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MEASURING VALUE AT RISK IN EQUITY POSITIONS

Key Words

*Value at Risk; Normal
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Abstract

This paper deals with value at risk (VAR), which is a new and popular approach to risk management. The paper describes the concept and illustrates its practical significance. Three approaches to measuring VAR are discussed: the parametric, the historical and the simulation approaches. The parametric and historical approaches are then used to calculate the VARs of portfolios consisting of shares listed on the Kuwait Stock Exchange. The results turn out to be highly sensitive with respect to the underlying assumptions. Since empirical testing reveals that the rates of return are not normally distributed, we tend to give more credibility to the VAR estimates obtained by using the historical approach.

Introduction

Value at risk (VAR), also called capital at risk, has in a relatively short time been established as a popular, or perhaps the most popular, device for measuring and consequently controlling financial risk⁽¹⁾. Indicative of its popularity and acceptability is the fact that the Bank for International Settlements has allowed banks to use their internal models of risk in setting capital requirements for market risk, provided that the models are based on the VAR methodology.

There are, however, mixed feelings towards this methodology. The concept of VAR is appealing in terms of simplicity, because it summarizes the risk of an entire portfolio in a single number indicating the potential decline in the value of the portfolio (or the security). However, this concept has been described by Beder (1995) as being "seductive but dangerous" in the sense that it is based on what could be unrealistic assumptions to the extent that the results could be misleading. Moreover, the results are highly sensitive with respect to the underlying assumptions.

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(1) Although VAR is primarily used to measure market risk, it can be modified to measure credit risk.

VAR is an estimate of the potential loss resulting from an adverse market movement over a specific time horizon or holding period. For example, if the underlying position is a long bond position, then an adverse market movement results if interest rates rise. If, on the other hand, it is a long equity position then an adverse movement is a fall in stock prices. Finally, a depreciation of a currency is an adverse market movement for a long position in the same currency.

The objective of this paper is to measure the value at risk in equity positions involving portfolios composed of the shares listed on the Kuwait Stock Exchange, including the shares of Kuwaiti and non-Kuwaiti (foreign) companies. For this purpose, we will use daily data from which we calculate the volatility as measured by the standard deviation of the daily rate of return and subsequently the value at risk. Before this task is undertaken, we will present a description of the VAR methodology.

The Concept of VAR

The objective of VAR analysis is to answer the following question: with a given probability, how much money is likely to be lost over the next day, week or whatever time horizon we have in mind. Let K be the value of the portfolio and α be the chosen probability. The VAR is then defined by the equation

$$Pr(\Delta K \leq -VAR) = \alpha \quad (1)$$

Equation (1) says that the probability that the loss resulting from the change in the value of the portfolio will not exceed VAR is equal to α which is specified a priori. This means that to calculate VAR three ingredients are required:

1. A unit of account, which is normally a currency. In this paper the unit of account is the Kuwaiti dinar (KD).
2. A probability, which normally ranges between one and five per cent. In this study we use two probabilities: one per cent and 2.5 per cent.
3. A time horizon which could be a day, a week (five trading days), two weeks, etc. Normally the choice depends on the liquidity of the assets in the portfolio, but it is assumed that the portfolio composition is maintained during the specified time horizon. For regulatory purposes, the time horizon should be sufficiently long for the authorities to detect potential problems.

The VAR methodology is relatively new, having been developed in the 1990s. In August 1994 the U.S. Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) formed a study group called the Derivatives Policy Group (DPG) to study the issue of risk measurement and control. The DPG released its methodology and recommendations in March 1995. At the same time, J.P. Morgan was developing its *Risk Metrics*, which was released in October 1994. The models developed by the DPG and J.P. Morgan can be used to calculate total risk by estimating the changes in portfolio values if certain scenarios occur. Both of the models are used to calculate VAR. In April 1995, the Basel Committee on Banking Supervision announced that it would base capital adequacy requirements on measures of VAR. Finally, in December 1995 the SEC issued a proposal that requires publicly traded U.S. companies to disclose information about derivatives

activity with VAR being one of the methods used for the measurement of risk.

For capital adequacy, VAR is compared with shareholders' equity. The concept is also useful for investors contemplating buying shares in a particular company. In this case the VAR is compared with the profit generated by the company. Other practical uses of VAR include the following: (i) setting position limits for traders, (ii) measuring return on a risk-adjusted basis, (iii) evaluating the performance of external portfolio managers and (iv) providing a convenient measure of the effect of hedging on total risk.

Estimation of VAR: Methodology

Once the three ingredients required to calculate VAR have been determined, it is possible to proceed by calculating the rate of return over the time horizon chosen for this purpose. This is followed by the construction of an empirical frequency distribution for the rate of return from which VAR is calculated.

Assume that the daily observations of stock prices at points in time (days) ranging between 0 and n are p_0, p_1, \dots, p_n . A one-day (or daily) rate of return in percentage terms is defined as

$$r_t = 100 \left(\frac{p_t - p_{t-1}}{p_{t-1}} \right) \tag{2}$$

for $t = 1, 2, \dots, n$.⁽²⁾ The mean of the rate of return is given by

$$\bar{r} = \frac{1}{n} \sum_{t=1}^n r_t \tag{3}$$

while the standard deviation, which measures volatility, is calculated as

$$\sigma = \sqrt{\frac{\sum_{t=1}^n (r_t - \bar{r})^2}{n-1}} \tag{4}$$

Suppose now that we have a portfolio consisting of m shares with weights w_1, w_2, \dots, w_m . The mean and standard deviation of the rate of return on the portfolio are given respectively by

$$\bar{r}(p) = \sum_{i=1}^m w_i \bar{r}_i \tag{5}$$

and

$$\sigma(p) = \sqrt{\sum_{i=1}^m w_i^2 \sigma_i^2 + \sum_{i \neq j}^m \sum_{i \neq j}^m w_i w_j \sigma_i \sigma_j \rho_{ij}} \tag{6}$$

where ρ_{ij} is the correlation coefficient between the rates of return on shares i and j . Once the mean and standard deviation have been calculated, it is possible to estimate the VAR of a security or a portfolio by using one of the approaches which have been suggested in the literature (see, for example, Beder, 1995; Simons, 1996; Hendricks, 1996).

The Parametric Approach

This approach is simple but it cannot handle nonlinear positions such as those involving options which produce asymmetric payoffs. The main assumption of this approach, which is also known as the variance-covariance approach, is that the rate of return is normally distributed, which means that the percentiles are known as multiples of the standard deviation. Table 1 shows some ranges of the values, which the rate of return can assume with certain probabilities under normality. It shows, for example, that 98 per cent of the values of the rate of return fall within 2.33 standard deviations of the mean, implying that the lowest value that the rate of return can take is the mean minus 2.33 standard deviations.

(2) In general, a k -day rate of return can be calculated by replacing P_{t-1} by P_{t-k} .

Table 1
The Implications of a Normally Distributed Rate of Return

Per cent	Lowest Value	Highest Value
68	$\bar{r} - \sigma$	$\bar{r} + \sigma$
90	$\bar{r} - 1.65\sigma$	$\bar{r} + 1.65\sigma$
95	$\bar{r} - 1.96\sigma$	$\bar{r} + 1.96\sigma$
98	$\bar{r} - 2.33\sigma$	$\bar{r} + 2.33\sigma$
99	$\bar{r} - 3\sigma$	$\bar{r} + 3\sigma$

To calculate the VAR at a probability of one per cent, we know that the maximum loss would be incurred if the rate of return assumes the lowest value, $\bar{r} - 2.33\sigma$, and hence the one per cent VAR will be equal to this value

multiplied by the value of the portfolio. Table 2 shows the VARs for a security or a portfolio with a nominal value of K at various probabilities corresponding to the percentiles listed in the first column of Table 1.

Table 2
The VAR at Selected Probabilities under Normality

Per cent	Probability (per cent)	VAR
68	16.0	$K(\bar{r} - \sigma)$
90	5.0	$K(\bar{r} - 1.65\sigma)$
95	2.5	$K(\bar{r} - 1.96\sigma)$
98	1.0	$K(\bar{r} - 2.33\sigma)$
99	0.5	$K(\bar{r} - 3\sigma)$

By making the assumption of serial independence, we can calculate the VARs for longer periods from daily VARs directly. This is because serial independence implies that the k -day standard deviation is equal to the square root of k multiplied by the daily standard deviation. Hence, the k -day VAR is equal to the square root of k multiplied by the one-day VAR. If serial correlation is present then VARs for longer periods must be calculated first by calculating the relevant rates of return themselves.

There are two problems with the parametric approach: the assumption of normal-

ity and the assumption of constant volatility (i.e. constant standard deviation). Let us start with the assumption of normality. Since the work of Mandelbrot (1963) and Fama (1965) most empirical studies of the statistical properties of asset returns have provided evidence for systematic deviations from normality. In particular, studies have found that distributions of asset returns are skewed to the left (i.e. there are more negative values than under a normal distribution), they exhibit excess kurtosis (i.e. they are more peaked at the mean value) and (iii) they have fat tails.⁽³⁾ Jorion (1996) suggests a method to deal with

(3) See also Mills (1993) and Taylor (1986).

the presence of fat tails by constructing a t distribution where the degrees of freedom control the size of the tails. As the degrees of freedom grow large, the distribution converges on normal. Fong and Vesicek (1997), on the other hand, suggest using the gamma distribution.

