

VALUE AT RISK IN EMERGING CURRENCY MARKETS:A CASE STUDY OF TURKISH LIRA

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ÖZET

Yedi ayrı para birimi için EWMA ve GARCH modelleri kullanılarak günlük VaR rakamları hesaplanmıştır. GARCH modeli EWMA'ya göre daha iyi bir sonuç vermiştir. %95 ve %99 güven seviyelerinde volatilitate tahminleri başarılı bulunmuştur. EWMA ve GARCH modelleri VaR modelinin başarısını artırmaktadır. Beklenmedik bir şekilde, VaR hesaplamaları Nisan 1994 ve Şubat 2001 devalüasyonlarını tahmin edebilmiştir. Ayrıca, kriz sonrası dönemlerde volatilitate tahminleri yüksek seyretmektedir. Kontrollü parite dönemlerinde Türk Lirasının volatiletisinin düşük, Şubat 2001'den sonra uygulanan serbest dalgalı dönemde ise volatilitate artış olduğu gözlenmiştir.

Anahtar Kelimeler: Volatilitate, EWMA, GARCH ve yabancı para.

ABSTRACT

Daily VaR numbers have been calculated by using EWMA and GARCH models for the seven currencies. The outcome is GARCH provides slightly more accurate analysis than EWMA. The results are satisfactory for forecasting volatility at 95% and 99% confidence level. These two methods enhance the quality of the VaR models. Interestingly, VaR calculations have predicted the April 1994 and February 2001 devaluation in Turkey. It is also observed that the Turkish Lira's volatility was low during the crawling peg period. However, after February 2001 free floating period caused the volatility to increase. Therefore, volatility forecasts tend to remain high in the post crises period.

Keywords: Volatility, EWMA, GARCH, VaR, and Currency.

JEL: C22, C53, and F31.

1. INTRODUCTION

Global investors tend to invest in emerging market financial instruments due to higher expected returns. A better expected return includes high volatility with uncertainty. During the last decade most emerging countries in Latin America, Asia and Eastern Europe had currency risks due to hefty devaluations. Global investors demand to control currency risks, thus they use derivative instruments to hedge their risks associated with currencies. However this is a challenging task because most of the emerging countries do not have derivative markets, or even if these countries have derivative markets generally it is not easily used for hedging purposes due to low volume.

After emerging market currencies crisis, local and international authorities have tried to establish and force companies to implement effective risk measurement systems for risks related to balance sheet or off balance sheet operations. However this is not easy to established such an effective system. Bilson (1999) stated that the risk management techniques for developed countries typically not applicable, because these techniques assume that volatility can be measured by sample variance measured over the recent past and that the distribution of returns is symmetric. In contrast, financial crises in emerging markets typically involve a switch from a regime of fixed or managed floating exchange rates to a devaluation followed by a period of high financial uncertainty. The volatility observed in the period prior to the devaluation will not provide a guide to the volatility in the post devaluation period. In addition, the correlations between exchange rates, interest rates and equity prices are also likely to be very different between the two regimes.

During the 1990s, increasing importance of private investment flows into emerging markets cause financial collapse. As Bilson (1999) mentioned, private portfolio investment is motivated by the profit motive. Private investment has exhibited a tendency to swamp small emerging markets and then create a financial crisis when the opportunities for profit are found to be less abundant than anticipated. When foreign investors decide to invest in a country, they must first exchange their foreign currency for the local currency. The foreign currencies find their way to the central bank where they are reflected in a higher ratio of foreign currency reserves to the monetary base. The higher reserve ratio tends to encourage an expansionary monetary policy by the central bank that is often associated with relatively unproductive lending to governments. When the foreign capital attempts to leave the market, it is not possible to rapidly reverse the domestic credit expansion that was

related to the initial inflow. As a consequence, a financial crisis ensues and the currency is devalued. It is clearly in the interests of both the international investment community and the emerging markets themselves to develop risk management systems that will lessen the probability that these types of events will occur.

The ability to forecast currency return volatility is crucial for global investors. As a result, investors are more interested in the forecasts of rate of return and its variance over the holding period. In order to forecast currency volatility, VaR is widely used in financial applications.

Basically VaR measures the worst expected loss that an institution can suffer over a given time interval under normal market conditions at a given confidence level. Event Risk Indicator (ERI) developed by Avinash Persaud for J.P. Morgan (1998). The ERI attempts to forecast the probability of a devaluation of 10% or more on the basis of economic conditions and contagion effects from other countries. But the ERI only forecasts the probability of the devaluation without attempting to measure the size.

Value at Risk (VaR) methodology has been used for interpreting the financial risk exposure since 1995. VaR is truly a measure of how volatile the financial instruments are. Risk managers, regulators and traders need to be aware of some of the characteristics in volatility when estimating future volatility.

In order to forecast currency volatility in emerging markets, there must be methodology to measure volatility modeling. Recently, EWMA and GARCH models have become critical tools for time series analysis in financial applications.

Although many emerging countries suffer from devaluation, in this study we will just concentrate on Turkish Lira. We will show how currency volatility changes over time to use EWMA and GARCH techniques. Turkish Lira return was calculated against seven heavily traded currencies, namely; U.S. Dollar, Euro, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Canadian Dollar. Turkish Lira returns volatility has been tested by using EWMA and GARCH methods. Using EWMA and GARCH results to reach VaR numbers and to test which techniques produce better results in the name of currency volatility forecasting.

2. REVIEW OF THE RELATED LITERATURE

Hendricks (1996) randomly selects 1,000 currency options portfolio to test the effectiveness of VaR models. The objective of his study is to demonstrate and compare the similarity of the risk number measured by VaR method and real risk. The one factor he considers is market risk along with utilizing three fundamental methods: (i) equally weighted moving average, (ii) exponentially weighted moving average, and (iii) historical simulation method. Based on the methods above, he has concluded with different VaR numbers. Yet, he cannot conclude that one method is superior to others. In his test, he also shows that 95% and 99% of confidence level produce different VaR numbers.

Simons (1996) defines the risks associated with financial assets and states two restrictions related to VaR: (i) VaR concentrates on only one point in distribution of profit and loss; however a representation of all distributions can be more favorable, (ii) VaR can be weak to measure the accurate risk number in extreme market conditions.

Dowd (1998) has listed three VaR restrictions: (i) Using historical data to forecast the future behavior, (ii) model was built under assumptions that are not valid for all conditions. Users should be aware of the model restrictions and formulate their calculations, and (iii) forecasting VaR numbers could be good for those who possess solid understanding and knowledge of VaR concepts.

Jorion (2000) has mentioned the intricate parts of VaR calculations in his work. During the time when portfolio position is assumed to be constant that in reality does not apply to practical life. The disadvantage of VaR is it cannot determine where to invest. Jorion (1997) has similar critics about VaR that it is not a perfect measurement tool. VaR simply illustrates the various speed of risk that are embedded from the derivative instruments.

It seems that VaR's use is multi purpose; reporting risk, limiting risk, regulatory capital, internal capital allocation and performance measurement. Yet, VaR is not the answer for all risk management challenges. No theory exists to demonstrate that VaR is the appropriate measure upon which to build optimal decision rules. VaR does not measure "event" (e.g., market crash) risk, so the portfolio stress tests are recommended to supplement VaR (Schachter: 2002).

VaR is a good tool that risk managers should be aware of in order to act on hedging their risky positions. VaR is also being accepted as a

standard measurement to specify banks regulatory capital by BIS (Karelse, 2001). Therefore, many parties in the financial markets such as institutions, wealthy investors, authorities, auditors, and rating agencies are able to monitor market risk regularly and accept different confidence level for their VaR calculations (Culp vd. 1999).

When comparing two different portfolios' VaR number, the time horizon must be the same. To compare one day and ten days, VaR numbers are not meaningful (Penza, 2001:63). In financial market, the typical time horizon is 1 day to 1 month. Time horizon is chosen based on the liquidity capability of financial assets or expectations of the investments. Confidence level is also crucial to measure the VaR number. Typically in the financial markets, VaR number calculates between 95% to 99% of confidence level. Confidence level is chosen based on the objective such as Basel Committee requests 99% confidence level for banks regulatory capital. For insiders, confidence level could be lower. For instance, J.P. Morgan use 95%, Citibank 95.4% and Bankers Trust 99% use confidence level for their VaR calculations (Nylund, 2001:2).

3. VOLATILITY

Volatility is a statistical measurement of assets prices movement. The higher the volatility means the possibility of higher return or loss. VaR measures the risk therefore estimate the accurate loss number volatility is used.

The methods that measure volatility demonstrate different characteristics that have direct effect on VaR numbers. The followings are the general volatility methods:

- Standard deviation
- Simple moving average
- Historical simulation
- EWMA (Exponential Weighted Moving Average)
- GARCH (Generalized Autoregressive Conditional Heteroscedasticity)

Volatility models accept volatility is constant in some period of time and return in any day is equal to other days. However in real life, volatility and correlations change through time. For instance, low volatility term can be followed by high volatility term. High return can be followed by another higher return term. This means that serial correlations between financial assets returns.

Economic news also explains the financial assets returns. Economic news have effects on that day's assets return while the following day the news effect will be gradually decline.

In order to forecast volatility, having serial correlations between assets returns are considered crucial inputs. In other words, the latest return give more insights about forecasting volatility than the old return data.

