Volatility Preference in Calculating the Capital Adequacy with VaR Methodology on a Typical Turkish Bank Trading Portfolio

K.Evren BOLGUN

Marmara Üniversitesi Bankacılık ve Sigortacılık Enstitüsü -

Bankacılık ve Sigortacılık Yüksekokulu, Göztepe Kampüsü

34722 Kadıköy-İstanbul

Tel: 0212 – 339 74 59

Email: ebolgun@superonline.com

Abstract

The factor GARCH(1,1),GARCH-T and MA&Riskmetrics EWMA volatility measurement preferenes in VaR calculations are generated on a typical trading portfolio of a Turkish Bank. The emphasis on volatility preferences in determining the capital adequacy of bank with three VaR methods are figured out with significant differences. The trading portfolio is demonstrated as a major benchmark instrument trades in the secondary market.(IMKB) Several Riskmetrics EWMA coefficients (0.90-0.99) are simulated on the portfolio with regard to different modelling parameters. The portfolio consists of Zero-Coupon Bonds, FRN's, Turkish Eurobonds issued on USD & EUR, Currency Swaps and FX Forwards. The three model outputs with different volatility methods are illustrated in the tables and major risk factor statistical data results are calculated in order to be informed about the distribution characteristics.

Keywords: Risk Management**,** Value At Risk Models, GARCH Models, Riskmetrics EWMA Volatility, Volatility Forecasting Techniques, BIS, Bank Capital Adequacy, Risk-Return Relationship.

1 Introduction

The banking industry has increased its awareness on the risk management practices because of high profile financial disasters occurrence on the world in the last decade. Especially, advances in technology and developments on financial systems, the regulatory process show tremendous changes in order to take precautions. There has been an increased emphasis on the quality of risk management systems and measurement tools since 1993 Baring's collapse. Advances in technology have enabled institutions to develop more sophisticated systems for monitoring and controlling their financial risks. On the other hand regulatory developments with BIS[1], have contributed by recognising the more accurate risk management methodology in banks with internal models for the purpose of setting market risk capital standards.

Risk measurement methodologies are becoming increasingly sophisticated and some form of Value at Risk (VaR) models are generally used to analyse and monitor market risks. VaR models aim to measure the potential loss on a portfolio that would result if relatively large adverse price movements were to occur in a predefined confidence level such as %99 or %95. VaR is used mainly as a high level management tool with structural limits, such as basis point values and net open positions, used to influence the trader behaviour and some credit risk related operations. VaR is however, starting to be driven down to the all bank traders abroad, as it becomes more sophisticated and measures such as risk adjusted performance (RAROC) & EAR (Earnings at Risk) applications shape corporates behaviour and help capital to efficient use.

2 Volatility Adjustments According to the Capital Adequacy Requirement

As we know on Feb 21th 2001, the IMF program was abolished by a rapid devaluation of Turkish Lira whose volatility magnititude is over %17.5/day on GARCH(1,1) estimation and %6.5/day on EWMA (λ:0.97) model. Over the last decade, such intraday price variations have occurred more and more frequently, highlighting the importance of valuation the price movements in financial markets.

Because of high volatility in the returns of stocks and financial assets there has been a growing amount of research focusing on volatility measurements. The most influential models were the first: the GARCH model of Bollerslev(1986), and the EGARCH of Nelson(1991). After the introduction of Value at Risk, a new role for ARCH models emerged. A variety of studies examined the usefulness of volatility models in computing VaR and comparing these methods with the exponential smoothing approach favored by Riskmetrics. Especially Christoffersen and Diebold(2000), Christoffersen, Hahn and Inoue(2001) and Alexander(1998). GARCH methods proved successfuly but suffered if errors were assumed to be Gaussian. As indicated in Christoffersen and Diebold (2000),volatility forecasts decays quickly with the time horizon of the forecasts.

---

[1] Bank for International Settlement

Actually VaR is a quantitative tool whose goal is to assess the possible loss that can be incurred in a bank over a given time period for a given portfolio of financial trading assets. After 1993, this methodology has been increasingly used with banks and regulators all over the world as a way to estimate the possible losses related with the trading portfolio of banks. The VaR calculation period (10day) is related with the amount of capital that a bank needs to put aside a cushion for possible market losses.

In a quantative point of view in the market risk, VaR can be easily defined if a sample of past returns on the trading portfolio of assets is available. Indeed, once the time series r_i of the returns is known and the VaR level α is specified, the VaR at level α for the given sample is the likely loss at the α percent probability level, which can simply be defined as the quantile at α %. The computation of the VaR portfolio of assets requires the computation of the quantile at level α of the distribution in the future returns of the portfolio. If the portfolio returns are assumed to be identically distributed, the predicted VaR is usually based on the past returns. That's why VaR is computed using two kinds of models, parametric & non-parametric models. In the parametric model specifies a certain type of distribution for the returns (especially normal distribution) and the quantile is computed from the VaR formula,[2] $VAR_t^i(N,\alpha)=\left[F_{t,N}^i\right]^{-1}\left(\frac{\alpha}{100}\right)$. If the non-parametric method is chosen, then the emprical quantile is directly computed from the available data without any model fitted on the returns.

In this research %1 level of significance is used. The VaR corresponding to %1 may be defined as that amount of capital (capital adequacy is determined by BIS requirements), expressed as a percentage of the initial value of the position, which will be required to cover %99 of probable losses. Besides with an assumption of normal distribution, the VaR amount can be calculated as;

$$VAR_t^i(N,\%1)=2.33\sigma_{t,N}^i$$

where $\sigma_{t,N}^i$ is the square root of the conditional variance forecast, made at time t (1 day) for forecast horizon of N.(10day) Then the forecasted volatility (Exponential MA or Conditional Variance methods) for the period (t,N) and calculate the amount of capital[3] required to cover expected losses on %99 of the investment horizons. The %95 confidence level is used by the popular Riskmetrics™ risk measurement software, while BRSA(Banking Regulatory & Supervisory Agency) in Turkey require capital to cover %99 of losses.

