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Degiannakis, Stavros and Floros, Christos and Livada, Alexandra

Portsmouth Business School, Department of Economics, University of Portsmouth, Department of Statistics, Athens University of Economics and Business

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Evaluating Value-at-Risk Models before and after the Financial Crisis of 2008: International Evidence

Stavros Degiannakis[*×], Christos Floros[×], and Alexandra Livada[#]

[×]Portsmouth Business School, Department of Economics, University of Portsmouth, Portsmouth, Portland Street, PO1 3DE, United Kingdom

[#]Department of Statistics, Athens University of Economics and Business, Patission 76, Athens, 104 34, Greece

Abstract

This paper focuses on the performance of three alternative Value-at-Risk (VaR) models to provide suitable estimates for measuring and forecasting market risk. The data sample consists of five international developed and emerging stock market indices over the time period from 2004 to 2008. The main research question is related to the performance of widely-accepted and simplified approaches to estimate VaR before and after the financial crisis. VaR is estimated using daily data from UK (FTSE 100), Germany (DAX30), USA (S&P500), Turkey (ISE National 100) and Greece (GRAGENL). Methods adopted to calculate VaR are: 1) EWMA of Riskmetrics, 2) classic GARCH(1,1) model of conditional variance assuming a conditional normally distributed returns and 3) asymmetric GARCH with skewed Student-t distributed standardized innovations. The results indicate that the widely accepted and simplified ARCH framework seems to provide satisfactory forecasts of VaR not only for the pre-2008 period of the financial crisis but also for the period of high volatility of stock market returns. Thus, the blame for financial crisis should not be cast upon quantitative techniques, used to measure and forecast market risk, alone.

Keywords: ARCH, Value-at-Risk, Volatility, Forecasting, Financial Crisis.

[*] Corresponding Author. E-mail address: Stavros.Degiannakis@port.ac.uk.

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1. Introduction

Since 1980s banks have provided several products to control risks, while more recently they have started to manage credit risks by providing bonds, derivatives and other financial products. Recent economic crisis of 2008 (or recession) resulted by a liquidity crisis in the US banking system.

The 2008 banking crisis appeared with the subprime mortgage crisis in the US following a collapse of international financial institutions as well as massive declines in stock prices around the world (Longstaff, 2010). As liquidity of the markets fell out, banks turned to the interbank market to fund their liquidity gap. The result was a fall in the values of the investments and a downward pressure on stock prices. The extend of the crisis began with the failure of three large US investment banks, which turned to unstable stock prices and high volatility of international indices (for more details see Alexander, 2008a). According to Alexander (2008a, p. xxxi), "*the main factor underlying this financial crisis is the intrinsic instability in the banking system resulting from the lack of unified and intelligent principles for the accounting, regulation, and risk management of financial institutions*".

In particular, risk management identifies and measures risks using risk metrics like VaR. For financial institutions, VaR is a commonly used risk measure[1], which is the maximum expected loss at a given confidence level over a given period of time. Given this definition, the role of risk management is highly important.

There is no empirical evidence on the usefulness of simple VaR models in measuring risk before and after a financial crisis. The aim of the article is to investigate the performance of three alternative risk models of VaR and show that in periods of strong fluctuations of asset prices (high volatility), such as the year 2008, the estimates of VaR can be calculated with satisfactory precision. We estimate VaR using daily data from five international markets. We adopt three widely used methods to calculate VaR as follows: 1) EWMA of Riskmetrics, 2) classic GARCH(1,1) model of conditional variance assuming a conditional normally distributed returns and 3) asymmetric GARCH with skewed Student-t distributed standardized innovations. The main contribution of this paper is that it provides evidence that widely accepted/used methods give reliable VaR estimates and

[1] Although the VaR is not a coherent measure of risk, i.e. VaR is not sub-additive, which means that the VaR of an overall portfolio may be greater than the sum of the VaRs of its component parts, it is widely used for modeling and forecasting risk. According to Artzner et al. (1999) a coherent measure shares the properties of sub-additivity, homogeneity, monotonicity and the risk-free condition.

forecasts for periods of financial turbulence (financial crises). To the best of our knowledge, this is the first evaluation of VaR models, before and after the financial crisis of 2008, using data from mature and emerging markets.

The paper continues as follows. Section 2 outlines the basics of VaR methodology, while Section 3 presents models of VaR estimation. Section 4 discusses parametric VaR modeling, and Section 5 illustrates the evaluation of VaR models. Data and empirical results are discussed in Section 6. Finally, concluding remarks are made in Section 7.

2. Value-at-Risk

VaR at a given probability level $(1-p)$, is defined to be the predicted amount of financial loss of a portfolio over a given time horizon. This is formally defined as follows. Let P_t be the observed value of a portfolio at time t, and let $y_t = \log(P_t / P_{t-1})$ denote the log-returns for the period from $t-1$ to t. For a long trading position[2] and under the assumption of standard normally distributed log-returns, VaR is defined to be the value $VaR_t^{(1-p)}$ satisfying the condition[3]:

$$p = P\left(y_t \leq VaR_t^{(1-p)}\right) = \int_{-\infty}^{VaR_t^{(1-p)}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} y_t^2\right) dy_t. \tag{1}$$

This implies that

$$VaR_t^{(1-p)} = \zeta_p, \tag{2}$$

where ζ_p is the $(100p)$-th percentile of the standard normal distribution.