For VaR calculations, EWMA and GARCH models assume returns on financial assets have serial correlations. Both models give more weight to the latest returns than the old ones. Therefore, volatility is estimated on latest return numbers by EWMA and GARCH models (Best, 1999:69).

Mandelbort (1963) and Fama (1965) observe on their work is, the big price changes in financial assets prices tend to follow another big price changes; while small price changes in financial assets tend to follow small price changes. Similar findings are also reported on Baillie (1996), Chou (1988) and Schwert (1989)'s works on financial assets behavior. The existence of today's volatility cluster the effect on future forecasted volatility. (Engle, 2000:6).

Risk managers cannot assume that volatility remains constant and certainly cannot relax in the belief that past volatility is a guide to future volatility. Therefore risk managers are advised to develop EWMA and GARCH methods to overcome these weaknesses.

4. EWMA MODEL

RiskMetrics measure the volatility by using EWMA model that gives the heaviest weight on the last data. Exponentially weighted model give immediate reaction to the market crashes or huge changes. Therefore, with the market movement, it has already taken these changes rapidly into effect by this model. If give the same weight to every data, it is hard to capture extraordinary events and effects. Therefore, EWMA is considered to be a good model to solve the problem. Bredin and Hyde (2001) studied on Irish currency risk and they have found that EWMA is the more appropriate method among the VaR modelling methodologies.

If the exponential coefficient choose as a big number, current variance effects will be small over total variance.

EWMA model assumes that the weight of the last days is more than old days. EWMA is a model that assumes assets price changes through time.

J.P. Morgan uses EWMA model for VaR calculation. EWMA responds the volatility changes and EWMA does assume that volatility is not constant through time.

Using EWMA to modelling volatility, the equation will be:

$$\sigma = \sqrt{(1-\lambda) \sum_{t=1}^{t=n} \lambda^t (X_t - \mu)^2} \quad (1)$$

Where λ is an exponential or decay factor and n is a number of days. In equation μ is the mean value of the distribution, which is normally assumed to be zero for daily VaR.

The equation can be stated for exponential weighted volatility:

$$\sigma = \sqrt{\lambda \sigma_{t-1}^2 + (1-\lambda) X_t^2} \quad (2)$$

This form of the equation directly compares with GARCH model. The crucial part of the performance of the model is the chosen value factor.

J.P. Morgan's RiskMetrics model uses factor value as of 0.94 for daily and 0.97 for monthly volatility estimations.

For EWMA calculation, the necessary number of days can be calculated by the following formula (Best, 1999:70).

Necessary data number = log (required accuracy) / log (factor value)

For asset i at time t , exponential weighted volatility can be written as follows:

$$\sigma_{i,t} = \sqrt{(1-\lambda) \sum_{j=0}^{\infty} \lambda^j r_{t-j}^2} \quad (3)$$

In equation λ is an exponential factor, $r_{i,t}$ represent logarithmic return of asset i at time t . Thus, $r_{i,t}$ is calculated by $\ln(P_{i,t} / P_{i,t-1})$ formula.

If there are loads of data for past years, the data chosen for the model should be selective. The criteria given by RiskMetrics is 99% of the all available data. This can be formulated as stated $1/(1-\lambda)$. Here n number of return data's serial weight is equal to $(1-\lambda^n)/(1-\lambda)$. Thus if 99% of the weight wants to be included, the number of data should be calculated as $n = \ln(0.01)/\ln(\lambda)$ formula. Effective data number for forecasting volatility is based on exponential factor numbers. As seen on the formula, high exponential factor number means more data requirements.

In this case RiskMetrics volatility can be formulate as follows:

$$\sigma_{i,t} = \sqrt{\frac{1-\lambda}{1-\lambda^n} \sum_{j=0}^n \lambda^j r_{i,t-j}^2} \quad (4)$$

This formula has been used in this research.

4.1. Choosing the Exponential Factor Number in EWMA Model

Assuming the daily average return is zero, it can be written as $E[r_{i,t+1}^2] = \sigma_{i,t}^2$. In order to minimize the average of error squares, it needs to identify the number of exponential factor with variance is the function of exponential factor. By using this methodology, it is determined that daily volatility forecasting for 0.94 and for monthly volatility forecasting is 0.97. The factor to choose the number of exponential factor is based on investors' time horizon. For individual investors, the time horizon is generally more than one day. As a result, the volatility forecasting is correct at some point of time. Using exponential factor 0.97 is much more stable than 0.94 (RiskGrades Technical Document, 2001:8).

4.2. Shadow Effect

Shadow effect is an interesting phenomena when constructing volatility modelling. Risk managers use 100 days of data to eliminate sampling errors. But, for example unexpected event happened in currency markets, its effects will continue during these 100 days. Only one day that peak happened in the market will affect the future volatility estimation and increase the volatility level which is deviate from the market reality. In order to solve this problem, risk mangers use EWMA model' to give more weight on the latest data and less on the previous data (Butler, 1999:200). In EWMA model, J.P. Morgan use λ as an exponential factor and the vaule could change between 0 and 1. Previous

data denotes by n number of days multiple by λ^n . As n getting higher, λ^n will be smaller. This kind of extraordinary events effect will be less on variance and covariance. Extraordinary events that are carried on past and shadow effects will not be valid for a long time (Alexander, 1996:4).

5. ARCH MODEL

ARCH (Auto Regressive Conditional Heteroscedasticity) process is commonly used in volatility forecasting that was initially introduced by Engle in 1982 that allows the conditional variance to change over time as a function of past realization of error terms. Parrondo (2004) has shown that ARCH type processes can play an important role in calculating VaR in emerging markets.

In ARCH(1) model, at time t conditional volatility depends on previous time $t-1$ volatility. If volatility in period $t-1$ is large, also at time t huge volatility is expected.

In ARCH model, it is possible to explain clustering volatility and that vary from high volatility to low volatility.

ARCH(p) is defined as follows;

$$R_t = \beta X_t + e_t \quad (5)$$

$$e_t | I_{t-1} \approx N(0, h_t) \quad (6)$$

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i e_{t-i}^2 \quad (7)$$

Where; R_t = explanatory variable (independent), linear functions of X_t , β = vector of dependent parameters, e_t = error term, assuming of mean is zero, variance h_t which is normally distributed, in time $t-1$ based on conditional information I_{t-1} , and h_t = conditional variance.

$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i e_{t-i}^2$ is the general ARCH model that is the weighted average of error squares that shows current volatility is strongly affected from the past volatility. In ARCH model, all parameters are calculated from the old data and use for future volatility forecasting. Furthermore, the

results should prove $\alpha_1 > \alpha_2$ implying that the older data have less effect on the current volatility.

6. GARCH MODEL

GARCH (Generalized Auto Regressive Conditional Heteroscedasticity) is widely used in financial markets researches but have many versions. GARCH method is initially developed by Bollerslev in 1986. Bollerslev developed the ARCH model after Engle to come up with GARCH model. Some other researchers have added different improvements through time. The equation for basic GARCH(1,1) model;

$$\sigma = \sqrt{\omega + \beta\sigma_{t-1}^2 + \alpha X_{t-1}^2} \quad (8)$$

where; σ_{t-1} = volatility of previous day.

α , β and ω are the predicted parameters. $\alpha + \beta$ values are called “persistence” and must be greater than 1. GARCH parameter is difficult to calculate for this estimation requires maximum likelihood functions. If GARCH parameters $\alpha + \beta$ are high means high average volatility.

Comparing EWMA and GARCH equations,

$$\sigma = \sqrt{\lambda\sigma_{t-1}^2 + (1-\lambda)X_t^2} \quad (9)$$

$$\sigma = \sqrt{\omega + \beta\sigma_{t-1}^2 + \alpha X_{t-1}^2} \quad (10)$$

As seen on the equations above, β parameter is the same as λ (exponential factor) in EWMA equation. Similarly, α parameter is the same as $(1-\lambda)$ in EWMA equation. In GARCH equation, the acceptance of $\omega=0$ makes EWMA equation a special version of GARCH equation.

Accumulating the accurate results in regression variance of error terms use h_t notation.

$$r_t = m_t + \sqrt{h_t}\varepsilon_t \quad (11)$$

In this equation, variance of error term is 1. GARCH model for variance:

$$h_{t+1} = \omega + \alpha(r_t - m_t)^2 + \beta h_t = \omega + \alpha h_t \varepsilon_t^2 + \beta h_t \quad (12)$$

In equation ω , α , β parameters should be calculated. Weights are $(1 - \alpha - \beta, \beta, \alpha)$ and long term average variance is $\sqrt{\omega / (1 - \alpha - \beta)}$. If $\alpha + \beta < 1$, the formula will be valid. Moreover, having acceptable results, coefficients must be positive.

Typical GARCH model is GARCH (1,1). The first notation of (1,1) shows ARCH effect and second one is moving average. In order to get GARCH parameters, it needs maximum likelihood estimation method. There are many softwares available to perform this task.

Basically, GARCH (p,q) model is given as follows.

$$R_t = \beta X_t + e_t \quad (13)$$

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i e_{t-i}^2 + \sum_{j=p+1}^q \alpha_j h_{t-j} \quad (14)$$

In truly determined process, parameters must be $\alpha_0, \alpha_i, \alpha_j \geq 0$. Moreover, Bollerslev (1986) mentions that for volatility process, it must satisfy $\alpha_i + \alpha_j < 1$ condition.

