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Department of Banking & Financial Management
Postgraduate Program in Banking & Financial Management

"EXTREME VALUE THEORY AND VALUE-AT-RISK: EMPIRICAL EVIDENCE FROM THE LONDON METAL EXCHANGE"

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M.Sc. DISSERTATION
submitted to the Department of Banking & Financial Management of the University of Piraeus in partial fulfilment of the requirements for the Degree of Master of Science in Banking and Financial Management.

-PIRAEUS-
JULY 2007

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ
Τμήμα Χρηματοοικονομικής & Τραπεζικής Διοικητικής
Μ.Π.Σ. στην Χρηματοοικονομική & Τραπεζική Διοικητική

‘‘EXTREME VALUE THEORY AND VALUE-AT-RISK: EMPIRICAL EVIDENCE FROM THE LONDON METAL EXCHANGE’’

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που υποβλήθηκε στο τμήμα Χρηματοοικονομικής & Τραπεζικής Διοικητικής του Πανεπιστημίου Πειραιώς ως μέρος των απαιτήσεων για την απόκτηση του Μεταπτυχιακού Διπλώματος Ειδίκευσης στην Χρηματοοικονομική & Τραπεζική Διοικητική

-ΠΕΙΡΑΙΑΣ-
ΙΟΥΛΙΟΣ 2007

Περίληψη

Στην εργασία αυτή συγκρίνουμε την προβλεπτική ικανότητα οκτώ διαφορετικών μεθόδων Αξίας-σε-Κίνδυνο (VaR), δηλαδή Γενικευμένη Αυτοπαλίνδρομη Υπό Συνθήκη Ετεροσκεδαστικότητα GARCH (1,1) με κανονικά και t-Student κατανεμημένα σφάλματα, Εκθετικά Γενικευμένη Αυτοπαλίνδρομη Υπό Συνθήκη Ετεροσκεδαστικότητα EGARCH (1,1) με κανονικά και t-Student κατανεμημένα σφάλματα, Εκθετικά Σταθμισμένους Κινητούς Μέσους (EWMA), Ιστορική Προσομοίωση, Block Maxima (Γενικευμένη Κατανομή Ακραίας Τιμής) και Peaks over Threshold (Γενικευμένη Παρέτο Κατανομή), για την περίοδο 1/6/1989-2/3/2007 σε λογαριθμικές αποδόσεις τιμών σε μετρητά και συμβολαίων μελλοντικής εκπλήρωσης τρίμηνης διάρκειας για τα εξής μέταλλα που διαπραγματεύονται στο Χρηματιστήριο Βιομηχανικών Μετάλλων του Λονδίνου: Χαλκός, Κασσίτερος, Ψευδάργυρος, Νικέλιο και Αλουμίνιο. Επίσης αναλύουμε δεδομένα από αγορές μετοχών (FTSE-100 και LIFFE FTSE-100) καθώς και Χρυσό για την ίδια περίοδο, για να συγκρίνουμε την αγορά βιομηχανικών μετάλλων με τις αγορές μετοχών και πολύτιμων μετάλλων.

Τα μέταλλα αποδεικνύονται πιο επικίνδυνα από τις μετοχές και το χρυσό, με το Νικέλιο να είναι το πιο επικίνδυνο μέταλλο σε όρους μέσης Αξίας-σε-Κίνδυνο. Τα αποτελέσματα μας υποστηρίζουν τα μοντέλα που λαμβάνουν υπόψη την χρονικά μεταβαλλόμενη μεταβλητότητα καθώς αποδεικνύονται πολύ σημαντικά στην πρόβλεψη του μέτρου της Αξίας-σε-Κίνδυνο, ειδικά τα GARCH και EGARCH με t-Student κατανεμημένα σφάλματα. Επιπλέον η προσομοίωση καταστάσεων κρίσεως (Stress Testing) απέδειξε ότι τα μοντέλα δεσμευμένης μεταβλητότητας ειδικά τα GARCH και EGARCH με t-Student κατανεμημένα σφάλματα μπορούν να προβλέψουν μεγάλες αρνητικές αποδόσεις.