Hence, under the assumption that $y_t \sim N(0,1)$, the probability of a loss less than $VaR_t^{(1-p)} = -1.645$ is equal to $p = 5\%$.[4] The value -1.645 is the value of VaR at a 95% level of confidence, or, in other words, for a capital of €10 million, the 95% VaR equals

[2] The state of owning a security is called long position. The sale of a borrowed security with the expectation that the asset will fall in value is called short position.

[3] Baumol (1963) was the first who attempted to estimate the risk that financial institutions face. He proposed a measure that is not different from the widely known VaR.

[4] Accordingly, for a short trading position, $VaR_t^{(95\%)}$ is obtained through the condition $5\% = P\left(y_t \geq VaR_t^{(95\%)}\right) = \int_{VaR_t^{(95\%)}}^{+\infty} (2\pi)^{-1/2} \exp\left(-y_t^2/2\right) dy_t$, i.e., $VaR_t^{(95\%)} = \zeta_{0.95}$. Note that in short trading positions a portfolio may encountered greater losses compared to a long trading position (see for example Cheong, 2008; Angelidis and Degiannakis, 2005).

€164500. Thus, if a risk manager states that the daily VaR of a portfolio is €164500 at a 95% confidence level, it means that there are five chances in a 100 for a loss greater than €164500 to incur.

In the case that i) the mean return of the portfolio the period from $t-1$ to t, that is denoted as μ_t, ii) the volatility fluctuation is denoted as σ_t^2 , and iii) the distribution for the logarithmic changes is denoted as $f(.)$, then the $VaR_t^{(1-p)}$ can be estimated as:

$$VaR_t^{(1-p)} = \mu_t + \zeta_p \sigma_t, \tag{3}$$

where f_p is p-percentage point of the assumed distribution $f(.)$. There are a lot of papers published on the application of simple VaR methods (and alternative approaches, such as the Conditional VaR) for developed (mature) markets (see Huang and Tseng, 2009; Alexander, 2008a; Alexander, 2009; Winker and Maringer, 2007 among others), while studies on the estimate of VaR with data from the Greek capital market have been published by Angelidis and Benos (2008), Angelidis and Degiannakis (2008b) and Diamandis et al. (2006). In addition, we have some recent evidence from previous studies on the performance of VaR models for emerging markets like Turkey. Assaf (2009) used the extreme-value theory (EVT) and estimated VaR daily losses from four emerging markets of Middle East and North Africa (Egypt, Jordan, Morocco and Turkey). He found that Turkey had the highest market risk according to the amount at loss. Furthermore, Huang and Tseng (2009) compared the performance of commonly used VaR methods with that of a nonparametric kernel estimator (KE) for 37 equity indices from both developed and emerging markets. They provided evidence that the KE method can generate reliable VaR estimates. Recently, Ozun et al. (2010) employed eight filtered EVT models to estimate VaR for the Istanbul Stock Exchange. The results indicated that filtered EVT models performed well in terms of capturing fat tails in stock market returns than parametric VaR models.

3. Models of VaR Estimation: A Review

VaR is approached with various techniques, which belong in three broad categories: i) non-parametric, ii) parametric and iii) semi-parametric techniques.

Non-parametric techniques: the Historical Simulation (HS), is one of the most common methods of VaR estimation because of its simplicity. Suppose that the distribution of portfolio returns remains constant, VaR can be calculated as the p-

percentage point of the empirical distribution of the available T logarithmic changes, y_t, for $t=1,2,...,T$:

$$\text{VaR}_t^{(1-p)} = f_p\left(\{y_{t+1-\tau}\}_{\tau=1}^{T}\right). \tag{4}$$

Parametric techniques: the widely used technique of VaR estimate is the calculation under the assumption of normally distributed log-returns with the use of the Autoregressive Conditionally Heteroscedastic (ARCH) model. Suppose that the logarithmic changes can be expressed by $y_t = \mu_t + \varepsilon_t$, where μ_t is the expected return of portfolio for the period from $t-1$ to t, and ε_t, ($\varepsilon_t = y_t - \mu_t$), is the error term. The unpredictable part of the log-return is expressed with an ARCH process as follows:

$$\begin{aligned} \varepsilon_t &= \sigma_t z_t \\ \sigma_t &= g(\theta \mid I_{t-1}) \\ z_t &\sim f(0,1;w). \end{aligned} \tag{5}$$

The unpredictable part of the log-return is the product of a non-negative functional form of the information set at time $t-1$, I_{t-1},(i.e. the standard deviation), and a random variable z_t, with probability density function, $f(.)$, mean equal to zero and variance equal to unity. The function $g(\theta \mid I_{t-1})$ expresses the standard deviation σ_t and can be modeled as a function of the information set at time $t-1$, I_{t-1}. θ and w are vectors with parameters to be estimated. The VaR estimate from an ARCH model is given by:

$$VaR_t^{(1-p)} = \mu_t + f_p(z_t;w)\sigma_t, \tag{6}$$

where $f_p(z_t;w)$ is the p-percentage point[5] of the distribution of z_t as it has been expressed in (5) with $f(0,1;w)$.

Semi-parametric techniques: alternative methods have been proposed to estimate Value at Risk such as the Filtered Historical simulation and applications of Extreme Value Theory[6].

4. Parametric Value-at–Risk Modeling

The one-step-ahead VaR, based on ARCH model, can be estimated as follows:

$$VaR_{t+1|t}^{(1-p)} = \mu_{t+1|t} + f_p\left(z_t;w^{(t)}\right)\sigma_{t+1|t}, \tag{7}$$

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[5]For long trading positions we have $f_p(z_t;w)$, while for short trading positions we have $f_{1-p}(z_t;w)$.