7. OBJECTIVE OF THE STUDY

In this study, we show how currency volatility changes over time to use EWMA and GARCH techniques. To test which techniques produce better results in the name of currency volatility forecasting.

Turkish Lira return was calculated against seven heavily traded currencies in the global markets. Turkish Lira returns volatility has been tested by using EWMA and GARCH methods and come up with VaR numbers.

8. DATA

Daily selected currencies data received from Central Bank of the Republic of Turkey. The data ranges from January 1990 to March 2003 (for Euro January 2002 to June 2003) and the closing effective selling prices are used. The currencies are namely: U.S. Dollar, Euro, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Canadian Dolar.

The reason the data begins on January 1990 is to have at least 1,000 trade days to obtain a more accurate calculation and result. Besides, during the time period, there were two big devaluations on Turkish Lira.

9. TESTING CURRENCY RETURN VOLATILITY BY USING EWMA AND GARCH METHODS

Before testing the return volatilities by EWMA and GARCH methods, table 1 presents a descriptive statistics about seven currencies. It includes the daily arithmetic returns, the standard deviation, highest and lowest returns.

The daily average return for currencies range from 0.063% (Euro) to 0.195% (Japanese Yen). The daily volatility ranges from 1.086% (Euro) to 1.442% (Japanese Yen) during the sample period.

10. EWMA RESULTS

EWMA model in RiskMetrics uses the following formula $\sigma_{i,t} = \sqrt{\frac{1-\lambda}{1-\lambda^n} \sum_{j=0}^n \lambda^j r_{i,t-j}^2}$ to calculate the volatility standard deviation.

The same formula is used to identify and determine the volatility in this research. 0.94 (for daily standard deviation) is accepted for exponential factor. 99% confidence level requires data number n and 74 days are found. For 95% confidence level required days are taken is 50 days. The findings of the standard deviation is to multiply for 99% confidence level 2.326 and for 95% confidence level, 1.645 to reach the daily currencies VaR numbers.

The required number of days have changed such as 5, 8, 15, 20, 26, 37, 50 and 74 means when the days number is getting smaller, the standard deviation is getting higher. However, this does not warrant to obtain better VaR number when considering small number of days. In this case, previous events cannot be impacted on standard deviation. Figure 1-4 demonstrates the standard deviation results of U.S. Dollar and Euro based on EWMA calculations. As it is shown on graphs when the number of days getting smaller, sharp movements are observed. These results verify that the more recent data are bound to have a more important influence on future volatility than past data.

Volatility values that are calculated by EWMA(0.94) model are compared with the currency returns. The results show that volatility forecasting values choosing 95% confidence level have produce more

deviations than choosing 99% confidence level. The results are given in tables 2 and 3. As it is shown in tables 95% confidence level produces much higher deviations from the expected currency return numbers. However, EWMA model in 99% confidence level capture the devaluations in Turkey for the periods in April 1994 and February 21, 2001 (see Figure 6).

11. OPTIMAL LAG LENGTHS

In order to calculate GARCH numbers, two steps should be taken. First step is to determine the optimal lag length. Second step is test the ARCH effects.

AIC and SIC methods apply for seven currencies. AIC criteria has given lower results than SIC. When using AIC and SIC, up to 24 lags are chosen to test the optimal lag length. For all the currencies' returns, the optimal lag length found one. Low lag lengths would help to increase the number of data used in forecasting returns and volatility.

12. ARCH EFFECTS

In order to test ARCH effects, the following equations are applied for seven currencies.

$$R_{i,t} = \beta_i I_{t-1} + e_{i,t} \quad (15)$$

$$h_{i,t} = \text{Var}(e_{i,t}) = \alpha_0 + \alpha_1 e_{i,t-1}^2 \quad (16)$$

That is, a test for the hypothesis α_1 is zero in equation is to obtain the OLS residuals and to test whether the coefficient of e_{t-1}^2 is zero. In the equation, the conditional variance is dependent on the lagged value of the squared residual. If the lagged value of e_{t-1}^2 is large, conditional variance result will be large as well. This explains the volatility clustering which means large changes in prices tend to follow large changes in prices, small changes are followed by small changes of either sign.

With a sample of T residuals, under the null hypothesis of no ARCH errors, the test statistics TR^2 converges to a χ^2 distribution. Where T is the usable observations and R^2 statistic is obtained from the

regression stated in the equation. In this study, the χ^2 distribution with one degree of freedom (the lag number is the degree of freedom) at 5% significance level provides a reference to accept or reject the null hypothesis. If TR^2 is sufficiently large, rejection of the null hypothesis of no ARCH errors.

Table 8 gives the result of ARCH (1) which is calculated by $h_{i,t} = Var(e_{i,t}) = \alpha_0 + \alpha_1 e_{i,t-1}^2$. Seven currencies show significant ARCH effect due to the fact that at the 5% significance level, the critical value of χ^2 with one degree of freedom is 3.842, which is less than TR^2 for all the currencies. Based on ARCH(1) test result, it is concluded that there is a heteroskedasticity in the error terms of regression. This shows that the residual variance enters the basic equation predicting currency returns, indicating that ARCH effects existed in the currency returns, indicating that ARCH effects existed in the currency returns data. While some currencies have higher TR^2 values than the others, this means currencies with higher TR^2 values such as Canadian Dollar 169.44 and Australian Dollar 65.83 have relatively more heteroskedasticity while Euro 8 and US Dollar 23.98 with lower TR^2 values means have relatively less heteroskedasticity.

If there is an ARCH effect, one forward step can be taken to test the GARCH model.

13. GARCH RESULTS

In the application GARCH(1,1) model is used to estimate the conditional expected currency returns and variances for seven currencies. The GARCH(1,1) model involves the joint estimation of a conditional expected return equation and a conditional variance equation.

The GARCH (1,1) results are obtained from the RATS econometric program. In order to get optimal coefficient BHHG optimization method has been chosen. The findings of GARCH parameters coefficients are similar for most of the currencies. For all currencies, $\alpha_0, \alpha_i, \alpha_j \geq 0$ and $\alpha_i + \alpha_j < 1$ constraints are successfully satisfied. The calculated standard deviation multiplied by 99% confidence level 2.326 and for 95% confidence level 1.645 to derive at the currencies daily VaR number.

Finally, volatility values that are calculated by GARCH (1,1) model are compared with the currency returns. The findings are given in tables 4 and 5. The results show that volatility is successfully forecasted

either choosing 95% or 99% confidence level. GARCH(1,1) model could capture the financial crises in Turkey in April 1994, November 20, 2000 and February 21, 2001 (see Figure 9 and Figure 10).

14. COMPARISON OF THE EWMA AND GARCH METHODS

Analyzing VaR numbers calculated from EWMA and GARCH methods, the results seem relatively close (see table 7). Yet, as it is shown in table 6, using GARCH number to calculate VaR provides better result than EWMA during the financial crises in Turkey (Figure 14 and 15). In addition, both methods' deviations can be at acceptable levels and EWMA is much simpler than GARCH method.

The VAR is calculated for each day which can then be compared to the following day's price change. If the following day's price change is greater, then that day is an exception.

The results are then tested through the following formula to see whether a standard error type I test rejects or accepts the volatility model for each currency..

$$Z = \frac{X - Np}{\sqrt{Npq}} \quad (17)$$

where; X = number of exceptions, N = number of days, p = desired level of confidence, and $q = 1-p$.

The total number of exceptions is totalled. The results (%number of exceptions) from each currencies collected in table 2 through 5. In the tables VAR coverages are calculated as exception numbers/number of observations. The Z scores are compared for 95% confidence level with a table number of 1.645 and for 99% confidence level the table number is 2.326. If Z scores are below the critical value (1.645 or 2.326), then two sided are being accepted.

Figures 13-16 compare the volatility values that are calculated by EWMA (0.94) and GARCH (1,1) methods. Generally GARCH results produce relatively higher numbers than EWMA results but the differences are not significantly big. Although these two methods have degree of deviations from the currency returns, the results have acceptable level. EWMA and GARCH results have acceptable level.

During the financial crisis or when the extraordinary events happened during the sample period, both methods could predict the crashes.

Finally, table 7 shows the correlations coefficients between EWMA and GARCH results in 95% and 99% confidence level. Correlations coefficients range from 59% to 77%.

15. CONCLUSION

Volatility forecasting is an important task for most of the investing parties in the financial markets. Calculating volatility number is not sufficient for currency portfolios to control risk but needs to be used in VaR calculations. VaR brings standardization when comparing risky portfolios. In recent years, the advantages of VaR make it a contemporary risk management tool.

Volatility tends to happen in clusters. The assumption is volatility that remains constant at all times can be fatal. Volatility changes through time, especially during the financial crises in Turkish economy that volatility tends to increase significantly.

In order to forecast volatility in currency market, there must be methodology to measure and monitor volatility modeling. Recently, EWMA and GARCH models have become critical tools for time series analysis in financial applications.

In this study, seven currencies return volatility have been tested by using EWMA and GARCH methods to compare results.

Number of days has been selected to use in calculations. It is determined that the most recent data have asserted more influence on future volatility than past data. ARCH effects have been recorded for all the currencies in this study. A later test is performed on GARCH model. Time series has been used to estimate volatility and give more weights to recent events as opposed to older events. The constraints of all GARCH parameters are satisfied.

