Modeling Risk for Long and Short Trading Positions

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Abstract

The accuracy of parametric, non-parametric and semi-parametric methods in predicting the one-day-ahead Value-at-Risk (VaR) measure in three types of markets (stock exchanges, commodities and exchange rates) is investigated, both for long and short trading positions. The risk management techniques are designed to capture the main characteristics of asset returns, such as leptokurtosis and asymmetric distribution, volatility clustering, asymmetric relationship between stock returns and conditional variance and power transformation of conditional variance.

Based on backtesting measures and a loss function evaluation method, we find out that the modeling of the main characteristics of asset returns produces the most accurate VaR forecasts. Especially for the high confidence levels, a risk manager must employ different volatility techniques in order to forecast accurately the VaR for the two trading positions.

Different models achieve accurate VaR forecasts for long and short trading positions, indicating to portfolio managers the significance of modeling separately the left and the right side of the distribution of returns.

The behavior of the risk management techniques is examined both for long and short VaR trading positions, while to best of our knowledge, this is the first study that investigates the risk characteristics of three different financial markets simultaneously. Moreover, we implement a two-stage model selection in contrast of the most commonly used backtesting procedures in the attempt to identify a unique model. Finaly, we employ parametric, non-parametric and semi-parametric techniques in order to investigate their performance in a unify environment.

Keywords: Asymmetric Power ARCH model, Evaluate Forecasting Ability, Skewed-t Distribution, Value-at-Risk, Volatility Forecasting.

JEL: C32, C52, C53, G15.

Introduction

Value-at-Risk (VaR) at a given probability level a, is the predicted amount of financial loss of a portfolio over a given time horizon. Given the fact that asset returns are not normally distributed, since they exhibit skewness and excess kurtosis, it is plausible to employ volatility forecasting techniques that accommodate these characteristics in order to accurate estimate the "true" but unobservable VaR.

A researcher can either implement parametric, semi-parametric or non-parametric methods in order to calculate the VaR number. In the case of the non-parametric techniques, the historical simulation is the most well known and simplifies the computation of the VaR as it does not make any distributional assumption about portfolio returns. Even if this method has been thoroughly examined by several authors, their conclusions are controversial. For example, Hendricks (1996) and Daníelsson (2002) argued that the sample size affects the precision of the VaR estimates, with the longer one producing the most accurate estimations. On the contrary, Hoppe (1998) proposed the use of a smaller one, since it can accommodate the structural changes of the trading behavior more efficiently.

On the other hand, many researchers prefer to parameterize the properties of the underlying distribution. Venkataraman (1996) and Zangari (1996) suggested to the market practitioners a mixture of normal distributions, while Billio and Pelizzon (2000) estimated a multivariate switching regime model in order to calculate the VaR for 10 Italian stocks. Their procedure is different from that of Zangari (1996) as the VaR forecasts were based on a two state Markov process instead of a Bernoulli. Alexander and Leigh (1997) estimated the exponentially weighted moving average (EWMA) and the autoregressive conditional heteroskedasticity (ARCH) models and found out that the ARCH is preferable to EWMA. Guermat and Harris (2002) extended the EWMA model allowing for time-variation in the higher moments of the return distribution and introduced the exponentially weighted maximum likelihood (EWML) model. In the case of US, UK and Japan equity portfolios, the EWML model, compared to the GARCH(1,1) specification under both the normal and the Student's-t distribution, improved the estimated daily VaR number at the higher confidence level. Mittnik and Paoella (2000) studied the exchange rates and introduced the Asymmetric Power ARCH (APARCH) model with an asymmetric generalized Student's-t distribution to allow for time varying skewness. Giot and Laurent (2003a, 2003b) considered a skewed Student's-t distribution, in order to accommodate the leptokurtosis and the observed skewness of the financial time series. They focused on the joint behavior of

VaR models for long and short trading positions and argued that for both equity indexes and commodities the APARCH model had the best overall performance. Huang and Lin (2004) reached to the same conclusion, as they argued that the normal APARCH model is preferred at lower confidence level, while the Student's-t APARCH model is more accurate than either the RiskMetrics™ or the normal APARCH models at higher confidence level. Furthermore, Brooks and Persand (2003) also concluded that the asymmetry is an important issue in the VaR framework and therefore it must be modeled either in the unconditional mean return distribution or in the volatility specification.