The second problem with the parametric approach is the variability of the standard deviation. By calculating the standard deviation from a data set covering a long period of time, we implicitly assume that the standard deviation is constant throughout the sample period. However, the standard deviation can change, sometimes quite abruptly, and so it may be a good idea to assign more weight to more recent observations. This boils down to calculating the standard deviation through the exponential smoothing of observations. In this case the standard deviation is given by

$$\sigma = \sqrt{(1 - \lambda) \sum_{t=1}^n \lambda^t (r_{n-t} - \bar{r})^2} \quad (7)$$

where λ is the decay factor such that the larger the value of λ the slower is the rate of decay and the heavier is the weight assigned to more distant observations.

The Historical Approach

In the case of the historical approach there is no need for the assumption of normality. This approach is based on the use of historical data on the rate of return to construct a frequency distribution and consequently to extract the percentiles. To calculate the VAR at one per cent, we need to identify the lowest percentile or 1% of the values of the rate of return. If the value of the percentile is f , then the one per cent VAR is given by fK . Since it has been found that the frequency distribu-

tions of asset returns have fatter tails than what is implied by the normal distribution, it is likely that this approach produces larger VARs than the parametric approach.

While the historical approach is preferable to the parametric approach, because it makes no assumption about the frequency distribution, it lacks the flexibility because it does not allow one to try different values for the standard deviation and correlation and to test the sensitivity of VAR to these parameters. Moreover, while the historical approach requires the actual historical data, the parametric approach only requires the parameters of the distribution which may be calculated from data covering a different sample period.

The Simulation Approach

This approach can handle nonlinear positions. It provides an alternative to calculate VAR in the absence of historical data. Simulation can be either historical, depending on the historical data of the relevant risk factors, or stochastic (Monte Carlo) which derives the values of the risk factors by specifying the parameters of their frequency distributions. In both cases the rate of return is generated and the values are used to construct empirical frequency distributions for the rate of return.

The risk factors are the characteristics or the factors that affect the value of a security or a portfolio. For example, the risk factors that are relevant to an option position are all of the variables that are incorporated in the Black-Scholes pricing formula. In general there is a relationship between the rate of return and the risk factors which may take the quadratic form

$$r_t = \sum_{i=1}^m a_i X_{i,t} + \sum_{i=1}^m b_i X_{i,t}^2 \tag{8}$$

Hence, if we have the historical data on (or the frequency distribution of) the risk factors X_i 's, a frequency distribution can be constructed for the rate of return and we can then proceed as previously to calculate the VAR.

Testing for Normality

To compare the reliability of the VAR estimates obtained by using the parametric approach with those obtained by using the historical approach we test the hypothesis that the rate of return is normally distributed. For this purpose, the following testing procedure is used.

Let μ and σ^2 be the mean and variance of the rate of return respectively. If

$$\mu_i = E(r - \mu)^i \tag{9}$$

it follows that

$$\sigma^2 = \mu_2 \tag{10}$$

The skewness and kurtosis of the rate of return are defined respectively as

$$\sqrt{\beta_1} = \frac{\mu_3}{\mu_2^{3/2}} \tag{11}$$

and

$$\beta_2 = \frac{\mu_4}{\mu_2^2} \tag{12}$$

The sample counterparts are

$$m_i = \frac{1}{n} (r_t - \bar{r})^i \tag{13}$$

$$\sqrt{b_1} = \frac{m_3}{m_2^{3/2}} \tag{14}$$

and

$$b_2 = \frac{m_4}{m_2^2} \tag{15}$$

For the rate of return to be normally distributed the following hypotheses must not be rejected

$$\sqrt{\beta_1} = 0 \tag{16}$$

and

$$\beta_2 = 3 \tag{17}$$

The corresponding test statistics are

$$s = \frac{n(\sqrt{b_1})^2}{6} \tag{18}$$

and

$$k = \frac{n(b_2 - 3)^2}{24} \tag{19}$$

which are distributed as $\chi^2(1)$.

A joint test for normality which is based on skewness and kurtosis is the Bowman-Shenton (1975) test. The test statistic, which has an $\chi^2(2)$ distribution, is calculated as

$$N_{BS} = s + k \tag{20}$$

Another joint test for normality is the Doornik-Hansen (1994) test. This test is based on Shenton and Bowman (1977), who give b_2 (conditional on $b_2 > 1 + b_1$) a gamma distribution, and D'Agostino (1970) who approximates the distribution of $\sqrt{b_1}$ by the Johnson S_u system. If s^* and k^* are the transformed skewness and kurtosis respectively, then the test statistic is given by

$$N_{DH} = s^* + k^* \tag{21}$$

which again has an $\chi^2(2)$ distribution.

Empirical Results

In this section we present the results of estimating VARs for KDI million portfolios consisting of shares listed on the Kuwaiti

Stock Exchange. We also report the results of testing for normality. The portfolios are taken to correspond to the ten stock price indices (prepared by the Kuwait Investment Company) of the whole market, Kuwaiti companies, foreign companies and various sectors of the Kuwaiti companies. Thus, we have the following portfolios: (i) market portfolio, A1; (ii) Kuwaiti companies, A2; (iii) banks, A3, (iv) investment companies, A4; (v) insurance companies, A5; (vi) real estate companies, A6; (vii) manufacturing companies, A7; (viii) services companies, A8; (ix) food companies, A9; and (x) foreign companies, A10 (see the appendix). Moreover, we will also show how the VARs of combinations of these portfolios can be calculated.

For this purpose we use a sample of 1130 daily observations on the stock price indices corresponding to the ten portfolios. This sample covers the period between 3 January 1993 and 2 August 1997. The following results will be presented in turn:

1. The basic statistics of the rates of return on the ten portfolios over the whole sample period.
2. The results of testing for normality.
3. The correlation matrix of these rates of return estimated over the whole sample period.
4. The estimated 1% and 2.5% VARs of the portfolios based on the parametric approach, using the parameters calculated over the whole sample period.
5. Estimates of the VARs of other portfolios that can be constructed by combining the original ten portfolios.
6. The means and standard deviations of the rates of return using sub-sample

periods that extend to the most recent observations.

7. The estimated 1% VARs of the portfolios based on the means and standard deviations estimated over the sub-sample periods.
8. The estimated 1% and 2.5% VARs using the historical approach.

We start with a graphical description of the daily rates of return over the whole sample period as shown in Figures 1-10. Each figure shows the actual behavior of the rate of return as well as a histogram describing the frequency distribution. A normal curve is superimposed on the frequency distribution to give some idea of the deviation, or otherwise, from normality. Table 3 reports the basic statistics of the rates of return on the ten portfolios. These statistics include the mean, standard deviation, skewness, excess kurtosis as well as the Box-Pierce (Q) test statistics for serial correlation for lags of one and ten days. The test statistics are distributed as $\chi^2(1)$ and $\chi^2(10)$ respectively. Two important observations can be made on the basis of these results. The first is that the skewness and excess kurtosis indicate that the rates of return are unlikely to be normally distributed, a proposition that is supported by the shapes of the frequency distributions shown in Figures 1-10. The second is that there seems to be strong evidence for serial correlation in all cases. The implications of these observations respectively are that the parametric approach may underestimate the VARs, and that it is not possible to estimate k -day VARs directly from the daily VARs.

Table 3
Basic Statistics of Daily Rates of Return (Whole Period)

Portfolio	Mean	Standard Deviation	Skewness	Excess Kurtosis	Q(1)	Q(10)
A1	0.06472	0.65799	0.05	4.26	27.63	41.29
A2	0.06886	0.88688	1.02	86.61	6.17	9.48
A3	0.04243	0.98996	0.36	5.15	7.02	17.93
A4	0.13973	1.08060	-0.18	20.32	1.34	8.00
A5	0.04311	0.96243	-0.03	9.54	0.05	26.52
A6	0.15489	1.14360	0.78	2.95	64.39	77.89
A7	0.07334	1.08610	-0.07	32.65	43.41	61.60
A8	0.11984	1.10050	0.53	4.69	15.02	27.68
A9	0.06754	1.09480	0.71	7.14	40.97	49.68
A10	0.04626	0.63740	0.82	7.90	50.00	64.65

Table 4 reports the results of testing for normality. The results show that the joint Bowman-Shenton and Doornik-Hansen tests decisively reject normality. The results also show that the test based on kurtosis rejects

normality in all cases. Only in three cases (A1, A5 and A7) does the frequency distribution have skewness, which is close to the skewness of a normal distribution. Thus, we conclude that the rates of return are not normally distributed.