Η Θεωρία Ακραίων Τιμών είναι ένα σημαντικό κομμάτι στην Διοικητική Κινδύνου, ωστόσο θα πρέπει να είμαστε πολύ προσεκτικοί με την χρήση των μεθόδων αυτών καθώς απαιτούν μεγάλα δείγματα παρατηρήσεων για την εκτίμηση τους και επιπλέον διαφορετικές υποθέσεις για το μέγεθος και τον αριθμό των blocks και για τον καθορισμό του κατωφλιού u μπορούν να οδηγήσουν σε διαφορετικά από του αναμενομένου αποτελέσματα.

Abstract

We compare the predictive ability of eight Value-at-Risk methods including GARCH(1,1) with Normal and t-Student innovations, Exponential GARCH(1,1) with Normal and t-Student innovations, Exponentially Weighted Moving Average (EWMA), Historical Simulation, Block Maxima (GEV Distribution) and Peaks over Threshold (GP Distribution) for the period 1/6/1989-2/3/2007 on cash and 3-month futures logarithmic price changes of Copper, Tin, Zinc, Nickel and Aluminium, metals that trade in the London Metal Exchange. We also analyzed equity market data (FTSE-100 & LIFFE FTSE-100) and Gold Bullion data for the same period, in order to compare the industrial metals market with equity and precious metals. The metals of the London Metal Exchange proved riskier than equity and gold, with Nickel being the riskier of all in terms of mean VaR. Our findings support the models that assume time-varying volatility as they proved very important in predicting the Value-at-Risk measure, especially the GARCH and EGARCH with t-Student distributed innovations. Block Maxima performed badly whereas Peaks over Threshold showed some forecasting ability especially in the Nickel time series. Moreover, Stress Testing proved that conditional volatility models and especially the t-Student GARCH(1,1) and EGARCH(1,1) can predict large negative returns. Extreme Value Theory is an important tool in Risk Management but one should be cautious as the methods of EVT need large data sets for the estimation process and moreover different assumptions about the block size and the number of blocks for Block Maxima and the determination of the threshold u for Peaks over Threshold may lead to different than expected results.

Acknowledgement

I would like to thank my supervisor, Mr. George Skiadopoulos for his guidance and his helpful comments; moreover i would like to thank Antonis Dendis for making me familiar with Extreme Value Analysis, Petros Dendis for the lessons in Matlab, Victoria Papadopoulou for her patience, George and Timos, my colleagues Sofia Mantafouni, George Voudouris and Ilias Tsirigotakis and last but not least my parents George and Fotini and my sister Helen for help and support all these years.

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Chapter 1: Introduction

Risk has always been a major problem that academics and practitioners had to cope with in the financial markets and over the last three decades there has been a lot of interest in the various ways we can deal with uncertainty. Risk can be defined as *the volatility of unexpected outcomes or as hazard, a chance of bad consequences, loss or exposure to mischance*. In terms of financial management, McNeil et al. (2005) define risk as ‘‘an event or an action that could adversely affect an organization’s ability to achieve its objectives and execute its strategies’’.

One of the first mathematicians who related risk with randomness was A.N. Kolmogorov. In 1933 he gave the axiomatic definition of randomness and probability and he used a probabilistic model described by the following elements: (Ω, F, P). Ω represents the state of nature, F is the set of all events and P is the probability measure.

However, since the times of Kolmogorov many other researchers extended the notion of risk and randomness and proposed many models to explain and understand risk. Many models and theories trying to describe risk and return have been proposed in the Finance literature as the Efficient Mean-Variance Portfolio framework of Markowitz (1952), the Capital Asset Pricing Model by Lintner (1965) and Sharp (1964), the Option Pricing Theory by Black, Scholes and Merton (1973) and the Arbitrage Pricing Theory by Ross (1976) being the most dominant and influential of all, the last decades.

A common underlying assumption of all these great theories was that the returns of the financial assets are normally distributed. The last years many academics have proposed other models that fit better the empirical distribution of the returns, as it is clear that the normal distribution underestimates risk and cannot take into account extreme returns.

Many financial disasters in the 80’s and the 90’s have brought up the problem of risk management and supervision with new powerful models and techniques. Recent examples of financial disasters include the stock market crash of October 1987 (Black Monday), the Asian Crisis of 1997-1998 and its effect on the rest economies of the world. As a response to major financial crises was the development of the Value-at-Risk (VaR) methodology which describes many basic issues involved in the measurement of the market risk. VaR concentrates on *market risk*, which is the risk of adverse and unexpected changes in the prices of financial instruments an investor may hold.