The filtered historical simulation approach was introduced by Hull and White (1998) and Barone-Adesi et al. (1999). This method is a mixture of parametric and non-parametric statistical procedures as it forecasts the variance through a parametric volatility model but it does not make any assumption about the distribution of standardized returns. According to Barone-Adesi and Giannopoulos (2001), who compared the filtered historical simulation with the historical one, the mixture of parametric and non-parametric statistical procedures produces more accurate VaR forecasts.

Our study sheds a light on the volatility forecasting methods under a risk management framework, since it juxtaposes the performance of the most well known techniques for different markets (stock exchanges, commodities and exchange rates) and trading positions. Specifically, the 95% and 99% one day VaR number is estimated by a set of ARCH models (assuming four conditional variance specifications and three distributional assumptions), historical and filtered-historical simulations and the commonly used variance-covariance method. Under the framework of the parametric techniques, the different distributions will allow the selection of a model for the return tails, while we have investigated three different markets in order the results not to be dependent on a specific financial market. Moreover, we employ a two-stage procedure to investigate the forecasting power of each volatility forecasting technique. In the first stage, two backtesting criteria are implemented to test the statistical accuracy of the models. In the second stage, we employ standard forecast evaluation methods to examine whether the differences between models (that have exhibited sufficient unconditional and conditional coverage) are statistically significant.

Although our analysis is similar to the presented papers, there are significant differences. First, we examine the behavior of the risk management techniques both for long and short VaR trading positions, while most of the research has been applied only on long ones. Therefore, we will be able to examine whether an asymmetric model is able to capture both the characteristics of the two tails. Second to best of our knowledge, this is the first study that investigates the risk characteristics of three different financial markets simultaneously. Hence, we are able to infer whether the financial markets of stock exchanges, commodities and exchange rates share common features in the field of VaR forecasting. Third, we implement a two-stage model selection in contrast of the most commonly used backtesting procedures in the attempt to identify a unique model. Last, we employ parametric, non-parametric and semi-parametric techniques in order to investigate their performance in a unify environment, on the contrary to the existent literature which focus only on one technique at time.

Our study shows that although there is not a specific model that accurate estimates the VaR number for all financial markets and trading positions, there are some characteristics that should be taken into account in order for a risk manager to calculate the VaR accurately. For all the financial markets under investigation, we infer that the normal distribution produces adequate one-day-ahead VaR forecasts at the 95% confidence level. On the other hand, models that parameterise the leverage effect for the conditional variance, the leptokurtosis and the asymmetry of the data, forecast accurate the VaR at the 99% confidence level. Moreover, short-trading positions should be modeled using volatility specifications different from that of portfolios with long trading positions, which implies that even asymmetric models are not sufficiently asymmetric.

The volatility forecasting models and the VaR evaluation methods are presented in the 2[nd] and 3[rd] sections, respectively. The fourth section illustrates the results of the study and the fifth section concludes.

Volatility Forecasting Models

Let $y_t = 100\ln(P_t / P_{t-1})$ denote the daily return series, where P_t is the price of an asset at day t. The ARCH models can be presented in the following general framework:

$$
\begin{aligned}
y_t &= c_0 + \varepsilon_t \\
\varepsilon_t &= z_t \sigma_t \\
z_t &\overset{i.i.d.}{\sim} f(0,1) \\
\sigma_t &= g\left(\{\varepsilon_{t-i}\};\{\sigma_{t-j}\} \forall i \geq 1, \forall j \geq 1\right),
\end{aligned}
\tag{1}
$$

where c_0 is a constant parameter, ε_t is the innovation process, $f(0,1)$ is a density function of zero mean and unit variance, and $g(.;.)$ is a functional form of the past innovations and their conditional standard deviation.

Surveys of Bollerslev et al. (1994), Li et al. (2001), Poon and Granger (2003), Degiannakis and Xekalaki (2004) cover a wide range of ARCH presentations. Bollerslev (1986) proposed a generalization of Engle's (1982) ARCH model and introduced the GARCH(1,1) specification:

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

where $\alpha_0 > 0, a_1 \geq 0$ and $b_1 \geq 0$. Riskmetrics™ suggested the exponentially weighted moving average, or EWMA, which is a special case of the GARCH(1,1), since $a_0 = 0$, $a_1 = 0.06$ and $b_1 = 0.94$:

$$\sigma_t^2 = 0.06\varepsilon_{t-1}^2 + 0.94\sigma_{t-1}^2. \tag{3}$$

Although the GARCH(1,1) model captures the volatility clustering phenomenon, it could not explain the asymmetric relationship between returns and conditional variance. Nelson (1991) proposed the exponential GARCH, or EGARCH(1,1), model:

$$\ln(\sigma_t^2) = a_0 + a_1(|\varepsilon_{t-1}/\sigma_{t-1}| - E|\varepsilon_{t-1}/\sigma_{t-1}|) + \gamma(\varepsilon_{t-1}/\sigma_{t-1}) + b_1\ln(\sigma_{t-1}^2), \tag{4}$$

where the parameter γ_1 accommodates the asymmetric effect. Glosten et al. (1993) presented the TARCH(1,1) specification, where good news $(\varepsilon_{t-i} > 0)$ and bad news $(\varepsilon_{t-i} < 0)$ have different effect on the conditional variance:

$$\sigma_t^2 = a_0 + (a_1 + \gamma d_t)\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2, \tag{5}$$

for d_t denoting an indicator function (i.e. $d_t = 1$ if $\varepsilon_{t-1} < 0$ and $d_t = 0$ otherwise). Ding et al. (1993) introduced the asymmetric power ARCH, or APARCH(1,1), model:

$$\sigma_t^\delta = a_0 + a_1(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + b_1\sigma_{t-1}^\delta, \tag{6}$$

for $a_0 > 0$, $a_1 \geq 0$, $b_1 \geq 0$, $\delta \geq 0$ and $|\gamma| < 1$.

In the influential paper of Engle (1982), the density function of z_t, $f(.)$, was considered as the standard normal distribution:

$$f(z_t) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{z_t^2}{2}\right). \tag{7}$$

Bollerslev (1987) proposed the Student's-t distribution in order to produce an unconditional distribution with thicker tails:

$$f(z_t;v)=\frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sqrt{\pi(v-2)}}\left(1+\frac{z_t^2}{v-2}\right)^{-\frac{v+1}{2}}, \quad v>2, \tag{8}$$

where v denotes the degrees of freedom of the distribution. Lambert and Laurent (2000) suggested that not only the conditional distribution of innovations may be leptokurtic, but also asymmetric and proposed the skewed Student's-t density function:

$$f(z_t;v,g)=\frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sqrt{\pi(v-2)}}\left(\frac{2s}{g+g^{-1}}\right)\left(1+\frac{sz_t+m}{v-2}g^{-d_t}\right)^{-\frac{v+1}{2}}, \quad v>2, \tag{9}$$

where g is the asymmetry parameter, $\Gamma(.)$ is the gamma function, $d_t=1$ if $z_t \geq -m/s$, $d_t=-1$ otherwise, $m=\Gamma((v-1)/2)\sqrt{(v-2)}\left(\Gamma(v/2)\sqrt{\pi}\right)^{-1}\left(g-g^{-1}\right)$ and $s=\sqrt{g^2+g^{-2}-m^2-1}$ are the mean and the standard deviation of the non-standardized skewed Student's-t distribution, respectively.

Under the framework of the parametric techniques, the one-day-ahead VaR is computed as:

$$VaR_{t+1|t}=F(z_t;a)\hat{\sigma}_{t+1|t}, \tag{10}$$

where $F(z_t;a)$ is the corresponding quantile of z_t distribution and $\hat{\sigma}_{t+1|t}$ is the one-day-ahead conditional standard deviation forecast given the information that is available at time t. Under the assumption that $\varepsilon_t \overset{i.i.d}{\sim} N(0,1)$, the calculation of the VaR can be simplified:

$$VaR_{t+1|t}=F(\varepsilon_t;a)\hat{\sigma}_{t+1|t}. \tag{11}$$

However, the conjecture of normality is not satisfied in financial returns and, hence, this method, which we will refer to as Variance-Covariance (VC), usually underestimates the "true" VaR.

The Historical Simulation (HS) method is a simple and intuitive non-parametric procedure, which relies on historical returns to calculate the VaR as the corresponding percentile of the past m returns[i]:

$$VaR_{t+1|t}=F\left(\{y_{t+1-\tau}\}_{\tau=1}^{m};a\right). \tag{12}$$

In the case of the parametric methods, the distribution choice is crucial; while in the non-parametric case there is no consistent approach in forecasting the volatility. The Filtered Historical Simulation (FHS) method, which was presented in Hull and White (1998) and Barone-Adesi et al. (1999), combines the two approaches in order to make the most of them. Given an adequate volatility model, such as the GARCH(1,1), the $VaR_{t+1|t}$ is computed based on the quantile of the standardized innovations:

$$VaR_{t+1|t} = F\left(\{\hat{\varepsilon}_{t+1-\tau|t} / \hat{\sigma}_{t+1-\tau|t}\}_{\tau=1}^{m}; a\right)\hat{\sigma}_{t+1|t}. \qquad (13)$$

Evaluate the Forecasting Ability of Value at Risk Measures

Our objective is to test these different volatility forecasting techniques under a risk management environment. Therefore, we employ a two-stage procedure to evaluate the various risk management techniques. In the first stage, two backtesting criteria (unconditional and conditional coverage) are implemented to examine the statistical accuracy of the models while, in a second stage, we employ a forecast evaluation method to investigate whether the differences between the VaR models, that exhibited sufficient unconditional and conditional coverage, are statistically significant.