Table 4
Results of Testing for Normality

	s	k	N_{BS}	N_{DH}
A1	0.5	852.5	853.0	378.4
A2	197.1	352830.0	353030.0	11435.0
A3	24.5	1245.5	1270.0	445.9
A4	6.1	19437.0	19433.0	2657.7
A5	0.1	4278.6	4278.7	1107.3
A6	113.3	409.9	523.2	127.6
A7	1.0	50147.0	50148.0	4410.0
A8	53.2	1036.2	1089.4	341.3
A9	93.5	2399.6	2493.1	560.1
A10	125.6	2935.7	3061.3	589.1

Table 5 reports the correlation matrix of the rates of return. It can be seen that there are no negative correlations, implying that the VAR of a portfolio consisting of the ten basic portfolios cannot be less than the sum of the VARs of the individual portfolios. It can be

seen from the correlation matrix that returns on foreign shares are weakly correlated with any of the other sectors, but even within the various sectors of Kuwaiti shares correlations are generally low.

Table 5
Correlation Matrix of the Rates of Return

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	1.00									
A2	0.77	1.00								
A3	0.91	0.71	1.00							
A4	0.39	0.30	0.22	1.00						
A5	0.22	0.15	0.13	0.07	1.00					
A6	0.48	0.38	0.33	0.31	0.08	1.00				
A7	0.32	0.24	0.09	0.15	0.05	0.15	1.00			
A8	0.45	0.35	0.28	0.18	0.05	0.20	0.15	1.00		
A9	0.23	0.20	0.13	0.13	0.07	0.16	0.08	0.07	1.00	
A10	0.17	0.08	0.09	0.09	0.05	0.09	0.03	0.06	0.07	1.00

Table 6 reports the 1% and 2.5% VARs using the estimates of the means and standard deviations given in Table 3. Take the market portfolio, A1, for example: The estimated VAR tells that there is a one percent chance that the daily loss on a KD1 million market portfolio will exceed KD14,684 and a two and

a half percent chance that the daily loss will exceed KD12,294. The highest VAR is found for A9, the portfolio of food companies' shares, while the lowest VAR is found in the case of the foreign companies' portfolio. Notice that VAR is not necessarily proportional to the standard deviation.

Table 6
Estimated VARs on KD1 million Portfolios

Portfolio	1%	2.5%
A1	14,684	12,249
A2	19,976	16,694
A3	22,641	18,979
A4	23,781	19,782
A5	21,994	18,432

Table 6
Estimated VARs on KDI million Portfolios (cont.)

Portfolio	1%	2.5%
A6	25,096	20,866
A7	24,573	20,554
A8	24,443	20,371
A9	24,833	20,783
A10	14,389	12,030

The VARs reported in Table 6 can be used to calculate the VAR on any combination of the portfolios. Suppose, for example, that we have a KDI million portfolio in Kuwaiti

shares, A2, and a similar size portfolio in foreign shares, A10. To calculate the combined VAR we utilize the equation:

$$\text{VAR}(A2 + A10) =$$

$$\sqrt{[\text{VAR}(A2)]^2 + [\text{VAR}(A10)]^2 + 2\text{VAR}(A2) \text{VAR}(A10) \rho(A2, A10)} \quad (22)$$

where $\rho(A2, A10)$ is the correlation coefficient between the rates of return on portfolios A2 and A10. Since $\text{VAR}(A2) = 19,976$, $\text{VAR}(A10) = 14,389$, and the correlation coefficient is equal to 0.08, it follows that .

$$\text{VAR}(A2 + A10) = 25,536.$$

To estimate the sensitivity of the VAR estimates with respect to the choice of the period chosen to calculate the mean and standard deviation, we estimate the means and standard deviations using sub-sample periods. These periods consist of the following, starting from the most recent observation: (i) the last 201 observations (930 to 1130), (ii) the last 401 observations (730 to 1130), (iii) the last 601 observations (530 to 1130), (iv) the last 801 observations (330 to

1130) and (v) the last 1001 observations (130 to 1130). The choice of these sub-samples is arbitrary as it is intended to be used for illustrative purposes only. Table 7 reports the means and the standard deviations over the five sub-sample periods. Most of the portfolios show an increase in volatility over the recent period. For example, the standard deviation of portfolio A2 (Kuwaiti companies) is 1.52640 when it is estimated from the last 201 observations, but it is 0.88532 when it is estimated over the last 1001 observations. Some other portfolios, such as A7, show a decline in volatility. What is important here is that the estimated standard deviation can differ significantly over time and this is bound to affect the estimated VAR.

Table 7
Means and Standard Deviations Estimated over Sub-Sample Periods

	930-1130	730-1130	530-1130	330-1130	130-1130
Mean					
A1	0.05849	0.09972	0.10174	0.07682	0.06663
A2	0.11323	0.11171	0.10994	0.08292	0.07131
A3	0.07083	0.09716	0.08669	0.06224	0.04286

Table 7 (Cont.)
Means and Standard Deviations Estimated over Sub-Sample Periods (cont.)

	930-1130	730-1130	530-1130	330-1130	130-1130
A4	0.17754	0.19600	0.17846	0.13634	0.13860
A5	0.06433	0.09971	0.09918	0.07780	0.06327
A6	0.22263	0.20805	0.20666	0.17324	0.15440
A7	0.08300	0.04437	0.08985	0.06808	0.07855
A8	0.10932	0.07808	0.10305	0.08443	0.09693
A9	0.01969	0.03608	0.04933	0.03905	0.07040
A10	0.01447	0.03009	0.05494	0.04310	0.04515
<u>Standard Deviation</u>					
A1	0.71945	0.61086	0.63277	0.59714	0.62766
A2	0.15264	1.13890	1.01340	0.91204	0.88532
A3	0.99944	0.92211	0.97422	0.91693	0.95537
A4	1.09690	1.01280	0.97256	0.92369	0.97431
A5	1.12440	1.12660	1.12440	1.03040	0.96505
A6	1.26420	1.04100	1.04300	0.97354	1.10310
A7	0.92314	0.83909	1.01360	0.95795	1.02150
A8	1.26890	1.20450	1.08970	1.00230	1.05660
A9	1.03830	1.01740	1.03130	1.02530	1.10480
A10	0.48311	0.50836	0.69947	0.63766	0.64306

Based on the means and standard deviations reported in Table 7, Table 8 reports the 1% VARs. It can be seen that the results differ significantly. For example, the VAR arising from portfolio A2 ranges between KD19,914

and KD34,432. The question that arises then is the following: which one? This question actually portrays one of the problematic features of the VAR methodology.

Table 8
One Per Cent VAR Estimates Based on Various Values of Means and Standard Deviations

Portfolio	930-1130	730-1130	530-1130	330-1130	130-1130
A1	15,805	13,236	13,726	13,145	13,958
A2	34,432	25,419	22,513	20,421	19,914
A3	22,579	20,514	21,832	20,742	21,832

Table 8 (Cont)
One Per Cent VAR Estimates Based on
Various Values of Means and Standard Deviations (cont.)

Portfolio	930-1130	730-1130	530-1130	330-1130	130-1130
A4	23,782	21,638	20,876	20,159	21,315
A5	25,555	25,253	25,207	23,230	21,853
A6	27,230	22,175	22,235	20,951	24,162
A7	20,679	19,107	22,718	21,639	23,015
A8	28,472	27,284	24,360	22,509	23,649
A9	23,996	23,345	23,536	23,499	25,038
A10	11,112	11,544	15,748	14,426	14,532

The final set of results pertains to the estimated 1% and 2.5% VARs using the historical approach. In this case we use the historical data to calculate the median of the lowest one and two and a half percent values of the rate of return. When these are identified, the VARs are calculated by multiplying these values by the value of the portfolio. Table 9 reports the VARs calculated on the

basis of this approach. It is obvious that the VARs based on the historical approach are larger than those calculated on the basis of the parametric approach. We tend to believe that these values are more reliable in the sense that they reflect more accurately the potential behavior of the rate of return. We have already seen that this behavior does not conform to normality.

Table 9
VARs Estimates Based on the Historical Approach

Portfolio	1 Per Cent		2.5 Per Cent	
	<i>f</i>	<i>VAR</i>	<i>f</i>	<i>VAR</i>
A1	-2.8322	28,322	-2.5172	25,172
A2	-7.1082	71,082	-6.7450	67,450
A3	-4.1255	41,255	-3.7133	37,133
A4	-6.9328	69,328	-6.6042	66,042
A5	-4.4840	44,885	-3.7956	37,956
A6	-3.4915	34,915	-3.1000	31,000
A7	-7.8595	78,595	-7.6116	76,116
A8	-4.0276	40,276	-3.7784	37,784
A9	-4.7462	47,462	-4.2560	42,560
A10	-2.4645	24,645	-2.1887	21,887

Concluding Remarks

Value at risk has become a widely-used method for measuring financial risk and justifiably so. The attractiveness of the concept lies in its simplicity as it measures the market risk of the entire portfolio in one number which is easy to comprehend. It thus conveys a simple message on the risk borne by an institution. The concept is also suitable for risk limit setting and for measuring performance based on the correlation between the return earned and the risk assumed. It can also take account of complex movements such as a non-parallel yield curve.

