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SENSITIVITY OF VaR MEASURES TO DIFFERENT RISK MODELS

by F. Drudi(*), A. Generale(*) and G. Majnoni(**)

Abstract

The paper provides an empirical assessment of the market risk exposure of several portfolios representative of real life investment positions. We employ the notion of value at risk made popular by the recent debate on capital budgeting policies of financial intermediaries and by the new capital requirements for banks established by the Basle Committee on Banking Supervision. We provide evidence of the extent to which market risk exposures may diverge according to the different methods of risk measurement. We test the sensitivity of risk assessment to the number of factors employed, measures of volatility (conditional versus unconditional) and correlations (stable versus unstable), and the linearization of non-linear payoffs. With reference to the latter, we provide evidence of the importance of risk assessment misalignments for positions in options that exhibit a reduced degree of delta exposure but entail a significant degree of payoff convexity and non-normality.

Contents

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1. Introduction[1]

"Value at risk" has gained increasing popularity in the last decade as a method for measuring downside risk, although techniques for quantifying risk have existed at least since the introduction of the notion of duration in the thirties. The subsequent development of portfolio theory in the fifties and of asset pricing theory in the two following decades provided solutions to the problem of risk aggregation and to that of a parsimonious representation of risk exposure. Once the different bricks had been put in place it is not surprising that the eighties were the decade in which risk management techniques started to acquire a more definite structure.

The notion of "value at risk" was originally developed by the financial industry as an instrument for capital budgeting. It is the amount of capital that a financial intermediary deems necessary to set aside to absorb the potential losses on a specific investment and that should be considered in order to properly assess investment profitability. The concept has undergone considerable refinement in the last few years and its use for computing risk-adjusted returns is now widely accepted among industry participants. Such risk-adjusted performance measures — RAPM in the current parlance — have found many empirical applications with the development of different

1. We are grateful to an anonymous referee and to Riccardo Cesari for helpful comments; to Claudio Doria, Fausto Felletti and Maria Pia Mingarini for their editorial assistance.

empirical specifications such as the risk-adjusted return on capital (RAROC) and the return on risk-adjusted capital (RORAC).

VaR is a measure of total risk — both diversifiable and non-diversifiable — and the related risk-adjusted returns therefore differ from the traditional applications of finance models to capital budgeting issues, where only non-diversifiable risk is considered. The reasons for this development, apparently at odds with the classical tenets of financial theory, are currently being studied and appear to be mainly related to the need — for a number of operational purposes — for a "conservative" measure of risk. Market imperfections that may reduce the operational viability of risk diversification, the low statistical precision or stability of measures of diversifiable risk, the wish not to diversify risk and to take positions on a specific "market view" are among the reasons that explain the widespread use of the VaR notion of risk measurement in the industry.[2]

The area in which the greatest consensus has been reached in risk evaluation and control is that of market-traded assets. No comparable framework has yet been defined, for instance, for the control of assets that are not marked to market.[3] This explains the recent burst of

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2. An analysis of the reasons that may explain the use of total risk measures in capital budgeting practices followed by the financial industry is contained in Froot and Stein (1996).

3. A recent effort in this direction is represented by J. P. Morgan (1997).

interest in market-risk control among regulators of financial institutions.

The notion – provided by VaR – of the capital required to absorb losses that may occur up to a specified level of probability, provided a natural criterion for the definition of capital requirements by supervisory authorities. The Basle Committee on Banking Supervision accordingly decided, after consultation with the banking industry, to introduce VaR as an instrument for the definition of capital requirements on the market-risk exposure of bank's trading portfolios. Provision was made in the Amendment to the Capital Accord for the incorporation of market risk, approved in January 1996, for banks to be able to compute their own capital requirements according to the "value-at-risk" calculated using their internal models of risk measurement.

The measurement methods based on the notion of VaR do not eliminate the uncertainties about the precision of different VaR models. This paper will try to provide some evidence in the debate on this issue by comparing the risk given by different measurement techniques for specific portfolios. We will consider only some of the important issues related to risk measurement with the aim of extending to different risk profiles and different market exposures some of the empirical assessments of VaR models contained in a series of recent papers by economists of the Federal Reserve (Ammer, 1995; Hendricks, 1995; Mahoney, 1995) and of the Bank of England (Maude, 1995).

The paper is divided into four sections. The next contains a concise description of value-at-risk methodology and of the possible shortcomings of a "naive" approach to risk measurement. The results of the estimation of the VaR of a portfolio characterized by linear exposure to interest rate risk (i.e. without options positions) are discussed in Section 3, where parametric estimates (based on the assumption of covariance stationarity) are contrasted with non-parametric ones for a bond and a swap portfolio. Section 4 shows how risk exposure evolves for the bond portfolio once the assumption of covariance stationarity has been dropped. Section 5 introduces the valuation of non-linear risk exposures to both interest and exchange rate risk. Our conclusions are illustrated in Section 6.

2. Value at risk: some available measurement criteria

The general purpose of risk measurement systems is to evaluate the potential losses for risk-taking institutions. Since losses must be estimated at a certain level of statistical probability, an intuitive approach is offered by the percentile method, which defines a certain portion of the lower tail of the return distribution as "worst cases" and considers as likely risks the losses falling short of such extreme outcomes.

The notion of value at risk can be formulated as follows:

$$(1)\quad \begin{aligned} &VaR = |V| * d\overline{V} \\ &P(dV < d\overline{V}) = predefined \quad probability \quad level \\ &dV = \sum_i w_i * dV_i \end{aligned}$$

where $|V|$ is the absolute value of the portfolio, dV, the percentage variation of portfolio value, $d\overline{V}$ the percentage variation related to the predefined level of probability and w_i represents portfolio shares. If we assume that asset returns (dV_i) follow a normal distribution, then the portfolio return (dV) will also be normally distributed and it will be possible to associate a predefined value dV to a certain probability level and express it as a multiple of the standard deviation. For instance, at the 1 per cent probability level proposed by the Basle Committee on Banking Supervision (corresponding to $2.33*\sigma$ for a normal distribution), the above relationships could be written as follows:

$$(2)\quad \begin{aligned} &VaR = |V| * \sigma_v * 2.33 \\ &P(dV < \sigma_v * 2.33) = 0.01 \\ &\sigma_v = \sqrt{\sum_i \sum_j w_i w_j \rho_{ij} \sigma_i \sigma_j}. \end{aligned}$$

For any portfolio of a certain complexity it would be extremely impractical, if feasible at all, to evaluate portfolio volatility from the historical volatilites and correlations of individual instruments. The most common solution is to model the dependence of individual asset prices with respect to a limited number of factors (F_m) in order to limit the scale of the problem. The volatilities of the individual instruments (σ_i) will then depend on factor sensitivities (or factor loadings) ($\frac{\partial V_i}{\partial F_m}$), and on factor volatilities (σ_m) and correlations (ρ_m). The volatilities of individual asset returns (σ_i) or portfolio returns (σ_v) can therefore be expressed as follows:

(3)
$$\sigma_i = \sqrt{\sum_m \sum_n \frac{\partial V_i}{\partial F_m} * \rho_{mn} \sigma_m \sigma_n}$$
$$\sigma_v = \sqrt{\sum_m \sum_n (\sum_i w_i) \frac{\partial V_i}{\partial F_m} (\sum_i w_i) \frac{\partial V_i}{\partial F_n} \rho_{mn} \sigma_m \sigma_n}$$

or more intuitively in terms of matrix notation:

(4)
$$\sigma_v^2 = \begin{bmatrix} w' \frac{\partial V}{\partial F_1} & .. & w' \frac{\partial V}{\partial F_m} \end{bmatrix} \begin{bmatrix} \sigma_{f1}^2 & .. & \sigma_{f1} \sigma_{fm} \rho_{1,m} \\ .. & .. & .. \\ \sigma_{fm} \sigma_{f1} \rho_{m,1} & .. & \sigma_{fm}^2 \end{bmatrix} \begin{bmatrix} w \frac{\partial V}{\partial F_1} \\ .. \\ w' \frac{\partial V}{\partial F_m} \end{bmatrix} = x' \Sigma x \ .$$

The dimension of the covariance matrix for a globally diversified portfolio can still be very high.