The simplest method in determining the adequacy of a VaR measure is to test the hypothesis that the proportion of violations[ii] is equal to the expected one. Kupiec (1995) developed a likelihood ratio statistic:

$$LR_{uc} = 2\ln[1-\frac{\mathrm{N}}{\mathrm{T}})^{T\text{-N}}(\frac{N}{T})N] - 2\ln[(1-\mathrm{p})^{\mathrm{T-N}} p^{N}] \sim X_1^2, \qquad (14)$$

under the null hypothesis that the observed exception frequency, N/T, equals to the expected one, p, where N is the number of days over a period T that a violation has occurred. Although the unconditional coverage test can reject a model that either overestimates or underestimates the "true" but unobservable VaR, it cannot examine whether the violations are randomly distributed.

Christoffersen (1998) developed a conditional coverage test, which jointly investigates whether i) the total number of failures is equal to the expected one and ii) the VaR violations are independently distributed. Under the null hypothesis that the failure process is independent and the expected proportion of violations equals to p, the appropriate likelihood ratio is:

$$LR_{cc} = -2\ln[(1-\mathrm{p})^{\mathrm{T-N}} p^{N}] + 2\ln[(1-\pi_{01})^{n_{00}} \pi_{01}{}^{n_{01}} (1-\pi_{11})^{n_{10}} \pi_{11}^{n_{11}}] \sim X_2^2, \qquad (15)$$

where n_{ij} is the number of observations with value i followed by j, for $i, j = 0,1$ and $\pi_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}$ are the corresponding probabilities. $i, j = 1$ denotes that a violation has been made, while $i, j = 0$ indicates the opposite. Contrary to Kupiec's (1995) test, Christoffersen's procedure can reject a VaR model that generates too many or too few clustered violations.

However, in most of the cases, there are more than one risk models that satisfy both the backtesting measures and therefore a risk manager can not select a unique volatility forecasting technique. Hence, in order to select one model among the various candidates, we compare the best performed models via a loss function.

Lopez (1999) proposed to market practitioners a procedure of evaluating VaR models based on a loss function approach. According to the Basle Committee on Banking Supervision (1996) proposal, he incorporated both the total number of violation and their magnitude term. More formally, Lopez's loss function can be described as:

$$\Psi_{t+1} = \begin{cases} 1 + (VaR_{t+1|t} - \mathrm{y}_{t+1})^2 & \textit{if violation occurs} \\ 0 & \textit{else.} \end{cases} \tag{16}$$

The magnitude term $(VaR_{t+1|t} - \mathrm{y}_{t+1})^2$ ensures that the larger the failure is the more the penalty is added to a model, while a score of one is added, similar to Kupiec's test, whenever a violation occurs. According to Lopez's loss function, a model, which minimizes the total loss, $\sum_{t=1}^{T} \Psi_t$, is preferred over the others.

Based on Diebold and Mariano (1995), Sarma et al. (2003) and Angelidis et al. (2004), we examine whether the forecast accuracy of two VaR models is statistically significant. Specifically, we test the null hypothesis of equivalent predictive ability of models A and B, against the alternative hypothesis that model A is superior to model B. The Diebold-Mariano statistic is the "t-statistic" for a regression of z_t on a constant with heteroskedastic and autocorrelated consistent standard errors (HAC), where $z_t = \Psi_t^A - \Psi_{\mathrm{t}}^{\mathrm{B}}$, and Ψ_t^A and $\Psi_{\mathrm{t}}^{\mathrm{B}}$ are the loss functions of models A and B, respectively. A negative value of z_t indicates that model A is superior to model B.