VaR has undoubtedly become the industry benchmark for the risk measurement of a portfolio because it tells us how bad things can go with a certain probability p. Moreover it is easily understood and summarizes the risk exposure in a single number.

On the other hand, in the early 00’s many academics like Jon Danielsson criticized VaR as a risk measure and stated that it is not sufficient for regulatory use because it may give misleading information about risk and in some cases may actually increase both idiosyncratic and systemic risk. VaR under the normal distribution ignores extreme losses and the empirical distribution of the returns is leptokurtic and more fat tailed than the normal distribution assumes. Moreover, VaR does not tell us what will happen in the p% worst cases, meaning how much we can lose once VaR is exceeded. Another issue is that the equity markets often exhibit very large drops but not equally large up- moves, implying a negatively skewed return distribution often referred to as the leverage effect. Many studies like the ones of Mandelbrot (1963) and Hull & White (1998) have shown that returns are not normal and i.i.d.

Although VaR has a lot of limitations, the Basel Committee on Banking Supervision has chosen it as a standard method for measuring market risk. However, research has shown that there is no perfect VaR Model to be preferred as we can get different results when we use different data sets and different portfolios. Therefore research should try to focus on *which VaR models can forecast the market risk best for different portfolios* (equity, bonds, derivatives, commodities, interest rates,…) *and data sets* (long or short time horizons).

During the 90's, a significant body of the academic society suggested that we should focus on the tails of the empirical distribution, giving rise to the Extreme Value Theory, a set of theorems, tools and techniques taken from the fields of Applied Statistics and Actuarial Science. Therefore, the theorems of Balkema & De Haan (1974) and Pickands (1975) and the propositions of Fisher & Tippett (1928) motivated a large number of academics to apply the methods of Extreme Value Theory (EVT) in several studies of financial markets. There are two main methods in this field of study, the *Block Maxima Method* (BM) which uses the Generalized Extreme Value Distribution (GEV) and the *Peaks over Threshold Method* (POT) which uses the Generalized Pareto Distribution (GPD). A lot of research has focused on EVT and has shown that we can take very good VaR estimates by fitting GEV and GP distributions in maximum losses and threshold exceedances.

Therefore, VaR prediction with different risk measurement models is a crucial issue for banks, regulators, central bankers and investors. The purpose of this dissertation is to test and compare different models of volatility and different models of tail estimation under the VaR statistic so as to see how the forecasts that VaR yields perform. We use data from the London Metal Exchange, namely daily cash and 3-month futures logarithmic price changes from Copper, Tin, Zinc, Nickel and Aluminium for the period 1/6/1989-2/3/2007. We also analyze FTSE-100, Gold Bullion and LIFFE FTSE-100 in order to compare the metals market with equity and gold. Moreover we thoroughly study Extreme Value Theory and see whether it is a set of tools and techniques that improves the Value-at-Risk forecasts, compared with traditional methods and whether it should be chosen instead of the other models proposed by the Basel I & II.

The rest of the dissertation is organized in the following way: in Chapter 2 we briefly review the notion of Value-at-Risk, in Chapter 3 we present Extreme Value Theory, in Chapter 4 we describe several volatility models of the GARCH family, in Chapter 5 we describe the Likelihood Ratio tests for the Backtesting process, in Chapter 6 we present a review of previous studies, in Chapter 7 we describe the data set and the empirical application in metals, in Chapter 8 we comment on the Backtesting results, and finally in Chapter 9 we conclude and present possible new research directions. Descriptive Statistics and Backtesting tables can be found in Appendixes I & II.

Chapter 2: An Overview of Value-at-Risk

2.1: A Definition of Value-at-Risk

In this chapter we aim to present the theory that underlies the notion of Value-at-Risk, to describe the various applications it has in financial risk management and finally to highlight its characteristics.

According to Christoffersen (2003), ‘‘*Value at Risk is a simple risk measure that answers the following question: What € loss is such that it will only be exceeded p*% of the time in the next N trading days?*’’. More formally, we can consider *e* as the future portfolio value for a certain period and let *f(e)* be the probability function of *e*. Then at the confidence level p, VaR is the worst realization to be expected such that the probability of exceeding it is p:

$$\int_{VaR}^{\infty} f(e)de = p \qquad (1) \qquad \text{or:}$$

$$Pr\,(\text{€}Loss > \text{€}VaR) = p \qquad (2) \qquad \text{or:} \qquad Pr\,(r_{pt} < -VaR) = p \qquad (3)$$

(r_{pt} is the portfolio return and VaR is the € VaR divided by the current value of the portfolio.)