There are, however, several shortcomings associated with this methodology. First, it can be misleading to the extent of leading to unwarranted complacency. And, as we have seen, the VAR is highly sensitive to the assumptions used to calculate it. Jorion (1996) argues that VAR is a number which itself is measured with some error or estimation risk. Thus, the VAR results must be interpreted with reference to the underlying statistical methodology. Moreover, this approach to risk management cannot cope with

sudden and sharp changes in market conditions. It neglects the possibility of discrete, large jumps in prices. Losses resulting from catastrophic occurrences are overlooked due to dependence on symmetric statistical measures which evaluate upside and downside risk equally.

Given the choice between the parametric and historical approaches, we tend to assign more credibility to the results based on the historical approach. This is because it has been demonstrated, and the results of this study have shown, that rates of return are not normally distributed. The results have also shown that the VAR estimates based on the historical approach are larger than those based on the parametric approach.

VAR is useful but it should be handled with care and should be used in conjunction with other measures of risk. For example, it can be complimented by a series of stress tests which account for extremely unfavorable market conditions. It is imperative, however, that VAR should not be viewed as a strict upper bound on the portfolio losses that can occur.

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المخلص

قياس القيمة المعرضة للخطر في محافظ الأوراق المالية

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يتعلق هذا البحث بمفهوم «القيمة المعرضة للخطر»، وهو أسلوب جديد نسبياً لإدارة المخاطر، حيث يتناول وصف هذا المفهوم ويبين أهميته التطبيقية. ويتناول أيضاً، يتناول بالشرح ثلاثة مداخل لقياس «القيمة المعرضة للخطر» هي: المدخل المعلمي والمدخل التاريخي ومدخل المحاكاة. وقد تم استخدام المدخلين المعلمي والتاريخي لحساب «القيمة المعرضة للخطر» لمحافظ مكونة من أسهم مدرجة في سوق الكويت للأوراق المالية. وجاءت النتائج شديدة الحساسية للافتراضات ذات الصلة. وحيث أن هذه النتائج قد كشفت عن أن عوائد الأسهم لا تنتمي إلى التوزيع الطبيعي، فإن إعطاء مصداقية أكبر «للقيم المعرضة للخطر» التي تم إيجادها باستخدام المدخل التاريخي هو المرجح.

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Appendix

Figure 1 : Market Portfolio (A1)

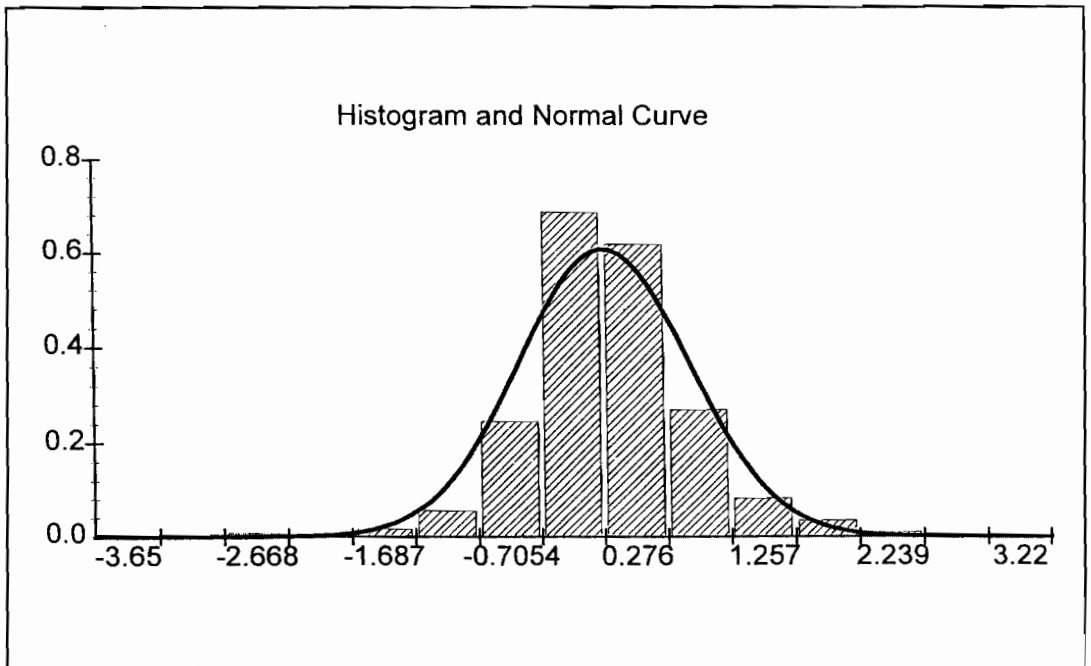
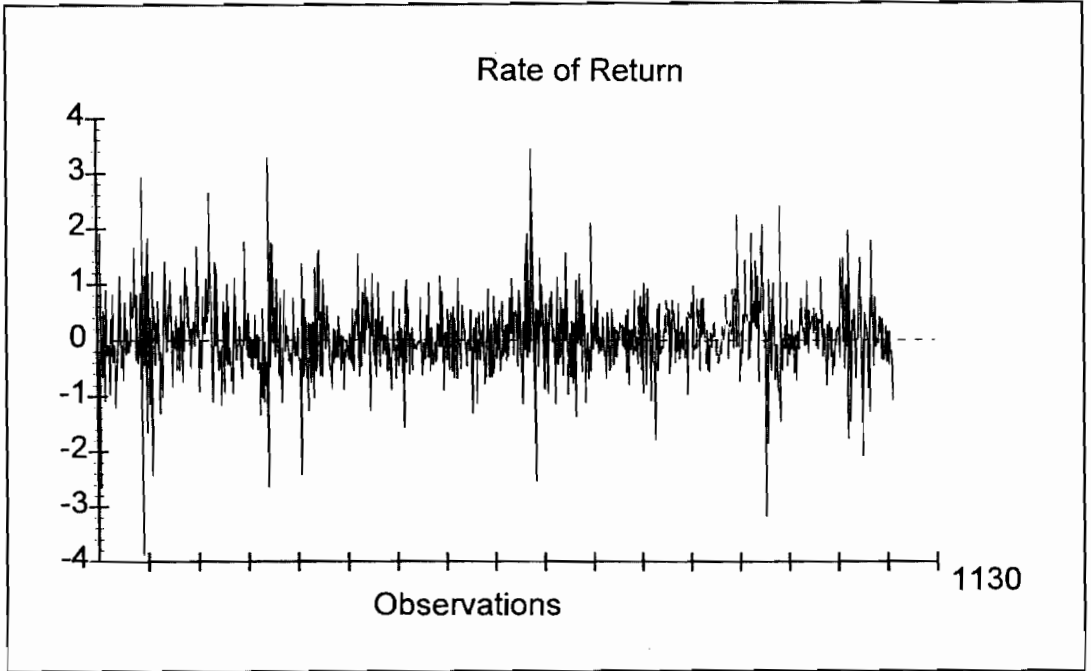


Figure 2 : Kuwaiti Companies (A2)