Daily VaR numbers have been calculated by using EWMA and GARCH models for the seven currencies. The outcome is GARCH provides slightly more accurate analysis than EWMA. The results are satisfactory for forecasting volatility at 95% and 99% confidence level. These two methods enhance the quality of the VaR models. Interestingly, VaR calculations have predicted the April 1994 and February 2001 devaluation in Turkey. It is also observed that the Turkish Lira's

volatility was low during the crawling peg period. However, after February 2001 free floating period caused the volatility to increase. Therefore, volatility forecasts tend to remain high in the post crises period.

The findings in this currency research, support the idea of EWMA and GARCH methods are good enough to forecast VaR numbers. The financial crisis that occurred in April 1994, November 2000 and February 2001 of Turkey signifies the fact that VaR number can capture the extraordinary events or crisis as VaR's role is to measure the bearing of currency portfolio risks.

These findings suggest that risk managers, regulators and traders are able to monitor the currency related positions and minimize risks if they obtain a better understanding of how volatility is being forecasted.

REFERENCES

- Alexander, C. (1996); *Risk Management and Analysis*, John Wiley & Son Ltd., London.
- Akaike, H. (1973); "Information Theory and the Extension of the Maximum Likelihood Principle" in 2nd International Symposium on Information Theory, B.N. Petrov and F. Csaki, eds., Budapest.
- Avinash, P. (1998); *Event Risk Indicator (ERI)*, J.P. Morgan Technical Document.
- Baillie, R., T. Bollerslev ve H.O. Mikkelsen (1996); "Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity" *Journal of Econometrics*, Vol.74, No.1, pp. 3-30.
- Barone, A. G. ve G. Kostas (2002); "Nonparametric VaR Techniques: Myths And Realities", <http://www.gloriamundi.org/var/pub/gbkgfhs.pdf>, 08.05.2002.
- Best, P. (1999); *Implementing Value At Risk*, Bidles Ltd., London.
- Bilson, J.F.O. (1999); "Value at Risk for Emerging Market Currencies" *Lecture Notes for a course on: Trading, Investment and Risk Management*, Summer School in Econometrics, Italy, June, pp.15-20.
- Bollerslev, T. (1986). "Generalised Autoregressive Conditional Heteroscedasticity" *Journal of Econometrics* 31, pp.307-327.
- Bredin, D. and Hyde, S. (2004). "FOREX Risk: Measurement and Evaluation Using Value-at-Risk," <http://www.gloriamundi.org/picsresources/dbsh.pdf>, 18.06. 2004.
- Butler, C. (1999); *Mastering Value at Risk, A step-by-step guide to understanding and applying VaR*, Financial Times Pitman Publishing, Market Editions, London.
- Ceylan, A. and T. Korkmaz, (2004); *Sermaye Piyasasi ve Menkul Deger Analizi*, 2. Baski, Ekin Kitabevi Yayinlari, Bursa.
- Chou, R. Y. (1988); "Volatility Persistence and Stock Valuations: Some Emperical Evidence Using Garch," *Journal of Applied Econometrics* 3, pp. 279-294.
- Culp, C. L., R. Mensink, and A.M.P. Neves, (1999); "Value at Risk for Asset Managers," *Derivatives Quarterly*, Vol.5, No.2.
- Dowd, K. (2000); *Beyond Value At Risk*, John Willey & Sons Ltd, London.
- Engle, R. F. (1982); "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, Vol.50, No.1, pp. 987-1007.
- Fama, E. F. (1965); "The Behavior of Stock Market Prices," *Journal of Business* 38, pp. 34-105.
- Hendricks, D. (1996); "Evaluation of Value at Risk Models Using Historical Data," *Economic Policy Review*, Vol.2, No.1, April, Federal Reserve Bank of New York.
- Jorion, P. (1997); *Value at Risk*, McGraw-Hill Companies, Inc., New York.

- _____. (2000). "Türk Bankacılık Sektöründe Risk Yönetimi Semineri," *Dünya Bankası ve Türkiye Bankalar Birliği*, 11-12 Şubat 2000, İstanbul.
- Karelse, J. (2001); "Risk Banished VaR, VaR Away," *Applied Risk Management*, June, pp. 75-81.
- Korkmaz, T. (2001); "The Investment of Emerging Capital Markets and the Role of Derivative Securities" *ISE Review*, Vol.5, No.17, pp. 63-93.
- Mandelbort, B. (1963); "The Variation of Certain Speculative Prices," *Journal of Business*, Vol.36, pp. 394-419.
- Morgan, J.P. (1998); *Event Risk Indicator Technical Documen*.
- Morgan, J.P. (2003); Web Page, <http://www.jpmorgan.com>, July, 2003.
- Nylund, S. (2001); <http://www.contingencyanalysis.com/archive>, 02.11.2001.
- Parrondo, J.M.R. (2004); *Calculation of the Value at Risk in Emerging Markets*, Research Project.
- Santander Investment, Final Report, <http://seneca.fis.ucm.es/parr/BANCO/report/report.html>, 06.07.2004.
- Penza, P. and V.K. Bansal (2001); *Measuring Market Risk with Value At Risk*, John Wiley & Sons Inc., U.S.A. RiskGrades Technical Document.
- Schacter, B. (2002); "All about Value at Risk, An Irreverent Guide to Value at Risk," <http://www.GloriaMundi.org/var/varintro.htm>, 26.06.2002.
- Schwert, G. W. (1989); "Why Does Stock Market Volatility Change Over Time?," *Journal of Finance*, Vol.44, pp.1115-1153.
- Simons, K. (1996); "Value at Risk-New Approaches to Risk Management," *New England Economic Review*, September/October.
- T.C.M.B. (2003); Web Page, <http://tcmbf40.tcmb.gov.tr/cbt.html>, 30.06.2003.

Table 1. Summary Statistics of Each Currency Returns**(02 January 1990–30 June 2003)**

Currencies	Starting	Average	Std. Dev.	Minimum	Maximum
Euro	2002:01	0.063%	1.086%	-4.174%	5.451%
Australian Dollar	1990:01	0.184%	1.403%	-12.162%	32.367%
Canadian Dollar	1990:01	0.185%	1.433%	-19.247%	33.642%
Swiss Franc	1990:01	0.193%	1.366%	-12.351%	33.132%
British Pound	1990:01	0.190%	1.348%	-12.695%	33.494%
Japanese Yen	1990:01	0.195%	1.442%	-12.572%	33.883%
US Dolar	1990:01	0.189%	1.306%	-12.564%	33.473%

Table 2. Results of Number of Exceptions Found for Each Currency Using the EWMA (0.94) Model and the Confidence Level Set on 95%

	VaR	Z	Accept?	Accept?
Currencies	Coverage	Score	2 sided	1 sided
Australian Dollar	3.20%	-4.768	No	Yes
Canadian Dollar	2.2%	-7.336	No	Yes
US Dollar	1.70%	-8.540	No	Yes
Euro	4.10%	-0.735	Yes	Yes
British Pound	2.10%	-7.497	No	Yes
Swiss Franc	1.80%	-8.379	No	Yes
Japanese Yen	2.30%	-7.015	No	Yes

Table 3. Results of Number of Exceptions Found for Each Currency Using the EWMA (0.94) Model and the Confidence Level Set on 99%

	VaR	Z	Accept?	Accept?
Currencies	Coverage	Score	2 sided	1 sided
Australian Dollar	0.80%	-1.136	Yes	Yes
Canadian Dollar	0.60%	-2.019	No	Yes
US Dollar	0.40%	-3.254	No	Yes
Euro	0.70%	-0.556	Yes	Yes
British Pound	0.40%	-3.430	No	Yes
Swiss Franc	0.50%	-3.077	No	Yes
Japanese Yen	0.50%	-2.725	No	Yes

Table 4. Results of Number of Exceptions for Each Currency Using the GARCH (1.1) Model and the Confidence Level Set on 95%

Currencies	VaR	Z	Accept?	Accept?
	Coverage	Score	2 sided	1 sided
Australian Dollar	0.80%	-1.136	Yes	Yes
Canadian Dollar	0.20%	-4.842	No	Yes
US Dollar	0.20%	-4.313	No	Yes
Euro	0.30%	-1.141	Yes	Yes
British Pound	0.20%	-4.313	No	Yes
Swiss Franc	0.40%	-3.430	No	Yes
Japanese Yen	0.60%	-2.548	No	Yes

Table 5. Results of Number of Exceptions Found for Each Currency Using the GARCH (1,1) Model and the Confidence Level Set on 99%

Currencies	VaR	Z	Accept?	Accept?
	Coverage	Score	2 sided	1 sided
Australian Dollar	2.10%	-7.737	No	Yes
Canadian Dollar	0.60%	-11.510	No	Yes
US Dollar	0.70%	-11.349	No	Yes
Euro	2.00%	-2.337	No	Yes
British Pound	0.70%	-11.189	No	Yes
Swiss Franc	1.30%	-9.824	No	Yes
Japanese Yen	1.70%	-8.700	No	Yes