Let’s assume that we want to calculate the p% VaR for the 1-day ahead return. We assume normality for the returns with zero mean and $\sigma_{pt,t+1}$ standard deviation. Then:

$$\Pr(r_{pt,t+1} < -VaR_{t+1}^{P}) = p \Rightarrow \qquad \Pr\left(\frac{r_{pt,t+1}}{\sigma_{pt,t+1}} < \frac{-VaR_{t+1}^{P}}{\sigma_{pt,t+1}}\right) = p \Rightarrow$$

$$\Phi\left(\frac{-VaR_{t+1}^{P}}{\sigma_{pt,t+1}}\right) = p \Rightarrow VaR_{t+1}^{P} = -\sigma_{pt,t+1} \times \Phi_{p}^{-1} \qquad (4)$$

(Φ_p is the cumulative density function of the standard normal distribution)

The interpretation we can give is that VaR gives us a number such that there is a p% chance of losing more than VaR % of our portfolio value today.

(The above ideas and formulas where derived from Christoffersen (2003), p.48-49)

Although the literature on VaR estimation is extensive, we can divide the methods in parametric and non- parametric. On the one hand, the parametric approaches include the use of Normal, Pareto, t-Student and other distributions. On the other hand, the non- parametric approach assumes that returns are free of distribution and we estimate the VaR directly from the empirical distribution of the data.

2.2: The Variance-Covariance Approach

A very popular parametric method is the ***Variance- Covariance Approach (V-CV)*** developed by JP Morgan (1996). The main assumption of this approach is that returns are normally distributed and it is a very flexible method as the normal distribution has a lot of convenient properties. Therefore, by using the Standard Normal Distribution, we can calculate VaR.

The choice of the confidence level and the time horizon is of great importance. In general, short horizons should be used because longer horizons reduce the number of estimations and thus the power of the statistical tests (i.e. calculate daily or 10-day VaR). In the case we want to use a long horizon VaR estimate, it could be useless and dangerous since financial markets are very dynamic while successive trading requires speed and accuracy. Extremely high confidence levels leave us with too few observations in the tails of the distribution of returns, reducing the power of statistical tests. On the other hand, it would be useless to calculate VaR with a very low confidence level, i.e. 50%. Therefore it is best to use confidence levels of 95 or 99%.

The V-CM approach provides us with a simple comprehensive number about the risk of a portfolio or a security. The volatility σ is calculated from the empirical data and can be a single number (univariate case) or a variance-covariance matrix (multivariate case).

2.3: The Historical Simulation Approach

Another popular and easy to compute method is the ***Historical Simulation***, which does not imply anything about the distribution of the returns. We estimate the VaR of the portfolio directly from the empirical data. The technique assumes that the distribution of tomorrow's portfolio returns $R_{pt,t+1}$ will be approximated by the empirical distribution of the past n observations . The VaR with coverage rate p will simply be calculated as the 100pth quantile of the sequence of the past n portfolio returns:

$$VaR_{t+1}^{p} = -Quantile\left(\left\{R_{pt,t+1-\tau}\right\}_{\tau=1}^{n}, 100\,p\right) \qquad (5)$$

More formally, let F_n denote the empirical process of the observed losses $X_1, X_2, \ldots, X_N$, that is:

$$F_n(t) = \frac{1}{n}\sum_{i=1}^{n} I(X_i \le t) \qquad (6)$$

(where $I_{(\,)}$ is the indicator function, and X_i is iid with unknown distribution F.)

By standard statistical results, the p quantile $F^{-1}(p)$ can be estimated by

$$F_n^{-1}(p) = X_{n(i)}, \quad p \in \left(\frac{i-1}{n}, \frac{i}{n}\right) \qquad (7)$$

where $X_{n(1)} \le X_{n(2)} \le X_{n(3)} \le \ldots\ldots \le X_{n(n)}$ are the order statistics.