[6] For more information, see Byström (2004), Gençay and Selçuk (2004) and Hull and White (1998).

where $\mu_{t+1|t}$ and $\sigma_{t+1|t}$ are forecasts for the mean and the standard deviation, respectively, the time $t+1$ given the information set that is available up to time t. At each point in time, we proceed in re-estimations of vectors of parameters θ and w, in order to take into consideration the most recently available information (in the information set of current time moment, I_t).

The applied parametric model can be described as follows:

$$
\begin{aligned}
y_t &= c_0(1-c_1)+c_1 y_{t-1}+\varepsilon_t \\
\varepsilon_t &= \sigma_t z_t \\
\sigma_t^2 &= g(\theta \mid I_{t-1}) \\
z_t &\sim f(0,1;w).
\end{aligned}
\tag{8}
$$

The expected return of portfolio can be modeled as a first order autoregressive model[7], AR(1), that is given by $\mu_t \equiv c_0(1-c_1)+c_1 y_{t-1}$.

The time-varying volatility estimation is conducted with the models: EWMA of Riskmetrics[TM] (J.P. Morgan, 1996), Bollerslev's (1986) GARCH(p,q) model, and Ding's et al. (1993) APARCH(p,q) model. The study is based on simplified and widely accepted models avoiding those that cannot be estimated easily and immediately. The EWMA is the classic unsophisticated way of volatility estimate, the GARCH is a well-known technique and the APARCH is a model which takes into account several characteristics of the markets without time-consuming estimation of its parameters. Note that the GJR-GARCH model of Glosten *et al.* (1993) is another popular asymmetric approach very well used in modeling financial crises (see Linton and Mammen, 2005; Iglesias and Linton, 2009). However, the GJR-GARCH is nested by the APARCH model incorporated in this paper[8]. For the case of the GARCH(p,q) and APARCH(p,q) models the order of lags, p=q=1, is used because it captures the dynamics of volatility adequately[9].

4.1 EWMA – Exponentially Weighted Moving Average

A typical technique for the calculation of volatility, that has been proposed by the J.P. Morgan (1996), is the so called exponentially weighted moving average (EWMA) given by:

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[7] This is due to the non-synchronous trading effect; for more information see Campbell et al. (1997, p.84).

[8] Ding et al. (1993) noted that the APARCH model includes the GJR-GARCH as a special case. There is usually very little to choose between the two formulations in practice. Results from either GJR-GARCH or APARCH model are often very useful, but we do not need to estimate them both (Alexander, 2008b; p. 150).

[9] The use of one lag has been proven to work effectively; see for details Angeldis and Degiannkis (2008a) and Hansen and Lunde (2005).

$$\sigma_t^2 = 0.06\varepsilon_{t-1}^2 + 0.94\sigma_{t-1}^2, \tag{9}$$

A detailed investigation of the performance of EWMA was provided by Pafka and Kondor (2001).

4.2 GARCH(1,1) – Generalized ARCH

The most widely used technique for the volatility estimate is the GARCH (1,1) model:

$$\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2, \tag{10}$$

which expresses the phenomenon observed in the financial markets that the volatility depends on its past prices (periods of intense volatility tend to be followed by periods of low volatility and vice versa, i.e. volatility clustering effect).

4.3 APARCH(1,1) – Asymmetric Power ARCH

Ding et al. (1993) proposed the APARCH model:

$$\sigma_t^\delta = a_0 + a_1\left(\left|\varepsilon_{t-1}\right| - \gamma_1\varepsilon_{t-1}\right)^\delta + b_1\sigma_{t-1}^\delta, \tag{11}$$

in which γ_1 is used to model the asymmetric relationship between volatility and information that comes to the market, as they are expressed from ε_{t-1} [10] (leverage effect). Moreover, the volatility is modeled neither as the variance, $\delta = 2$, nor as the standard deviation, $\delta = 1$. The power δ is a parameter to be estimated (Box-Cox power transformation).

Finally, for the probability density function, $f(.)$, of the random variable z_t (which expresses the ratio of the residuals to the time-varying standard deviation) we assume not only the classic normal distribution[11] but also the skewed Student-t distribution. Note that the skewed Student-t distribution captures the leptokurtic tails and the asymmetry that cause the extreme log-returns. For the normal distribution we have:

$$z_t \sim f(0,1), \tag{12}$$

and for the skewed Student-t distribution[12] we get:

$$z_t \sim f(0,1;v,g). \tag{13}$$

For more details on the probability density function of the skewed Student-t distribution, the reader is referred to Lambert and Laurent (2000, 2001) and Xekalaki and Degiannakis

[10] ε_t denotes the log-return that we are not able to estimate. It expresses the information that flows into the market about the difference between actual and estimated log-returns, as $\varepsilon_t = y_t - \mu_t$, where y_t is the actual return and μ_t is the estimated return.

[11] The Bollerslev and Wooldridge's (1992) robust quasi-maximum likelihood standard errors were taken into consideration.

[12] The skewed Student-t distribution was proposed by Fernandez and Steel (1998).

(2010). Obviously for equation (12) we do not have to estimate any parameter of the distribution while in the case of equation (13) we have to estimate $w = (v, g)'$, where g and v are the asymmetry and kurtosis parameters respectively.

In the literature there is a huge number of volatility models. The present study uses parsimonious models which can be estimated easily without any calculating cost[13].