Depending on the complexity of the portfolio, several procedures are available for VaR estimation (i.e. for the evaluation of the portfolio loss associated with the predefined level of probability). In extreme synthesis we can devise four major strategies. The first, which can be called the covariance approach, relies on the volatility of market factors expressed by their covariance matrix (historical parametric approach) and it is usually supplemented by the assumption of normality of returns in order to generate inferences on the probability of losses.

The second approach, known as historical simulation, does not use parametric estimation (i.e. does not estimate the covariance matrix): for a given portfolio composition, the distribution of the losses (and profits) is empirically generated from factor loadings and historical occurrences of risk factors. The third approach, known as parametric statistical simulation, assumes a given structure of the correlation matrix and factor distribution (not necessarily normal) and by means of statistical simulation generates the portfolio profit and loss distribution. The fourth approach, known as non-parametric statistical simulation, estimates the empirical distribution of factors (or directly of the overall portfolio profits and losses) by means of "bootstrapping techniques" (i.e. repeated extractions from a predefined sample of factor occurrences).

The covariance approach has the appeal of simplicity, but may seriously misrepresent risk exposure whenever:

- factor occurrences are not normally distributed. This case arises when factor distributions, typically represented by asset returns, have more observations in the tails of the distribution (unusually large changes) and in the center (corresponding to small changes) than is consistent with the normal distribution. In this case, tail probabilities cannot be defined as multiples of the standard deviation (i.e. portfolio volatility times 2.33 does not define a level of losses to be exceeded only once in a 100 cases). With distributions of this nature (leptokurtic distributions) the probability of larger losses is certainly greater;

- the correlation matrix is not stable. In this case it is not possible to define the benefits of diversification with an adequate degree of confidence. Consequently, the quantification of the cross-product term in (3) and its contribution to overall riskiness becomes uncertain;

- the portfolio has non-linear exposure to risk factors. In this case the linearization of options exposure to risk (delta approximation) may be inadequate, making it necessary to include the quadratic term of the Taylor expansion (gamma approximation). This can be done in principle, but at the cost of a large increase in the number of parameters to be estimated (the dimension of the covariance matrix exactly doubles in order to include the quadratic terms and their cross-products with the linear ones);

- factors exhibit non-stationary volatilities. The estimation of moving volatilities for multivariate distribution by GARCH methodologies faces considerable computational difficulties. On the other hand the alternative solution based on the definition of a common process for all the asset returns, adopted by J. P. Morgan (1995), may introduce undesired biases.

The historical simulation (not parametric) approach has the appeal of simplicity, but does not help to detect the effect of different risk factors on the overall portfolio riskiness. Its univariate and distribution-free nature makes the estimated profit and loss an ideal candidate for GARCH modelling in order to properly account for time-varying volatilities.

The Monte Carlo (parametric statistical) approach is required whenever the portfolio considered has strong non-linear risk exposures. Its implementation is somewhat more complex. The simulation of factor distributions requires a positive-definite covariance matrix if one wants to perform the Cholesky decomposition to simulate extraction from the return distribution. The latter requirement amounts to a limit on the dimension of the matrix (i.e. the number of factors).

The fourth approach shares the advantages of the second, being non-parametric in nature and makes it possible to estimate the empirical distribution of individual factors. It is therefore particularly suitable for portfolios with significant non-linear risk positions.

The importance of the pros and cons of the different approaches cannot be assessed in general terms; they need to be empirically tested with reference to specific portfolios. The following sections of the paper will try to evaluate the effects on capital requirements of some of the different risk measurement approaches just described. The exercise has two different objectives: the first is to verify the degree of similarity of risk exposure assessment provided by the different models of risk measurement when applied to positions representative of real life portfolios, such as those of some Italian banks and security firms. The second objective is to throw some light on the criteria that may underlie the choice of a specific risk measurement model. As a matter of fact there is no reason to think that one model will be consistently considered superior to the others. In general, superiority should be assessed in terms of measurement accuracy and computational efficiency. At one extreme, policies aimed at keeping risk exposure simple may justify the adoption of relatively simple models of risk evaluation where simplifying assumptions are not likely to distort the risk representation. In these cases small gains in precision may come at the cost of a large increase in computation expenses. The opposite appears to be true for portfolios where non-linear risk may present features of increasing complexity.

3. A portfolio with linear exposure to market risk

In this section we measure the market risk of portfolios exposed to interest rate risk on lira-denominated assets. To this end we built two different portfolios: the first is composed of private and public bonds; the second is a portfolio of interest rate swaps, and is therefore characterized by the presence of levered positions. Both were structured in order to represent a realistic portfolio allocation by an Italian bank.[4] Their duration is equal to respectively 1.3 and 8.6 years (Tables 1 and 2). A similar exercise was performed on the aggregate portfolio of Italian investment firms.

The exposure to market risk was specified according to common practice in the marketplace. The overall positions in coupon bonds and swaps were first decomposed into elementary cash flows (zero-coupon bonds). These cash flows were then discounted with discount factors provided by the term structure of interest rates.[5] The present values of these future income flows were subsequently grouped into a number of time intervals (buckets) according to their maturity. Subsequently, each selected time interval was assigned a risk factor represented by the zero-coupon rate whose maturity coincided with the central point of each time bucket. The risk features associated with each zero-coupon rate – i.e. their volatility – was then derived from interest rate swaps quoted on the Euromarket.[6] Finally, each bucket exposition to interest

4. The first was constructed on the basis of data provided on a regular basis by banks on their portfolio composition. The second on the basis of information provided by a number of institutions on their interest rate swap activity.

5. Discount factors were obtained by the estimation of the Nelson and Siegel model (Nelson and Siegel, 1985) on Eurolira interest rates (Eurodeposits and interest rate swaps). This approach may lead to an inaccurate evaluation of bond portfolio volatility since issuer premium volatility is not considered.

6. In order to reduce measurement errors, zero-coupon rates were not derived from a term-structure model but extracted through a recursive computation of the swap curve.

rate changes – i.e. the factor loadings – was put equal to the duration of the zeros of each time interval.

This approach does not rely on any specific term structure model. Like the "key-rate duration" approach, proposed by Ho (1990), it provides a method for computing interest rate exposures (durations) and can be used with any pricing model. In this respect the notion of "factors" is different from the more rigorous one of equilibrium or arbitrage models of asset pricing, where factors must be orthogonal among themselves (i.e. not correlated). In this context, factors are identified on the basis of their observability (interest rates on specific maturities, for instance) rather than for the sake of a parsimonious specification of the model.

