CONSEQUENCES OF THE EURO INTRODUCTION ON MARKET RISK: AN ECONOMETRIC EVIDENCE FROM 1995 to 2004

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Abstract
In the last years the interest in the Value at Risk (VaR) estimation has significantly growth due to international financial instability. We modelled the daily VaR estimation trough different static and non-static variance techniques in order to evaluate the changes produced in financial risk caused by the Euro introduction. Our analysis covers 10 European indices and neutral DJIA as a mirror for common world developments. Estimations are made on 1000 ex-ante and 1000 ex-post data points and backtested on the next 250 for each index by Kupiec's (1995) methodology. At this stage of the ongoing research it is already clear that in general VaR has grown significantly after introducing Euro, which in turn claims for new commercial bank capital requirements according to Basle Accord. We also have shown how the non-static models are more suitable for the variance prediction.

JEL. Code: G28, G24
Key words: Value at Risk, Euro, Financial Markets

1. INTRODUCTION

Financial market - the most sensitive segment of economic body - is the best mirror for any process within the system. In nowadays world introduction of Euro at January 1, 1999 is normally to touch rather international than only European financial market. It was more than just a shock or an event, as most probably it has made changes even in the life rhythm of particular markets. We do not touch the deep macroeconomic aspects of Euro Zone establishment in this paper, though the final explanations may really need some macroeconomic approaches.

In this paper we shall solely be concerned with financial market risk (Jorion, 1995) before and after the Euro. Financial risk, caused by movements in financial markets, is one of the three types of risk distinguished in the financial literature. In turn financial risk is broken down further into different categories. Among them the market risk brought on by changes in the prices of financial assets and liabilities is our target.

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Uniform methodology of risk measurement called Value-at-Risk (VaR) has received a great attention both from regulatory and academic fronts. It was made popular by US investment bank J.P. Morgan (1996), who incorporated it in their risk management model RiskMetrics^{TM}. During a short span of time, a serious number of papers have studied various aspects of VaR methodology (Hull and White, 1997), (Goorberg and Vlaar, 1999; Lee and Saltoglu, 2002). The availability of information from financial markets allows us to empirically examine this type of risk better than any other kind. VaR is defined as the maximum potential change in value of a portfolio of financial instruments with a given probability over a certain time horizon, with assumption that the composition of the portfolio remains the same. We will return to this indicator's definition and to its detailed characteristics a little later in our next chapters.

VaR measures can have many applications, such as in risk management, to evaluate the performance of risk takers and for regulatory requirements. In particular, the Basel Committee on Banking Supervision (1996) at the Bank for International Settlements imposes to financial institutions to meet capital requirements based on VaR estimates. Thus, providing accurate estimates is of crucial importance. If the underlying risk is not properly estimated, this may lead to a sub-optimal capital allocation with consequences on the profitability or the financial stability of the institutions.

We did not try to find the best possible model for VaR estimation as many other authors do before, making the process into Holy Grail search. We used variance techniques of VaR estimation previously used by the other authors (Goorberg and Vlaar (1999)) and applied them on the exante and expost periods of Euro introduction. We evaluated VaR using Maximum Log-likelihood method for normally and t-student distributed returns, along with RiskMetriks and GARCH(1.1) models with Gaussian innovations. The analysis cover 10 European indexes corresponding to Netherlands, Austria, Belgium, Germany, France, UK, Spain, Denmark, Italy and Swiss (AEX, ATX, BFX, DAX, FCHI, FTSE, IBEX, KFX, MIB30, SSMI) and DJIA for USA, covering larger geographical area than most other related studies. Kupiec's (1995) back-testing procedure is run for the estimation results. We compare exante and expost VaR estimations to evaluate the "Euro effect". Then several ideas are discussed to characterize changes in world financial markets caused by Euro.

The outline of the paper is as follows: Section 2 revisits the general view about Value at Risk. In the 3rd section VaR regulation is described. Section 4 examines different techniques for VaR computing. Section 5 summarizes the empirical results and backtesting of VaR estimates. Finally in the 6th section present our conclusions.

2. Value at risk: definition

Three aspects need to be kept in mind when judging the Value-at-Risk of a portfolio. In the first place, we need to know the initial value of the portfolio. For analytical purposes, the initial portfolio value is usually normalised to 100 currency units, but it could be any other amount, of course. A second ingredient is the holding period to which the VaR pertains. And finally, the confidence level is of importance. Evidently, the higher the confidence level the larger the Value-at-Risk of the portfolio. By varying the confidence level, one is able to explore a whole risk profile, i.e. the entire distribution of results is revealed.

Defined as the maximum potential change in value of a portfolio of financial instruments with a given probability over a certain time horizon the VaR estimation is a complex. However, VaR indicator is suitable to be defined analytically. It just runs into the idea of probability distribution.

$$\begin{aligned} &\Pr\left[r_t < -VaR(h)\right] = a, \qquad or \\ &\Pr\left[V_t - V_0 < -VaR(h)\right] = a \end{aligned} \qquad (1)$$

where r_t is the return at time t, V_0 and V_t are the initial and final values of the asset portfolio respectively, a is the left tail probability and $VaR(h)$ is the VaR for time horizon h.

We shall evaluate and compare daily VaR, so in our observation $h = 1$.
Analytically, the VaR is defined by the top limit of integral of the function of expected returns $r(s)$:

$$a = \int_{-\infty}^{E(r)-VaR} r(s)\,ds \qquad (2)$$

?
Usually it is assumed that the expected value of the returns is zero so we can transform (2) into

$$a = \int_{-\infty}^{-VaR} r(s)\,ds \qquad (3)$$

An alternative representation consists of considering the VaR through the following expression:

$$VaR(h) = a\sqrt{s^2 \cdot h} \qquad (4)$$

where a is the factor that defines the area of returns loss[1], s^2 is returns variance and h is the time horizon for which the factor of risk will be calculated.

Value at Risk concept, or valuation of the risk, comes of the need from quantifying with certain level of significance or uncertainty the amount or percentage of loss that a

1

Percentage	10%	5%	1%	0.5%
a	1.282	1.645	2.325	2.575

portfolio will face in a predefined period of time (Jorion 2000, Penza and Bansal 2001). Its measurement has statistical foundations and the standard of the industry is to calculate the VaR with a significance level of 5 %. This means that only 5% of times, or 1 of 20 times we can consider too that once a month with daily information, or once every five months with weekly information the return of the portfolio will fall down of what indicates the VaR, in relation with the expected return.

If we consider a series of historical returns of a portfolio that has N number of assets, it is feasible to visualize the distribution of density of those returns across the analysis of the histogram. It is common to find fluctuations of returns around an average slightly different value of zero, in other words, to find mean reversion process and which distribution comes closer one normally. Skewness is sometimes perceived in the returns and from a practical point of view it is not so realistic to assume symmetry in the distribution. That is why the assumption about the distribution, in order to compute the Value at Risk, is a very important issue.

3. Value at risk regulation: market and asset liquidity risks

Market risk refers to the potential losses arising from the changes in the value or price of an asset, such as those resulting from fluctuations in interest rates, currency exchange rates, stock prices and commodity prices. Asset liquidity risk is clearly allied with market risk and represents the risk that an entity will be unable to unwind a position in a particular financial instrument at or near its market value because of a lack of depth or disruption in the market for that instrument.

Market risks, together with liquidity risks, are the most important risks for securities firms, which typically operate on a fully mark-to-market basis. Securities firms, which engage in the business of underwriting, trading, and dealing in securities, must necessarily maintain proprietary positions in a wide range of financial instruments. Therefore, the aim of such firms is not to eliminate all market risk, but rather to manage it to a level at which acceptable returns, net of market losses, can be generated.