Empirical Results

Table I summarizes the basic descriptive statistics of the 6 series, while the daily log-returns graphs are presented in Figure 1. Volatility clustering is clearly visible in Figure 1, which suggests the presence of heteroskedasticity. Moreover, based on Jarque-Bera statistic, the null hypothesis of normality is rejected at any level of significance, as there is evidence of excess kurtosis relative to that of the normal distribution and non-zero skewness. The preliminary descriptive statistics indicate that the characteristics of the two tails are different and therefore, it is interesting to evaluate the risk models for different trading positions.

<<Take in Table I>>

We generate out-of-sample VaR forecasts for two equity indices (S&P500, FTSE100), two commodities (Gold Bullion $/Troy Ounce, London Brent Crude Oil Index U$/BBL) and two exchange rates (US $ to Japanese ¥, US $ to UK £), obtained from Datastream for the period of January 3rd 1989 to June 30th 2003. For all models, we use a rolling sample of 2000 observations in order to generate, approximately, 1600 forecasts and calculate the 95% and the 99% $VaR_{t+1|t}$ for long and short trading positions.

<<Take in Figure 1>>

The framework in (1) is estimated for (2), (4), (5) and (6) conditional variance specifications and (7) to (9) density functions by adopting the maximum likelihood method. The EWMA model, the variance-covariance procedure and the techniques of historical and filtered historical simulation are applied, giving a total of 16 volatility-forecasting models.

Under the framework of the loss function approach, we evaluate all the models with p-value greater than 10% for both unconditional and conditional coverage tests. A high cut-off point is preferred in order to ensure that the successful risk management techniques will not a) over or under estimate statistically the “true” VaR, as in the former case, the financial institution does not use its capital efficiently, while in the latter case it can not cover future losses and b) generate clustered violations, since an adequate model must wide the VaR forecasts during volatile periods and narrow them otherwise. In the case of a smaller cut-off point, an incorrect model could not be easily rejected, which might turn to be costly for a risk manager.

Table II summarizes the two-stage model selection procedure[iii]. In the first stage (columns 2 and 3) the models that have not been rejected by the statistical backtesting procedures are presented, while in the second stage (column 4), the volatility methods that are preferred over the others, based on the loss function approach, are exhibited. For example, in panel A, for the S&P500 index, the GARCH(1,1)-normal model achieves the smallest value of the loss function, while its forecasting accuracy is not statistically different to that of the EWMA, EGARCH(1,1) and APARCH(1,1) models with normally distributed innovations.

<<Take in Table II>>

The VC method underestimates the "true" VaR, since portfolio returns exhibit excess kurtosis relative to that of the normal distribution. For example, the average exception rate at the 99% confidence level for long (short) trading positions is 2.67% (2.80%). Therefore, in most of the cases, the p-values of the backtesting measures are close to zero. Examining the 95% confidence level we reach to similar conclusion, thus this method is not an appropriate technique for risk management.

On the other hand, the RiskMetrics™ method is more appropriate technique than the VC one, as for the 95% confidence level the exception rates are statistically equal to the theoretical values. However, in some cases this method generates clustered violations indicating that the risk model is misspecified. At the higher confidence level it underestimates the “true” value of VaR, since the average exception rate is 68% greater than it is expected.

More sophisticated techniques that accommodate the features of the financial time series are needed, in order to calculate the one-day-ahead VaR. ARCH models based on the normal distribution (GARCH(1,1), EGARCH(1,1), TARCH(1,1) and APARCH(1,1)) perform better than the VC and the RiskMetrics methods. Especially, for the 95% confidence level the failure rates are statistically equal to the theoretical values, irrespectively of the trading position. However, they underestimate the VaR at the higher confidence level, even if this underestimation is smaller than that of the RiskMetrics™. Thus the degree of leptokurtosis induced by the ARCH process does not capture all the leptokurtosis presented in the data. Hence, in order to model more adequately the thickness of tails, we use two different distributional assumptions for the standardized residuals: Student’s-t and skewed Student’s-t distributions.

Brooks and Persand (2003) pointed out that models, which do not allow for asymmetries either in the unconditional return distribution or in the volatility specification, underestimate the “true” VaR. Giot and Laurent (2003a) proposed the skewed Student’s-t distribution and argued that it performed better than the pure symmetric one, as it reproduced the characteristics of the empirical distribution more accurately. These views are confirmed for both confidence levels and trading positions, as most of the selected models parameterise these features.

The volatility specifications, which parameterise the leverage effect for the conditional variance and the asymmetry of the innovations' distribution, forecast the VaR at the 99% confidence level more adequately. However, the models that must be employed for the short and the long trading positions are not the same. This finding is in contrast with that of Giot and Laurent (2003a) who argued that the APARCH model based on the skewed Student's-t distribution forecasts the VaR adequately for both trading positions.