5. Evaluation of Models of Estimate of Value at Risk

The performance of the models was evaluated through the tests of Kupiec (1995) and Christoffersen (1998). One of the most popular tests, Kupiec's (1995) test, examines whether the observed percentage of violations[14] is statistically equal to the expected percentage of violations. Under the null hypothesis that the observed and the expected percentage of violations are statistically equal, the likelihood ratio is given by:

$$LR_{uc} = 2\log\left(\left(1-\frac{N}{\tilde{T}}\right)^{\tilde{T}-N}\left(\frac{N}{\tilde{T}}\right)^{N}\right) - 2\log\left((1-p)^{\tilde{T}-N}p^{N}\right) \sim X_1^2, \tag{14}$$

where N denotes the number of days over the period $\tilde{T}$ where violation was observed and p is the expected ratio of violations. A risk model is considered inadequate if it produces either more or less violations than those expected. However, under the Kupiec test, risk manager can accept a model that provides dependent violations[15].

Christoffersen (1998) proposed a test which examines simultaneously (i) whether the total number of violations is equal with the expected number of violations and (ii) if the violations are independently distributed. The hypothesis (i) is tested by equation (14), while for the second hypothesis the equation (15) was proposed:

$$LR_{in} = 2\left(\log\left((1-\pi_{01})^{n_{00}}\pi_{01}^{n_{01}}(1-\pi_{11})^{n_{10}}\pi_{11}^{n_{11}}\right) - \log\left((1-\pi_0)^{n_{00}+n_{10}}\pi_0^{n_{01}+n_{11}}\right)\right) \sim X_1^2, \tag{15}$$

where n_{ij} is the total number of observations i following j, for $i, j = 0,1$ and $\pi_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}$ is the respective probability. For $i, j = 1$ a violation is observed, while for $i, j = 0$ there is no violation. Through equation (15) we control if the violations are

[13] For a widely presentation of univariate and multivariate ARCH models, as well as their applications on the forecasting volatility and VaR, see Xekalaki and Degiannakis (2010).

[14] For long trading positions we have a violation when the return is less than the predicted VaR, $y_{t+1} < VaR_{t+1|t}^{(1-p)}$.

[15] The Kupiec test has a high probability of statistical errors II in the rejection-acceptance of the VaR models.

independently distributed across time. Christoffersen (1998) proposed to test simultaneously the hypotheses (i) and (ii), adding equations (14) and (15), i.e $LR_{uc} + LR_{in} \sim X_2^2$. The advantage of using these two tests is that the risk managers can reject a VaR model that produces either too few or too many clustered violations.

In the literature, alternative approaches have been proposed with comparative advantages and disadvantages against Kupiec's (1995) and Christoffersen's (1998) test statistics. Indicatively, we report the studies of Engle and Manganelli (2004), Lopez (1999) and Sarma et al. (2003). However, we should report that the focus of this paper is not on the general comparison of the three models considered but on the question whether any of these models is suitable to forecast VaR measure[16].

6. Application

In this paper, we use data from both mature (US, UK, Germany) and emerging (Greece and Turkey) markets with specific characteristics, i.e. markets following low/high volatile periods. In particular, we evaluate the out-of-sample forecasting accuracy before the 2008 financial crisis (i.e. from 2004 to 2007), when the global economy was in the expansion stage of the economic cycle (e.g. Greece organised the Athens Olympic Games in 2004; US Stock Market recovered in 2004; Turkey was one of the fastest growing economies in the world with GDP growth rate averaged 7% after 2004; UK entered a recession in 2008 after a fast growth in 2004-2006; German economy experienced a high growth after 2005). However, we don't consider data before 2004, mainly because of (i) the dot-com bubble in the US (1995-2000) and the September 11th attacks, (ii) the European and US Stock market downturn of 2002, (iii) the Turkish financial crisis of 2000-2001, (iii) the Greek financial crisis of 2001-2003, and (iv) the fact that German economy stagnated in the beginning of 2000s.

Table 1 reports information on the dataset used. The second column of Table 1 refers to the total number of observations (daily trading days), T, the third column reports the date for which we get the first observation (first trading day), the fourth column reports the date for which we get the last available price (for all indices the last trading day of 2008). Afterwards, the fifth column reports the first day for which we proceed in forecast

[16] If we were interested in the comparison of models we could use methodologies such as Angelidis and Degiannakis (2007) and Hansen (2005).

of VaR, the sixth column reports for how many trading days the forecasts of VaR are calculated, $\tilde{T}$, and the last column reports the size of rolling sample of constant size that is used for the estimate of models, $\breve{T}$.

[Insert Table 1 about here]

The models are applied in the framework of equation (8) for the three conditional volatility specifications of equations (9), (10) and (11). For the EWMA and the GARCH(1,1) models we assumed that z_t is normally distributed, whereas for the APARCH(1,1) model the skewed Student-t distribution was considered.

The models: EWMA, AR(1)-GARCH(1,1)-n and AR(1)-APARCH(1,1)-skT have been estimated in the following forms:

EWMA

$$\begin{gathered} y_t = c_0(1-c_1) + c_1 y_{t-1} + \varepsilon_t \\ \varepsilon_t = \sigma_t z_t \\ \sigma_t^2 = 0.06\varepsilon_{t-1}^2 + 0.94\sigma_{t-1}^2 \\ z_t \sim f(0,1). \end{gathered} \tag{16}$$

AR(1)-GARCH(1,1)-n

$$\begin{gathered} y_t = c_0(1-c_1) + c_1 y_{t-1} + \varepsilon_t \\ \varepsilon_t = \sigma_t z_t \\ \sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2 \\ z_t \sim f(0,1). \end{gathered} \tag{17}$$