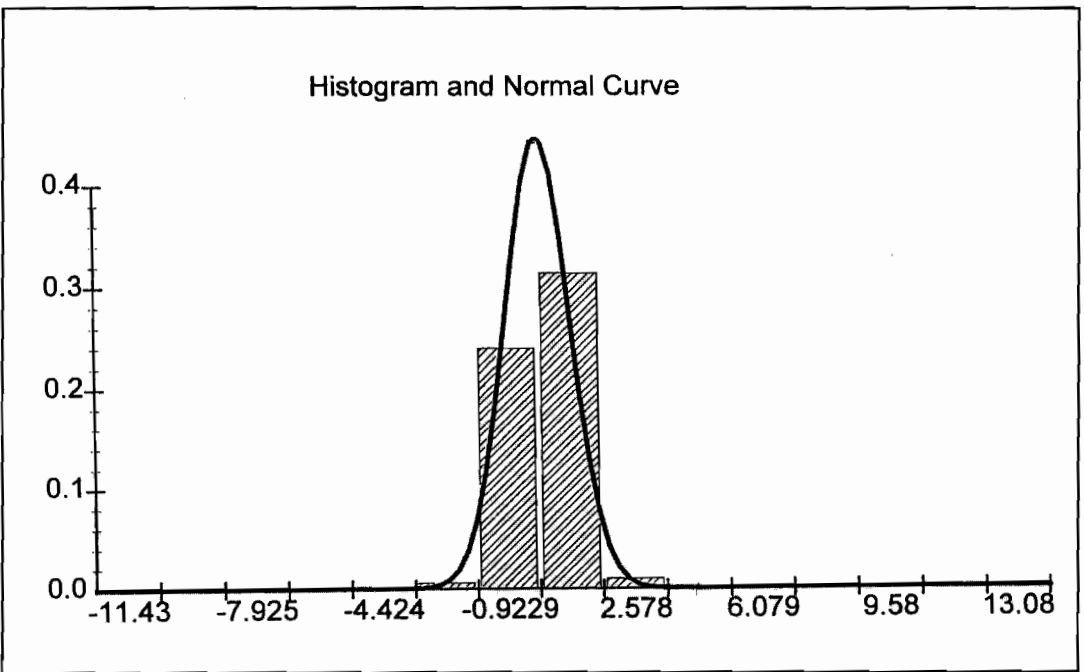
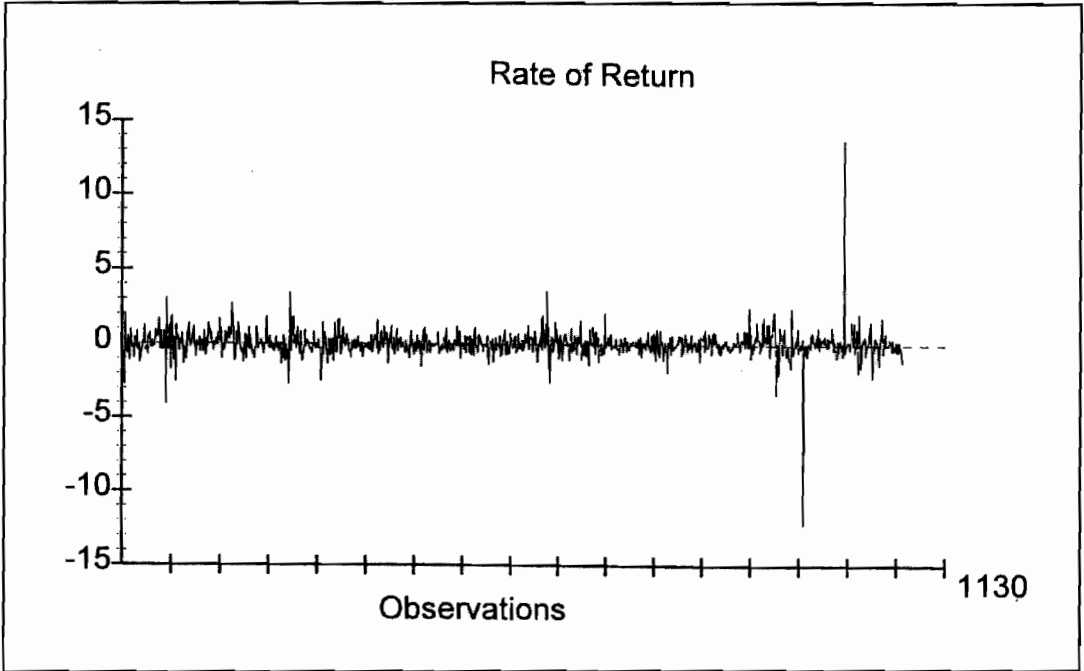


Figure 3 : Banks (A3)

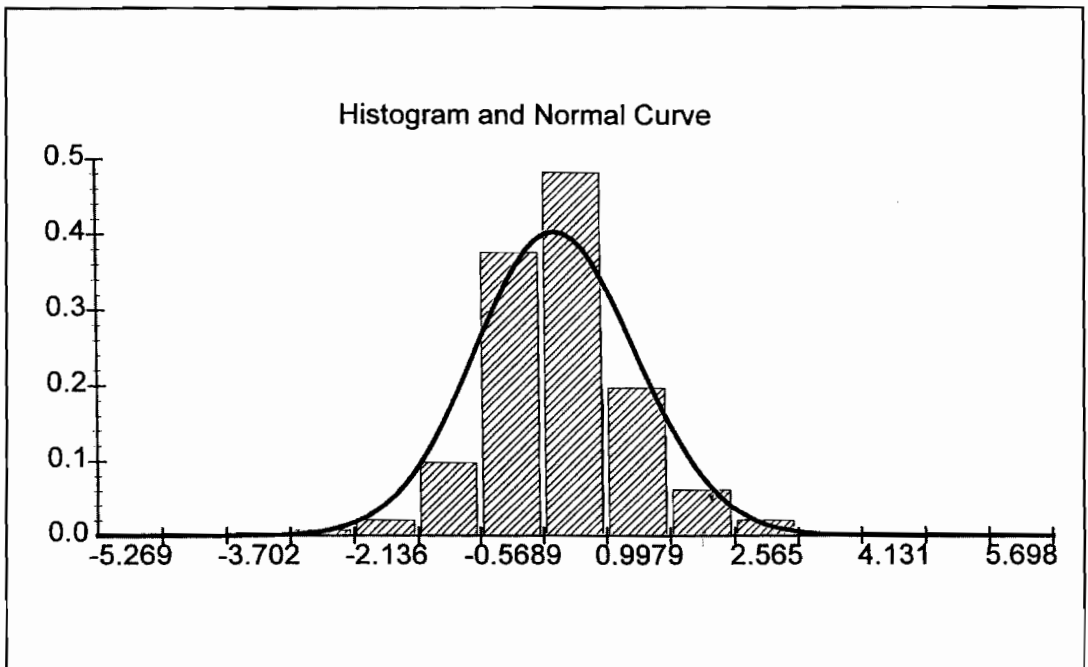
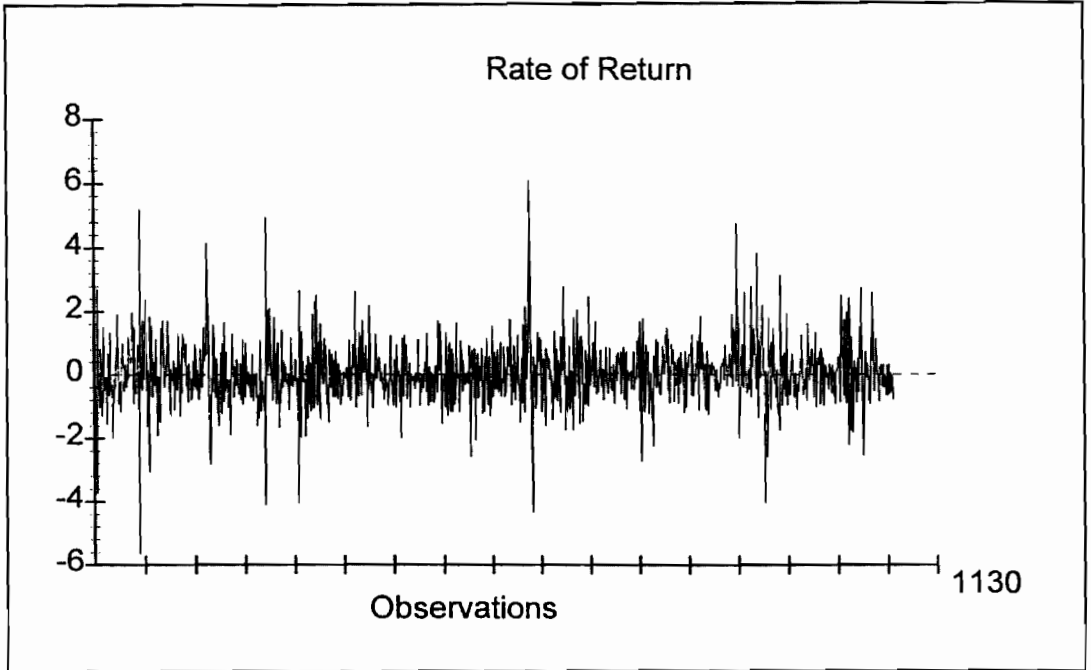


Figure 4 : Investment Companies (A4)