Market risks are also important for banks and their affiliates that hold significant positions that are marked to market. Banks typically manage market and liquidity risks associated with such positions in the same manner and with the same kinds of tools as their securities firm counterparts. The situation is somewhat different in regard to assets that the firms intend to hold to maturity and may be illiquid. Insurance companies are also subject to market risks. Here, such risks are generally classified as asset or investment risks in insurance activities. The investment of premiums must generate income and have a realisable liquidation value sufficient to meet the firms' liabilities. Shifts in market prices could affect achievement of this objective.

Most securities firms and banks, together with insurance companies running significant trading positions, use statistical models to calculate how the prices and values of assets are potentially impacted by the various market risk factors. These models generate a Value-at Risk estimate of the largest potential loss the firm could incur, given its current portfolio of financial instruments. More precisely, the VaR number is an estimate of maximum potential loss to be expected over a given period a certain percentage of the time.

A number of vast VaR models depend on statistical analyses of past price movements that determine returns on the assets. The VaR approach evaluates how prices and price volatility behaved in the past to determine the range of price movements or risks that might occur in the future. These models are commonly back-tested to evaluate the accuracy of the assumptions by comparing predictions with actual trading results. In practice, while VaR models provide a convenient methodology for quantifying market risks and are helpful in monitoring and limiting market risk.

The Basel Committee has developed a so-called "internal models" approach to the calculation of a market risk capital charge. For those banks that meet a series of qualifying criteria, this approach effectively relies on their own value-at-risk calculations of market risk. Banks and securities firms choosing to use an internally developed VAR model to calculate market risk capital charges must demonstrate to their supervisor that their model meets minimum qualitative and quantitative standards, including incorporation of VAR into the firm's daily risk management process, back-testing to determine the precision of the model and continuous adjustment of the model.

For back-testing proposal we used Kupiec (1995) methodology performed according to the Basel Internal Model approach regulations.

4. MODELLING var: EMPLOYED VARIANCE METHODS

To measure VaR we used so-called variance methods based on some assumption concerning distribution of returns. Applied methods include both static Maximum Log-likelihood method and non-static methods [Risk Metrics and GARCH (1.1)], which take into account volatility clustering phenomenon.

4.1.Normality Assumption

One of the static models that we use in our paper is that assumed that high frequency financial return data have fatter tails than can be explained by the normal distribution, this artefact seems odd. However, the normal distribution entails some very convenient characteristics that do not carry over to other distributions.

First of all the parameters of normal distribution are easier to estimate as there is often an analytical solution for them. One of the other advantages is the additivity of the normal distribution and this characteristic is especially important for the calculation of the multi-day VaR based on one-day VaR.

Hence, if we assume independence of normally distributed returns and a mean return of zero(Figlewski, 1994) it can be show that:

$$VaR^{(T)} = \sqrt{T} \cdot VaR^{(1)} \tag{5}$$

Also assuming i.i.d log-returns we can express the Value at Risk as:

$$VaR = -V\left(e^{m + sf^{-1}(a)} - 1\right) \tag{6}$$

Where V represents the initial value of our portfolio and $f(\cdot)$ is the cumulative distribution function of the standard normal probability distribution. For this model we can estimate the parameters of m and s by means of normal distribution's log-likelihood function maximization.

4.2. t-Student Distribution Assumption

As we can see the results related on the application of the first model based on the assumption that our portfolio returns follow normal distribution are underestimates the portfolio risk.
So it seems obvious to try the estimation with the consumption that the log returns of portfolio are Student-t distributed, as it is known that Student-t distribution is the most suitable for VaR estimation because of its fatter tails (Goorberg and Vlaar ,1999).

The Student-t probability distribution has three main characteristics which are the scale (g >0), degrees of freedom (u >0) and location parameter (m). At this stage we can say that any variable distributed by means of Student-t distribution has a variance $\frac{u g^2}{u-2}$ for u >2[2], mean (m) and provided (u >1)[3]

Hence, assuming that our portfolio log returns follow t-distribution the log likelihood function is given by:

$$ML_{t-dist} = T\left[\log\Gamma\left(\frac{u+1}{2}\right) - \log\Gamma\left(\frac{u}{2}\right) - \frac{1}{2}\log p\, u - \log g\right] - \frac{u+1}{2}\sum_{t=1}^{T}\log\left(1 + \left(\frac{r_t - m}{g\sqrt{u}}\right)^2\right)$$

Gamma function is defined as $\Gamma(x) = \int_0^{\infty} e^{-x} x^{x-1}\,dx$ and for this case the maximum likelihood optimisation has to be done numerically. There is no analytical expression for g ,u and m .

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[1] For $u \to \infty$ the t-distribution is reduced to the normal one with mean (m) and variance (g^2).

[3] The smaller u get, the fatter the tails are.

The Value at Risk for Student-t distribution assumption can be expressed as:

$$VaR = -V\left(e^{m + g F_v^{-1}(a)} - 1\right) \tag{8}$$

Where $F(\cdot)$ is the cumulative distribution function of a standardised t- distributed random variable.

4.3. Non Static Models

The static models are that they do not take the volatility clustering into account. By far the most popular model to model this phenomenon is the so called Generalised Autoregressive Conditional Heteroskedasticity, or GARCH, model introduced by Bollerslev (1986). It is an extension of the Autoregressive Conditional Heteroskedasticity, or ARCH, model by Engle (1982). In the GARCH model we start by defining an innovation ?$_{t+1}$, i.e., some random variable with mean zero conditional on time t information, I_t. This time t information is a set including the innovation at time t, ?$_t$? I_t, and all previous innovations, but any other variable available at time t as well. In finance theory, ?$_{t+1}$ might be the innovation in a portfolio return. In order to capture serial correlation of volatility, or volatility clustering, the GARCH model assumes that the conditional variance of the innovations depends on the latest past squared innovations as is the assumption in the less general ARCH model, possibly augmented by the previous conditional variances. In its most general form, the model is called GARCH(p, q), and it can be written as

$$s_t^2 = w + \sum_{j=1}^{p} b_j s_{t-1}^2 + \sum_{i=1}^{q} a_i h_{t-i+1}^2 \tag{9}$$

p lags are included in the conditional variance, and q lags are included in the squared innovations. In this section, we shall regard these innovations as deviations from some constant mean portfolio return:

$$r_{t+1} = m + h_{t+1} \tag{10}$$

so that s_t^2 is also the conditional variance of the portfolio returns. We can write the innovation h_{t+1} as $s_t e_{t+1}$, where e_{t+1} is assumed to follow some probability distribution with zero mean and unit variance, such as the standard normal distribution.

A great many empirical studies have proved it unnecessary to include more than one lag in the conditional variance, and one lag in the squared innovations. This is why our point of departure will be the GARCH(1,1) model:

$$s_t^2 = w + b s_{t-1}^2 + a h_t^2 \tag{11}$$

with $w \succ 0$, $b \geq 0$ and $a \geq 0$ to ensure positive variances. If the market was volatile in the current period, next period's variance will be high, which is intensified or offset in accordance with the magnitude of the return deviation this period. If, on the other hand, today's volatility was relatively low, tomorrow's volatility will be low as well, unless today's portfolio return deviates from its mean considerably. Naturally, the impact of these effects hinges on the parameter values. Note that for $a + b \prec 1$, the conditional variance exhibits mean reversion, i.e., after a shock it will eventually return to its unconditional mean $w/(1 - a - b)$. If $a + b = 1$, this is not the case, we should have persistence.