---

[2] where VAR_t^i is the Value at Risk for a given asset at time t, i is determined from the volatility model, N is the investment horizon, $\left[F_{t,N}^i\right]^{-1}$ is a cumulative distribution function (cdf) and α is a percentage significance level.

[3] $VAR_1^{\lambda}(10,\%1), VAR_1^{GARCH}(10,\%1)$

3 **Riskmetrics Model**

After the Baring's bank collapse in 1993, emerging markets present a high instability which considerably decreases the efficiency of the usual statistical methods. In this time period of markets, jumps or discontinuities characterize the temporal behavior of macroeconomic factors, such as FX or interest rates, and these discontinuities are usually followed by periods of large volatilities which slowly goes back to normal values. The presence of such discontinuities indicates that the rate of change of a factor can be no longer modeled by normal random variables. Additionally, the existence of well differentiate periods of large volatility which slowly relax to low volatility tells us that the rate of change cannot be considered as uncorrelated in time. Nevertheless, these two assumptions are on the very basis of one of the most popular methods to calculate the Value at Risk: RiskMetrics from JPMorgan.

In this approach, the volatility at time t+1 is calculated averaging the historical data with weights decaying exponentially in time. In doing as like this, we can give more emphasis into the recent the data and there is a strong influence in the present or tomorrow volatility. The mathematical expression is;

$$\sigma_{t+1}^2 = (1-\lambda)\sum_{k=0}^{t} \varepsilon_{t-k}^2 \lambda^k \qquad (1.1)$$

where λ is called as decay factor. This decay factor has been calculated to be optimal by JPMorgan for each financial market. In the first versions of RiskMetrics, JPMorgan recommended an optimal decay factor equal to 0.94. For emerging markets, however, this value must be modified between 0.80-0.99. However most of the factors are bigger than the standard 0.94. This means that related markets have a "short memory", since the weights for the EWMA decay more rapidly.

4 **Moving Average (MA) Model**

According to these models the best forecasting of weekly volatility is equally weighted average of realized volatilities in the last α weeks. [4]

$$\sigma_{f,m}(MA-\alpha) = (1/\alpha)\sum_{f=1}^{\alpha} \sigma_{a,m-j} \qquad (1.2)$$

where m= 63,126,.....252 and α =5,10,22,43. We can take the length of window (α) arbitrarily to name them very short term (α=5), short term (α=10) and medium term (α=43) and long term (α=63).

5 **The Factor GARCH Model**

Autoregressive Conditional Heteroscedasticity or ARCH processes were introduced by Engle in 1982 to account for the so-called heteroscedasticity in economic time series. Heteroscedasticity stands for the lack of stationary volatility, the presence of periods of time with large volatilities irregular with periods of small volatility. In an ARCH(q)

[4] Balaban,Ercan (2003), Forecasting Stock Market Volatility Evidence From Turkey,The University of Edinburgh, pg.12

process the volatility at time t is a function of the observed data at $t-1, t-2, \ldots\ldots t-q$. In 1986, Bollersev introduced the Generalized ARCH or GARCH(q,p) process, where volatility at time t depends on the observed data at $t-1, t-2, \ldots\ldots t-q$, as well as on volatilities at $t-1, t-2, \ldots\ldots t-p$. When we focus the attention to the GARCH(1,1) process with the following evolution equation;

$$\begin{aligned} \varepsilon_t &= \sigma_t z_t \qquad\qquad z_t \approx N(0,1) \qquad (1.3) \\ \sigma_t^2 &= a\sigma_{t-1}^2 + b\varepsilon_{t-1}^2 + c \end{aligned}$$

where z_t are uncorrelated normal random variables. Therefore, the conditional probability for ε_t is normal;

$$p(\varepsilon_t | \text{ information }_{t-1}) \sim N(0, \sigma_t) \qquad (1.4)$$

with zero mean and dispersion equal to σ_t. On the other hand, one can easily show that the unconditional probability is not normal. We can see that, if a+b> 1, the volatility explodes $(\lim_{t\to\infty} \sigma_t = \infty)$. Assuming a+b<1, the process reaches a stationary regime where $(\sigma_t^2) = (\sigma_{t-1}^2) = \sigma_{st}^2$ and, therefore;

$$\sigma_{st}^2 = \frac{c}{1-a-b} \qquad (1.5)$$

ML method to calculate optimal decay factors and the rest of GARCH coefficients is more dependable than minimizing E(λ). Especially, like in the RiskMetrics approach, it is not necessary to update the parameters of the GARCH or TARCH model every day. The parameters can be estimated once per month, while the calculation of the volatility is carried out every day. If the model is correct, the residuals are uncorrelated normal random variables. It is not hard to test these properties for a series of data. In fact, any standard statistical software contains a number of tools to accomplish this task. We can also modify our original model if the statistical assumptions do not hold. For instance, if the residuals are not normally distributed, one can derive their probability distribution and use it for further predictions. If the residuals are correlated, one can assume that they form an ARIMA process and apply the standard techniques from the theory of time series analysis.

5.1. Student GARCH (GARCH-T)

The GARCH(1,1) model often matches the emprical properties of the data quite well, it is usually cant fully take into account the fat tails of the returns distribution. Besides the GARCH model allow for a kurtosis coefficient larger than 3, but emprical daily or intradaily data shows a still much larger kurtosis coefficient. In order solve this problem, the student GARCH(GARCHT) is used which specifies the underlying e_i as being drawn from a t (0,1,v) distribution.