AR(1)-APARCH(1,1)-skT

$$\begin{gathered} y_t = c_0(1-c_1) + c_1 y_{t-1} + \varepsilon_t \\ \varepsilon_t = \sigma_t z_t \\ \sigma_t^\delta = a_0 + a_1(|\varepsilon_{t-1}| - \gamma_1\varepsilon_{t-1})^\delta + b_1\sigma_{t-1}^\delta \\ z_t \sim f(0,1;v,g). \end{gathered} \tag{18}$$

Each trading day the models were re-estimated. As an example, for the ISE100 index, each model has been estimated $\tilde{T} = 1027$ times, based on a rolling sample of constant size[17] $\breve{T} = 4000$. The models were estimated with the G@RCH tool of Ox Metrics, i.e. for the

[17] We consider a rolling sample of length 4000 for the parameter estimates to be non-sensitive to the size of the sample.

model (18), the vector of parameters that have been estimated for the trading days t, $t = \breve{T}+1,...,\breve{T}+\tilde{T}$, is given by $(\theta, w)' = (c_0, c_1, a_0, \delta, a_1, \gamma_1, b_1, v, g)'$.

The one-day-ahead VaR is computed according to equation (7), i.e. for the model (18), the VaR forecast is computed as:

$$\begin{aligned} VaR_{t+1|t}^{(1-p)} &= \mu_{t+1|t} + f_p\left(z_t; w^{(t)}\right)\sigma_{t+1|t}, \\ \mu_{t+1|t} &= c_0^{(t)}\left(1-c_1^{(t)}\right)+c_1^{(t)} y_t, \\ \sigma_{t+1|t} &= \left(a_0^{(t)} + a_1^{(t)}\left(\left|\varepsilon_{t|t}\right| - \gamma_1^{(t)}\varepsilon_{t|t}\right)^{\delta^{(t)}} + b_1 \sigma_{t|t}^{\delta^{(t)}}\right)^{1/\delta^{(t)}} \end{aligned} \tag{19}$$

We proceed to the evaluation of the above models considering their forecasting VaR for five stock indices based on the statistics of Kupiec (1995) and Christoffersen (1998). Figures 1 to 5 present the indices and their logarithmic changes on a daily base. Obviously, the capital markets in year 2008 are characterized from a strong down turn course as well as from a high volatility.

In order to investigate whether the models have the ability to forecast the next-trading-day VaR even in periods as the year 2008, which was a period of high volatility and clearly down turn for the capital markets, we evaluate the models separately for year 2008. For example, for the ISE100 index we evaluate the three models separately for the period from 2/12/2004 up to 31/12/2007 and then for year 2008.

[Insert Figure 1 About here]

[Insert Figure 2 About here]

[Insert Figure 3 About here]

[Insert Figure 4 About here]

[Insert Figure 5 About here]

Table 2 presents the estimates of the three models for the five indices and the two periods. For the ISE100, the selected model gives 6.3% of violations over the period before the financial crisis, while for the period of financial crisis the selected model has 5.9% of violations. For GRAGENL index we have 4.8% of violations for the period of financial crisis and 5.8% of violations for the period before the financial crisis. We get similar percentages for the indices S&P500 and FTSE100, while we observe a higher deviation for DAX30 index, i.e. 4.3% of violations for the period before the economic crisis, and 7.5% of violations for the period during the economic crisis. For the major international markets the percentages of violations are marginally higher during the period of financial crisis. On the contrary, for the capital markets of Turkey and Greece, the percentages of violations are lower during the period of financial crisis. A possible explanation could be their characterization as emerging markets in the first years of the investigated sample period.

More specifically, for the period before the economic crisis of 2008, the AR(1)-GARCH(1,1)-n model had globally the most satisfactory performance; it produces adequate VaR forecasts for all the indices but the ISE100. In the case of General Index of Athens, the Riskmetrics model has the same forecasting ability with AR(1)-GARCH(1,1)-n. On the contrary, for the period of financial crisis 2008 (highly volatile period), the model AR(1)-APARCH(1,1)-skT had the ability to forecast the VaR satisfactorily. In the case of ISE100 index, all the models provide accurate VaR forecasts. Overall, the findings suggest that the models gave satisfactory VaR forecasts for the period before the financial crisis of 2008 as well as for the highly volatile period of year 2008.

What it would be ideally required is a model which is useful for all time periods. However, according to Angelidis and Degiannakis (2008a), there is not a unique model for all financial periods/markets, and therefore modelers must be aware of that. In this paper, we find that there is at least one adequate model for each index in every period[18]. The AR(1)-APARCH(1,1)-skT model works better than the other models in the period of crisis because it captures the leptokurtic tails and the asymmetry to the left that cause the extreme negative log-returns.

[Insert Table 2 about here]

7. Conclusions

Since 2008, financial markets across the world have suffered huge losses. The US subprime crisis led rapidly to massive declines in the market values of assets and portfolios around the world (Longstaff, 2010). The banking panic of 2008 led to unstable stock prices, while the cost of bank borrowing as well as the financial market volatility (risk) rose substantially.

Daily VaR measures are widely used in financial institutions for assessing the risk of trading activities. According to Stulz (2008, p. 61), "*VaR is an estimate of the minimum worst loss expected, as opposed to the expected worst loss*".

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[18] Except for the ISE100 index during the period before the economic crisis, in terms of independence in the distribution of violations across time. The hypothesis that the one-day-ahead VaR violations are independently distributed across time is rejected, but there is not enough evidence to reject the hypothesis that the observed percentage of VaR violations is statistically equal to 5%.