In order to estimate these parameters by means of likelihood maximisation, one has to make assumptions about the probability distribution of the portfolio return innovations h_{t+1}. We shall consider Gaussian innovations.

$$e_t \overset{iid}{\sim} N(0,1), \qquad h_{t+1} \mid I_t \sim N(0, s_t^2) \tag{12}$$

leading to a conditional log likelihood of h_{t+1} equal to:

$$\ell_t(h_{t+1}) = -\log \sqrt{2p} - \frac{1}{2}\log s_t^2 - \frac{h_{t+1}^2}{2s_t^2} \tag{13}$$

The log likelihood of the whole series $h_1; h_2; ::::; h_T$ is

$$L = \sum_{t=1}^{T} \ell_t(h_{t+1}) \tag{14}$$

As an alternative to the GARCH(1,1) model, or as a special case of this model is US investment bank J.P. Morgan introduced RiskMetrics™ one, a VaR assessment method that basically restricts both m and w to 0, and a to $1 - b$ in formula (11). The parameter b, called the decay factor and renamed l, is set at 0.94 for daily data. This makes estimation elementary, since there are no parameters to estimate left. The portfolio return variance conditional on time t information is just:

$$s_t^2 = l s_{t-1}^2 + (1 - l) r_t^2 \tag{15}$$

or

$$s_t^2 = l^t s_0^2 + (1 - l) \sum_{k=0}^{t-1} l^k r_{t-k}^2 \tag{16}$$

From the formulae above, it is clear that the conditional variances are modelled using an exponentially weighted moving average: the forecast for time t is a weighted average of the previous forecast, using weight l, and of the latest squared innovation, using weight $1-l$. The RiskMetrics™ approach essentially boils down to keeping track of the return data and using these along with the decay factor to update the conditional volatility estimates.

The imposition of the restriction that a and b should sum to unity implies persistence in the conditional variance, i.e., a shock moving the conditional variance to a higher level does not die out over time but `lasts forever'. If there are no shocks offsetting this volatility increase, the conditional variance will remain high, and will not display mean-reverting behaviour. Hence, today's volatility affects forecasts of volatility into the future.

As you will make sure the non-static models can better predict VaR than the comparably naïve static ones. All these methods are applied to those 11 indexes under observation.

5. Estimating and backtesting the daily VaR

Before estimating VaR it is suitable to verify the existence of autocorrelation in the daily returns of our time series for every eleven indexes. The correlograms[4] of the returns shows hardly any evidence of autocorrelation in the first six lags.

Therefore, following the techniques described in the past section of the paper we compute VaR estimation for 11 countries. The analysis cover 10 European indexes and 1 USA index: the time series of every country comprises data from the end of January of 1994 till December of 2003 or 2500 daily data. Dividing our data in two subsets, before and after Euro introduction in the EU markets, obtain 1250 daily data for every period. Hence, the estimation sample consists in 1000 daily data and 250 for evaluation sample, for both periods. For the purpose of not overloading the paper we attach VaR estimates results only for left tail probability of 1% (see table 1).

Once we have estimated VaR our goal is focused on Kupiec back-test which is one of the most popular tests applied in backtesting. The likelihood ratio developed by, will be used to conclude if the VaR model has to be rejected or otherwise has to be accepted. For this proposal we split our indexes returns into an estimation sample and an evaluation sample. The estimation sample were used to estimate the model and to predict the VaR, whereupon a statistically back-test is applied by means of the evaluation sample in order to find the adequacy of the model.

[4] In order not overloading the paper, the correlograms will be provided upon request

Table 1. Ex-ante and Ex-post VaRs for 1% Confidence Level

VaR Estimates	AEX	ATX	BFX	DJIA	FCHI	FTSE	IBEX	KFX	MIB30	SSMI	DAX
Normal (ex-ante)	-2,39	-2,29	-1,87	-2,03	-2,68	-1,85	-2,67	-1,93	-3,21	-2,33	-2,65
Normal (ex-post)	-3,94	-2,27	-3,08	-3,15	-3,95	-3,19	-3,82	-3,06	-3,76	-3,23	-4,37
Student-t (ex-ante)	-2,74	-2,62	-2,12	-2,32	-2,86	-1,98	-2,95	-2,12	-3,43	-2,62	-3,02
Student-t (ex-post)	-4,53	-2,53	-3,55	-3,47	-4,38	-3,52	-4,10	-3,40	-3,43	-3,71	-4,88
RM (ex-ante)	-3,69	-3,50	-2,91	-2,67	-3,39	-2,83	-3,33	-2,82	-3,80	-2,71	-3,88
RM (ex-post)	-5,42	-2,17	-3,66	-3,22	-5,11	-3,49	-3,91	-2,60	-4,20	-3,80	-6,30
GARCH(1,1) (ex-ante)	-3,59	-2,40	-2,83	-2,40	-3,69	-2,87	-2,76	-2,74	-4,37	-2,65	-3,33
GARCH(1,1) (ex-post)	-4,68	-2,42	-3,66	-3,07	-4,55	-3,46	-3,77	-2,57	-4,20	-3,62	-6,06

Note: The results for the rest confidence levels are attached at the end of the paper in Annex 1-4

Be N the number of failures (it is the number of cases in which loss exceeds the one forecasted by VaR model) in a sample of size T, then the number of VaR violations follows a binomial distribution and the failure rate N/T should be equal to the left tail probability p. The likelihood ratio statistic is:

$$LR = -2\,Ln\left[(1-p^*)^{T-N}\cdot p^{*N}\right] + 2\,Ln\left[(1-N/T)^{T-N}\cdot(N/T)^{N}\right] \qquad (17)$$

with the null hypotheses: H_o: $N/T=p^*$, H_1: $N/T\neq p^*$

The likelihood ratio is asymptotically c^2 distributed under the null hypotheses that p is the true probability the VaR is exceeded. So, we can construct rejection/acceptance intervals with certain confidence level that advice us whether a model has to be rejected or not. Conventionally the confidence level is set to 0,05. The table 2 shows the rejection/acceptance regions according to likelihood ratio statistic.