Data

In order to calculate the VaR on the dummy trading portfolio of XYZBank the following datas were used; CBRT Spot Currency Fixings and ISE Stock Exchange closings on daily from Feb 06th 2003- Feb 06th 2004. Libor rates of the basic currencies like, AUD,CAD,CHF,GBP,EUR,USD,JPY were used. Turkish Eurobond Yields (EUR,USD issues), Turkish Repo Rates(IMKB), Turkish Goverment Zero Coupon Yields & US Goverment Bond Yields are gathered on daily basis same as analysed. Besides the data period given above for the VaR calculations, additional market datas collected between 2001-2004 in order to see the volatility jumps of 2001 financial crisis. The summary of major risk factor data statistics are figured out below. The risk factor return & volatility graphics are shown on Appendix A&B.

Table 1
Summary Statistics

	Mean	St.Deviation	Variance	Skewness	Kurtosis	Maximum	Minimum
TRL/USD	-0.0008503	0.0078009	0.0000609	0.9345408	2.97	0.0342820	-0.0218237
TRL/EUR	-0.0002157	0.0097200	0.0000945	0.1949983	2.87	0.0362282	-0.0417359
TRLGOV.90	0.0001622	0.0010931	0.0000012	-0.147818	10.21	0.0054531	-0.0066345
TRLGOV.360	0.0009608	0.0089300	0.0000797	0.3087864	10.07	0.0534283	-0.0392867
TRLGOV.720	0.0018904	0.0183924	0.0003383	0.248621	8.25	0.1053928	-0.0774971
USDEBOND.1800	0.0006274	0.0096541	0.0000932	-2.24	16.6	0.0432307	-0.0627430
USDEBOND.3600	0.0014613	0.0162702	0.0002647	-1.54	7.91	0.0547809	-0.0830607
USDEBOND.10800	0.0038113	0.0561669	0.0031547	-0.6443937	8.35	0.2678158	-0.2621356
EUREBOND.1800	0.0006804	0.0121166	0.0001468	-1.11	15.97	0.0695015	-0.0708328
EUREBOND.3600	0.0014024	0.0243532	0.0005931	-1.11	15.63	0.1390030	-0.1416655
USDGOV.90	0.0000024	0.0000997	0	-0.4275452	4.62	0.0003982	-0.0005486
USDGOV.360	0.0000045	0.0004799	0.0000002	-0.5583894	1.77	0.0015894	-0.0021079
USDGOV.1800	-0.0000067	0.0034437	0.0000119	-0.3212388	0.6944968	0.0110361	-0.0121465
USDGOV.3600	-0.0000400	0.0078961	0.0000623	-0.930387	7.4	0.0320073	-0.0501854
USDGOV.10800	-0.0001449	0.0179355	0.0003217	-0.6561261	1.69	0.0495786	-0.0828550

Notes: Summary statistics are presented for the major risk factors in the trading portfolio from 6 Feb 2003 to 6 Feb 2004.

Table 2
Summary Statistics

	Mean	St.Deviation	Variance	Skewness	Kurtosis	Maximum	Minimum
TRL/USD	0.0025726	0.0284700	0.0008105	5.64	66.47	0.3347325	-0.1256366
TRL/EUR	0.0027133	0.0282975	0.0008007	5.29	60	0.3245128	-0.1226618
TRLGOV.90	-0.0001614	0.0111719	0.0001248	0.9320462	20.32	0.0903771	-0.0493912
TRLGOV.360	-0.0005315	0.0380974	0.0014514	-0.5341556	37.12	0.3211853	-0.3265695
TRLGOV.720	-0.0006533	0.0821107	0.0067422	-0.4126491	27.67	0.633571	-0.6441919
USDEBOND.1800	0.0000567	0.0129737	0.0001683	-1.35	6.69	0.038864	-0.0647638
USDEBOND.3600	0.0000565	0.0220592	0.0004866	-0.790009	4.43	0.0724951	-0.1170918
USDEBOND.10800	-0.0003034	0.0618024	0.0038195	-0.3745106	4.34	0.3067641	-0.2703335
EUREBOND.1800	N/A	N/A	N/A	N/A	N/A	N/A	N/A
EUREBOND.3600	N/A	N/A	N/A	N/A	N/A	N/A	N/A
USDGOV.90	0.0000406	0.0001851	0	1.4	16.99	0.0014131	-0.0010237
USDGOV.360	0.0001118	0.0006381	0.0000004	1.46	10.25	0.0047359	-0.0017894
USDGOV.1800	0.0002931	0.0035180	0.0000124	-0.0514401	2.73	0.0174483	-0.0132796
USDGOV.3600	0.0003590	0.0069393	0.0000482	-0.4002291	1.64	0.0261742	-0.0270882
USDGOV.10800	0.0000120	0.0155424	0.0002416	0.1046581	3.31	0.0842048	-0.0500592

Notes: Summary statistics are presented for the major risk factors on financial crises period from 01 Nov 2000 to 31 Dec 2001.

6 Capital Adequacy & VaR Results on a Turkish Bank Trading Portfolio with different volatility models

Value at Risk results for the trading portfolio of XYZBank with 3 methods are stated in the tables below.

Table 3 VaR Results
Portfolio PV: 548,589,003,997,530

	VCV'		HS'		MC'	
MODELS	**%1 VaR'**	**%5 VaR'**	**%1 VaR'**	**%5 VaR'**	**%1 VaR'**	**%5 VaR'**
EWMA λ: 0.90	21,926,922,601,559	14,861,083,898,603	40,891,417,921,975	17,381,374,494,386	25,748,523,391,211	18,971,820,738,417
EWMA λ: 0.94	21,735,944,718,884	14,725,069,502,512	40,891,417,921,975	17,381,374,494,386	25,622,963,905,125	19,075,506,790,097
EWMA λ: 0.97	21,003,862,230,772	14,209,683,519,137	40,891,417,921,975	17,381,374,494,386	24,991,400,772,595	18,259,090,567,752
EWMA λ: 0.99	20,934,979,282,782	14,204,088,445,864	40,891,417,921,975	17,381,374,494,386	24,776,203,597,637	18,585,126,446,641
GARCH	29,669,096,017,618	20,369,516,477,420	40,891,417,921,975	17,381,374,494,386	N/A	N/A
GARCHT	29,577,771,398,854	20,280,552,144,730	40,891,417,921,975	17,381,374,494,386	N/A	N/A
MA	37,305,382,230,097	25,734,706,481,505	40,891,417,921,975	17,381,374,494,386	28,255,873,484,104	20,726,342,815,076