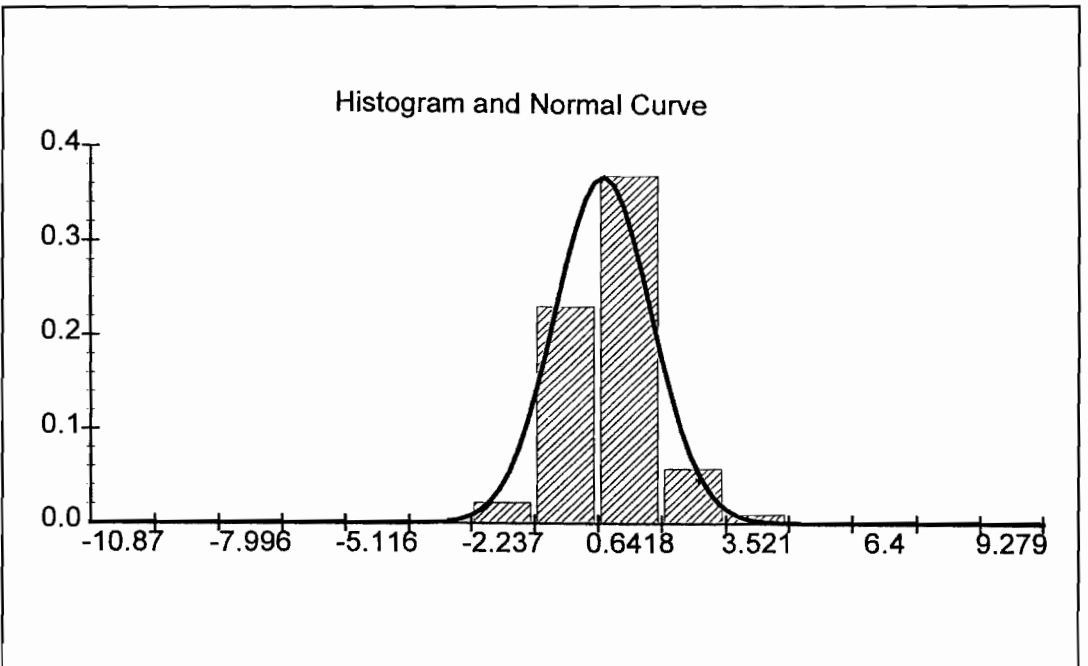
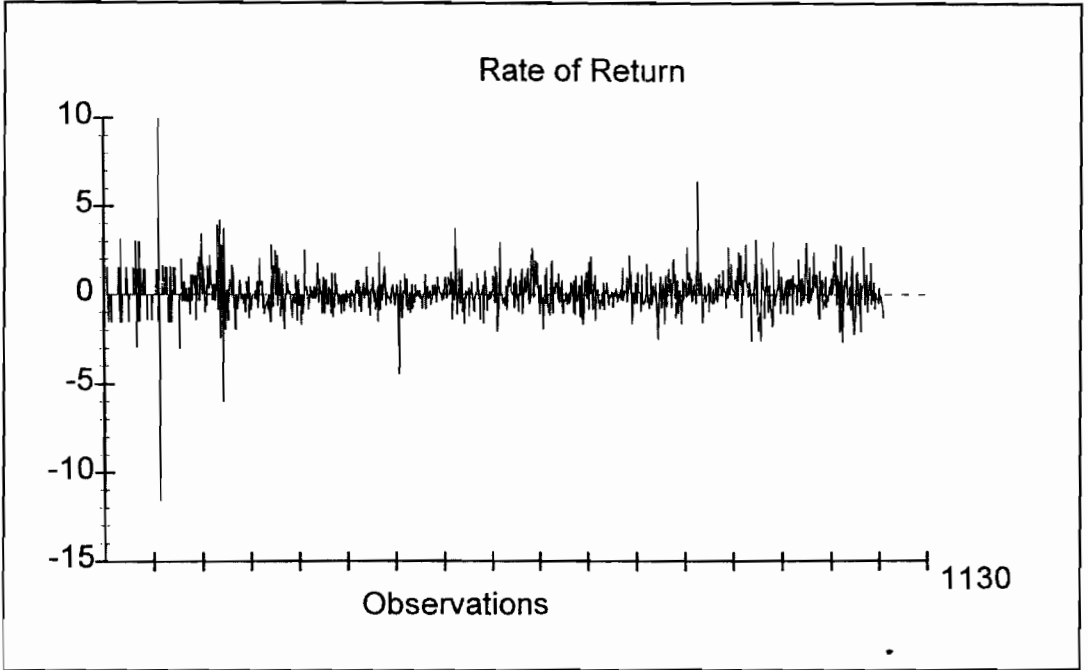


Figure 5 : Insurance companies (A5)

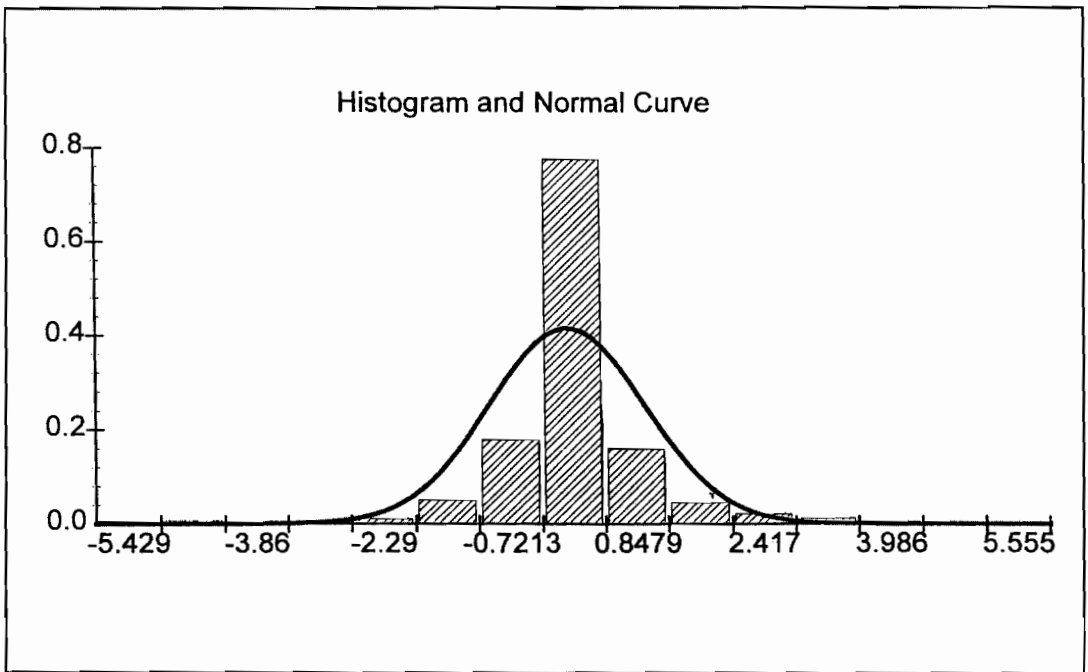
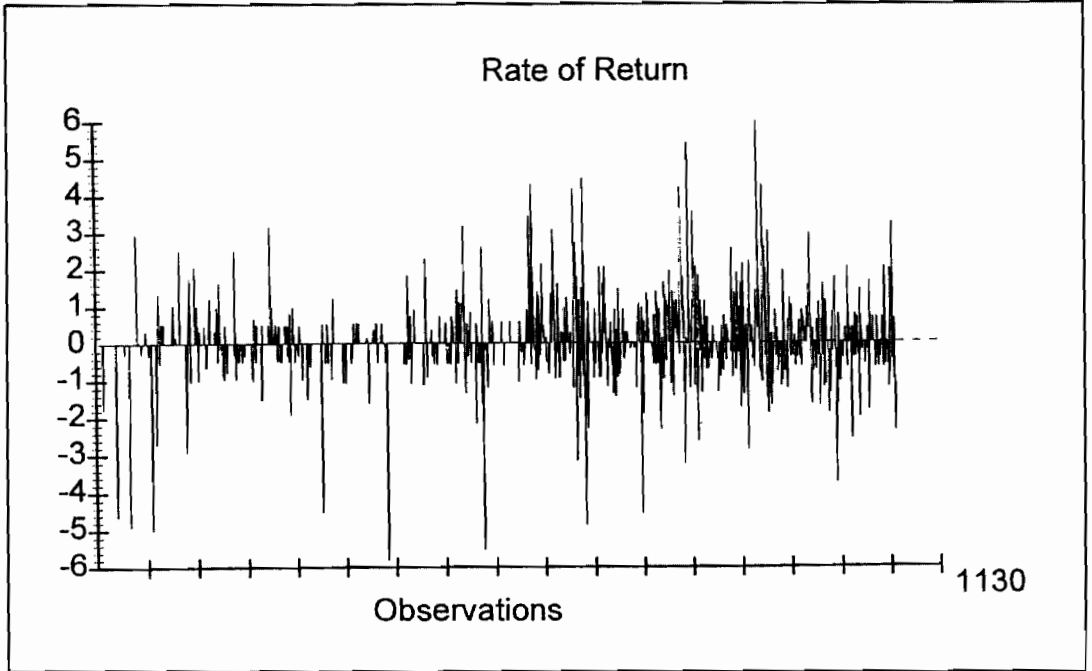


Figure 6 : Real Estate Companies (A6)