The interest rate exposures were estimated separately for the bond and swap portfolios. The methodology follows the Supplement to the Capital Accord of the Basle Committeee on Banking Supervision: the value of the exposure, corresponding to the 1 per cent tail probability, was therefore multiplied by the square root of ten and by three.

In order to detect biases associated with the violation of normality of returns, the absence of correlation of returns and a possibly inadequate factor specification, we compared two different volatility estimation procedures. In particular we estimated a VaR based on:

a) a stationary covariance matrix with a growing number of factors (2, 4, 8 and 12)[7] and an estimation window of increasing length, ending December 31st 1995 and going back 50, 100, 250, 500 and 1,000 working days;

b) the volatility of the historical simulation of daily profits and losses with reference to the same factor specifications of the previous case but considering only the samples of greater length (250, 500 and 1,000 days, corresponding to periods of 1, 2 and 4 years).

The results of experiment a) are reported in Tables 3 and 4 in terms of the ratio of VaR to portfolio value. The experiment shows that the increase in the number of "factors" does not significantly alter the value of the risk estimates. The result appears encouraging given the "naive" procedure followed for factor specification and confirms the "a priori" of a limited number of factors affecting the term structure. It should be confirmed by procedures, such as Ho's "key-rate duration", that do not limit each factor's influence to a single bucket. More generally, this result appears to be in line with previous tests that limit the dependence of the term structure of interest rates to no more than three factors; at the same time there are no signs that an overparametrization of the model affects the quantification of the risk exposure.

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7. The factors selected were the interest rates on Eurodeposits of 1, 6 and 12 months maturity and zero-coupon rates with maturities ranging from 2 to 10 years, computed from interest rate swap quotations.

By contrast, the sample length significantly affects the estimates of the overall volatility. This is hardly surprising since the extension of the sample period from one year (250 working days) to four years results in the inclusion of the 1992 crisis. The value at risk increases constantly with the length of the sample period for all factor specifications, thus indicating the need to base unconditional variance estimates on sample periods that are long enough to capture at least some of the extreme price occurrences.

A check on the validity of the assumption of normality is offered by the capital requirements based on the selection of the lower one percentile of profits and losses obtained by historical simulation. The results are reported in Tables 5 and 6. Whenever the reported values differ significantly from those obtained by parametric estimation, there is an indication of fat-tailed distributions. In our case the VaR based on empirical distributions exceeded the values obtained with parametric estimates by 26, 14 and 21 per cent on average in the one, two and four-year sample periods.

The effect on VaR measurement of changes in the number of factors and in the length of the sample period was also checked for a multicurrency bond portfolio. We considered for this purpose the aggregate portfolio of Italian investment firms obtained by summing the positions of all firms.[8] Previous results are confirmed as we find a richer factor specification of interest rate risk does not affect the quantification of risk exposure in this case either (Table 7). At the same time, lengthening the period over which the covariance matrix is computed generates higher value at risk.

4. The conditional estimation of portfolio variance

In this section we compare two measures of volatility which take explicit account of the time-variability of the variance of financial time series. As Dockner and Scheicher (1995) argue, the disadvantage in relying on the sample variance, used in the preceding section, is that: "it gives equal weight to all observations in the sample, thus neglecting the stronger impact of recent innovations. This is the reason why this model is not capable of mimicking volatility clustering present in financial time series".

The first measure, currently implemented in J. P. Morgan (1995), calculates the variance as a weighted average of past observations, with exponentially declining

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8. Italian investment firms report their portfolio position by maturity classes, aggregating them in 15 time bands. Non-linear postions are linearized and their delta equivalent values summed to the value of linear positions. Overall, the value of this aggregate portfolio at the end of 1995 was 4,611 billion lire. It includes positions exposed to interest rate risk denominated in lire and in foreign currencies.

weights (Exponentially Weighted Moving Average: EWMA) and can be expressed as follows:

(5) $$\sigma_t^2 = (1-\lambda)\sum_{1=0}^{n} \lambda^i (r_{t-i} - \mu)^2 \cong \lambda\sigma_{t-1}^2 + (1-\lambda)(r_{t-1} - \mu)^2$$

where *r* is the return on the investment, μ its average value and λ the weight attributed to past observations.

The second estimator of the variance is obtained from a GARCH model (Generalized Autoregressive Conditional Heteroscedasticity), which is particularly suitable for tracking the non-linear behaviour of financial series and permits account to be taken of the time-varying volatilities (heteroscedasticity) of many financial time-series. The model that we consider is a GARCH (1,1):

(6) $$Y_t = \omega + \varepsilon_t$$

(7) $$h_t = \varsigma + \varphi\varepsilon_{t-1}^2 + \beta h_{t-1}$$

and

$$E(\varepsilon_t) = 0 \qquad Var(\varepsilon_t) = h_t .$$

Equation (6) defines the conditional mean of Y_t and equation (7) gives the conditional estimate of the variance, which follows an autoregressive process that is stationary if $\varphi+\beta$ is less than 1.

GARCH modelling has been extensively applied to financial series (Barone-Adesi and Giannopoulos, 1996;

Giannopoulos and Eales, 1995, Fornari and Mele, 1995; Dockner and Scheicher, 1995). It permits the econometric estimation of the parameters that link the actual variance to the squares of past observations instead of postulating a value for the time decay factor l as in the case of the EWMA.

The choice of one of the two alternatives will be based not only on theoretical grounds, but also on the empirical results. Many empirical applications to financial series have not shown that either is preferable; in general, the superiority of GARCH largely depends on the greater flexibility of model specification that it allows with respect to the EWMA.

Volatility estimation was performed on the bond portfolio described in the previous chapter. We used the series of profits and losses generated by the 8-factor portfolio; the results do not change when the other factor specifications are considered. We calculated daily returns over the period 1993-95 by holding the composition of the portfolio fixed and letting the discount values vary. This makes it possible to preserve the distributional properties of return distributions, as shown in Barone-Adesi and Giannopoulos (1995). As regards the estimation with GARCH models, this method makes it possible to bypass the calculation of the parameters that express the value of the time-varying covariances, thereby allowing a faster convergence of the estimations. Moreover comparison between different portfolios is feasible when the composition is varied.[9]

Volatility patterns based on GARCH estimated parameters[10] and on time-decay factors, λ, of 0.78 and 0.94 for the EWMA model are reported in Figures 1 and 2. The GARCH estimates appear to be more sensitive to changes in the behaviour of the series, particularly if compared to the EWMA model with λ equal to 0.94 (Figure 2). The ability of the two models to estimate market risk has to be judged against their predictive performance.

Following Dockner and Scheicher (1995), we calculated the variance on the first 760 observations, re-estimating it recursively on a window of the same number of observations, using the naive model, the EWMA (with λ = 0.94 and an initial sample of 110 observations) and the univariate GARCH. Each run gave 10-day-ahead forecasts for the three models.[11]

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9. See Barone-Adesi and Giannopoulos (1995).

10. The GARCH (1,1) model estimation provides the following parameter values: ω= 0.004, ζ= 0.003, φ= 0.219, β= 0.625, with $\varphi+\beta$ = 0.84.