Advocates of historical simulation approach highlight its «*model free*» nature; however it is clearly not «*assumption free*» as Christoffersen (2006) states, because it assumes that asset returns are independent and identically distributed which is unfortunately not the case empirically. The method yields estimates with high standard errors, thus we can't be very confident for its results. The approach focuses only on a simple quantile of the distribution and discards the information provided from the whole distribution. Extreme quantiles are very difficult to estimate, as extrapolation beyond past observations is impossible. The quantiles are very volatile whenever a large observation enters the sample and the method is unable to distinguish between periods of high and low volatility.

The following diagram depicts the VaR forecasts derived from the Historical Simulation Approach, using two moving estimation windows of 100 and 252 observations, for Nickel Cash for the period1993-2007.

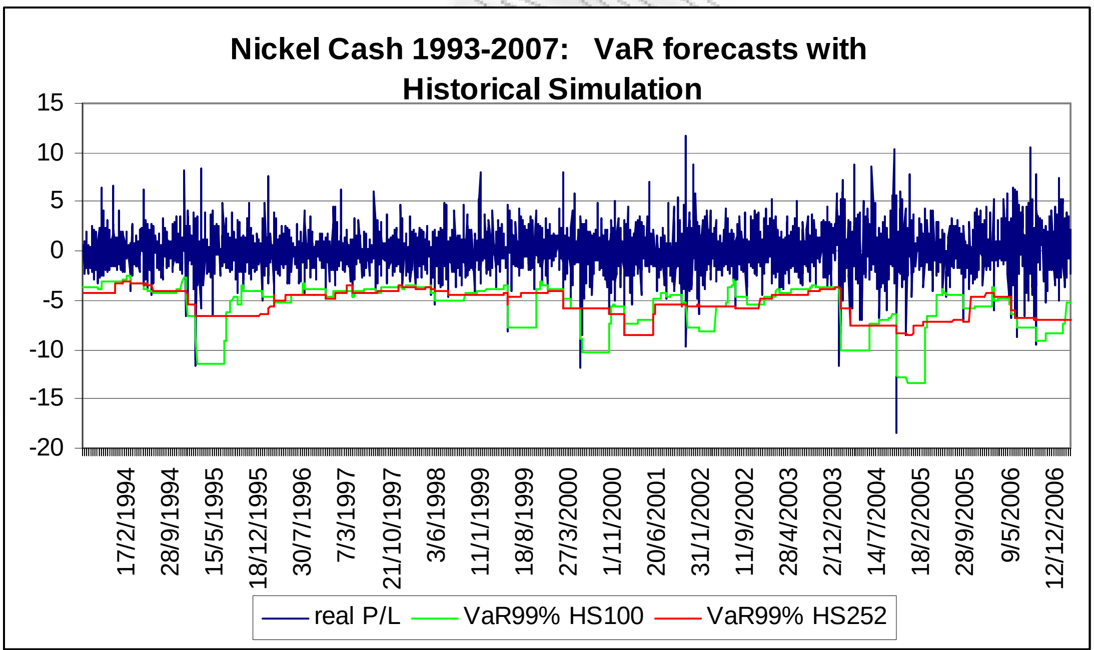


Diagram 2.a: Historical Simulation VaR forecasts for Nickel Cash 1993-2007

2.4: Coherent Risk Measures – Expected Shortfall

Undoubtedly, the Value at Risk consists one of the most powerful tools in financial markets. However it has been proved that it does not always work in a perfect way, failing sometimes to predict the future extreme losses. By considering this fact and the whole theory behind VaR, Artzner et al. (1999) proposed that the VaR is not such a good risk measure because it does not satisfy the four axioms of coherence and that VaR is not subadditive. Therefore they proposed another risk measure called **CVaR** or **Expected Shortfall**, which is coherent and a better risk measure than VaR. Although we will not study CVaR in this dissertation, it is worth mentioning some of the underlying assumptions:

Let us denote as *X* and *Y* as risky trading positions and *a* as a risk less trading position. Furthermore let *p* be the general risk measure. According to Artzner et al. (1999), a risk measure *p* is coherent if it satisfies the following axioms:

- Positive Homogeneity: for all $\lambda \geq 0$, $p(\lambda X) = \lambda\, p(X)$
- Translation Invariance: for all $X \in G$ and all real numbers a, $p(X + ap) = p(X) - a$
- Subadditivity: for all X_1 and $X_2 \in G$, $p(X_1 + X_2) < p(X_1) + p(X_2)$
- Monotonicity: for all X and $Y \in G$ with $X < Y$, we have $p(X) < p(Y)$

Therefore they define the expected shortfall as the «average loss a portfolio will have given that the loss is above VaR» and they proved that it is a coherent risk measure.

$$ES_P = E[X / X \geq VaR_P] = \frac{E[X; X \geq q_p(X)]}{1-p} = \frac{1}{1-p}\int_p^1 VaR_u(X)du \qquad (8)$$

(Where X is the loss and VaR is the value at risk at p confidence level.)