Stulz (2008) argues that risk models are generally not designed to capture risks associated with crises and help companies manage them. He reported that "*The models use historical data and, particularly when using risk measures such as VaR, are most precise for horizons that are numbered in days; and when using such short horizons, crises appear to be highly improbable events. But, when the horizon expands to years, the probability of a crisis becomes material, something clearly worth management's attention*". The present study provides evidence that the classic risk measurement technique of VaR estimation works satisfactorily even in periods such as the year 2008 with extreme highly volatility and strong down turn tendency of the markets.

Recent studies[19] suggest that there is not a suitable model for any capital market at any time period. Therefore, a suitable method of model selection is necessary. In this study, the simple AR(1)-GARCH(1,1)-n model has satisfactory performance for the period before the crisis of 2008, but during 2008 it does not provide satisfactory VaR forecasts of the next trading day. Something, however, that is available by the AR(1)-APARCH(1,1)-skT model.

Moreover, we conclude that the models for stock markets of Turkey and Greece give similar results compared with the major international stock markets. A possible reason is the similarity of the Turkey and the Greek capital markets to the major international markets, during the last years. Hence, these countries can be modeled by applying techniques that have common characteristics with those from U.K., Germany and U.S.A. markets.

The present study provides evidence that the tools of quantitative finance may achieve their objective. We argue that the simple VaR approach provides adequate forecasts of losses over a one-day-ahead period of trading. During the period of the serious financial crisis of 2008, a lot of critical opinions have been heard that put against the quantitative tools developed in the last two decades. However, the blame for financial crisis should not be cast upon quantitative techniques used to measure and forecast market risk alone. After each market crash, fiscal policies should take action (e.g. cut in interest rates). Knowledge of modern risk management techniques is required to resolve the next financial crisis. The next crisis can be avoided only when financial risk managers acquire the necessary quantitative skills to measure uncertainty and understand risk. Further

[19] For more information, see Angelidis and Degiannakis (2005, 2008a) and Bao et al. (2006). Bao et al. (2006) study the forecasting ability of several models to predict VaR for the Asian stock markets that were affected by the crisis 1997-1998.

research should examine multi-period forecasting and apply models and backtest procedures that deal with identifying large losses over a number of periods for several countries.

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Tables

Table 1. Data Information.

Index	T	Date of 1st obs.	Date of last obs.	Forecasts Start	$\tilde{T}$	$\breve{T}$
ISE100	5027	03/10/1988	31/12/2008	2/12/2004	1027	4000
GRAGENL	4985	03/10/1988	31/12/2008	21/01/2005	985	4000
DAX30	5101	03/10/1988	31/12/2008	06/09/2004	1101	4000
S&P500	5102	03/10/1988	31/12/2008	17/08/2004	1102	4000
FTSE100	5113	03/10/1988	31/12/2008	09/08/2004	1113	4000

Source: DataStream™.

We have excluded days that stock markets were closed, but Datastream™ has given closing prices Note that most studies use data for these days and they don't exclude them.

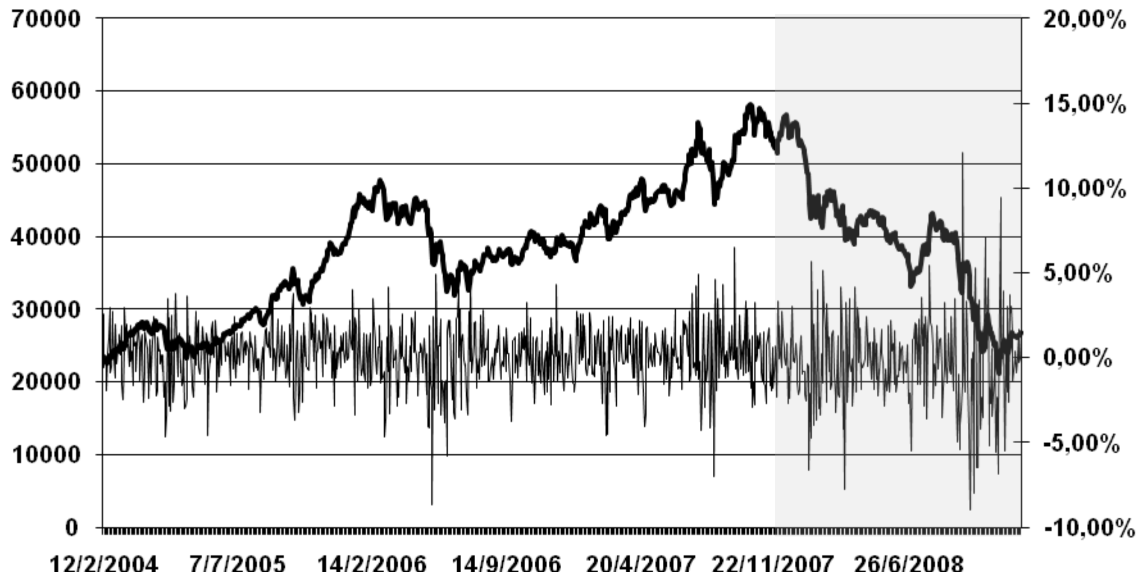
Table 2. Percentage of violations of the one-day-ahead 95% VaR, and p-values of Kupiec and Christoffersen tests for three models.