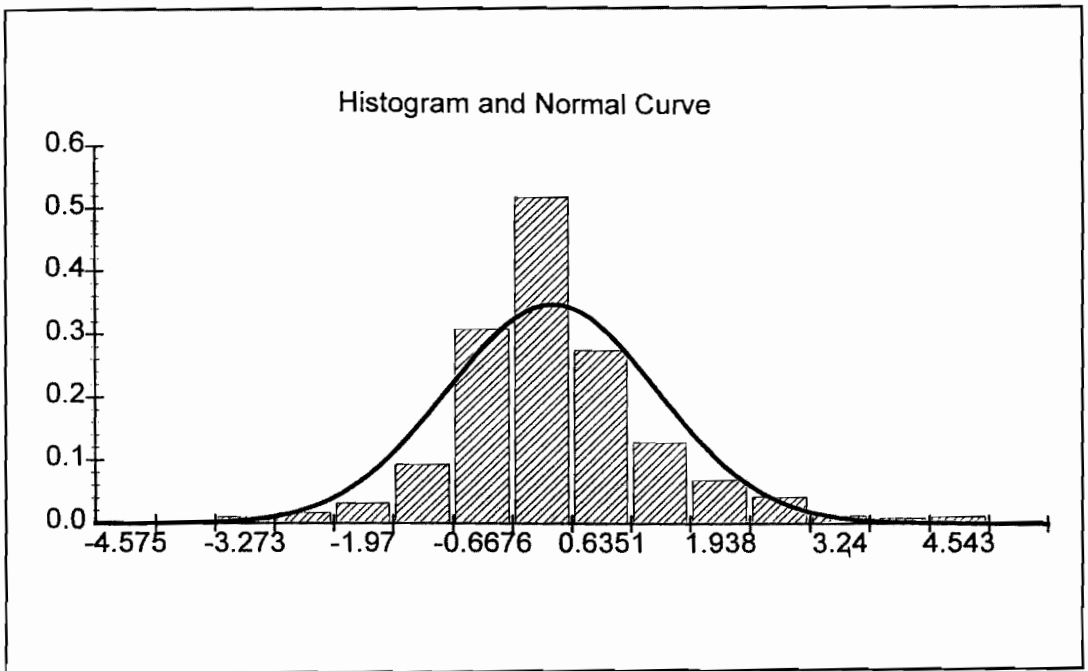
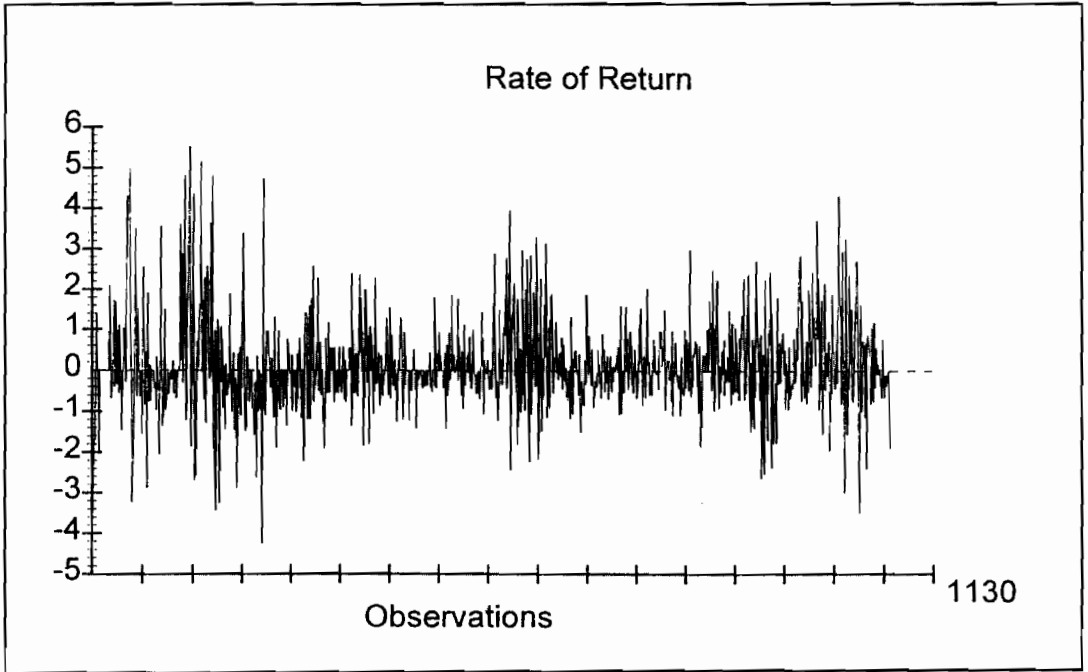


Figure 7 : Manufacturing Companies (A7)

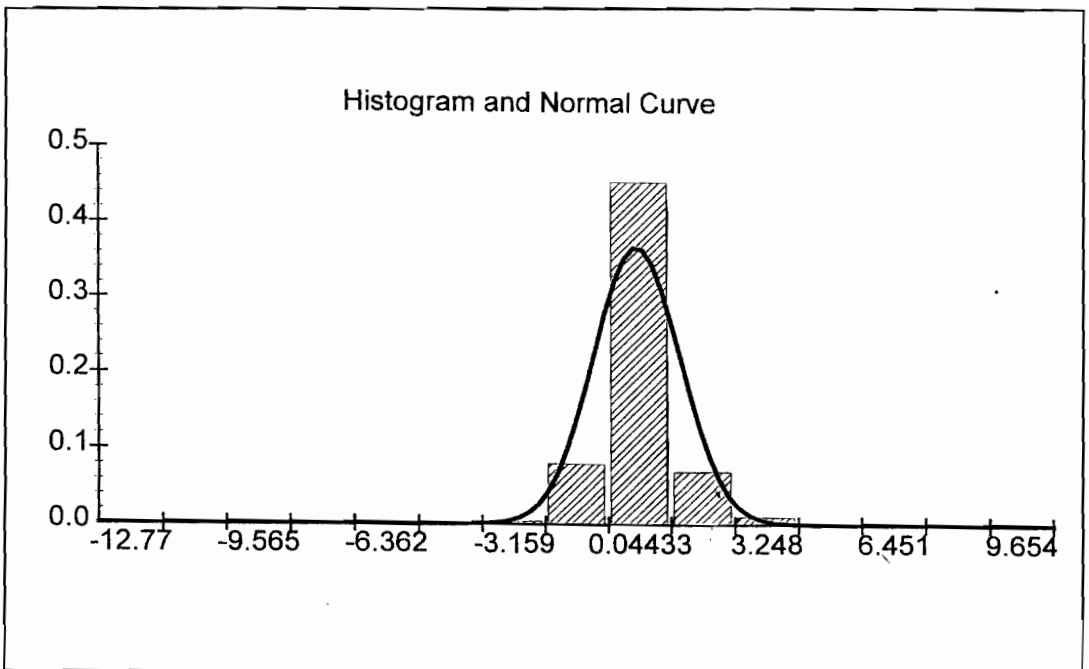
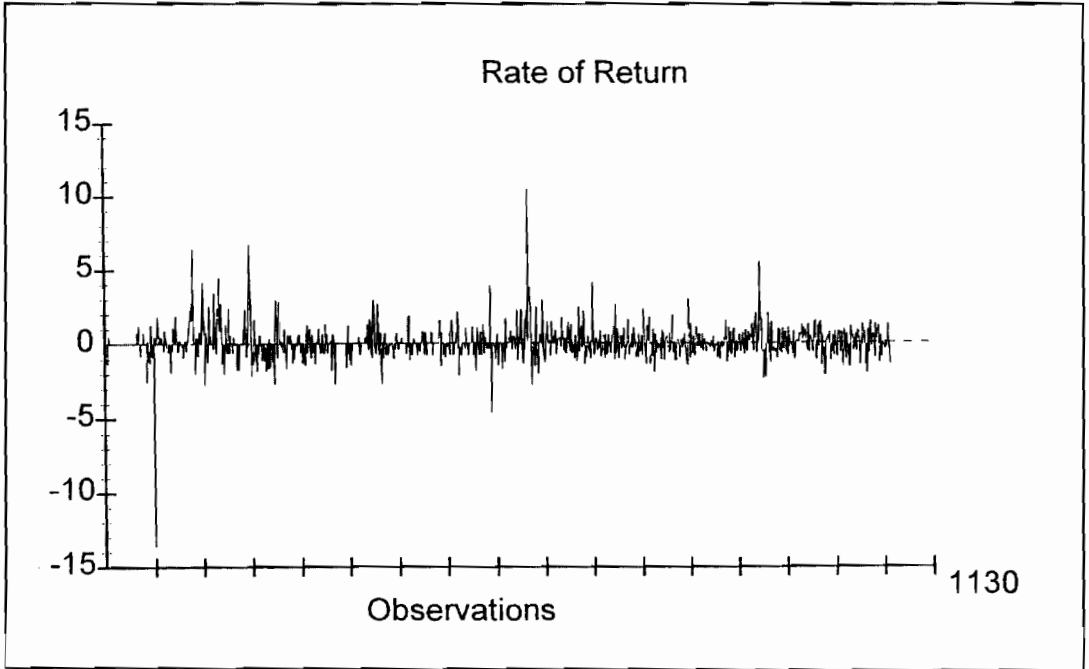


Figure 8 : Service Companies (A8)