Chapter 3: An Overview of Extreme Value Theory

3.1: Block Maxima with GEV Distribution

The first method we are going to study is the ***Block Maxima (BM)*** and is based upon the Generalized Extreme Value Distribution (GEV).

Let $R_1, R_2, R_3, \ldots\ldots, R_n$ be a sequence of independent and identically distributed random variables from the same unknown distribution and let the sequence represent the returns of a portfolio. Moreover let Y_n be the maximum return over this period:

$$Y_n = \max\{R_1, R_2 R_3, \ldots\ldots, R_n\}$$

An early study by Fisher & Tippett (1928) proved that « in the limit, the asymptotic distribution of the maximum variable Y_n, reduced by the location parameter μ and a scale parameter σ, converges to a generalized extreme value distribution » as follows:

$$\frac{Y_n - \mu}{\sigma} \xrightarrow{d} H$$

$$H_\xi(Y) = \begin{cases} \exp\{-(1+\xi Y)^{-\frac{1}{\xi}}\}, \xi \neq 0 \\ \exp\{-e^{-Y})\}, \xi = 0 \end{cases}, \quad \text{for } 1+\xi y > 0 \qquad (9)$$

where Y is the **normalized maximum** and ξ is the tail index parameter.

The theorem states that the shape of the tails of the returns' distribution is closely related to the estimate of the tail index parameter. According to Fisher & Tippett (1928), if the tail index is negative (ξ < 0), then the returns follow the ***Weibull Distribution***, which is a thin tailed distribution. If the tail index equals zero (ξ = 0), then the distribution of returns belongs in the domain of the ***Gumbel Distribution***.

Lastly if the tail index is positive ($\xi > 0$), then the distribution of returns belongs in the domain of the ***Frechet Distribution*** which is a heavy tailed distribution.

H_ξ is called the Generalized Extreme Value Distribution (GEV). In other words, there is one an only one possible family of limiting distributions for sample maxima. The random variable Y, with distribution function F is said to belong to the maximum domain of attraction of an extreme value distribution; in short, $F \in MDA(H_\xi)$. The parameter ξ is crucial because it governs the tail behaviour of F.

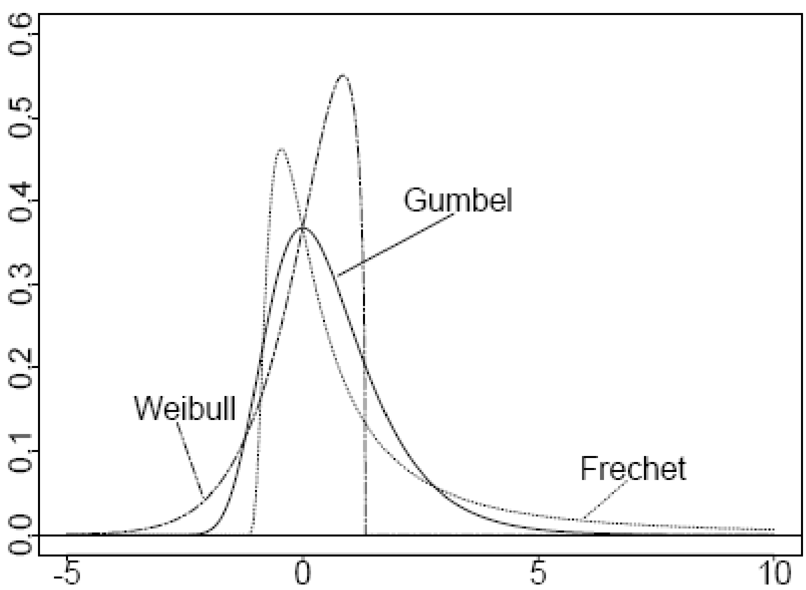


Diagram 3.a (taken from Embrechts et al. (1998)): Some examples of extreme value distributions $H_{\xi;0,1}$ for ξ=0,75 (Frechet), ξ=0 (Gumbel), and ξ=-0,75 (Weibull)

Concerning the estimation of the parameters of the GEV distribution, Longin (2005) mentions that, there has been developed a variety of methods (parametric and non-parametric), with the Maximum likelihood (ML) method presented in Tiago de Oliveira (1973) and the Regression method covered in Gumbel (1958), being the dominant among them. Furthermore, Longin (2005) suggested that Hill (1975) and Pickands (1975) developed two non-parametric estimators of the GEV tail index. The first one is the Hill estimator while the second one is the Pickands's estimator.