	$\tilde{T}$	Date of 1st forecast	Date of last forecast	Percentage of violations of 95%VaR	Kupiec's p-value	Christoffersen's p-value
PART A. Period before the financial crisis of 2008						
ISE100	776	12/02/2004	31/12/2007	(16) **6.3%**	**0.11**	0.01*
				(17) 3.4%	0.03*	0.30
				(18) 2.6%	0.00*	0.54
GRAGENL	738	21/01/2005	31/12/2007	(16) **5.8%**	**0.32**	**0.75**
				(17) 4.2%	0.31	0.55
				(18) 2.7%	0.00*	0.29
DAX30	847	06/09/2004	28/12/2007	(16) 6.4%	0.08	0.18
				(17) **4.3%**	**0.30**	**0.63**
				(18) 3.0%	0.00*	0.21
S&P500	850	17/08/2004	31/12/2007	(16) 6.1%	0.15	0.91
				(17) **5.2%**	**0.81**	**0.84**
				(18) 4.0%	0.17	0.09
FTSE100	859	09/08/2004	31/12/2007	(16) 6.1%	0.12	0.87
				(17) **5.2%**	**0.75**	**0.67**
				(18) 4.4%	0.43	0.80
PART B. Period of financial crisis of 2008 (highly volatile period)						
ISE100	251	02/01/2008	31/12/2008	(16) **5.9%**	**0.49**	**0.17**
				(17) **5.9%**	**0.49**	**0.17**
				(18) 6.4%	0.65	0.32
GRAGENL	247	02/01/2008	31/12/2008	(16) 8.1%	0.04*	0.57
				(17) 9.7%	0.00*	0.28
				(18) **4.8%**	**0.92**	**0.27**
DAX30	254	02/01/2008	31/12/2008	(16) 8.3%	0.03*	0.51
				(17) 8.6%	0.02*	0.43
				(18) **7.5%**	**0.09**	**0.08**
S&P500	252	02/01/2008	31/12/2008	(16) 8.7%	0.01*	0.04*
				(17) 8.7%	0.01*	0.04*
				(18) **5.9%**	**0.50**	**0.17**
FTSE100	254	02/01/2008	31/12/2008	(16) 9.1%	0.01*	0.18
				(17) 8.3%	0.03*	0.10
				(18) **6.3%**	**0.36**	**0.34**

For each index, the first row represents the EWMA model (eq. (16), the second row shows the results from the AR(1)-GARCH(1,1)-n model (eq. (17) and the third row is for the AR(1)-APARCH(1,1)-skT model (eq. (18). With bold face the best performed models are presented. With asterisk we denote models which are considered inadequate for one-trading-day-ahead VaR forecasting (p-value<0.05).

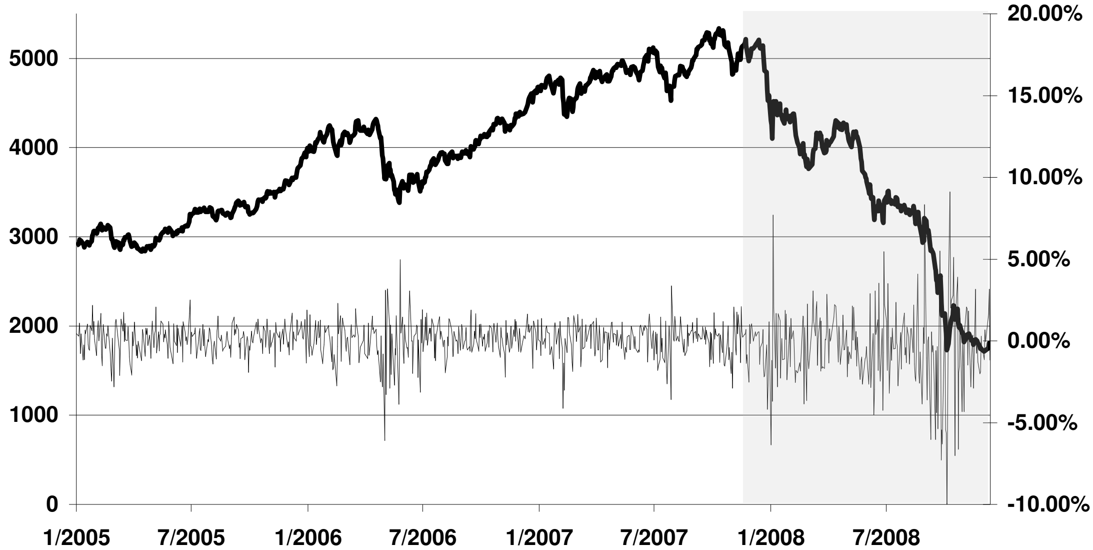
Figures

Figure 1. ISE100 stock index (left axis) and daily logarithmic change of prices (right axis) for the period 2/12/2004 - 31/12/2008.



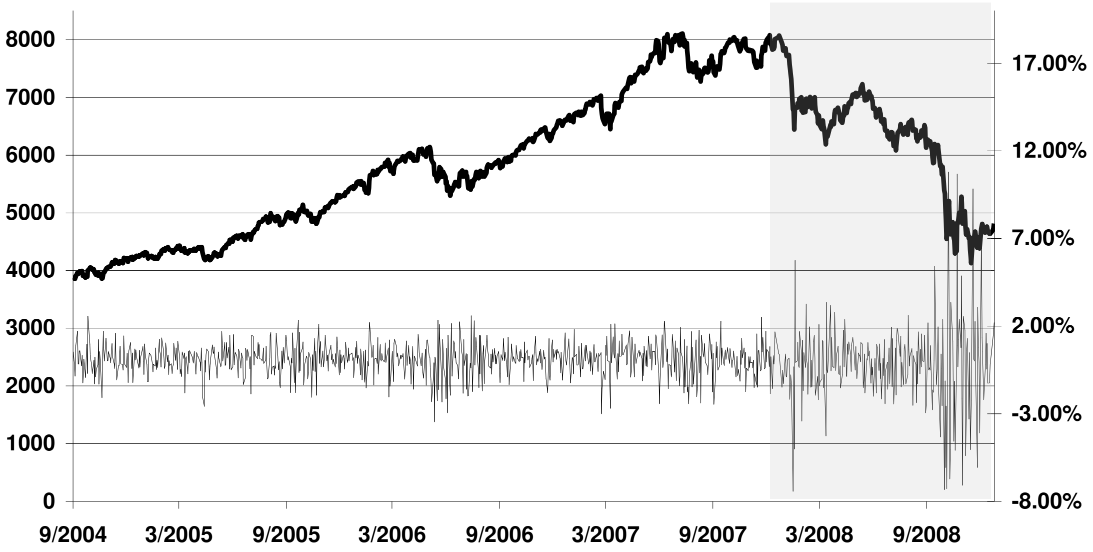
The plot in different pattern presents year 2008.