Notes: VaR Calculations are based on the period between 06-02-2003_06-02-2004.
VCV' : Diversified VaR
MC' : Monte Carlo Simulation Trial Number 10000 & Path is 1500.
HS' : Portfolio Valuation Method
VaR' : 1 day VaR
TRL/$: 1.350.000

Table 4 Capital Adequacy Results'

Portfolio PV: **548,589,003,997,530**

	VCV'		HS'		MC'	
MODELS	**%1 VaR**	**%5 VaR**	**%1 VaR**	**%5 VaR**	**%1 VaR**	**%5 VaR**
EWMA λ: 0.90	208,011,943,951,948	140,981,158,512,490	387,920,525,258,611	164,890,147,278,440	244,265,942,003,058	179,978,074,617,071
EWMA λ: 0.94	206,200,213,170,166	139,690,844,342,528	387,920,525,258,611	164,890,147,278,440	243,074,809,382,355	180,961,702,714,935
EWMA λ: 0.97	199,255,239,438,442	134,801,583,672,645	387,920,525,258,611	165,071,976,503,795	237,083,422,569,299	173,216,688,580,033
EWMA λ: 0.99	198,601,774,464,041	134,748,505,450,537	387,920,525,258,611	164,890,147,278,440	235,041,933,049,340	176,309,660,548,707
GARCH	281,458,846,280,733	193,237,455,014,688	387,920,525,258,611	165,071,976,503,795	N/A	N/A
GARCHT	280,592,486,152,372	192,393,485,976,199	387,920,525,258,611	165,071,976,503,795	N/A	N/A
MA	353,901,239,064,037	244,134,866,507,449	387,920,525,258,611	165,071,976,503,795	268,052,169,394,303	196,622,523,749,504

Notes: VaR Calculations are based on the period between 06-02-2003_06-02-2004.
VCV' : Diversified VaR
MC' : Monte Carlo Simulation Trial Number 10000 & Path is 1500.
HS' : Portfolio Valuation Method
Capital Adequacy Results' : VaR' * 3 * sqrt(10)
TRL/$: 1.350.000

Table 5 VaR Results

Portfolio PV: **548,589,003,997,530**

	VCV''		HS''		MC''	
MODELS	**%1 VaR**	**%5 VaR**	**%1 VaR**	**%5 VaR**	**%1 VaR**	**%5 VaR**
EWMA λ: 0.90	44,831,987,392,806	31,058,476,700,724	41,308,130,284,092	19,830,221,908,283	26,528,694,756,757	19,527,973,346,372
EWMA λ: 0.94	44,831,987,392,806	31,058,476,700,724	41,308,130,284,092	19,830,221,908,283	26,036,689,805,341	19,141,316,373,258
EWMA λ: 0.97	44,831,987,392,806	31,058,476,700,724	41,308,130,284,092	19,830,221,908,283	24,678,779,659,687	18,048,447,186,096
EWMA λ: 0.99	44,831,987,392,806	31,058,476,700,724	41,308,130,284,092	19,830,221,908,283	24,572,445,635,556	18,512,264,256,123
GARCH	55,474,007,077,261	38,582,150,113,527	41,308,130,284,092	19,830,221,908,283	N/A	N/A
GARCHT	52,804,673,557,868	36,694,990,135,888	41,308,130,284,092	19,830,221,908,283	N/A	N/A
MA	70,052,998,897,666	48,889,176,072,601	41,308,130,284,092	19,830,221,908,283	28,637,836,529,306	21,005,635,186,201

Notes: VaR Calculations are based on the period between 06-02-2003_06-02-2004.
VCV'' : Undiversified VaR
MC'' : Monte Carlo Simulation Trial Number 5000 & Path is 1500.
HS'' : Standart Method
TRL/$: 1.350.000

Table 6 Capital Adequacy Results'

Portfolio PV: **548,589,003,997,530**

	VCV''		HS''		MC''	
MODELS	**%1 VaR**	**%5 VaR**	**%1 VaR**	**%5 VaR**	**%1 VaR**	**%5 VaR**
EWMA λ: 0.90	425,303,131,600,589	294,639,345,069,086	391,873,708,753,063	188,121,383,155,115	251,667,115,679,449	185,254,071,947,697
EWMA λ: 0.94	425,303,131,600,589	294,639,345,069,086	391,873,708,753,063	188,121,383,155,115	246,999,661,507,349	181,586,011,906,551
EWMA λ: 0.97	425,303,131,600,589	294,639,345,069,086	391,873,708,753,063	188,121,383,155,115	234,117,711,119,584	171,218,399,075,619
EWMA λ: 0.99	425,303,131,600,589	294,639,345,069,086	391,873,708,753,063	188,121,383,155,115	233,108,962,766,270	175,618,446,092,141
GARCH	526,259,715,539,141	366,013,425,266,986	391,873,708,753,063	188,121,383,155,115	N/A	N/A
GARCHT	500,936,816,174,075	348,110,693,423,111	391,873,708,753,063	188,121,383,155,115	N/A	N/A
MA	664,564,779,342,594	463,792,057,730,340	391,873,708,753,063	188,121,383,155,115	271,675,700,018,918	199,272,058,757,415

Notes: VaR Calculations are based on the period between 06-02-2003_06-02-2004.
VCV'' : Undiversified VaR
MC'' : Monte Carlo Simulation Trial Number 5000 & Path is 1500.
HS'' : Standart Method
Capital Adequacy Results' : VaR' * 3 * sqrt(10)
TRL/$: 1.350.000