Let's present the BM approach formally:

Let $R_1, R_2, R_3, \ldots\ldots, R_n$ be a sequence of independent and identically distributed random variables from the same unknown distribution and let the sequence represent the returns of a portfolio (we multiply the return series with -1 so as the losses to be in positive values). Next we divide the random variables in m blocks, each block of size k (n = k*m). Then let $Y_n^{(J)} = \max(R_1^{(J)}, R_2^{(J)}, \ldots\ldots\ldots, R_k^{(J)})$ be the maximum return of block J. The maxima of all blocks will be $Y_n = (Y_k^{(1)}, Y_k^{(2)}, \ldots\ldots\ldots, Y_k^{(m)})$. We then apply the Fisher & Tippett Theorem, so that the only possible limiting distribution for normalized maxima $Y = \frac{Y_n - \beta_n}{\alpha_n}$ is the generalized extreme value distribution. The Value at Risk estimation will be:

$$VaR_p = -\left(\beta_n - (\frac{\alpha_n}{\xi})\left[1 - (-\ln(p^n)^\theta)^{-\xi}\right]\right) \tag{10}$$

Where β_n corresponds to the estimated location parameter, while α_n is the scale parameter and is assumed to reflect the estimated volatility. The parameter ξ is the estimated tail index and shows the shape of the tails of the distribution (Fat tailed - Thin tailed). Moreover, the probability p is the confidence level of the corresponding VaR and n is the size of each block. The parameter θ is called the extremal index and it shows us the relationship between the dependence structure and the extremal behaviour of the process, as Longin (2000) states. The extremal index is 1 if we have independence and close to zero if we have full dependence in the maxima.

A major disadvantage of Block Maxima is that we can loose observations which are extreme; due to the fact that we choose the maximum of each block, we discard all the other observations. Consider a period of great volatility where we have many big negative daily returns; in this block of returns we will choose only the greatest return and we will lose the others. Similarly in a period of low volatility, the highest observation that we will choose may be lower than one other observation from the former block that we already didn't take into consideration. Therefore, in order to use this method we need to have large samples so that the blocks we construct correspond to months, quarters, semesters or years. Moreover, in determining the size and number of blocks, we face a tradeoff: a large block size helps us approximate more accurately the block maxima by a GEV distribution and leads to low bias in the parameter estimates. On the other hand, a large number of blocks is in favor of the Maximum Likelihood Estimation process and leads to low variance in the parameter estimates. Moreover, convergence to the GEV distribution is slower when we have dependence in the maxima and in practice this means we need a larger sample size.

3.2: Peaks Over Threshold with GP Distribution

Next we will present the ***Peaks over Threshold Method (POT)*** which is based on the Generalized Pareto Distribution. The idea behind the POT method and the Generalized Pareto is similar to that of the Generalized Extreme Value Distribution. Instead of using the Block Maxima, we will use return excesses over a high threshold.

Let there $R_1,R_2,R_3,\ldots\ldots,R_n$ be a sequence of independent and identically distributed returns from the same unknown distribution F(R). Moreover, let us consider y as the excess returns over a high threshold u ($y = R - u$) and let $F_u(y)$ be the distribution function of the excesses over this threshold. An early study by Balkema & De Haan (1974), Pickands (1975) proposed that "for a high threshold u, the distribution of the excesses y over this threshold can be asymptotically approximated by the Generalized Pareto distribution":

$$F_u(y) = \Pr(R - u \le y / R > u), \qquad y \ge 0$$

$$G_{\xi,\sigma}(y) = \begin{cases} 1 - (1 + \dfrac{\xi}{\sigma} y)^{-\frac{1}{\xi}}, \xi \ne 0 \\ 1 - \exp(\dfrac{y}{\sigma}), \xi = 0 \end{cases} \tag{11}$$

$$F_u(y) \cong G_{\xi,\sigma}(y) \qquad u \to \infty \qquad y = R - u$$

Where σ is the scale parameter (volatility), u is the corresponding threshold and ξ is the tail index.