Figure 2. GRAGENL stock index (left axis) and daily logarithmic change of prices (right axis) for the period 21/01/2005 - 31/12/2008.



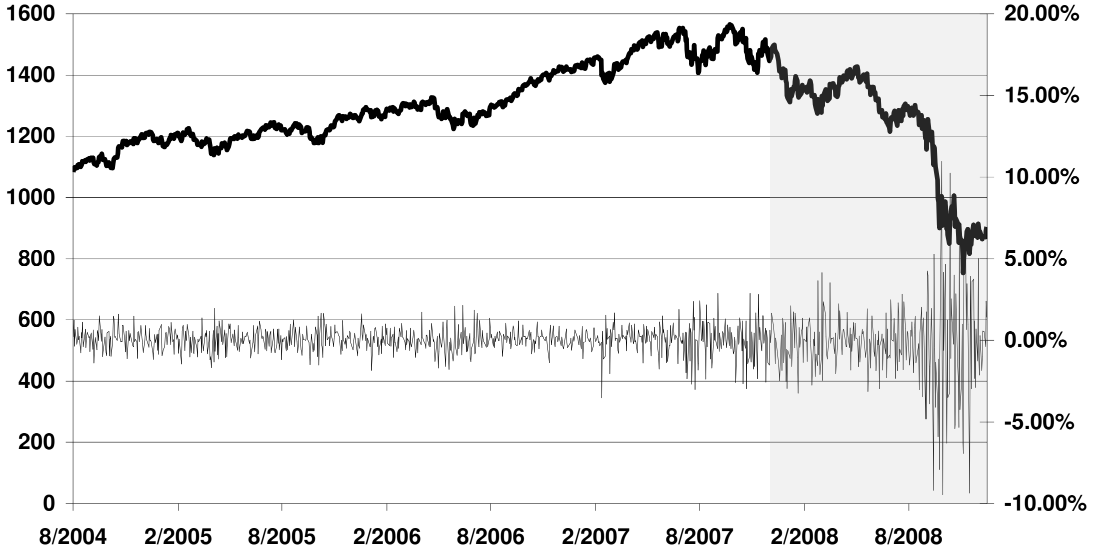
The plot in different pattern presents year 2008.

Figure 3. DAX30 stock index (left axis) and daily logarithmic change of prices (right axis) for the period 06/09/2004 - 31/12/2008.



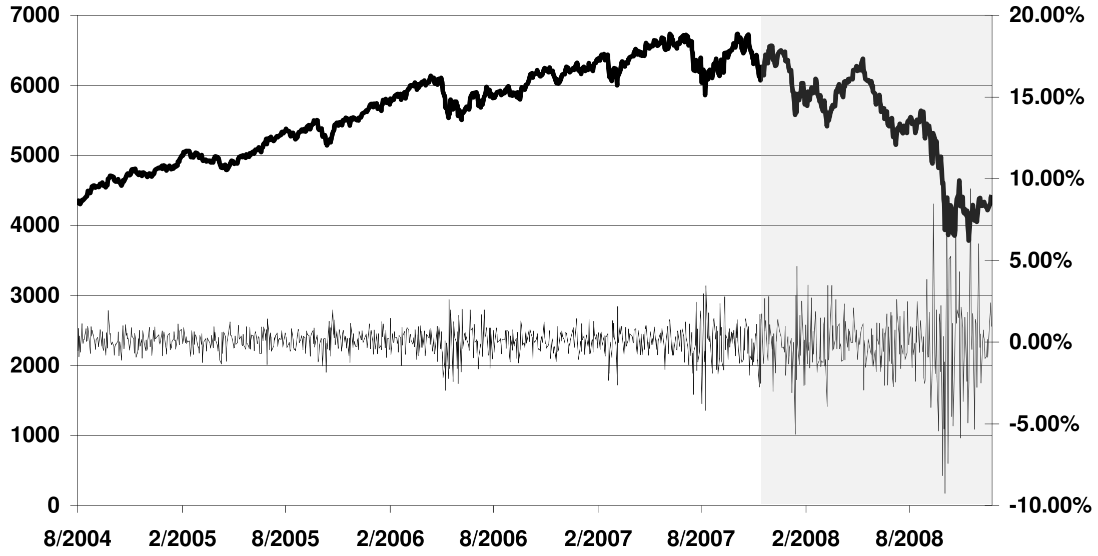
The plot in different pattern presents year 2008.

Figure 4. S&P500 stock index (left axis) and daily logarithmic change of prices (right axis) for the period 17/08/2004 - 31/12/2008.



The plot in different pattern presents year 2008.

Figure 5. FTSE100 stock index (left axis) and daily logarithmic change of prices (right axis) for the period 09/08/2004 - 31/12/2008.



The plot in different pattern presents year 2008.