11. Following Dockner and Scheicher (1995): "Forecasting is continued by discarding 10 observations at the beginning and adding 10 at the end. Again GARCH and the sample variance are reestimated and new forecasts are computed". This method of rolling forecasts leaves a constant sample length of 760 observations. "An alternative to the rolling sample is the updated sample method, which implies a sample length that grows over time. We believe that rolling forecasts are more useful as the influence of innovations from the past is diminished".

With the EWMA model the volatility forecasts will be:

$k = 1 \qquad \hat{h}_{t+1} = 0.06\ \varepsilon_t^2 + 0.94\ h_t$

$k = 2\text{-}10 \qquad \hat{h}_{t+k+1} = h_{t+k}$

where *k* denotes the number of forecasts.

For the GARCH model, they will be:

$k = 1 \qquad \hat{h}_{t+1} = \zeta + \varphi\ \varepsilon_t^2 + \beta\ h_t$

$k = 2\text{-}10 \qquad \hat{h}_{t+k} = \zeta + (\varphi + \beta)\ h_{t+k-1}.$

The forecasting performance of the two models was evaluated using the test proposed by Pagan and Schwert (1990), which is based on the estimation of the following equation:

$$\varepsilon_t^2 = c_0 + c_1\ h_t + u_t$$

where ε^2 is the realized volatility, given by the squares of the residuals of equation (6), and *h* is the forecast. Correct forecasts are signalled by estimates of c_0 not significantly different from zero and estimates of c_1 close to 1. Moreover, the value of the R^2 can be interpreted as a measure of the variability of the forecast errors. The test results, reported in Table 8, indicate a similar performance of the two models, whereas the predictions of the naive model show a bias, related to a c_1 coefficient significantly different from 1.

More generally, the GARCH approach has the advantage of a more flexible model specification for the estimation of the appropriate time-decay factor. Since the time-decay factor is also related to the memory of the process (i.e. how many past observations influence the present value of the volatility parameter), extracting it from the entire history of returns does not involve the risk of ignoring relevant elements of information. The selection of an arbitrary λ time-decay factor, as is sometimes done in empirical applications of the EWMA, may lead to very imprecise volatility estimation. The difference in the variance estimates associated with a different choice of the autoregressive parameter (Figure 3) reveals the role of direct estimation in the selection of that parameter's value.

The foregoing considerations led us to use the GARCH(1,1) model to compute the evolution of the bond portfolio's volatility. The estimation was made on the 1,000 observations sample described in the previous paragraph (Figure 4). The results show the high variability of daily earnings at risk compared to their average value. In the period from April to December 1995 daily earnings showed large swings, with maximum values of 4.5 per cent of the portfolio value, followed by rapid convergence to a lower bound located in the neighbourhood of 2 per cent. The average value of the conditional variance estimates was 2.7 over the whole sample, as opposed to the value of 4 obtained with the unconditional estimation procedure and reported in Table 3.

5. Simulation of derivatives portfolios

In this section we explicitly consider the definition of VaR for portfolios exposed to non-linear risk, with account also being taken of the time horizon issue, i.e. whether the simple scaling of daily variations leads to severe errors in the measurement of the value at risk.

We perform our analysis in two steps: in the first we consider some portfolios with a limited number of options in order to present cases which might be particularly interesting. In the second we analyze the actual portfolio of an intermediary with a higher number of securities in order to assess the merits of the different ways of measuring risk by looking at hedged portfolios.

5.1 *Value at risk of selected strategies*

The simplest way to treat the risk exposure of option portfolios is to consider the linear approximation of the prices with respect to the underlying. For options which can be priced with the Black and Scholes formula, the linearization is particularly simple. As an example, consider a European option, maturing at time T with strike price K, on an asset whose price is S and which does not pay dividends.

The price at time t is given by:

(8) $$C(t,T) = SN(d_1) - K\exp(-r(T-t))N(d_2)$$

$$d_1 = \frac{\log(S/K) + (r - \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}, d_2 = d_1 - \sigma\sqrt{T-t}$$

where r is the short-term interest rate, $N(x)$ is the cumulative distribution of the standard normal distribution computed in x and σ is the standard deviation of the percentage variations of S.

The percentage variation in the price of the option can be approximated by:

(9) $$\frac{dC}{dS}\frac{1}{C} = \frac{N(d_1)}{C}$$

where $N(d_1)$ is the so-called delta of the option.

With linear approximation and assuming normality, the value at risk (VaR) is given by the number of standard deviations associated with a given probability level. As an approximation, the VaR can be computed considering the standard deviation of the percentage variations in the position, and multiplying it by the value of the position; for a 1 per cent probability level:

(10) $$VaR = N(d_1)\frac{S}{C}\sigma_{\frac{dS}{S}} 2.33$$

where $\sigma_{\frac{dS}{S}}$ is the standard deviation of the percentage variation of the price of the underlying. To evaluate risk with a one-day horizon, the distribution of the daily variations is considered. For longer horizons, the one-day variation is scaled up by multiplying it by the square root of the time.[12]

An alternative way to compute the risk of the position is to perform a Monte Carlo simulation. With a one-day horizon, the price of the asset is simulated a number of times from a predefined distribution. For each price realization of the underlying, the price of the option is computed, via, for example, the Black and Scholes formula. The value at risk can be obtained from the frequency distribution of the option payoffs as the loss corresponding to a given probability value.[13] For longer horizons (more than one day), a path can be simulated; based on the asset's value today, a simulation of its price tomorrow is obtained. Then, given the value tomorrow, that of the following day is generated and so on for each day in the simulation.[14]

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12. This approximation is based on the assumption of independence of price variations.

13. For example, if the 1 per cent probability level is selected, the Var is given by ordering the losses and discarding those corresponding to the first 1 per cent of the simulations. With 20,000 simulations, the Var is equal to the 200th biggest loss.

14. The usual procedure is to consider the following expression: given $S(t)$, $S(t+1) = S(t)\exp((m - \frac{1}{2}\sigma^2)dt + \sigma\varepsilon\sqrt{dt}$ where ε, in the univariate case, is extracted from a univariate standard normal distribution, m and σ are the drift and volatility parameters of

A first exercise shows the difference between the two methods in assessing the risk of one simple option. We consider a BTP futures option, of the type traded on LIFFE and MTO.[15] In Table 9 we report the simulations for both a short and a long call.[16] We generated 20,000 paths for the evaluation of each risk position. The standard deviation of the return is quite comparable with both methodologies. However, the distributions of the option payoffs are very different with the two approaches: linear approximation preserves normality but the Monte Carlo method does not. Consider, for instance, the limiting case of a call payoff at expiration. The simulated payoffs of a long position in the call give rise to the following distribution: if the simulated value of the underlying is lower than the strike price (the option is out of the money), we observe a mass point corresponding to the initial cost of the option. On the other hand, if the simulated values of the underlying are greater than the strike price (the option is in the money) the call's payoffs have a positive-valued continuous distribution. In general, Monte Carlo simulations of a long

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the process of the percentage variations of the price of the underlying.

15. Such options are American but paid on the exercise day. They can be priced as European options since the early exercise is not optimal. Furthermore, given the margining system, the effect of the short-term interest rate can be neglected. MTO is the Italian screen-based options market connected to the Italian futures market (MIF). The two contracts differ only in that the basket of bonds deliverable on the underlying futures contract is slightly different.

16. The volatility of the underlying was estimated with one year of data and was equal to 11 per cent.

(short) position in a call do not have the extreme negative (positive) values obtained with linear approximation and show lower (higher) risk exposure for long (short) positions.