Table 6. Number of Exceptional Days in 95 and 99 Percent Confidence Level

	95% CONFIDENCE LEVEL					99% CONFIDENCE LEVEL				
	Number of days	EWMA number of exceptional days	EWMA percentage of exceptional days	GARCH number of exceptional days	GARCH percentage of exceptional days	Number of days	EWMA number of exceptional days	EWMA percentage of exceptional days	GARCH number of exceptional days	GARCH percentage of exceptional days
Australian Dollar	3347	104	3.11%	67	2.00%	3323	26	0.78%	24	0.72%
Canadian Dollar	3347	72	2.15%	20	0.60%	3323	21	0.63%	5	0.15%
US Dollar	3347	59	1.76%	24	0.72%	3323	14	0.42%	8	0.24%
Euro	374	12	3.21%	6	1.60%	350	2	0.57%	1	0.28%
British Pound	3347	70	2.09%	25	0.75%	3323	13	0.39%	8	0.24%
Swiss Franc	3347	77	2.30%	41	1.22%	3323	15	0.45%	13	0.39%
Japanese Yen	3347	76	2.27%	54	1.61%	3323	17	0.51%	16	0.48%

Table 7. Correlations of GARCH and EWMA Results in 95% and 99% Confidence Level

Currencies	95% C.L.	99% C.L.
Australian Dollar	0,599	0,594
Canadian Dollar	0,617	0,611
US Dollar	0,656	0,650
Euro	0,774	0,774
British Pound	0,674	0,668
Swiss Franc	0,673	0,683
Japanese Yen	0,660	0,655

Table 8. ARCH Test Results for 7 Currencies

Currencies	Constant	ε_{t-1}^2	$T \times R^2$
Australian Dollar	0.0001637891	0.1392554300	65.836105
Canadian Dollar	0.0001575860	0.2234073942	169.447384
US Dollar	0.0001471876	0.0840457385	23.981222
Euro	0.0000998910	0.1476814544	8.114250
British Pound	0.0001564443	0.0972124803	32.083666
Swiss Franc	0.0001627575	0.0951851287	30.759445
Japanese Yen	0.0001807182	0.1047759456	37.270361
Critical value of Chi-Squared (1) with 95% confidence level 3.842			

Figure 1. US Dollar - EWMA Values for Various Required Number of Days with 95% Confidence Level

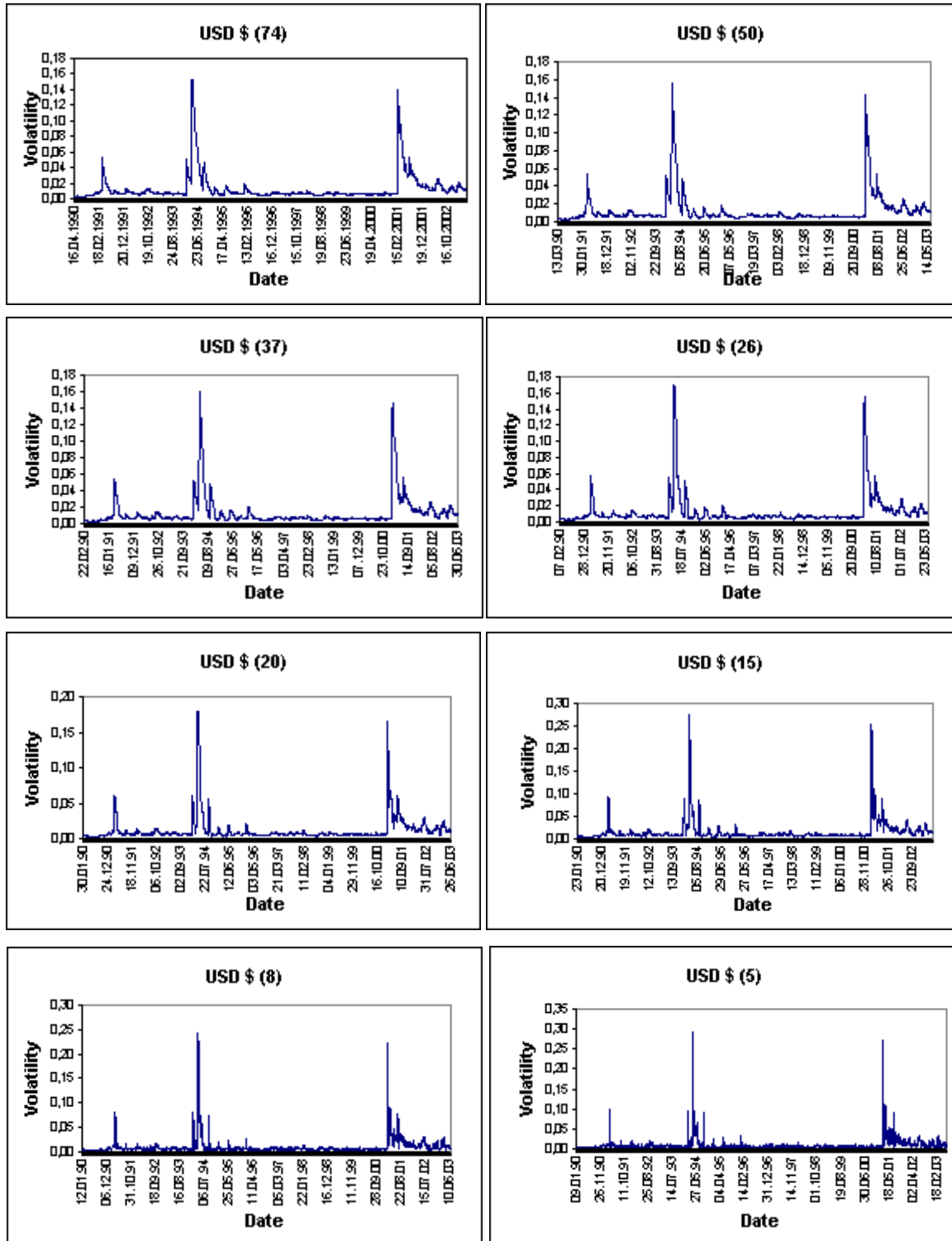


Figure 2. US Dollar - EWMA Values for Various Required Number of Days with 99% Confidence Level

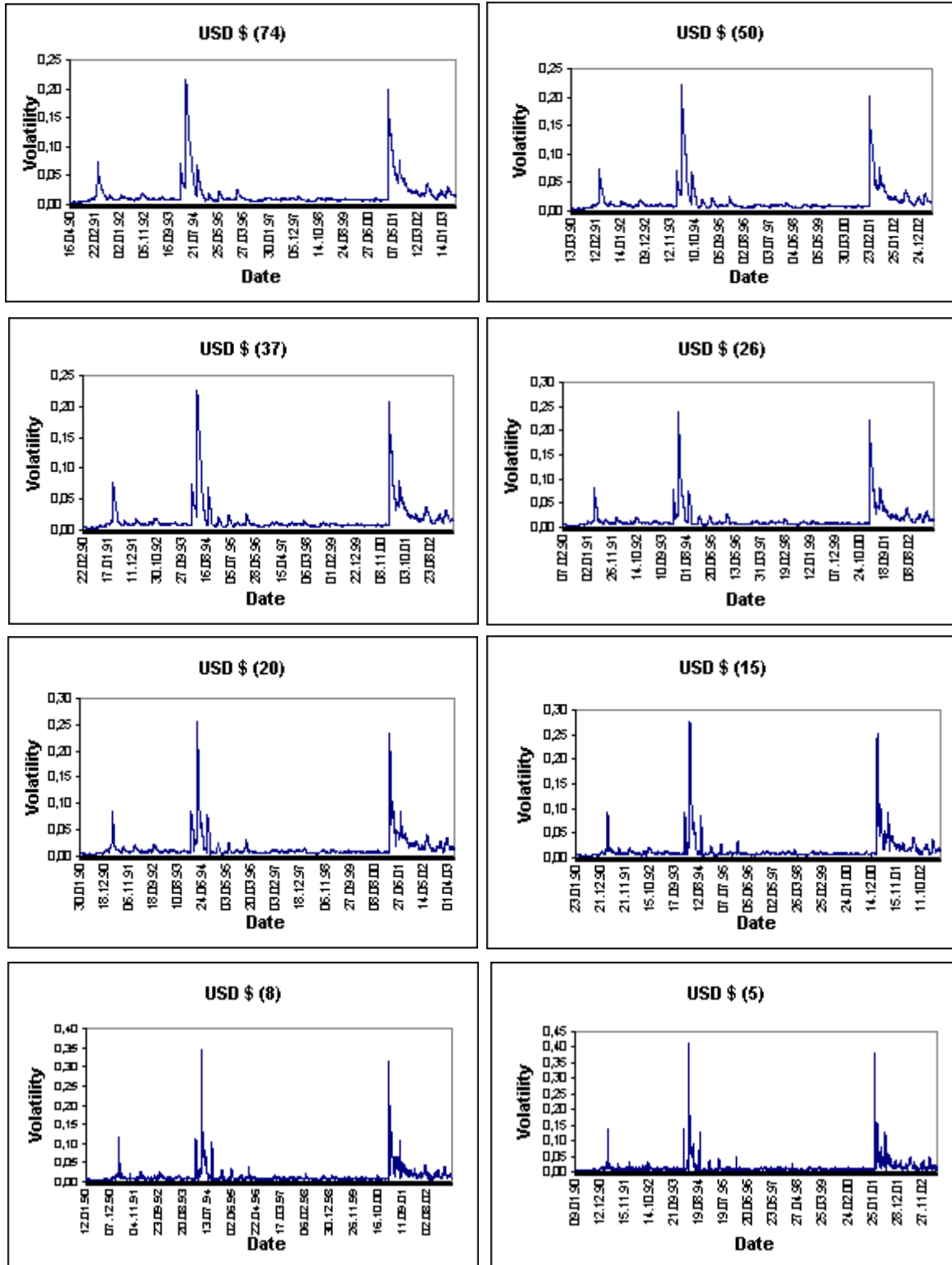


Figure 3. EURO - EWMA Values for Various Required Number of Days with 95% Confidence Level