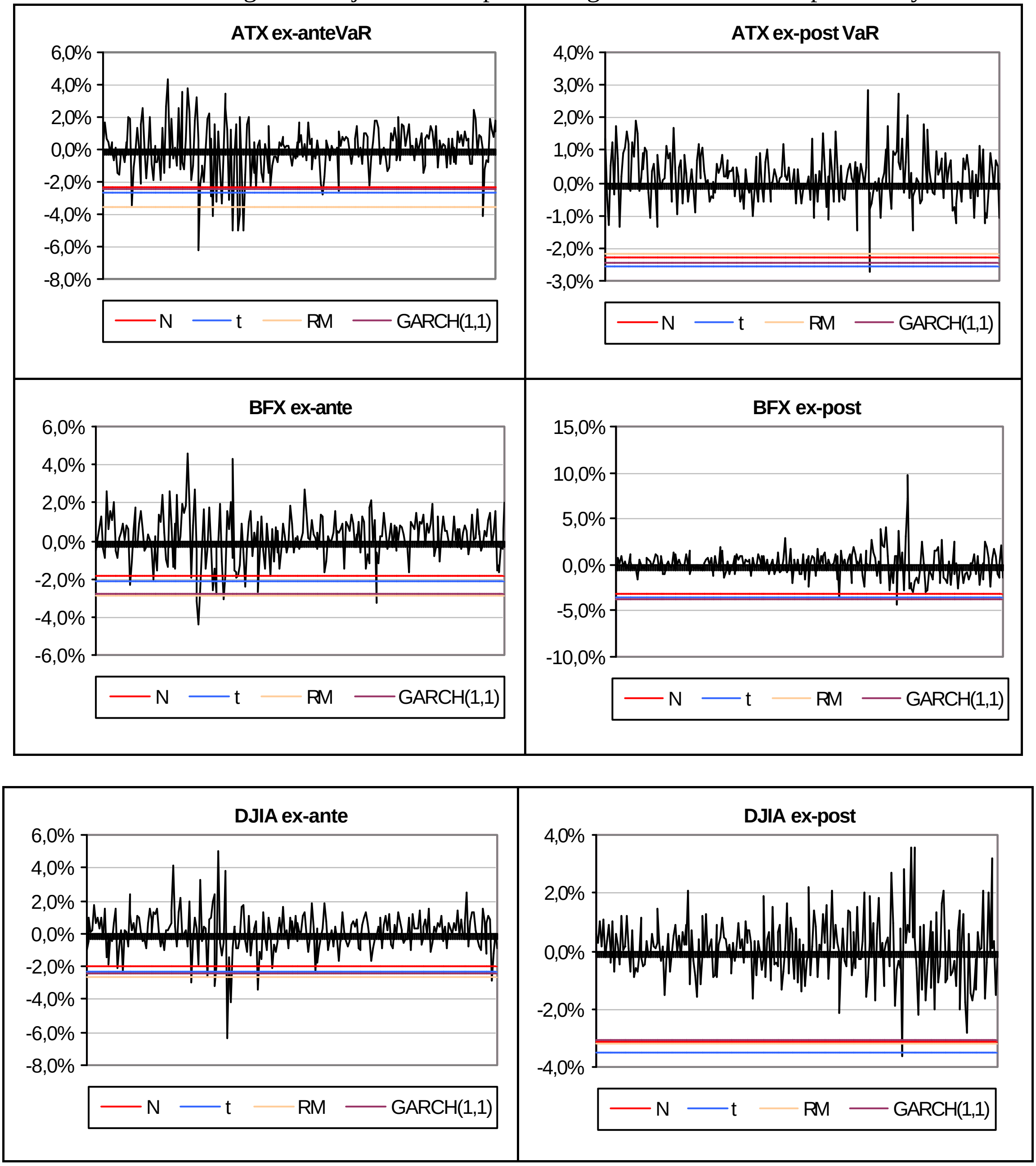
Table 2: Rejection/Acceptance regions

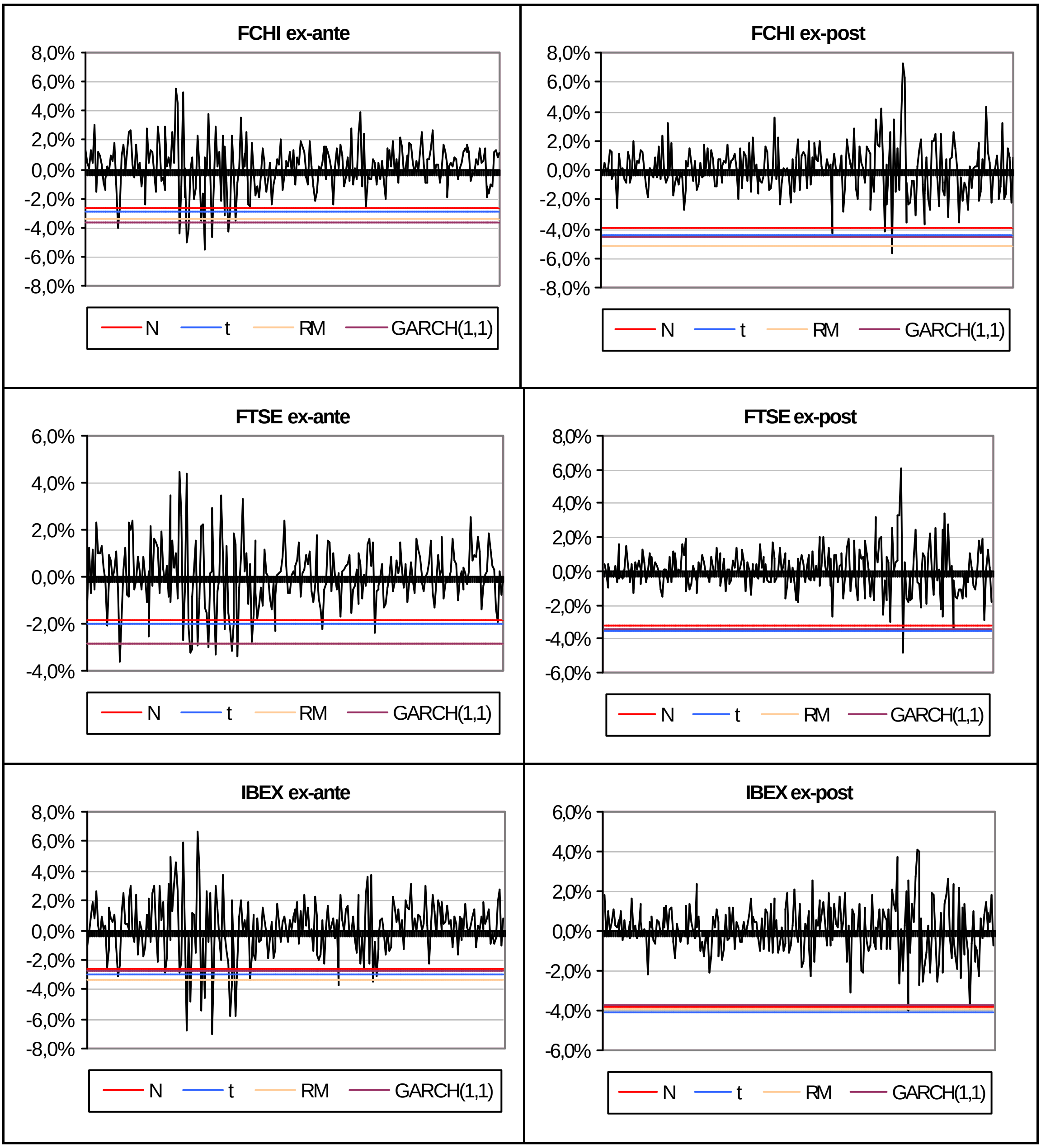
Left Tail Prob.	Evaluation Sample Size (T) 250	500	750	1000	1500
0.05	$7\leq N\leq 19$	$17\leq N\leq 35$	$27\leq N\leq 49$	$38\leq N\leq 64$	$60\leq N\leq 92$
0.01	$1\leq N\leq 6$	$2\leq N\leq 9$	$3\leq N\leq 13$	$5\leq N\leq 16$	$9\leq N\leq 23$
0.005	$0\leq N\leq 4$	$1\leq N\leq 6$	$1\leq N\leq 8$	$2\leq N\leq 9$	$3\leq N\leq 13$
0.001	$0\leq N\leq 1$	$0\leq N\leq 2$	$0\leq N\leq 3$	$0\leq N\leq 3$	$0\leq N\leq 4$

The size of the test is 5%

According to the rejection/acceptance regions we present the results for left tail probability of 1% and 250 evaluation sample size (see figure 1). The numerical results for the failure rates for 0.05, 0.01, 0.005, 0.001 and 0.0001 left tail probabilities are tabulated and annexed at the end of the paper (see annex 5).