The effect of the pronounced distribution difference between the two approaches are minimized for short time intervals such as a single day, but increase rapidly with the length of the simulated path. As a matter of fact the price dispersion of the underlying increases at a rate equal to the square root of time due to the independence of daily returns in the price generating process.

The combined effect of the convexity and non-normality of the option's payoffs is so strong that, for a deep out-of-the-money call (strike equal to 115), the value at risk for short positions computed with Monte Carlo simulations is almost twice that obtained with linear approximation.

Similar results apply to the value at risk associated with a put (Table 10). The risk of the short, out-of-the-money position computed with Monte Carlo simulations, is almost double that obtained with linear approximation. On the other hand, the risk of the at-the-money long position is approximately 30 per cent lower when it is computed with Monte Carlo simulations.

We then compared a portfolio of options, including at-the-money options on BTPs, Bunds and foreign currency.[17] The simulation throws light on the ability of linear approximation to take account of cross effects. The results (Table 11) show that the differences across methodologies are very pronounced for the two-week horizon, while, as in the previous exercise, linear approximation predicts a higher risk for long positions and a lower risk for short ones.

In a third exercise we compared the risk associated with standard option strategies. The first two are called spreads, i.e. combinations of short and long calls with different strikes (Table 12). In the first (bull spread), the option which is long is the one with a higher strike, while in the second (bear spread), the option which is purchased is the one with a lower spread. No significant differences are found between the risks computed with the two methods, since they are approximately balanced.

Finally, we performed a more severe test, by considering portfolios whose value should vary only for very large changes in the price of the underlying. The

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17. The portfolio included 1,000, 1,000 and 10 contracts respectively on futures on BTPs, Bunds and DMs, with at the money strikes equal to 108, 99.3 and 1,105 (prices at the end of 1995). The volatilities were respectively 11, 7.9 and 11.6 per cent. The full covariance matrix was considered in the simulations. For Monte Carlo purposes, the prices of assets were simulated by generating a random sample of 20,000 paths for each asset, the returns on which were are extracted from the joint distribution. For the linear approximation, the evaluation was made as in Section 3, where the coefficients were given by the deltas of the options.

first is the so-called straddle, where a put and a call are purchased for the same amount and at the same strike (Table 13). The second is a strangle, where a call and a put are bought for the same amount but at different strikes (Table 14). The risk which is involved is much smaller since the position is very well hedged. However, the residual risk is tracked very differently by the two methods. With straddles, even the long position leads to a risk with the Monte Carlo method that is double that obtained with linear approximation. For the short position, the two-week risk obtained with the Monte Carlo method is 20 times that computed with the alternative methodology. Very similar results are obtained for strangle positions.

5.2 *Analysis of a given portfolio*

In this exercise we consider a portfolio of exchange-traded options similar to that of some Italian intermediaries. We analyzed the portion of options on long-term bonds that includes futures options on BTPs and Bunds. The BTP part is much larger. The portfolio is almost exactly matched for both underlyings. Our task is to analyze whether the residual risk is tracked similarly by the Monte Carlo method and linear approximations.

The portfolio does not present any directional position. The Monte Carlo simulation should show whether there is significant convexity which is not disclosed by linear approximation.

The results of the exercise (Table 15)[18] suggest that the portfolio is almost perfectly hedged, not only as regards the notional amount (which is close to 0 for BTPs and 0 for Bunds) and the delta but also for convexity. The risk is modest; the higher value obtained with linear approximation may be due to the presence of some in-the-money long positions.

The results described for both simple options positions and the empirically observed portfolio reveal the importance of a careful treatment of risk when it comes to instruments with a non-linear relationship between payoffs and the prices of the underlying asset. The real life portfolio did not show a significant difference between the risk assessment of the two approaches but the earlier exercises showed that the combined effect of the convexity and non-linearity of payoffs may strongly bias the linear approximation of even extremely simple positions

6. Conclusions

This paper examines the risks associated with some real life portfolios exposed to interest rate and non-interest risk, and to linear and non-linear risk, with the aim of contributing empirical evidence to the current debate on the relative merits of different risk measurement models. Different measurement models have been used to

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18. Each option price was simulated 5,000 times. Only the one-day horizon was considered.

verify the consistency of risk assessment. Although some models are clearly not suitable for measuring certain kinds of risk exposure, the purpose of the paper was not to provide a ranking. In general, each of the models considered presents a different combination of the two desirable properties of a system of risk measurement and control: measurement precision and computational simplicity. The trade-off between these two objectives suggests that the search for a superior risk measurement system cannot be successful and that different solutions are needed for portfolios with different risk exposures.

The evidence obtained for a portfolio exposed in a linear way to interest rate fluctuations on lira-denominated assets shows that fat-tailed distributions of portfolio payoffs exert a significant influence on VaR estimates. In particular, higher risk values were obtained with models that do not impose restrictions on return distributions than with the "naive" unconditional covariance approach. On the other hand the average value of the conditional estimation of one-day value at risk was lower than the unconditional estimation (performed on the whole sample). The large swings in the VaR estimates based on conditional variance estimations leave open the issue of their practical utilization for capital requirement purposes and suggest that the presence of adjustment costs calls for caution in using such VaR indications for capital allocation purposes.

The VaR computed for selected portfolios of options provided a quantitative assessment of the considerable differences arising from a simplified approach based on the linearization of risk positions (delta method) and the results obtained with simulation techniques (Monte Carlo method). Owing to the pronounced non-normality of simulated option payoffs, these differences increase with the length of the holding period over which the VaR is measured. When applied to a balanced option portfolio that mimics the position taken by some Italian financial institutions, the two techniques did not show significant differences in the estimated VaR.

Table 1

DISTRIBUTION OF PORTFOLIO CASH-FLOWS
(present value; billions of lire)

Maturity	Bond portfolio	Swap portfolio
0-6 m	4313	15905
6-12 m	2264	-4196
1-2 y	3300	-5302
2-3 y	517	-2880
3-4 y	495	-3233
4-5 y	177	693
5-6 y	74	2342
6-7 y	95	-319
7-8 y	52	-12
8-9 y	57	-621
9-10 y	92	-267
> 10 y	43	-94

Table 2

PORTFOLIO CASH FLOWS' DURATION
(years)

Maturity	Bond portfolio	Swap portfolio
0-6 m	-0.25	-0.08
6-12 m	-0.69	0.58
1-2 y	-1.45	1.00
2-3 y	-2.36	2.23
3-4 y	-3.14	2.90
4-5 y	-4.03	-3.74
5-6 y	-5.12	-5.06
6-7 y	-5.83	5.26
7-8 y	-6.83	-8.33
8-9 y	-7.81	7.71
9-10 y	-8.74	7.58
> 10 y	-14.38	12.26

Table 3

VaR ON A BOND PORTFOLIO: COVARIANCE APPROACH
(as a percentage of portfolio value)

Number of factors	Sample length: days				
	50	100	250	500	1000
2	2.099	2.117	2.629	3.078	3.639
4	2.032	2.019	2.693	2.980	3.882
8	2.026	2.029	2.710	2.997	3.996
12	2.048	2.057	2.692	2.972	3.945

Table 4

VaR ON A SWAP PORTFOLIO: COVARIANCE APPROACH
(as a percentage of portfolio value)