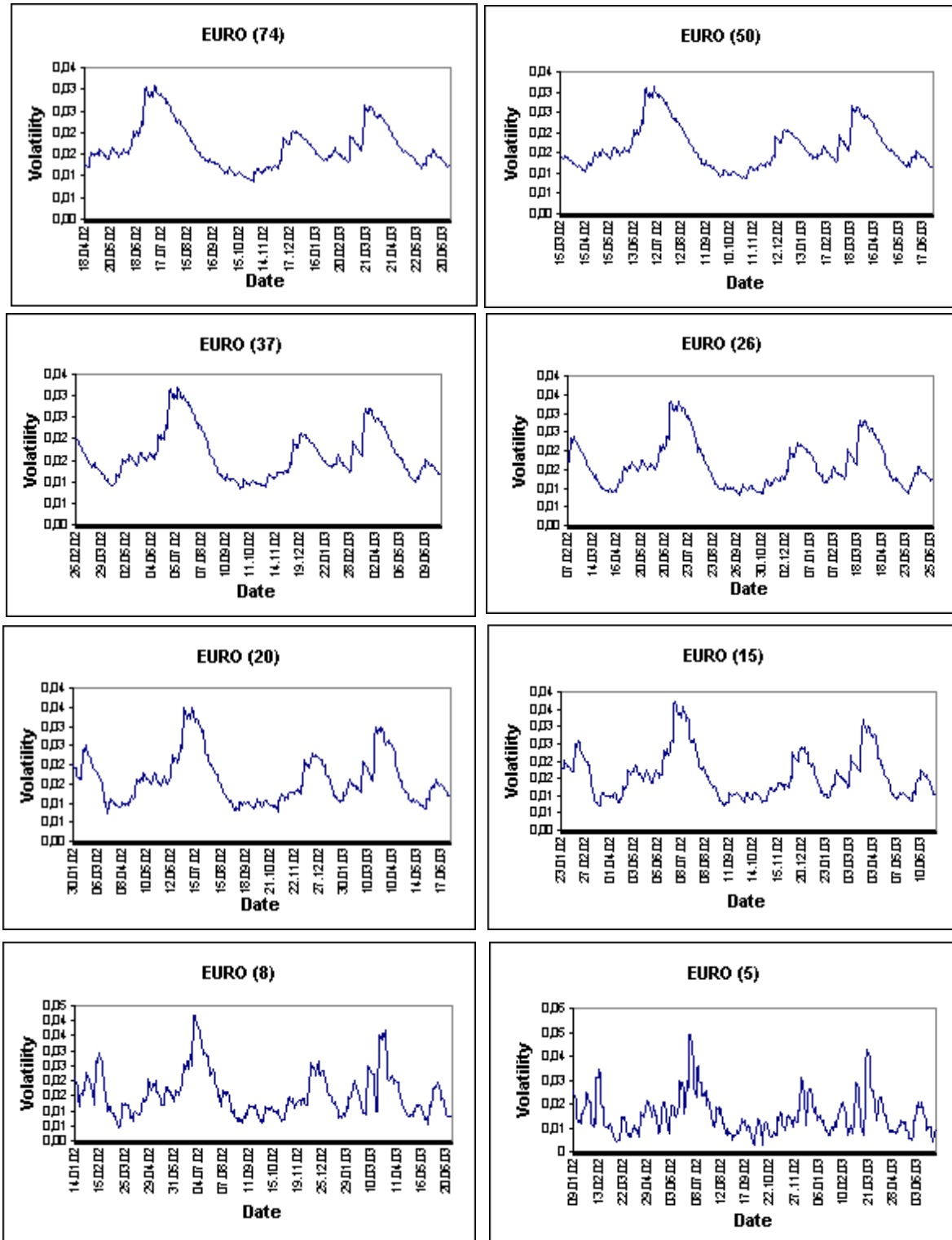
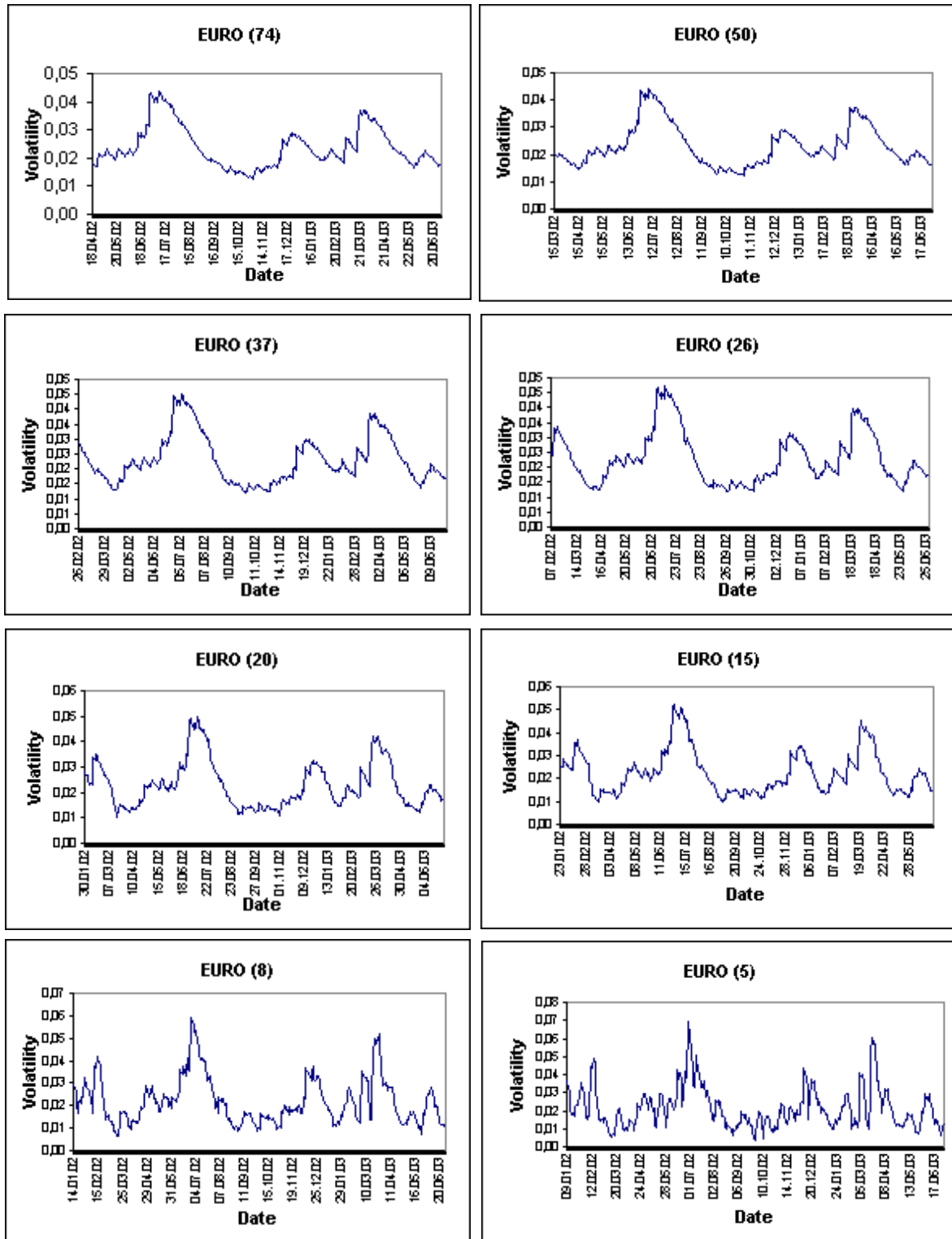
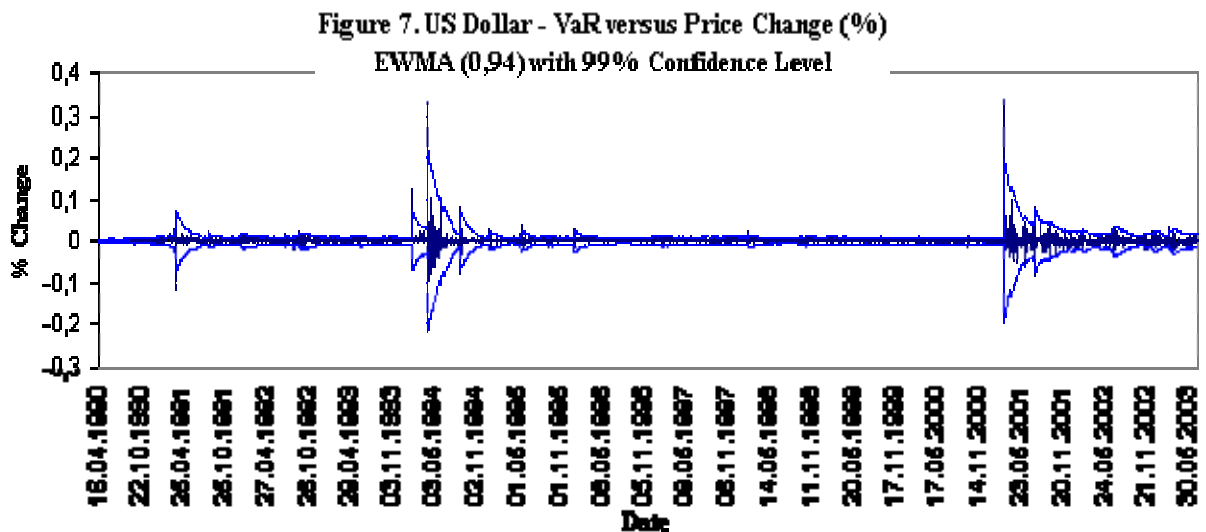
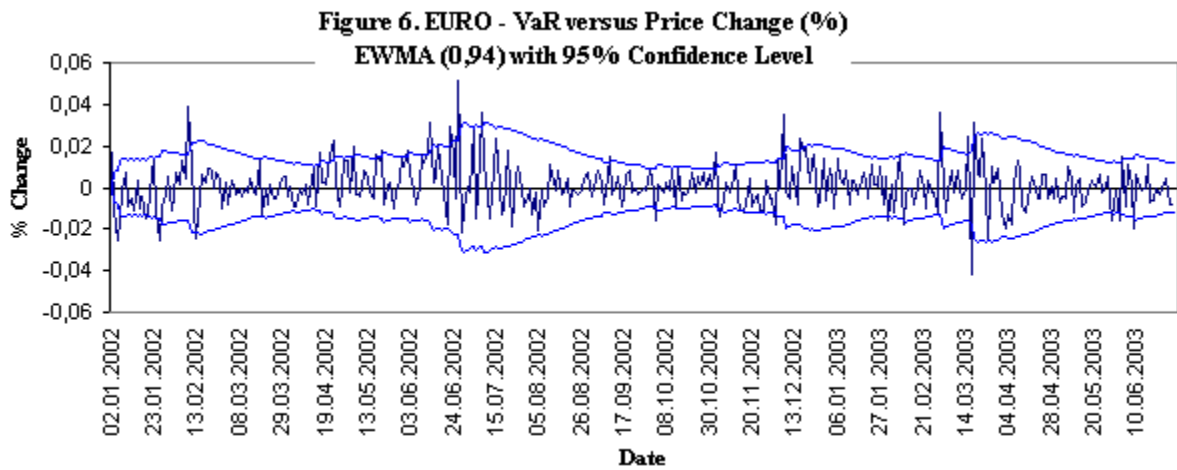