7 Conclusion

According to these results, GARCH processes can be considered as suitable models for volatility jump estimations in the emerging markets. During the crises periods, volatility jumps could be 4 times more than the normal market condition movements in Turkey. When evaluating all models, lowest VaR results (%3.8/Portfolio PV) were taken with VCV method with an EWMA 0.99 by considering portfolio structure. On the contrary, changing volatility models to GARCH family, capital adequacy differs approximately %40 more. Monte Carlo Simulation estimations were the second lowest method when the trial number of 5000 & path is 1500. Besides, Monte Carlo Simulation trial number increases like 10.000 doesn't make a significant change on the VaR results. Undiversified VCV needs around 2 times more capital which can be thought as a stress scenario with correlation effect neglected on the portfolio. Major risk factor volatility numbers are nearly 10 times lower than financial crises period between 2000-2001. When we look at history, extreme events has occurred more often since 1990 in Turkey. Large movements makes abnormal returns or losses that have distributions of thicker tails. When we look at the volatility graphs, we can say that Turkish financial markets have high volatility and fat-tailed distributions history. According to the statistical results most of the risk factors show skewness & excess kurtosis which implies that fatter tails than normal distribution assumptions. As a result:

- To estimate the volatility is necessary to develop a model that considers the movements of the volatility in the time series, for that reason, the traditional volatility doesn't follow the market variations.
- The asymmetric GARCH models, like TARCH an EGARCH model, not only fulfill with the movements of the volatility, also it is not necessary to use the heavy tails distributions, because the negative impact or the negative returns are included by the model form.
- The models observed in VaR results are dynamic, and is very important the revision of these models periodically. (3 months)
- The final objective is present an exact reserve which covers the maximum loss possible, and this reserves may have a value that corresponds with the reality. When we introduce the VaR restrictions for the traders and for the managers, the forecast of the reserve may be a credible value at effect that traders and managers use this information for decision-making. Also the market VaR jointly with the credit risk and operational risk serves to calibrate the total risk of a performance of the bank.

Nevertheless, in both approaches discontinuities appear as random events which cannot be predicted at all. One can just compute the statistical properties of these events: mean time between each other, probability distribution of the size of the jumps, and it goes so on.

References

1. Alexander Carol.(2001); Market Models, A Guide to Financial Data Analysis, John Wiley & Sons
2. Alexander Carol.(1996); Evaluating The Use of Riskmetrics TM: As a Risk Measurement Tool for your Operation: What are its Advantages & Disadvantages?, ISMA Centre, s.1-10
3. Alexander Carol.(1998); Risk Management and Analysis Volume 2, New Markets and Products, Wiley and Sons
4. Bessis Joel.(2001); Risk Management in Banking, Wiley Pub. NewYork.
5. Best Philip.(1998); Implementing Value At Risk, Wiley & Sons
6. Christoffersen & Diebold.(1997); How relevant is Volatility Forecasting for Financial Risk Management?, pg.1-5

7. CMRA.(1998); Calculating VaR, Capital Market Risk Advisors
8. CMRA.(1998); 3 VaR Methodologies, Capital Market Risk Advisors, s.7
9. Crouhy Micheal, Galai Dan, Mark Robert.(2001); Risk Management; McGraw-Hill; New York
10. Dowd Kevin.(1998); Beyond Value At Risk, John Wiley & Sons
11. Hendricks Darryll, Hirtle Beverly.(1997); Bank Capital Requirements for Market Risk: The Internal Models Approach, FRBNY Economic Policy Review, December.
12. J.P. Morgan & Co.(1996); Riskmetrics-Technical Document. Third Edition, May 26, www.riskmetrics.com .
13. J.P. Morgan & Co.(2001); Return To RiskMetrics®: The Evolution of a Standard, March 01, www.riskmetrics.com .
14. Jackson Patricia, Maude David J., Perraudin William.(1998); Bank Capital and VaR, Bank of England Working Paper Series, No.79, England
15. Jorion Philippe.(2002); Financial Risk Manager Handbook 2001/2002, John Wiley & Sons
16. Jorion Philippe.(2000); Value at Risk: The new Benchmark for Controlling Market Risk, McGraw-Hill, New York.
17. Matten Chriss.(2000); Managing Bank Capital, Capital Allocation & Performance Measurement, 2nd.Edition, Wiley Sons, s.167-184
18. Neftçi N.Salih.(2000); VaR Calculations, Extreme Events & Tail Estimation, Journal of Derivatives, s.1-5
19. Teker Suat, Akçay Barış M.(2001); VaR:An Implementation on Three Turkish Banks; METU-ERC: International Economins Congre-V; September; Ankara
20. Teker Suat, Akçay Barış M.(2002); VaR Computations under various VaR Models and Stress Testing; METU-ERC: International Economins Congre-VI; September; Ankara

APPENDIX A   Figure_1.Major Risk Factor Returns[5]