Number of factors	Sample length: days				
	50	100	250	500	1000
2	13.99	14.06	16.98	20.31	21.89
4	12.94	12.96	17.95	20.54	24.38
8	14.25	14.30	18.60	21.59	24.75
12	13.76	14.30	17.95	20.23	22.98

Table 5

VaR OF A BOND PORTFOLIO: HISTORICAL SIMULATION APPROACH
(as a percentage of portfolio value)

Number of factors	Sample length: days		
	250	500	1000
2	3.634	3.712	4.378
4	3.833	4.111	4.784
8	3.946	4.318	4.709
12	3.998	4.211	4.289

Table 6

VaR OF A SWAP PORTFOLIO: HISTORICAL SIMULATION APPROACH
(as a percentage of portfolio value)

Number of factors	Sample length: days		
	250	500	1000
2	17.066	17.066	27.132
4	20.954	20.402	28.918
8	20.314	19.942	32.706
12	19.359	19.359	29.896

Table 7

VaR OF INVESTMENT FIRMS: COVARIANCE APPROACH

(as a percentage of portfolio value)

Number of factors	Sample length: days				
	50	100	250	500	1000
2	2,077	2,162	2,716	3,155	3,405
4	1,984	2,029	2,597	2,791	3,345
8	2,046	2,113	2,757	3,067	3,524

Table 8

FORECASTING PERFORMANCE OF NAIVE, GARCH AND EWMA MODELS

(in parenthesis t statistics of the null hypothesis: co=0, c1=1)

NAIVE	R^2 NAIVE	GARCH	R^2 GARCH	EWMA (0,94)	R^2 EWMA
Co = -0.15 (-2.3) C1 = 9.6 (-2.5)	$R^2 = 0.24$	Co = 0.003 (-0.5) C1 = 0.40 (-1.7)	$R^2= 0.23$	Co = 0.006 (-8.7) C1 = 0.44 (-2.1)	$R^2= 0.22$

Table 9

VaR OF A CALL OPTION

(parameters value: s = 0.11; S = 108; number of contracts = 1000)

Strike price	Monte Carlo simulation				Linear approximation			
	one day		two weeks		one day		two weeks	
	I	II	I	II	I	II	I	II
				Long position				
108	0.16	817	0.52	1958	0.16	909	0.51	2876
115	0.26	196	0.92	380	0.26	243	0.81	769
101	0.09	1535	0.29	4431	0.09	1584	0.29	5008
				Short position				
108	0.16	1017	0.52	3800	0.16	909	0.51	2876
115	0.26	302	0.92	1402	0.26	243	0.81	769
101	0.09	1648	0.29	5393	0.09	1584	0.29	5008

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Table 10

VaR OF A PUT OPTION

(parameters value: s = 0.11; S = 108; number of contracts = 1000)

Strike price	Monte Carlo simulation				Linear approximation			
	one day		two weeks		one day		two weeks	
	I	II	I	II	I	II	I	II
				Long position				
108	0.16	790	0.51	1897	0.16	870	0.49	2751
115	0.09	1504	0.28	4295	0.09	1536	0.28	4858
101	0.26	158	0.96	304	0.26	196	0.81	619
				Short position				
108	0.16	961	0.51	3666	0.16	870	0.49	2751
115	0.09	1581	0.28	5243	0.09	1536	0.28	4858
101	0.26	243	0.96	1193	0.26	196	0.81	619

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Table 11

VaR OF A PORTFOLIO CALLS ON BTP, BUND AND FOREIGN CURRENCY

(number of contracts = 1000, 1000, 10; options at the money)

Monte Carlo simulation				Linear approximation			
one day		two weeks		one day		two weeks	
I	II	I	II	I	II	I	II
Long position							
0,13	1322	0,42	3128	0,13	1336	0,42	4224
Short position							
0,13	1366	0,42	5244	0,13	1336	0,42	4224

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Table 12

VaR OF A SPREAD

(parameters: $\sigma = 0.11$; S = 108; number of contracts = 1000)

Strike price (short/long)	Monte Carlo simulation				Linear approximation			
	one day		two weeks		one day		two weeks	
	I	II	I	II	I	II	I	II
	Bull spread							
110.106	0.10	463	0.31	1338	0.10	462	0.32	1460
	Bear spread							
106.110	0.10	459	0.31	1341	0.10	462	0.31	1460

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Table 13

VaR OF A STRADDLE

(parameters: σ = 0.11; S = 108; number of contracts = 1000)

Strike price (call/put)	Monte Carlo simulation				Linear approximation			
	one day		two weeks		one day		two weeks	
	I	II	I	II	I	II	I	II
	Straddle long							
108.108	0.01	28	0.11	273	0.00	40	0.01	125
	Straddle short							
108.108	0.01	245	0.11	2236	0.00	40	0.01	125

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Table 14

VaR OF A STRANGLE

(parameters: σ = 0.11; S = 108; number of contracts = 1000)

Strike price (call/put)	Monte Carlo simulation				Linear approximation			
	one day		two weeks		one day		two weeks	
	I	II	I	II	I	II	I	II
	Strangle long							
110.106	0.02	27	0.17	258	0.01	42	0.02	132
	Strangle short							
110.106	0.02	234	0.17	2131	0.01	42	0.02	132

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Table 15

ACTUAL PORTFOLIO

Monte Carlo simulation		Linear approximation	
I	II	I	II
0.50	0.37	0.46	0.62

(I) Standard deviation of percentage daily variations.
(II) Value at risk.

Figure 1

GARCH AND EWMA VOLATILITY ESTIMATES
(annualized data)