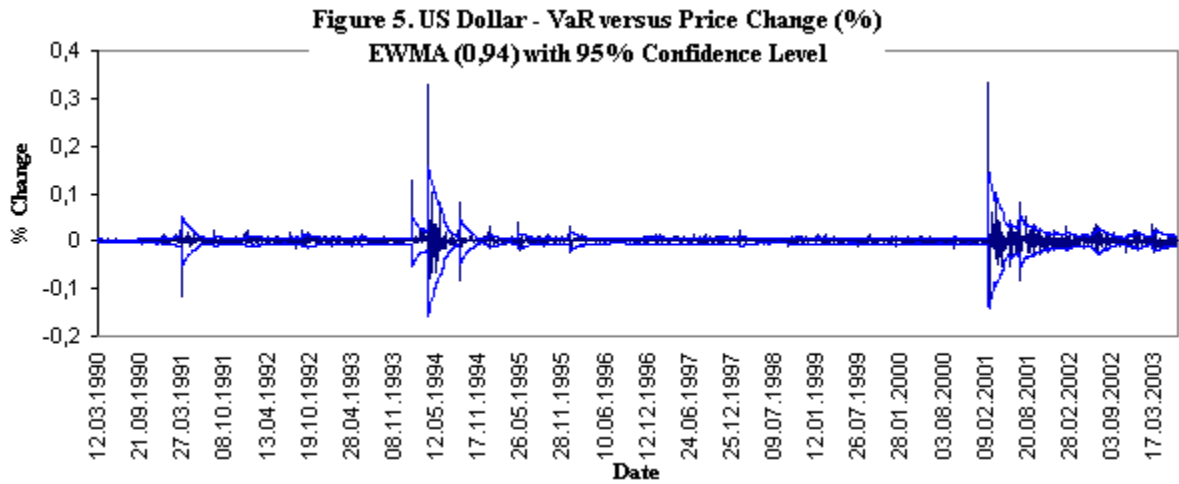
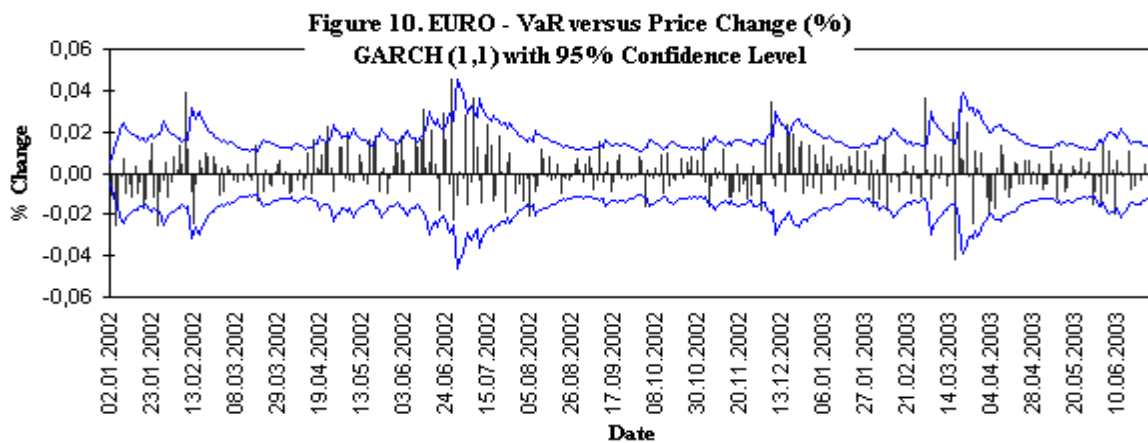
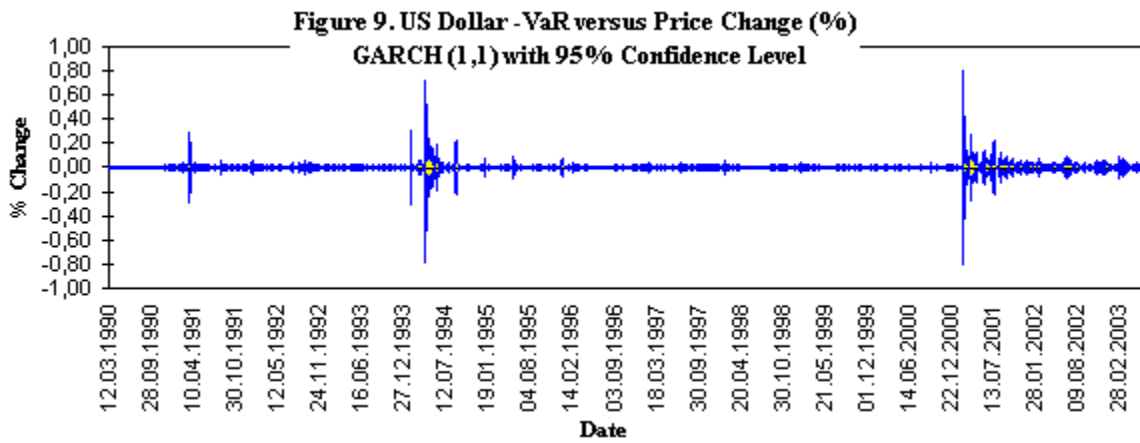
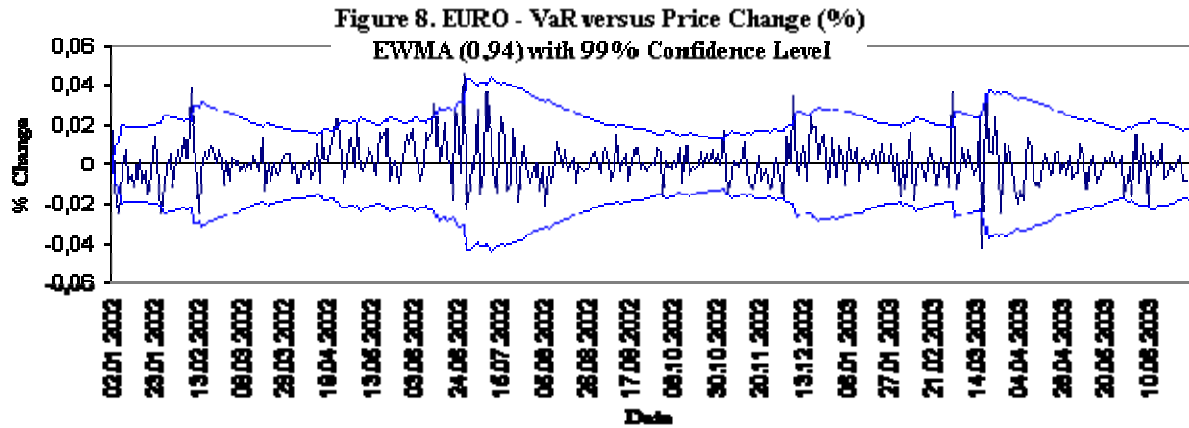