Contrary to the findings for the 99% confidence level, the ARCH models under the Student's-t and the corresponding skewed distribution overestimate the 95% VaR numbers for both trading positions, a result that is also documented by Guermat and Harris (2002) and Billio and Pelizzon (2000) among others. Therefore, even if the leptokurtic distributional assumption seems to be a better choice overall for the 99% confidence level, it should not be applied for the lower confidence interval as it produces higher than excepted VaR forecasts.

Turning the discussion to the non-parametric methods, the HS method underestimates total risk, as for most of the cases the exception rates are greater than the expected ones. The inadequate performance of the HS may is due to the fact that the underlying distribution does not remain constant.

In terms of the coverage tests, the FHS procedure combined with a GARCH(1,1) updating volatility technique offers a major improvement over both the parametric and the non-parametric methods, as the exception rates are too close to the theoretical ones for both trading positions. For example, at 95% confidence level, the average proportion of failures for the long (short) trading position is 5.55% (5.78%). This is also the case for the 99% confidence level, as the corresponding percentages are 0.96% and 1.13%, respectively. However, the FHS method does not yield the best VaR forecasts, as, for example, it underestimates the risk for the FTSE100 index at the 95% confidence level.

Furthermore, for long position on OIL index (95% VaR) and short position on GOLD index (99% VaR), there are no models that produce adequate VaR forecasts. Given the fact that for these cases the models have been rejected by the conditional coverage test, there is evidence that clustered violations were generated. So, all the models are very slow at updating the VaR number when market volatility changes rapidly.

Finally, we can not compare directly the models based on the backtesting measures, as a greater p-value of a model does not indicate its superiority among its competitors. However, under the framework of the loss function, this is possible as we evaluate statistically the differences between the various risk models. No model seems to systematically produce globally acceptable VaR estimates for all securities, trading positions and confidence levels. However, based on the proposed model selection procedure, we manage to conclude to a smaller set of models and in some cases we identify a unique risk management model.

Conclusion

In this paper we examined the most recently developed VaR methods for stock exchanges, commodities, and exchange rates. In an out-of-sample study we compared parametric, non-parametric and semi-parametric techniques both for long and short trading positions. As the backtesting tests do not identify a unique model for each portfolio, we define a loss function to evaluate the models that have met the prerequisite of the correct unconditional and unconditional coverage. Under the new framework, a model that minimizes the total loss is preferred over the remaining ones, while by implementing a test for the differences of the forecast error we provide statistical inference for the forecasting ability of the models.

Assuming normality for the conditional return distribution, we forecast accurate the one-day-ahead VaR at the 95% confidence level. However, gains in forecasting the 99% VaR with models that allow for asymmetries either in the conditional return distribution or in the volatility specification are substantial. Different models achieve accurate VaR forecasts for long and short trading positions, indicating to portfolio managers the significance of modeling either the left or the right side of the distribution of returns. Using data from three types of financial markets (stock exchanges, commodities, and exchange rates) there is evidence that our results hold for different types of markets.

An interesting issue for further research would be the implementation of the described two-stage model selection procedure for the expected shortfall risk measure, which is the value of the loss conditioned that a VaR violation has occurred and has been considered as an alternative downside risk measure.

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Table I. Descriptive Statistics of S&P500, FTSE100, Gold Bullion $/Troy Ounce, London Brent Crude Oil Index U$/BBL, US $ to UK £ and US $ to Japanese ¥, for the period of January 3rd 1989 to June 30th 2003.

	S&P 500	FTSE100	GOLD	OIL	US_UK	US_YEN
Mean	0.034%	0.022%	-0.005%	0.016%	-0.002%	0.001%
Median	0.039%	0.043%	-0.015%	0.118%	0.015%	-0.024%
Maximum	5.573%	5.903%	7.382%	12.556%	3.058%	6.574%
Minimum	-7.113%	-5.885%	-7.218%	-22.521%	-3.081%	-3.568%
Std. Dev.	1.048%	1.070%	0.786%	2.017%	0.586%	0.705%
Skewness	-0.164	-0.105	-0.026	-0.986	-0.162	0.552
Kurtosis	6.894	5.770	14.571	15.981	5.482	7.653
Jarque-Bera	2325	1176	19784	25572	934	3523

Figure 1. Daily log-returns for the period of January 3rd 1989 to June 30th 2003.