Figure 1. Rejection/Acceptance Regions for 1% left tail probability




FCHI ex-ante
8,0%
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-2,0%
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RM
GARCH(1,1)
FCHI ex-post
8,0%
6,0%
4,0%
2,0%
0,0%
-2,0%
-4,0%
-6,0%
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RM
GARCH(1,1)
FTSE ex-ante
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GARCH(1,1)
FTSE ex-post
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IBEX ex-ante
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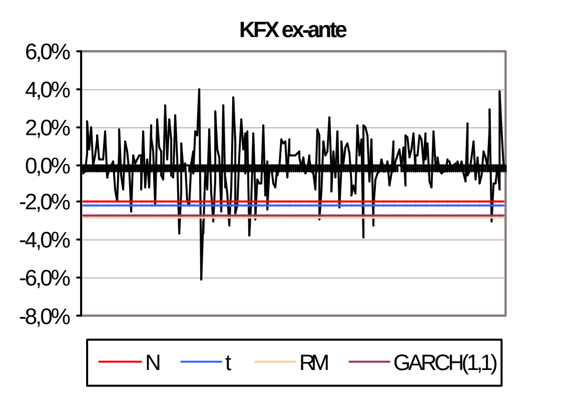
KFX ex-ante
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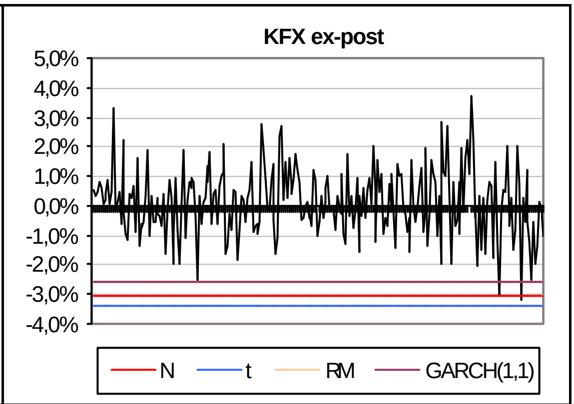
KFX ex-post
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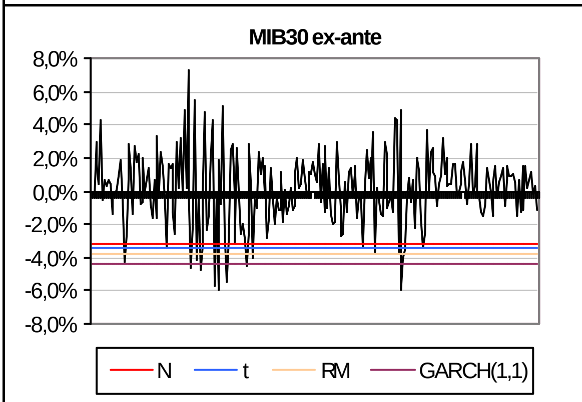
GARCH(1,1)


MIB30 ex-ante
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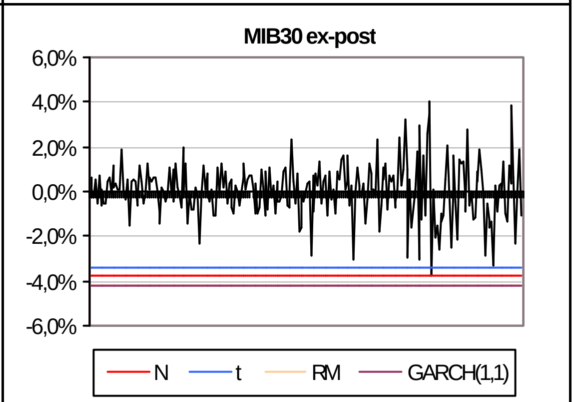
RM
GARCH(1,1)


MIB30 ex-post
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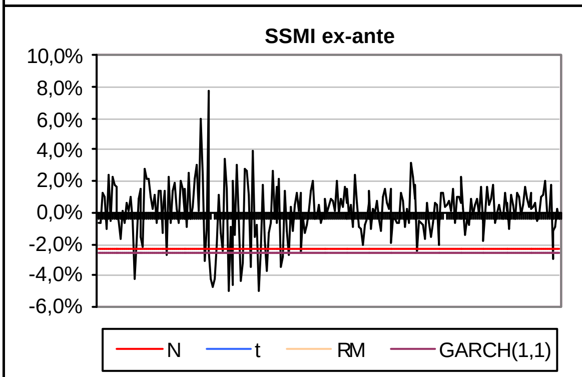
GARCH(1,1)


SSMI ex-ante
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-4,0%
-6,0%
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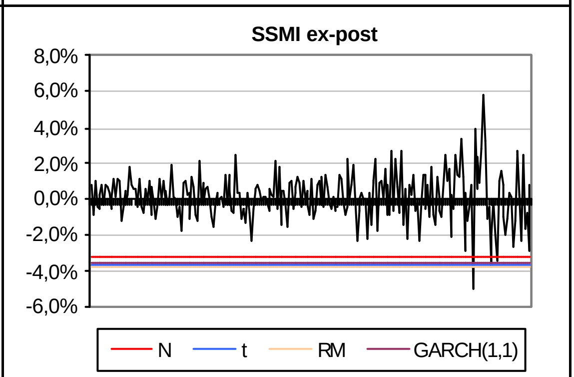
RM
GARCH(1,1)


SSMI ex-post
8,0%
6,0%
4,0%
2,0%
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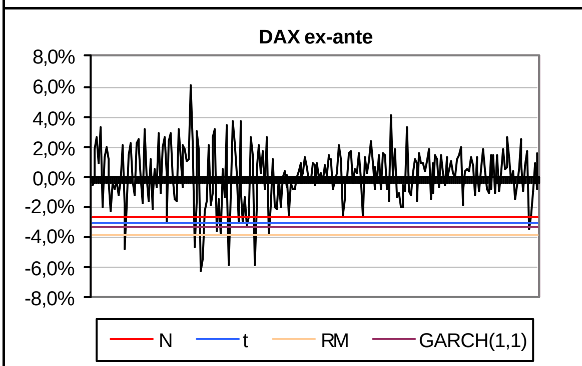
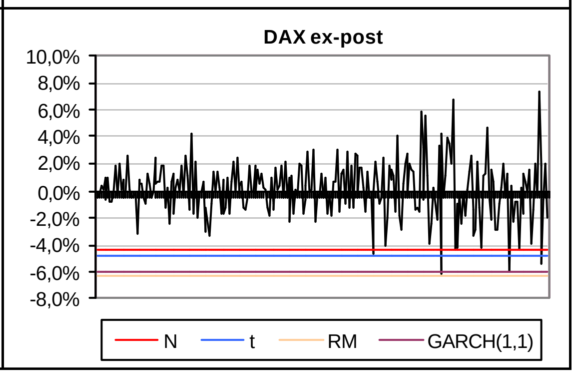
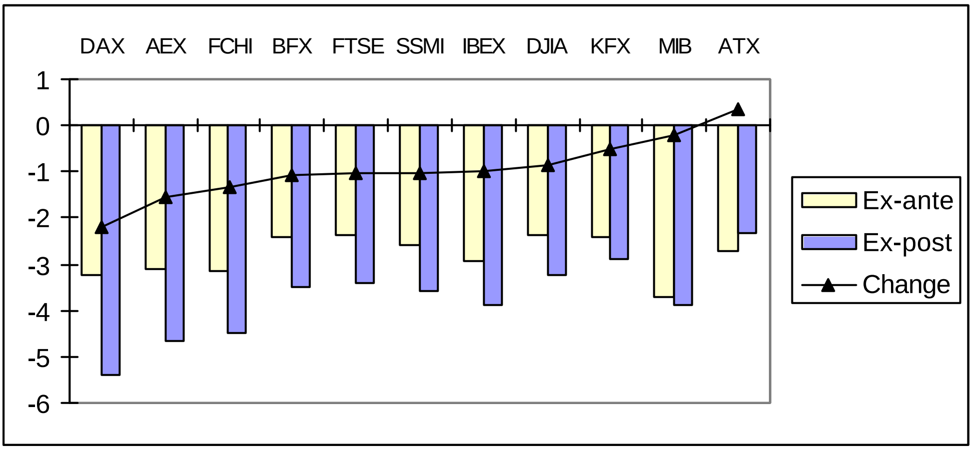
-6,0%
N
t
RM
GARCH(1,1)