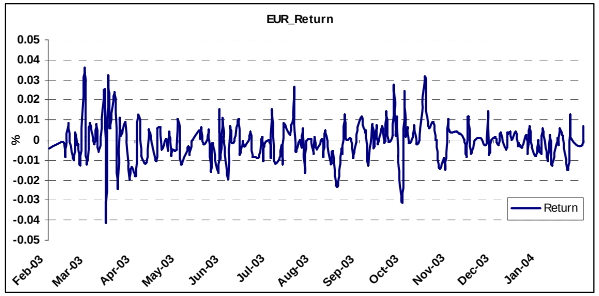

Figure.1a_EUR Spot

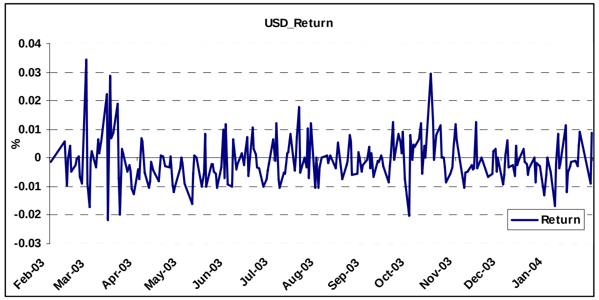

Figure.1b_USD Spot

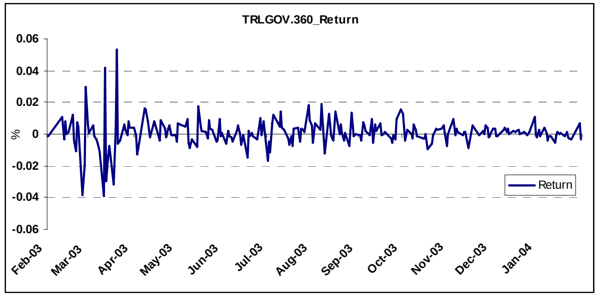

Figure.1c_TRLGOV.360

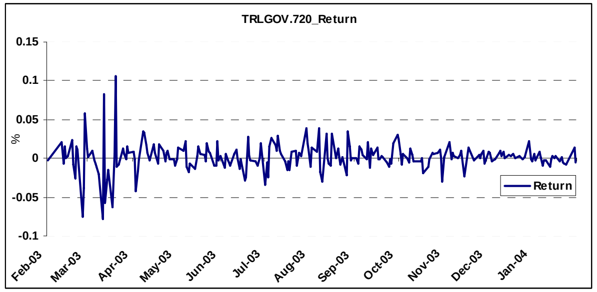

Figure.1d_TRLGOV.720

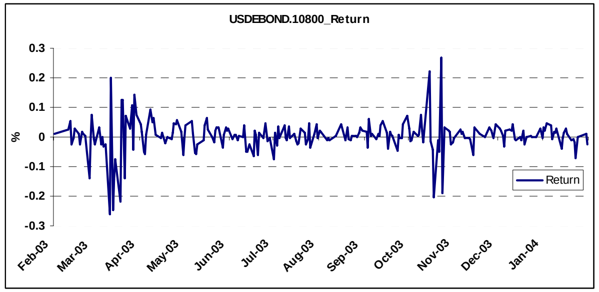

Figure.1e_USDEBOND.10800

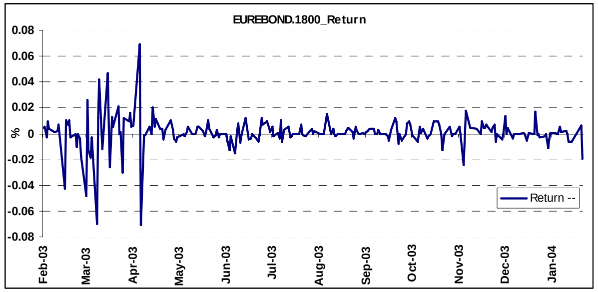

Figure.1f _EUREBOND.1800

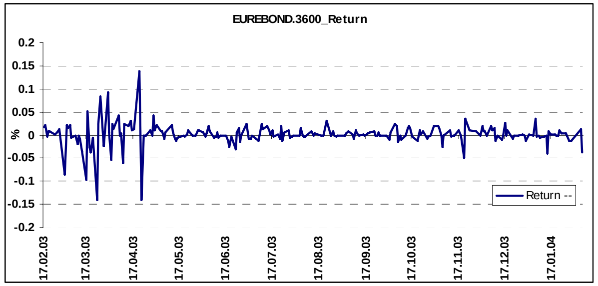

Figure.1g_EUREBOND_3600

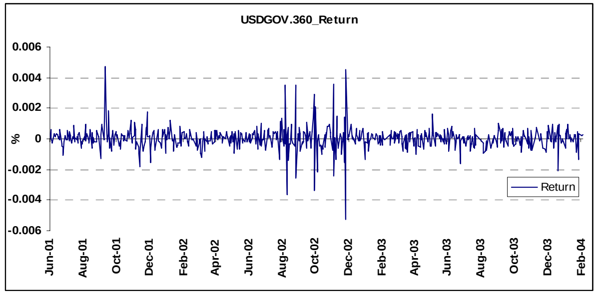

Figure.1h_USDGOV_360

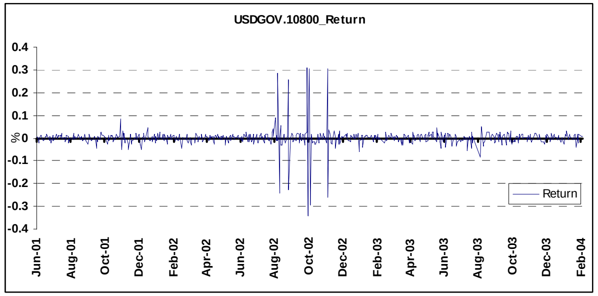

Figure.1I_USDGOV_10800

---
[5] All risk factor returns are on logarithmic basis.

APPENDIX B   Figure_2.Major Risk Factor Volatilities[6]

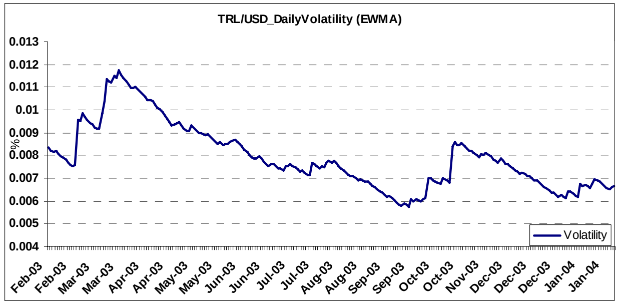

Figure.2a_TRL/USD Spot (EWMA)