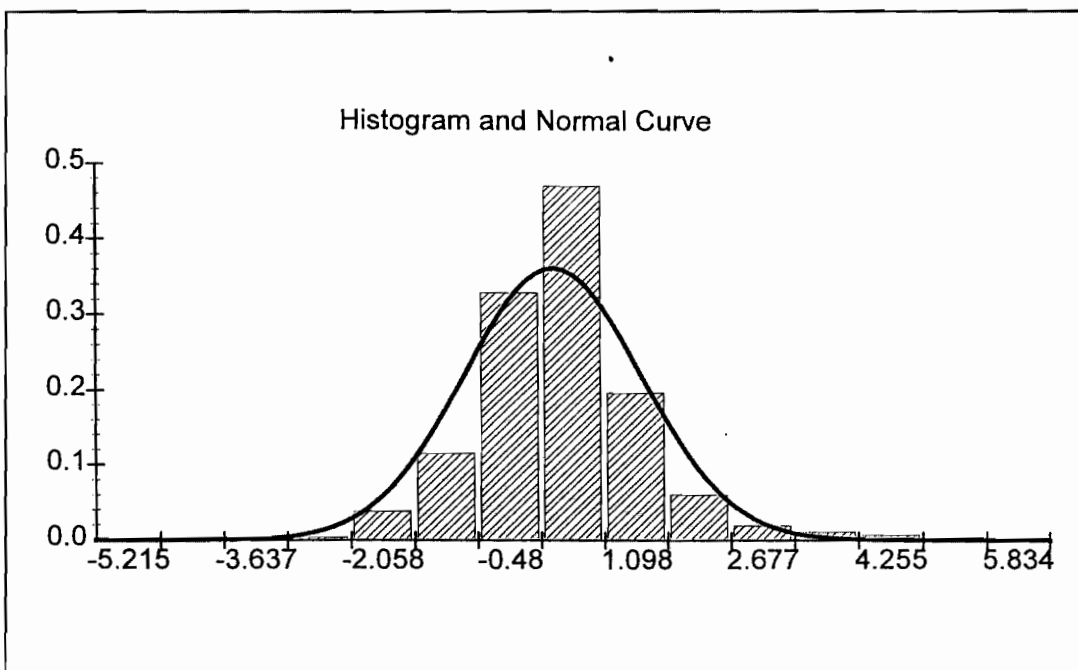
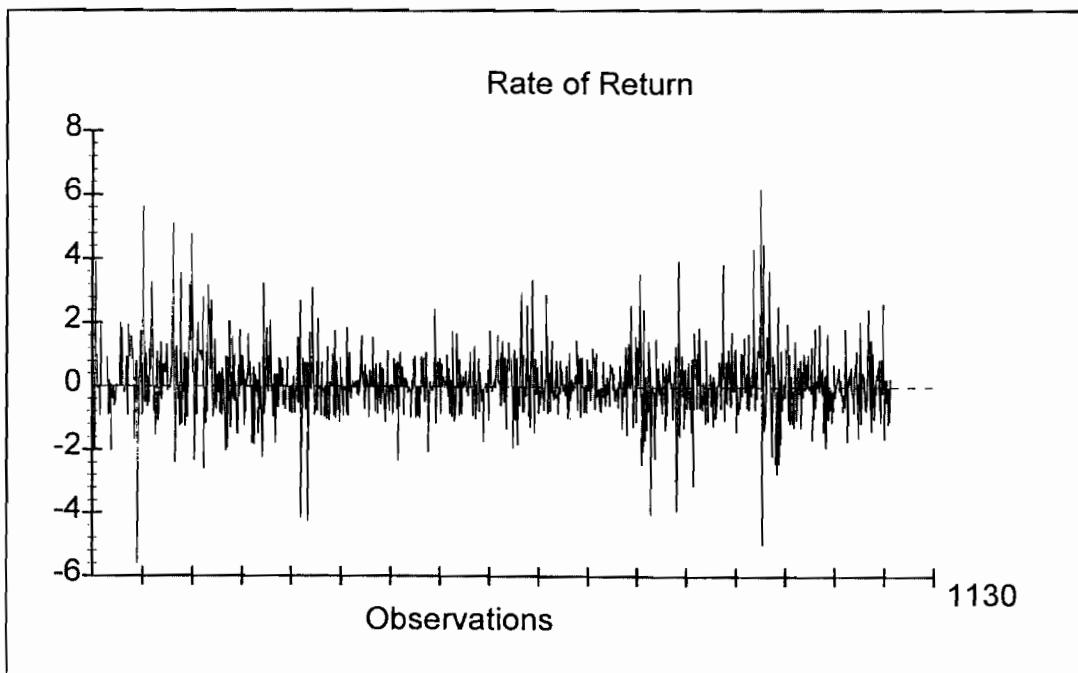


Figure 9 : Food Companies (A9)

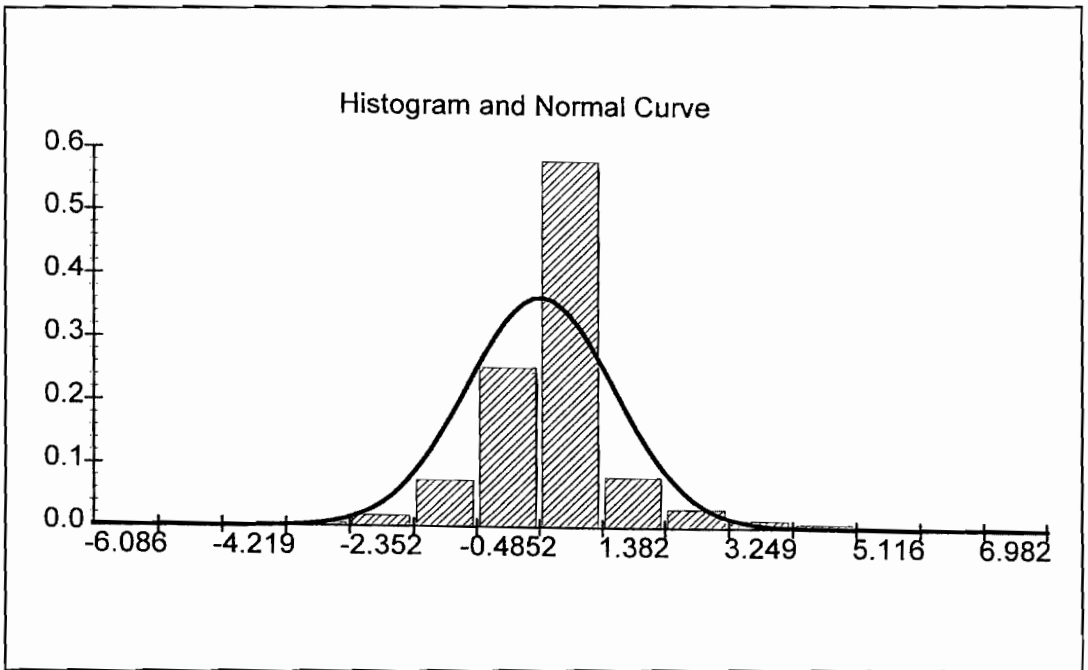
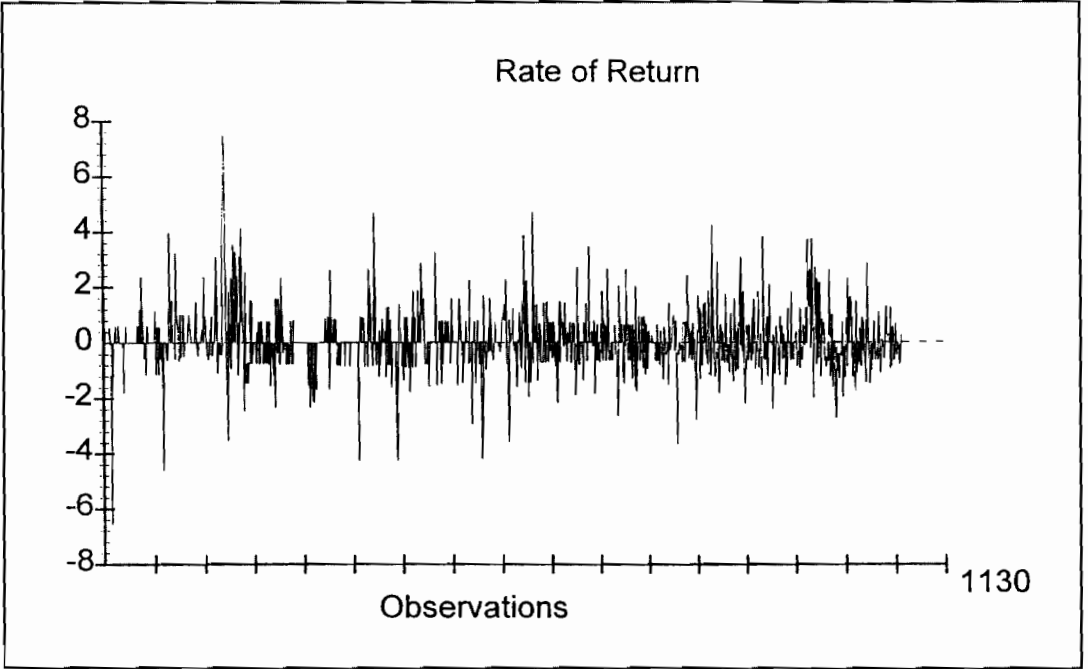


Figure 10 : Foreign Companies (A10)