DAX ex-ante
8,0%
6,0%
4,0%
2,0%
0,0%
-2,0%
-4,0%
-6,0%
-8,0%
N
t
RM
GARCH(1,1)


DAX ex-post
10,0%
8,0%
6,0%
4,0%
2,0%
0,0%
-2,0%
-4,0%
-6,0%
-8,0%
N
t
RM
GARCH(1,1)

According to the results, the ex-Euro period presents violations in case of Normal, t-Student, Riskmetrics and Garch(1,1) . The assumption of normality is rejected at almost all left tail probability levels, except for DJIA in which one is accepted at 5% of left tail probability. In case of t-Student assumption we improve the failure rates time due to the fatter tails that generates more realisations in the tails than is to be expected on the basis of a normal distribution. The accepted regions for t-Student distribution mostly corresponds to 0,1%. The last two assumption, Riskmetrics and Garch(1,1), fit better. Kupiec back-test does not reject them mostly for 5%, 1% and 0,1% for 11 countries (see annex 5). As can be observed in the above figures for 1% left tail probability, not the same occurs for post Euro period. Both, Normal and t-Student assumption improve VaR estimates compared with the previous period but still exists regions in which ones VaR estimates are rejected according to the Kupiec back-test. On the contrary, the back-test results for Riskmetrics and Garch(1,1) models are very successful. They are accepted at all levels and for entire group of countries (see annex 5). Other of our remarks is the comparison of the financial risk before and after the Euro. We used average VaR arrived by different methods for 1% confidence level. As we one can see from the figure 2 only in Greece the average VaR was reduced. In all remaining countries VaR tends to grow after Euro Zone establishment. The largest jump in VaR was registered in Germany, Netherlands and France.

Figure 2. Ex-ante and Ex-post Average VaR Estimates for 1% Confidence Level



Therefore, after Euro introduction the world financial markets have a quite different model with higher but more predictable Value at Risk.

6. Conclusion

After introducing the Euro Europe has pretended to deepen the economic integration. The most important component of the economy is the financial market. Thus we tried to evaluate the effect of Euro on the financial markets stability through VaR estimations. We conclude that after Euro VaR has grown in European and world financial markets as well. Only in Greece the average VaR was reduced. In all remaining observed countries VaR trends to grow after Euro Zone establishment. The largest jump in VaR was registered in Germany, Netherlands and France. Though it is a bit difficult to be sure that the Euro zone establishment is the very source for those changes, several hypotheses can be suggested however. E.g. a common currency for EU member states, the Euro/Dollar exchange rate now concerns entire competitiveness of the both industrial giants of the world – EU and USA. The same is true also for relative competitiveness of EU products compared with any other trade partners of its own. The often changes in competitiveness may by the events preconditioning changes in prices of company shares all over the world. So slight changes in exchange rates now are more significant for the indices under observation. The often fluctuations in exchange rates after establishment of Euro can explain the higher VaR indicated after creation of Euro zone. In fact, in spite of higher financial risk, now it is more predictable, as it is obvious from Kupiec back-testing of our VaR measures. This fact makes other explanations of VaR levels jump even less persuasive. Higher VaR does not mean that we must loose in market regulation. Only accurate evaluation of potential risk makes it harmless for the business. Concluding remarks we have to state that non static models of VaR estimation (GARCH(1.1) and RiskMetrics) are more suitable and non rejectable on all the left tail probability confidence levels. However after the Euro the static models also became more efficient, characterizing with lower failure rates.

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Annex on line at the journal web site

Annex 1. Normality Assumption (Ex-ante)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (p=0,05)	-1,70840	-1,61290	-1,33060	-1,45490	-1,89410	-1,31640
VaR (0,01)	-2,39090	-2,28580	-1,86520	-2,03300	-2,67670	-1,84740
VaR (0,005)	-2,64190	-2,53320	-2,06160	-2,24540	-2,96470	-2,04250
VaR (0,001)	-3,16130	-3,04530	-2,46780	-2,68490	-3,56100	-2,44600
VaR (0,0001)	-3,79980	-3,67470	-2,96650	-3,22460	-4,29470	-2,94130
LLF	3137,70	3063,60	3310,50	3290,90	2947,80	3375,40
s	0,00980	0,00970	0,00770	0,00830	0,01120	0,00770
µ	0,00080	-0,00001	0,00052	0,00073	0,00030	0,00046
	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*	
VaR (p=0,05)	-1,90160	-1,37570	-2,27770	-1,66410	-1,88640	
VaR (0,01)	-2,67040	-1,92530	-3,20610	-2,32860	-2,64710	
VaR (0,005)	-2,95320	-2,12720	-3,54810	-2,57300	-2,92700	
VaR (0,001)	-3,53900	-2,54480	-4,25680	-3,07860	-3,50650	
VaR (0,0001)	-4,25950	-3,05770	-5,12960	-3,70010	-4,21930	
LLF	2964,60	3318,60	2355,30	3137,40	2996,60	
s	0,01100	0,00790	0,01330	0,00960	0,01090	
µ	-0,00070	0,00061	0,00071	0,00078	0,00074	

Annex 1.1. Normality Assumption (Ex-post)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-2,75610	-1,59750	-2,15020	-2,21590	-2,76610	-2,23100
VaR (0,01)	-3,94170	-2,26530	-3,08060	-3,15180	-3,94610	-3,18720
VaR (0,005)	-4,37920	-2,51090	-3,42340	-3,49650	-4,38150	-3,53950
VaR (0,001)	-5,28700	-3,01910	-4,13370	-4,21090	-5,28490	-4,26960
VaR (0,0001)	-6,40730	-3,64370	-5,00860	-5,09100	-6,39990	-5,16910
LLF	2662,70	3222,30	2897,70	2892,70	2667,60	2871,50
s	0,01680	0,00960	0,01330	0,01340	0,01680	0,01370
µ	-0,00050	0,00004	-0,00061	-0,00008	-0,00027	-0,00041
	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*	
VaR (0,05)	-2,67310	-2,14930	-2,62900	-2,25930	-3,05350	
VaR (0,01)	-3,82350	-3,05750	-3,75730	-3,23350	-4,37040	
VaR (0,005)	-4,24790	-3,39200	-4,17350	-3,59240	-4,85670	
VaR (0,001)	-5,12840	-4,08510	-5,03680	-4,33640	-5,86650	
VaR (0,0001)	-6,21470	-4,93860	-6,10190	-5,25320	-7,11400	
LLF	2691,90	2921,90	2710,90	2853,10	2561,50	
s	0,01630	0,01300	0,01600	0,01390	0,01860	
µ	-0,00051	-0,00099	-0,00044	-0,00054	-0,00057	