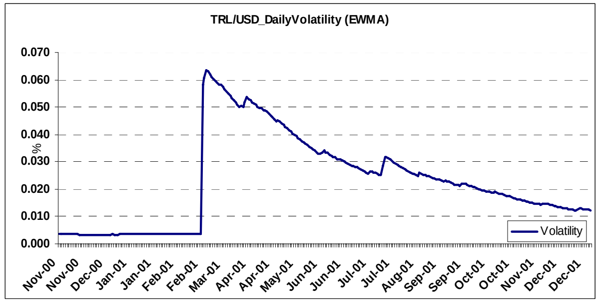

Figure.2b_TRL/USD Spot (EWMA)

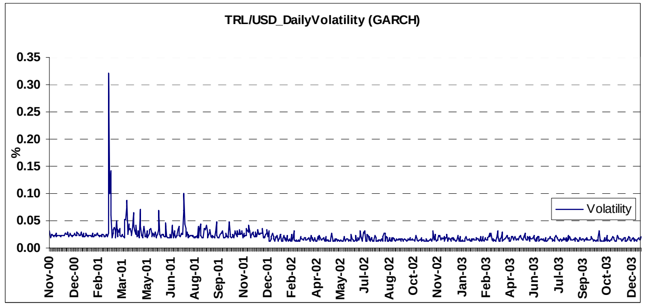

Figure.2c_TRL/USD Spot (GARCH)

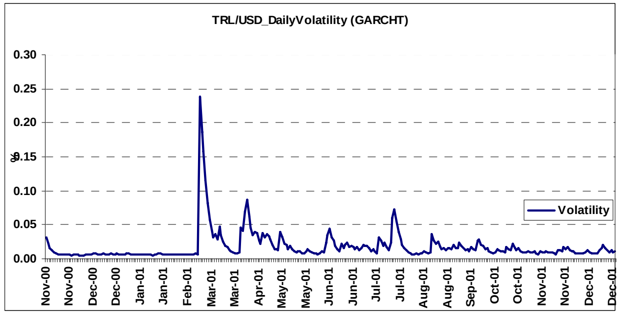

Figure.2d_TRL/USD Spot (GARCHT)

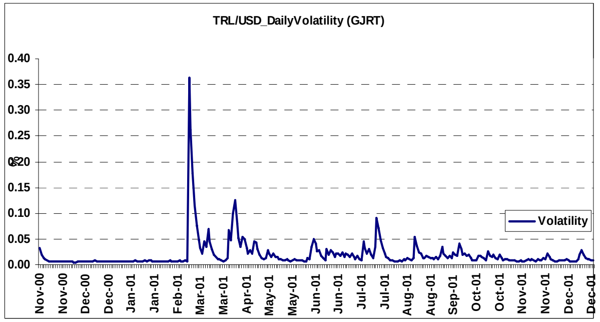

Figure.2e_TRL/USD Spot (GJRT)

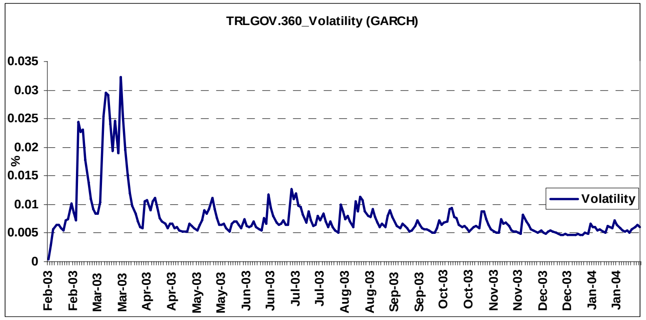

Figure.2f_TRLGOV.360 (GARCH)

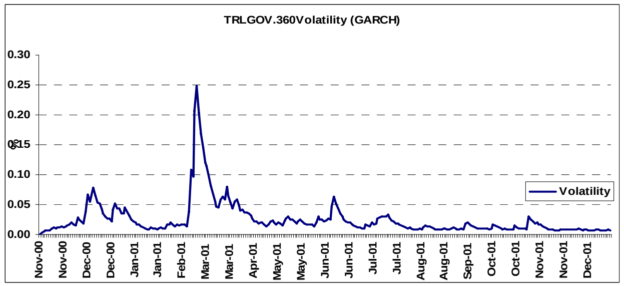

Figure.2g_TRLGOV.360 (GARCH)

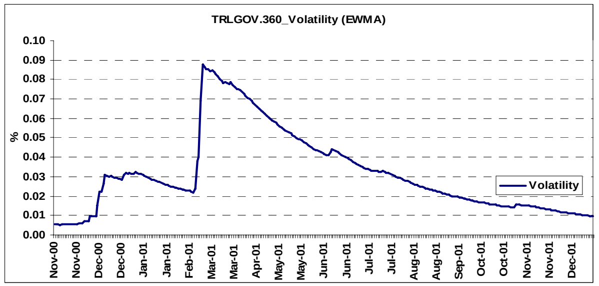

Figure.2h_TRLGOV.360 (EWMA)

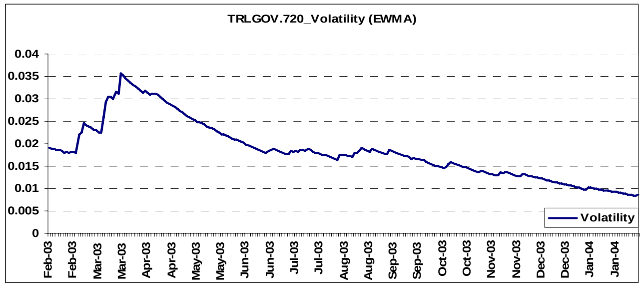

Figure.2gI_TRLGOV.720 (EWMA)

[6] All volatility period assumptions are determined as similiar as in the summary statistics analysis selections.

