the case of both portfolios for the CCC GARCH model, the parametric model with mixture distributions and the HS models (99% confidence level). Capital requirements were much higher for the stock portfolio due to an excessive volatility on the capital market in Romania in 2008-2011. In addition, according to new regulation introduced by Basel III, we conducted a series of stress testing scenarios to capture the capital adequacy under crisis conditions.

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