Annex 2. Student-t Assumption (Ex-ante)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-1,59660	-1,54300	-1,26100	-1,37900	-1,86970	-1,30900
VaR (0,01)	-2,74000	-2,61870	-2,11850	-2,31580	-2,86430	-1,98210
VaR (0,005)	-3,35090	-3,17110	-2,55960	-2,80200	-3,29620	-2,27310
VaR (0,001)	-5,20030	-4,77690	-3,84320	-4,23000	-4,35350	-2,98270
VaR (0,0001)	-9,53100	-8,29050	-6,65300	-7,40640	-6,09170	-4,14040
LLF	3203,10	3130,50	3357,80	3359,10	2959,40	3385,10
s	0,00980	0,00970	0,00770	0,00830	0,01120	0,00770
?	0,00700	4,52140	4,47680	4,36190	9,29270	9,40240
µ	0,00100	0,00038	0,00065	-0,00092	0,00035	0,00058
?	0,00700	0,00720	0,00570	0,00610	0,01000	0,00680
	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*	
VaR (0,05)	-1,85860	-1,35630	-2,21810	-1,60890	-1,83630	
VaR (0,01)	-2,94900	-2,11950	-3,43370	-2,61940	-3,02480	
VaR (0,005)	-3,46090	-2,47180	-3,97340	-3,11850	-3,62480	
VaR (0,001)	-4,81800	-3,38920	-5,32540	-4,51220	-5,33870	
VaR (0,0001)	-7,36850	-5,06150	-7,63570	-7,36540	-8,98520	
LLF	2991,20	3335,80	2367,20	3172,60	3054,20	
s	0,01100	0,00790	0,01330	0,00960	0,01090	
?	6,27630	6,69700	8,23660	5,14450	4,79310	
µ	0,00085	0,00079	0,00055	0,00098	0,00120	
?	0,00910	0,00660	0,01150	0,00750	0,00830	

Annex 2.2. Student-t Assumption (Ex-post)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-2,52620	-1,54070	-1,96720	-2,13720	-2,67950	-2,16350
VaR (0,01)	-4,53230	-2,53480	-3,54870	-3,47310	-4,38260	-3,52460
VaR (0,005)	-5,61980	-3,01800	-4,40720	-4,10440	-5,19550	-4,16640
VaR (0,001)	-8,96960	-4,34540	-7,05240	-5,78950	-7,38390	-5,87640
VaR (0,0001)	-17,1012	-6,99020	-13,4538	-8,99550	-11,6439	-9,11900
LLF	2725,70	3249,80	2962,40	2921,30	2692,00	2892,30
s	0,01680	0,00960	0,01330	0,01340	0,01680	0,01370
?	3,92780	5,45010	3,87990	6,15130	5,96210	6,20710
µ	-0,00034	0,00014	-0,00045	-0,00012	-0,00014	0,00033
?	0,01180	0,00770	0,00930	0,01100	0,01370	0,01130
	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*	
VaR (0,05)	-2,62230	-2,08140	-2,21810	-2,08060	-2,93280	
VaR (0,01)	-4,09780	-3,39880	-3,43370	-3,71090	-4,87890	
VaR (0,005)	-4,74450	-4,02840	-3,97340	-4,58420	-5,82570	
VaR (0,001)	-6,34330	-5,72900	-5,32540	-7,23810	-8,43180	
VaR (0,0001)	-9,01640	-9,02830	-7,63570	-13,5169	-13,6633	
LLF	2702,00	2945,60	2746,10	2918,50	2590,70	
s	0,01640	0,01300	0,01610	0,01390	0,01860	
?	8,95400	5,86760	6,12770	4,03300	5,57060	
µ	-0,00056	0,00002	-0,00045	-0,00043	-0,00050	
?	0,01440	0,01050	0,01320	0,00990	0,01490	

Annex 3. RiskMetrics (Ex-ante)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-2,59330	-2,46300	-2,04550	-1,88030	-2,38410	-1,99610
VaR (0,01)	-3,68730	-3,50190	-2,90510	-2,66970	-3,38850	-2,83480
VaR (0,005)	-4,09080	-3,88470	-3,22170	-2,96020	-3,75860	-3,14350
VaR (0,001)	-4,92750	-4,67830	-3,87740	-3,56170	-4,52600	-3,78300
VaR (0,0001)	-5,95950	-5,65670	-4,68450	-4,30190	-5,47170	-4,57010
s	0,01560	0,01480	0,01230	0,01130	0,01430	0,01200
	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*	
VaR (0,05)	-2,34280	-1,98510	-2,67340	-1,91060	-2,72470	
VaR (0,01)	-3,32950	-2,81910	-3,80180	-2,71290	-3,87530	
VaR (0,005)	-3,69300	-3,12610	-4,21800	-3,00810	-4,29970	
VaR (0,001)	-4,44670	-3,76200	-5,08140	-3,61960	-5,18030	
VaR (0,0001)	-5,37540	-4,54460	-6,14660	-4,37200	-6,26670	
s	0,01410	0,01200	0,01600	0,01150	0,01630	

Annex 3.1. RiskMetrics (Ex-post)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-3,80300	-1,53060	-2,57340	-2,26320	-3,58710	-2,45320
VaR (0,01)	-5,42070	-2,17160	-3,65890	-3,21580	-5,11070	-3,48710
VaR (0,005)	-6,01920	-2,40730	-4,05910	-3,56670	-5,67410	-3,86820
VaR (0,001)	-7,26400	-2,89490	-4,88930	-4,29410	-6,84520	-4,65850
VaR (0,0001)	-8,80500	-3,49410	-5,91300	-5,19020	-8,29440	-5,63260
s	0,02270	0,00920	0,01540	0,01360	0,02140	0,01470
	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*	
VaR (0,05)	-2,74740	-1,82950	-2,95090	-2,67320	-4,41360	
VaR (0,01)	-3,90770	-2,59730	-4,19890	-3,80160	-6,29890	
VaR (0,005)	-4,33580	-2,87980	-4,65950	-4,21780	-6,99750	
VaR (0,001)	-5,22390	-3,46470	-5,61570	-5,08120	-8,45250	
VaR (0,0001)	-6,31980	-4,18430	-6,79640	-6,14620	-10,2580	
s	0,01650	0,01100	0,01770	0,01600	0,02630	

Annex 4. GARCH(1,1) (Ex-ante)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-2,54550	-1,69960	-2,00770	-1,71870	-2,60500	-2,03530
VaR (0,01)	-3,58530	-2,40190	-2,82880	-2,40130	-3,68860	-2,87000
VaR (0,005)	-3,96860	-2,66010	-3,13100	-2,65240	-4,08820	-3,17730
VaR (0,001)	-4,76340	-3,19480	-3,75700	-3,17190	-4,91690	-3,81370
VaR (0,0001)	-5,74320	-3,85200	-4,52730	-3,81050	-5,93890	-4,59700
LLF	3282,80	3152,50	3391,10	3369,20	2977,80	3420,60
s	0,01480	0,01010	0,01180	0,00980	0,01540	0,01200
µ	0,00078	0,00024	0,00053	0,00090	0,00036	0,00049
?	0,00000	0,00001	0,00000	0,00000	0,00000	0,00000
ß	0,88890	0,73980	0,89110	0,85660	0,96950	0,97010
a	0,09410	0,16130	0,08600	0,11430	0,02850	0,02690
Std.Error						
µ	0,00026	0,00028	0,00023	0,00023	0,00034	0,00023
?	0,00000	0,00000	0,00000	0,00000	0,00000	2,59E-07
ß	0,02126	0,04230	0,02218	0,01971	0,00994	0,01245
a	0,01772	0,01938	0,01680	0,01175	0,00789	0,00926