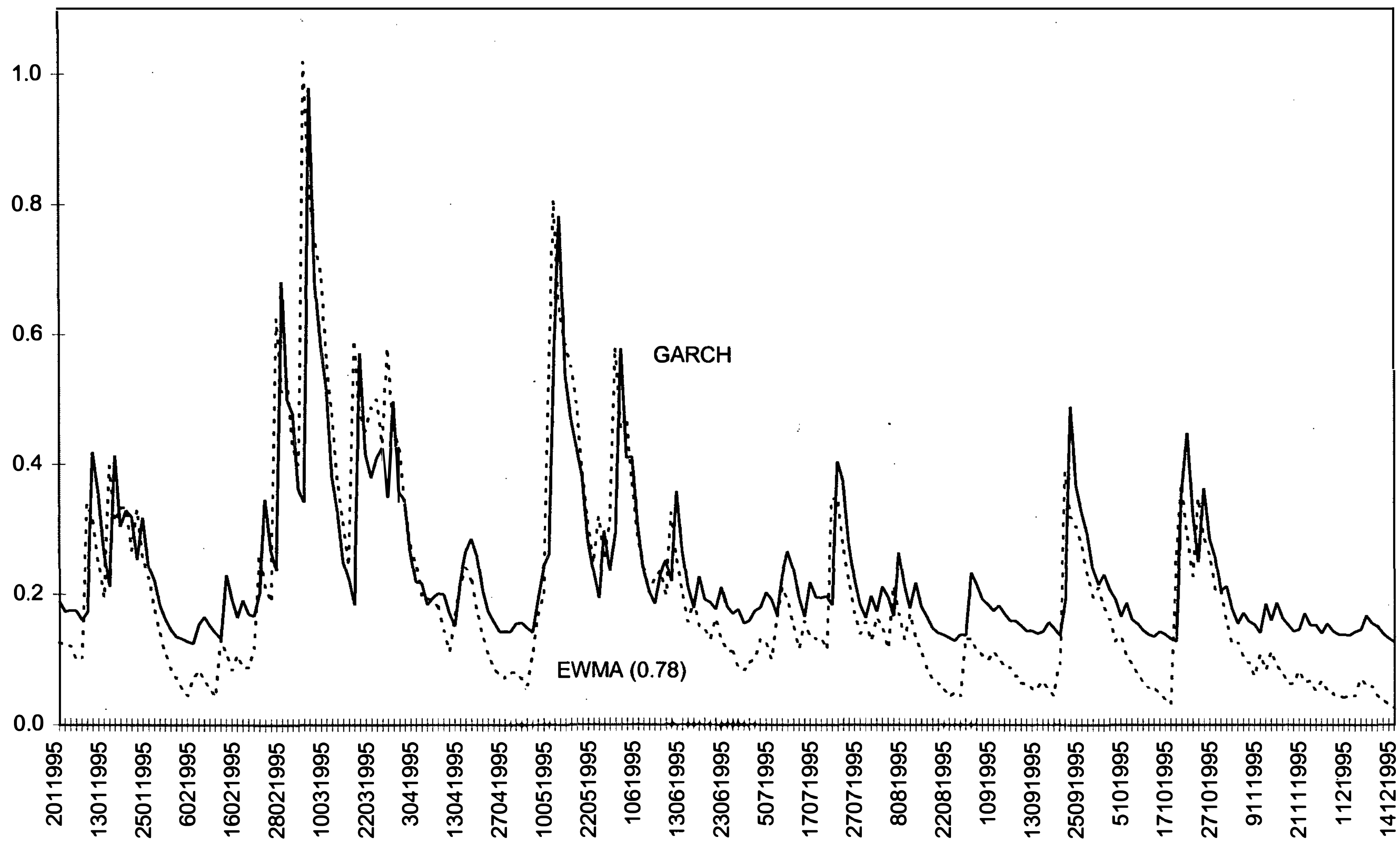


Figure 2

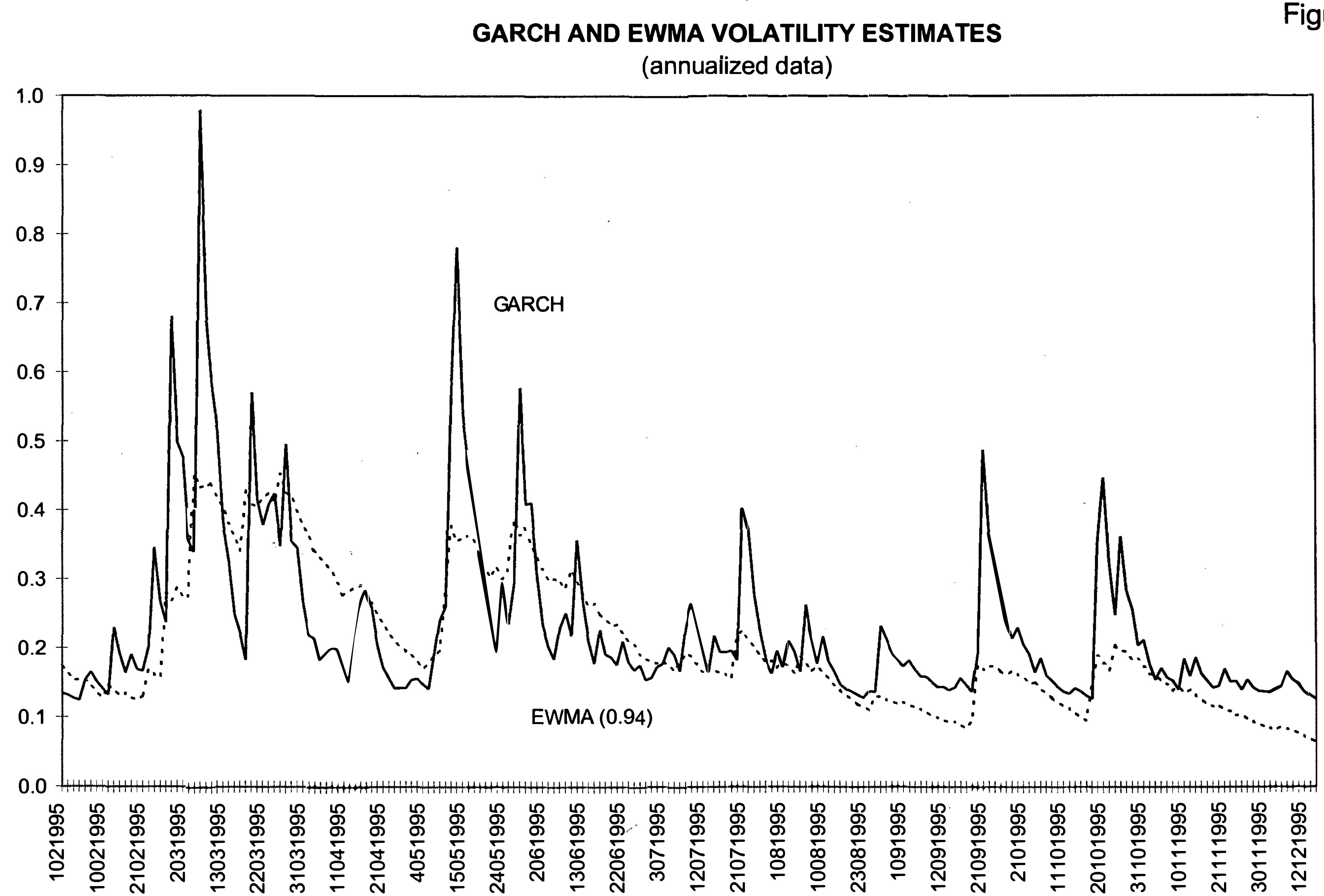
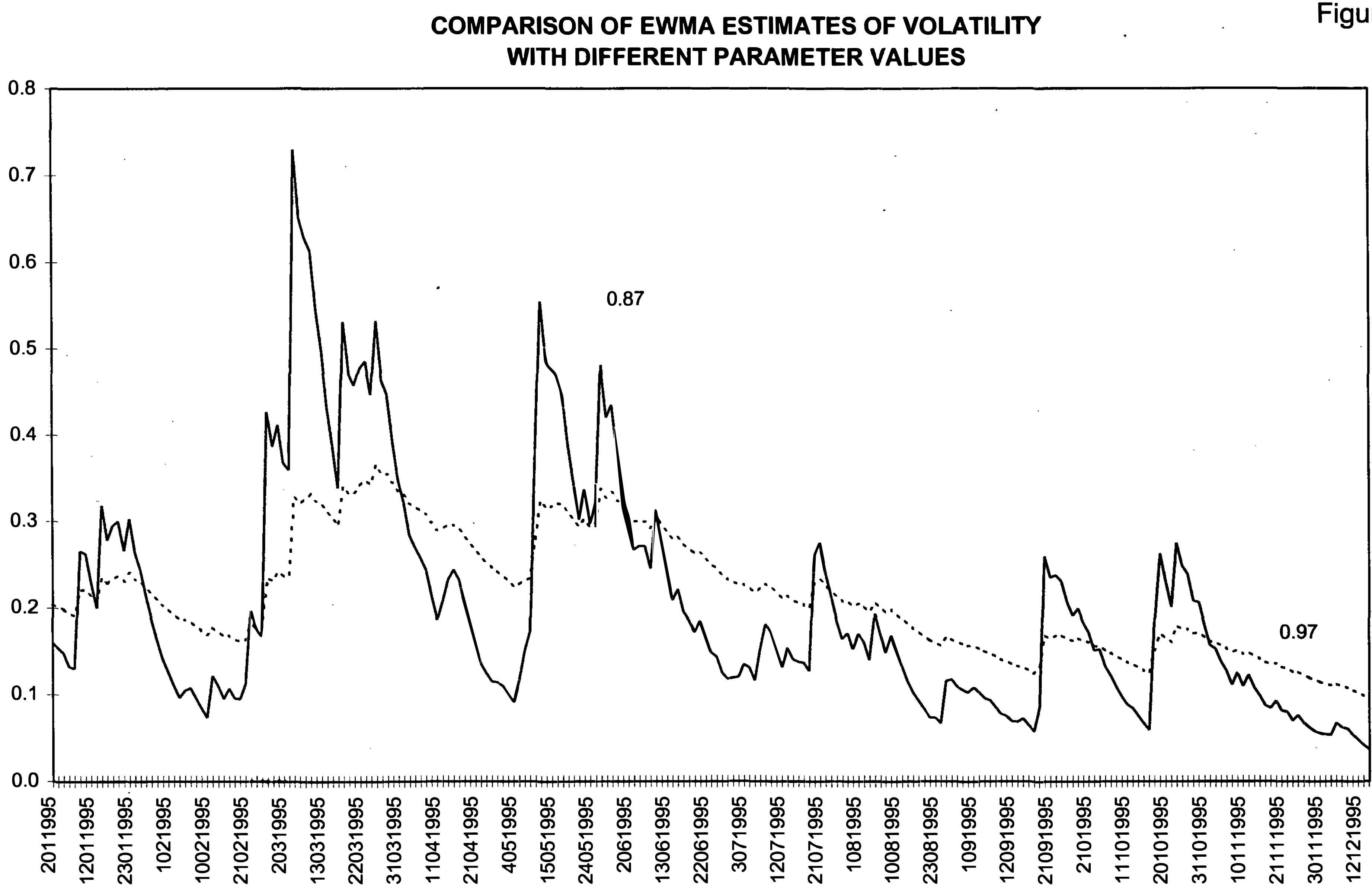