Figure 4. EURO - EWMA Values for Various Required Number of Days with 99% Confidence Level







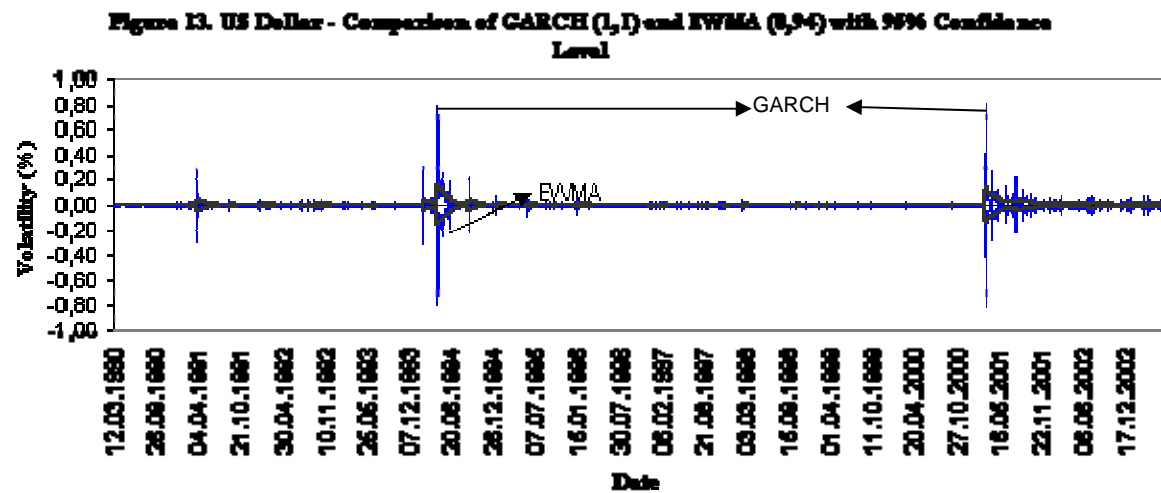
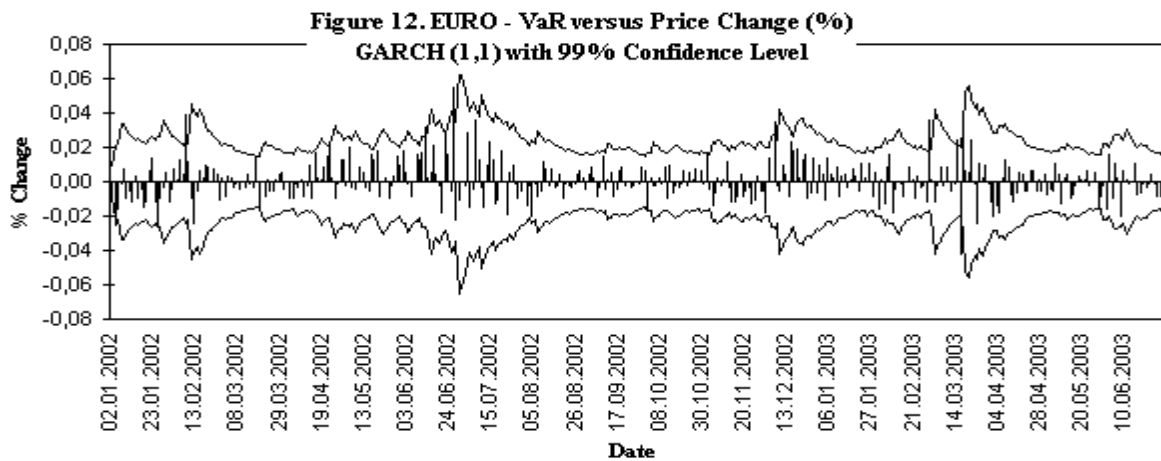
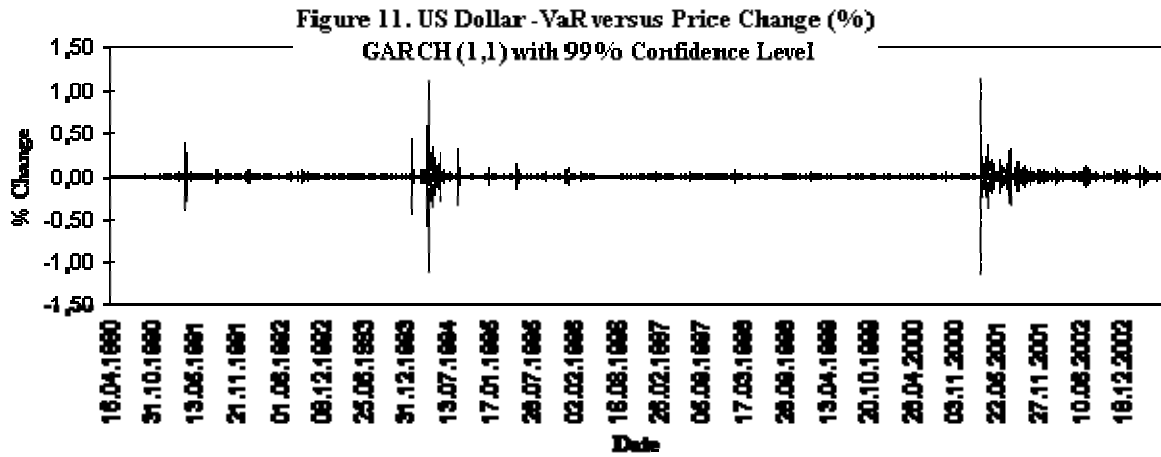


Figure 14. EURO - Comparison of GARCH (1,1) and EWMA (0,94) with 95% Confidence Level

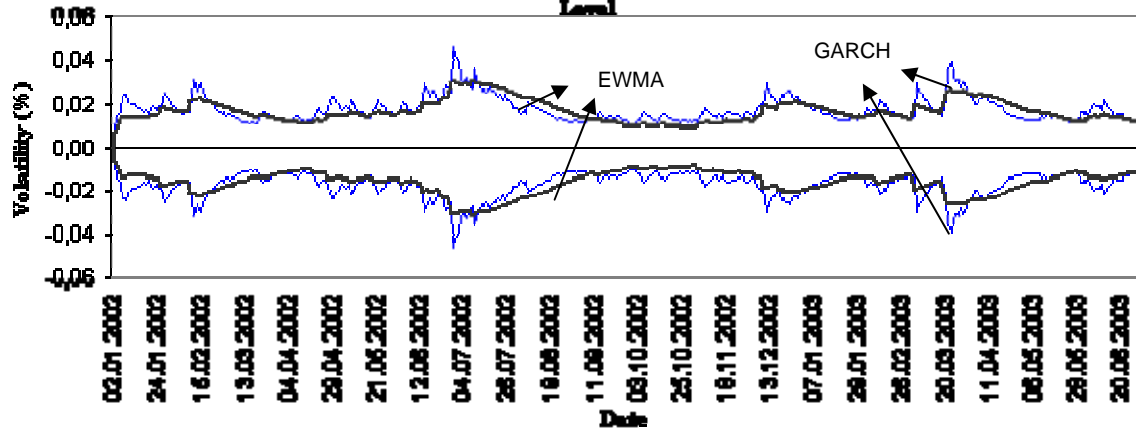


Figure 15. US Dollar - Comparison of GARCH (1,1) and EWMA (0,94) with 99% Confidence Level

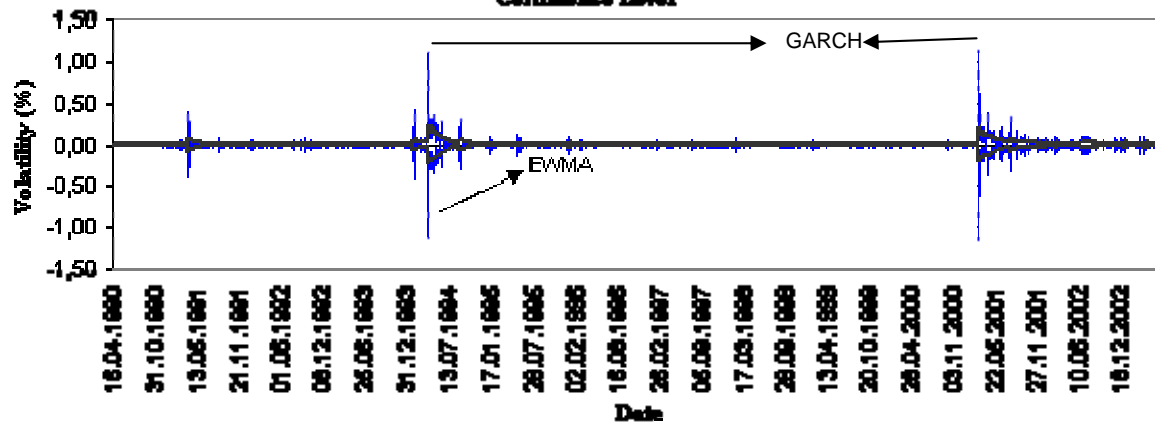


Figure 16. EURO - Comparison of GARCH (1,1) and EWMA (0,94) with 99% Confidence Level