APPENDIX B Figure_3.Major Risk Factor Volatilities

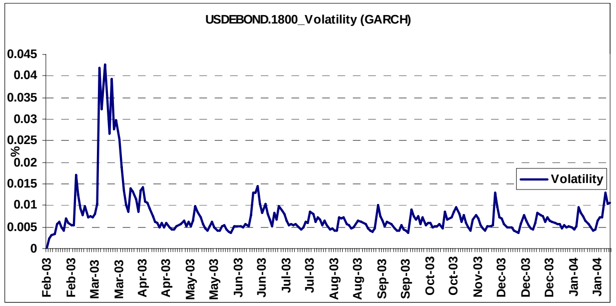

Figure.3a_USDEBOND.1800 (GARCH)

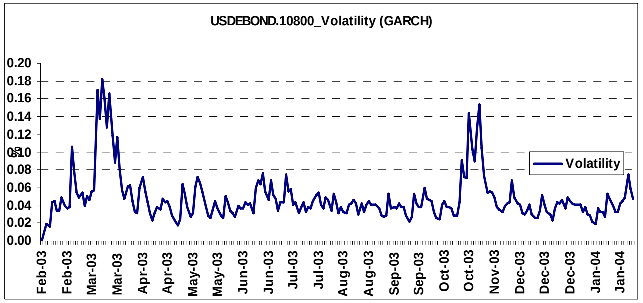

Figure.3b_USDEBOND.10800 (GARCH)

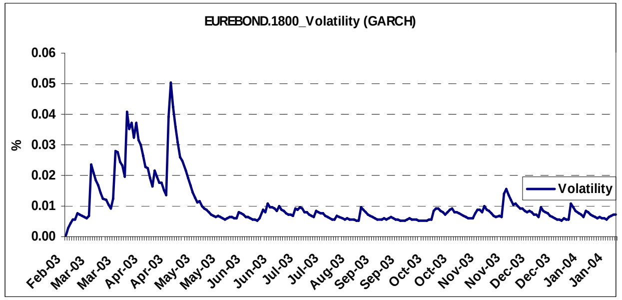

Figure.3c_EUREBOND.1800 (GARCH)

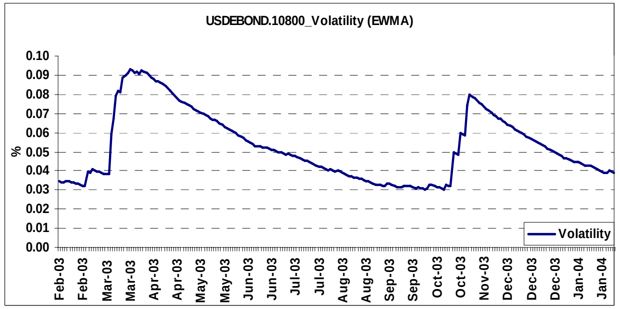

Figure.3d_USDEBOND.10800 (EWMA)

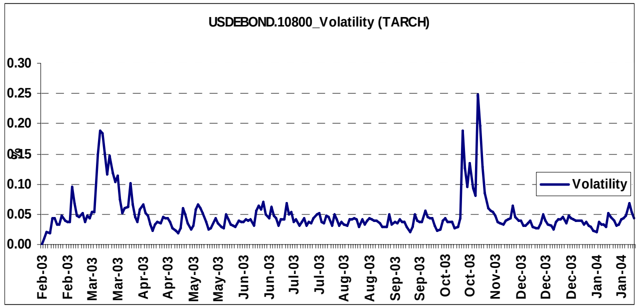

Figure.3e_USDEBOND.10800 (TARCH)

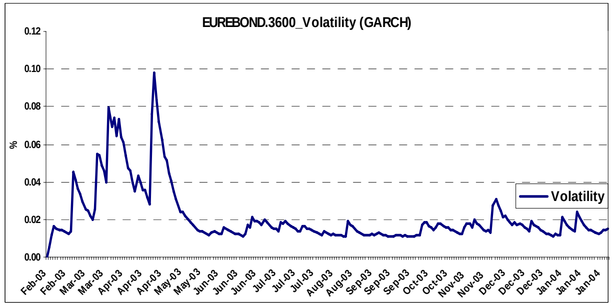

Figure.3f_EUREBOND.3600 (GARCH)

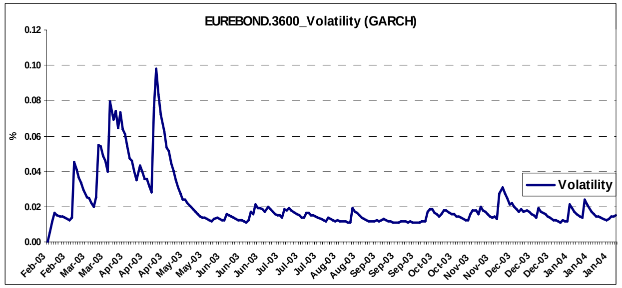

Figure.3g_EUREBOND.3600 (GARCH)

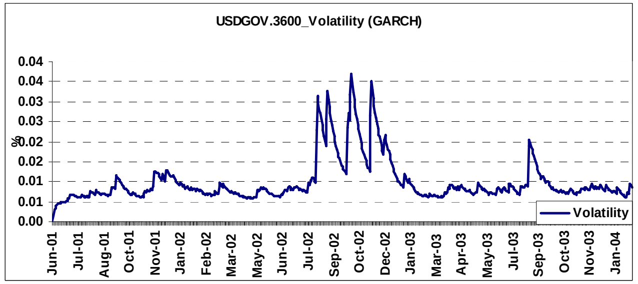

Figure.3h_USDGOV.3600 (GARCH)

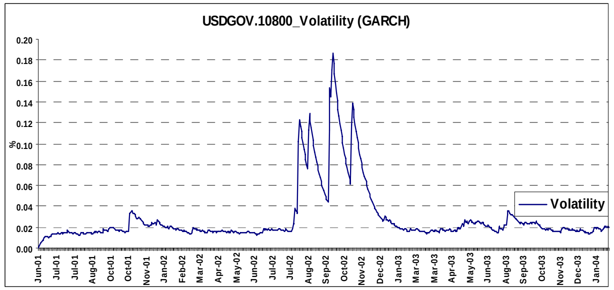

Figure.3I_USDGOV.10800 (GARCH)