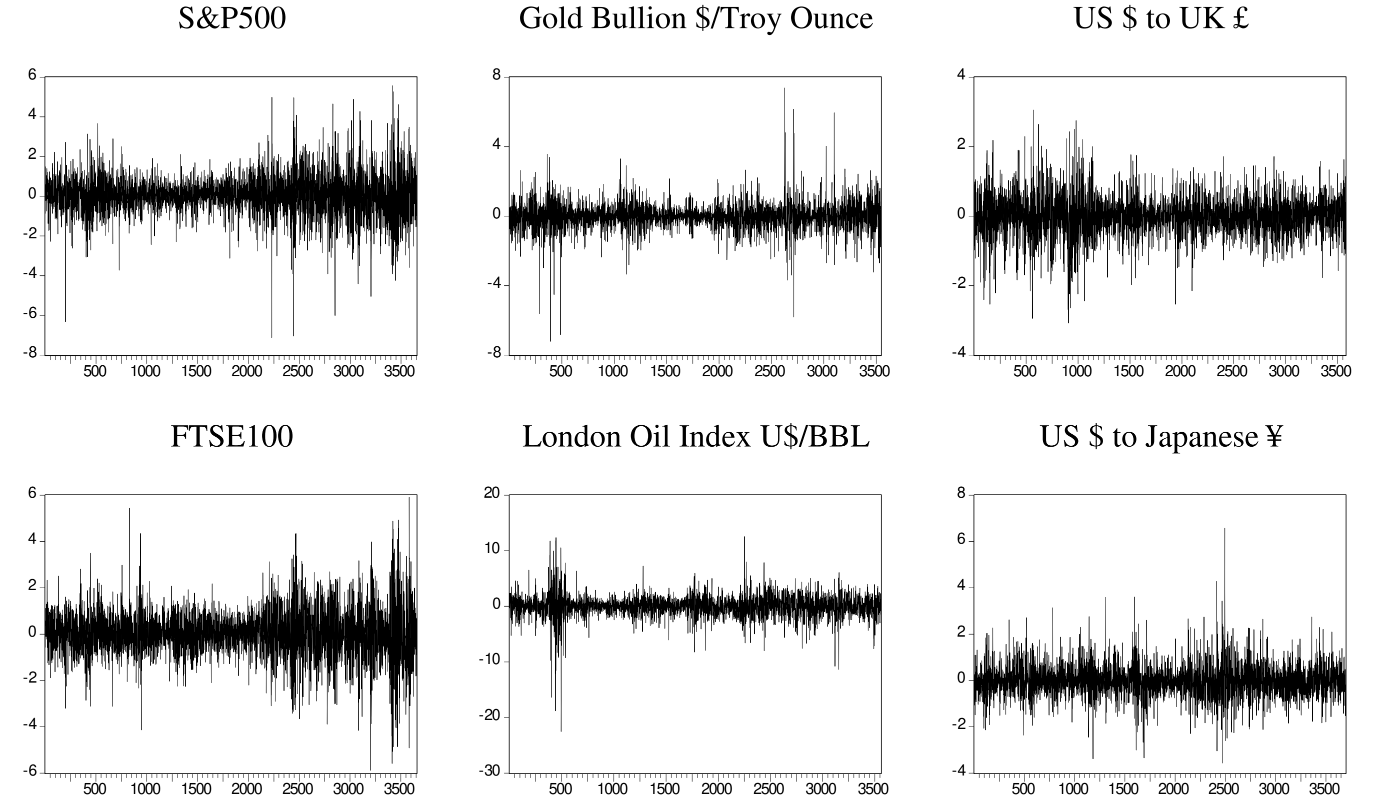

Table II. Exhibit 4. The two-stage model selection procedure. Column 2 presents the models that have not been rejected by the unconditional coverage backtesting criterion (Kupiec 1995), Column 3 presents the models that have not been rejected by the conditional coverage backtesting criterion (Christoffersen 1998), Column 4 presents the models that are preferred over the others based on the loss function approach. In Column 4, the model with the lower value of the loss function is bold faced.