	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*
VaR (0,05)	-1,9715	-1,9477	-3,0907	-1,8942	-2,3646
VaR (0,01)	-2,7637	-2,7388	-4,3746	-2,6498	-3,3275
VaR (0,005)	-3,0552	-3,0299	-4,8486	-2,9279	-3,6823
VaR (0,001)	-3,659	-3,6327	-5,8328	-3,5035	-4,4176
VaR (0,0001)	-4,4017	-4,3744	-7,0484	-4,2115	-5,3235
LLF	3015,30	3357,20	2376,70	3202,60	3090,20
s	0,0114	0,0113	0,0182	0,0108	0,0137
µ	8,45E-04	6,35E-04	5,64E-04	9,31E-04	7,72E-04
?	7,58E-06	2,83E-07	4,07E-05	5,78E-06	5,26E-06
ß	0,8211	0,9637	0,614	0,8104	0,8343
a	0,1191	0,0326	0,1565	0,1274	0,1217
Std.Error					
µ	0,00	0,00	0,00045	2,85E-04	2,95E-04
?	2,11E-06	2,04E-07	1,36E-05	1,61E-06	1,34E-06
ß	0,03448	0,00863	0,0952	0,03836	0,02621
a	0,02188	0,00782	0,03302	0,02467	0,01941

Annex 4.1. GARCH(1,1) (Ex-post)

	AEX	*ATX*	*BFX*	*DJIA*	*FCHI*	*FTSE*
VaR (0,05)	-3,28270	-1,71590	-2,57100	-2,16440	-3,19740	-2,42800
VaR (0,01)	-4,68450	-2,42360	-3,66410	-3,06840	-4,55030	-3,46270
VaR (0,005)	-5,20250	-2,68390	-4,06720	-3,40130	-5,04990	-3,46270
VaR (0,001)	-6,27850	-3,22260	-4,90320	-4,09120	-6,08770	-4,63490
VaR (0,0001)	-7,60870	-3,88500	-5,93420	-4,94070	-7,37020	-5,60980
LLF	2852,70	3252,20	3080,10	2950,10	2766,30	2969,40
s	0,01980	0,01020	0,01560	0,01290	0,01910	0,01470
µ	-0,00024	0,00028	-0,00020	0,00015	0,00004	-0,00027
?	0,00000	0,00000	0,00000	0,00001	0,00000	0,00001
ß	0,87110	0,88390	0,82500	0,87630	0,90750	0,85540
a	0,11170	0,06970	0,16600	0,08930	0,07350	0,11400
Std.Error						
µ	0,00037	0,00031	0,00030	0,00039	0,00045	0,00035
?	0,00000	0,00000	0,00000	0,00000	0,00000	1,89E-06
ß	0,01909	0,02434	0,01877	0,02036	0,02326	0,02855
a	0,01649	0,01282	0,01904	0,01491	0,01693	0,0249

	IBEX	*KFX*	*MIB30*	*SSMI*	*DAX*
VaR (0,05)	-2,6423	-1,8111	-2,9475	-2,5435	-4,2442
VaR (0,01)	-3,7658	-2,5684	-4,1985	-3,6194	-6,0567
VaR (0,005)	-4,1801	-2,8471	-4,6602	-4,016	-6,7281
VaR (0,001)	-5,0397	-3,424	-5,6187	-4,8387	-8,1258
VaR (0,0001)	-6,1001	-4,1336	-6,8024	-5,8531	-9,8593
LLF	2761,60	2988,70	2797,30	3003,00	2679,20
s	0,016	0,0109	0,0177	0,0153	0,0253
µ	-1,9E-04	6,19E-05	-1,0E-04	-7,3E-05	-3,9E-05
?	5,99E-06	9,29E-06	7,63E-06	4,83E-06	5,72E-06
ß	0,8894	0,8352	0,8388	0,8399	0,894
a	0,0879	0,1076	0,1392	0,1378	0,0893
Std.Error					
µ	0,00047	0,00037	0,00043	3,23E-04	0,00048
?	2,81E-06	2,83E-06	3,07E-06	1,45E-06	2,53E-06
ß	0,0273	0,03421	0,02925	0,02551	0,01999
a	0,02002	0,02185	0,01988	0,02233	0,01557

Annex 5. Failure Times Number for 250 evaluation sample size

a	0,05	0,01	0,005	0,001	0,0001	0,05	0,01	0,005	0,001	0,0001
	AEX ex-ante					AEX ex-post				
Normal	32	18	13	9	7	18	7	5	2	0
Student-t	35	13	9	2	0	10	1	1	0	0
RM	14	7	5	4	0	13	4	2	1	0
GARCH(1,1)	15	0	0	0	0	21	10	7	4	1
	ATX ex-ante					ATX ex-post				
Normal	28	16	14	11	7	1	1	1	0	0
Student-t	30	13	9	4	0	1	1	0	0	0
RM	14	7	7	4	1	1	1	1	0	0
GARCH(1,1)	27	8	13	9	7	1	1	1	0	0
	BFX ex-ante					BFX ex-post				
Normal	32	13	10	8	4	16	2	2	1	0
Student-t	33	10	7	1	0	23	1	0	0	0
RM	10	4	1	1	0	7	1	1	0	0
GARCH(1,1)	10	4	3	1	0	7	1	1	0	0
	DJIA ex-ante					DJIA ex-post				
Normal	19	12	10	6	3	3	1	1	0	0
Student-t	21	10	6	1	0	4	1	0	0	0
RM	13	8	4	2	1	2	1	1	0	0
GARCH(1,1)	16	8	8	4	2	3	1	1	0	0
	FCHI ex-ante					FCHI ex-post				
Normal	25	12	10	7	4	9	3	1	1	0
Student-t	20	9	6	0	0	13	1	1	0	0
RM	16	9	7	3	1	5	1	0	0	0
GARCH(1,1)	13	7	6	2	0	6	1	1	0	0
	FTSE ex-ante					FTSE ex-post				
Normal	32	20	18	11	7	7	2	1	1	0
Student-t	32	18	13	7	0	9	1	1	0	0
RM	18	8	5	0	0	7	1	1	1	0
GARCH(1,1)	18	8	5	0	0	7	1	1	1	0
	IBEX ex-ante					IBEX ex-post				
Normal	31	15	13	9	7	4	2	0	0	0
Student-t	33	13	9	6	0	5	0	0	0	0
RM	20	10	8	7	5	3	2	0	0	0
GARCH(1,1)	29	15	13	8	7	4	2	0	0	0
	KFX ex-ante					KFX ex-post				
Normal	33	22	21	12	7	4	1	0	0	0
Student-t	33	21	15	5	1	4	0	0	0	0
RM	21	12	7	3	1	11	2	2	0	0
GARCH(1,1)	22	12	8	5	1	11	2	2	0	0
	MIB30 ex-ante					MIB30 ex-post				
Normal	31	18	14	7	4	7	1	0	0	0
Student-t	31	18	11	4	0	11	1	0	0	0
RM	24	11	8	4	0	5	0	0	0	0

GARCH(1,1)	19	7	4	2	0	5	0	0	0	0
	SSMI ex-ante					SSMI ex-post				
Normal	32	22	17	13	9	11	3	2	1	0
Student-t	32	17	12	4	0	13	2	1	0	0
RM	27	17	14	9	5	5	2	1	0	0
GARCH(1,1)	27	17	14	10	7	6	2	1	1	0
	DAX ex-ante					DAX ex-post				
Normal	30	15	14	10	6	31	19	16	11	7
Student-t	32	14	8	4	0	32	15	11	3	0
RM	14	7	6	4	0	6	0	0	0	0
GARCH(1,1)	19	10	8	6	4	6	1	0	0	0