GARCH AND EWMA VOLATILITY ESTIMATES
(annualized data)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
GARCH
EWMA (0.94)
1021995
10021995
21021995
2031995
13031995
22031995
31031995
11041995
21041995
4051995
15051995
24051995
2061995
13061995
22061995
3071995
12071995
21071995
1081995
10081995
23081995
1091995
12091995
21091995
2101995
11101995
20101995
31101995
10111995
21111995
30111995
12121995

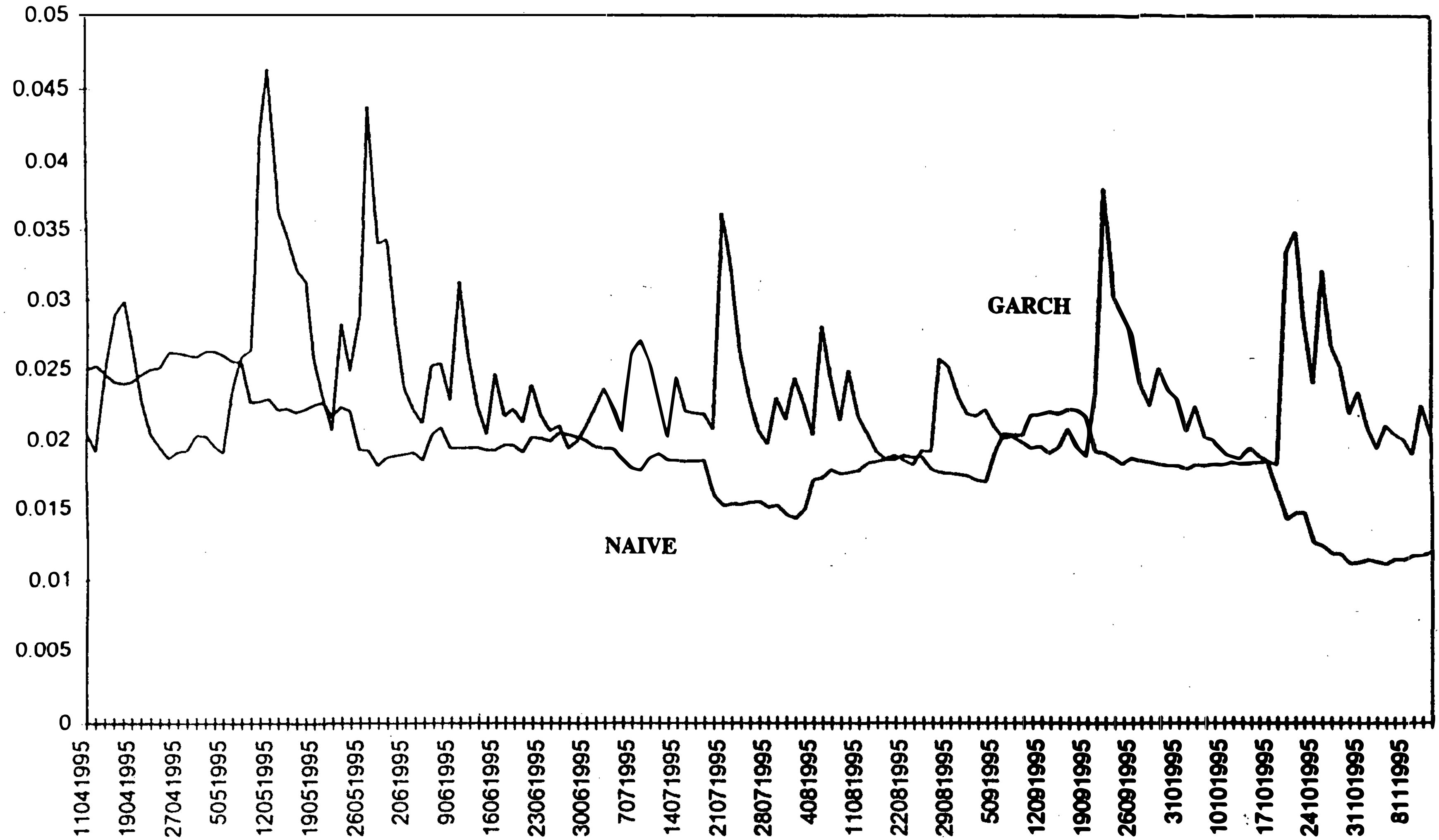
Figure 3



COMPARISON OF EWMA ESTIMATES OF VOLATILITY
WITH DIFFERENT PARAMETER VALUES
0.87
0.97
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
2011995
12011995
23011995
1021995
10021995
21021995
2031995
13031995
22031995
31031995
11041995
21041995
4051995
15051995
24051995
2061995
13061995
22061995
3071995
12071995
21071995
1081995
10081995
23081995
1091995
12091995
21091995
2101995
11101995
20101995
31101995
10111995
21111995
30111995
12121995

Figure 4

COMPARISON OF GARCH AND NAIVE MODEL ESTIMATION OF DEAR



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