Series	Unconditional Coverage	Conditional Coverage	Loss Function
		95% VaR	
		Long Positions	
S&P 500	EWMA, G-N, E-N, A-N, FHS	EWMA, G-N, E-N, A-N, FHS	EWMA, **G-N**, E-N, A-N
FTSE100	G-T, T-T, G-ST, E-ST, T-ST	G-T, T-T, G-ST, E-ST, T-ST	G-ST, **T-ST**
OIL	VC, EWMA, G-N, E-N, T-N, A-N, FHS	-	-
GOLD	EWMA, G-N, E-N, T-N, A-N, FHS	EWMA, G-N, E-N, T-N, A-N, FHS	G-N, **E-N**, T-N
US_UK	EWMA, G-N, E-N, T-N, A-T, A-ST, FHS	EWMA, G-N, E-N, T-N, A-T, A-ST, FHS	EWMA, G-N, **E-N**, T-N, A-T, A-ST, FHS
US_YEN	EWMA, G-N, E-N, T-N, HS, FHS	EWMA, G-N, E-N, T-N, HS, FHS	G-N, **E-N**, T-N
		Short Positions	
S&P 500	EWMA, G-N, E-N, T-N, A-N	G-N, A-N	**G-N**, A-N
FTSE100	EWMA, G-N, E-N, T-N, A-N, A-ST	EWMA, G-N, E-N, T-N, A-N, A-ST	**EWMA**, T-N, A-ST
OIL	VC, EWMA, G-N, E-N, T-N	VC, EWMA, G-N, E-N, T-N	G-N, **E-N**, T-N
GOLD	EWMA, G-N, E-N, T-N, A-N, FHS	G-N, E-N, T-N, FHS	G-N, **T-N**
US_UK	G-N, E-N, T-N, A-ST, FHS	G-N, E-N, T-N, A-ST, FHS	**E-N**
US_YEN	VC, EWMA, G-N, E-N, T-N, A-N, HS, FHS	VC, EWMA, G-N, E-N, T-N, A-N, HS, FHS	VC, **G-N**, E-N, T-N, HS, FHS
		99% VaR	
		Long Positions	
S&P 500	E-T, T-T, A-T, A-ST, FHS	E-T, T-T, A-T, A-ST, FHS	E-T, T-T, A-T, **A-ST**, FHS
FTSE100	G-T, E-T, T-T, A-T, G-ST, E-ST, T-ST, A-ST	G-T, E-T, T-T, A-T, G-ST, E-ST, T-ST, A-ST	G-T, E-T, G-ST, **E-ST**, T-ST, A-ST
OIL	E-N, A-N, G-T, E-T, T-T, A-T, G-ST, E-ST, T-ST, HS, FHS	A-N, A-T, G-ST, FHS	**A-T**, G-ST
GOLD	G-N, FHS	G-N, FHS	**FHS**
US_UK	VC, EWMA, G-N, E-N, T-, A-T, A-ST	VC, EWMA, G-N, E-N, T-, A-T, A-ST	VC, G-N, E-N, A-T, **A-ST**
US_YEN	VC, G-N, T-N, HS, FHS	VC, G-N, T-N, HS, FHS	T-N, **HS**, FHS
		Short Positions	

S&P 500	G-N, T-N	G-N, T-N	G-N, **T-N**
FTSE100	A-N, FHS	A-N, FHS	**A-N**
OIL	VC, EWMA, G-N, E-N, T-N, A-N, HS, FHS	VC, EWMA, G-N, E-N, T-N, A-N, HS, FHS	VC, E-N, A-N, HS, **FHS**
GOLD	A-T, A-ST, FHS	-	-
US_UK	VC, A-T, A-ST, FHS	VC, A-T, A-ST, FHS	VC, A-T, A-ST, **FHS**
US_YEN	G-T, E-T, T-T, A-T, G-ST, T-ST, A-T, HS, FHS	G-T, E-T, T-T, A-T, G-ST, T-ST, A-T, FHS	G-T, E-T, A-T, G-ST, **T-ST**, A-T

Models: G-N (GARCH(1,1)-normal), G-T (GARCH(1,1)-Student's-t), G-ST (GARCH(1,1)-skewed-t), E-N (EGARCH(1,1)-normal), E-T (EGARCH(1,1)-Student's-t), E-ST (EGARCH(1,1)-skewed-t), T-N (TARCH(1,1)-normal), T-T (TARCH(1,1)-Student's-t), T-ST (TARCH(1,1)-skewed-t), A-N (APARCH(1,1)-normal), A-T (APARCH(1,1)-Student's-t), A-ST (APARCH(1,1)-skewed-t), EWMA (RiskMetrics), VC (Variance Covariance Method), HS (Historical Simulation Technique), FHS (Filtered Historical Simulation Technique).

[i] For more information about HS method see Hendricks (1996), Van den Goorbergh and Vlaar (1999) and Daníelsson (2002) among others.
[ii] A violation occurs if the predicted VaR is not able to cover the realized loss.
[iii] Exhibits with detailed results are available upon request.