In specific, Balkema & De Haan (1974), Pickands (1975) proposed that for $\xi>0$, the returns follow the "ordinary Pareto distribution" while for $\xi<0$, the returns follow a thin tailed distribution. Lastly, if $\xi=0$, then the returns could be approximated by the exponential distribution.

There are two main approaches: The first and more general makes use of the limit result for peaks over threshold and is not confined to heavy tailed data. The second assumes fat tailed data and makes use of an estimator for the tail index.
Suppose that the R_t are iid. with distribution function $F \in$ MDA (H_ξ). Then for a chosen threshold $u = R_{k+1,n}$ given by the (k+1)st descending order statistic, we define

$$F_u(y) = \Pr(R - u \leq y / R > u) = \frac{F(u+y) - F(u)}{1 - F(u)}, \quad y \geq 0 \qquad (12)$$

or:

$$\overline{F}(u+y) = \Pr(R \geq u+y) = \Pr(R \geq u+y / R > u)\Pr(R > u) = \overline{F}(u) \times \overline{F_u}(y) \quad (13)$$

We can estimate $\overline{F}(u)$ by the empirical $\overline{F_n}(u) = \frac{N_u}{n}$ where the $F_n(u)$ is the empirical distribution function of X. For a high threshold:

$$\overline{F_u}(y) \approx 1 - G_{\xi,\sigma(u)}(y).$$

Thus the tail probability for $R > u$ can be estimated by:

$$\overline{F}(R) = \frac{N_u}{n}(1 + \xi\frac{R-u}{\sigma})^{-\frac{1}{\xi}} \qquad (14)$$

Unbiased estimators of ξ and σ can be derived through the Maximum Likelihood Estimation, while some other non- parametric estimators like the Hill estimator have been proposed as well.

A crucial point here is the choice of the correct threshold point. On the one hand, if we do not choose a high threshold, then the GPD will not be a good approximation of the distribution of the excesses. On the other hand, if we choose a very high threshold, then we will leave inadequate number of observations in the tails of the distribution, resulting with this way to inaccurate estimates.

The findings of Balkema & De Haan (1974), Pickands (1975) motivated lots of academics to study the behavior of popular risk measures in the implementation of the GP distribution. Therefore, Mc Neil (1999) suggested that the Value at Risk with confidence level p is:

$$VaR_p = -\left(u + \frac{\sigma}{\xi}\left(\left(\frac{n}{\mathrm{N}_u}(1-p) \right)^{-\xi} - 1 \right) \right) \qquad (15)$$

where u is the chosen threshold point, p is the corresponding VaR confidence level, σ is the scale parameter and represents the estimated volatility of the returns, n is the number of observations and N_u is the number of observations that are considered as extreme. Lastly, ξ is the tail index and shows the shape of the tails of the "parent" distribution of the returns.

3.3: Pros and Cons of Extreme Value Theory

As argued in the introduction, financial returns often exhibit leptokurtic behaviour, fat tails and dependence. If we choose the Normal Distribution for the statistical analysis of the financial returns, we know a priori that we will have underestimation of risk derived by the probability of large negative returns. The tails of the empirical distribution are definitely not normal.

In that case, the GPD and the GEV can offer higher accuracy because they usually fit well the extreme data while there is no need to impose unnecessary conditions. Additionally, the EVT approach is based on a strong statistical theory. However, we have to point out that the estimation of the GEV and GPD provides higher standard errors compared to the estimation of the normal distribution. This fact probably happens because the EVT focuses only in the tails of the returns' distribution. Last but not least, the EVT may result in inaccurate estimates when it has limited number of data in the tails of the distribution.

Therefore, as Paul Embrechts states, ''*Extreme Value Theory is not a panacea for financial risk management, as there are several theoretical issues that are unresolved*''. EVT usually gives larger VaR numbers than other methods like historical simulation and the convergence of the estimated parameters is not always guaranteed. One should be careful with the use of the models proposed and should always take into consideration the traditional methods proposed before applying EVT.

Extreme Value Theory aims at quantifying the probabilistic behaviour of very large losses and according to Fernandez (2003), Peaks over Threshold is more efficient than Block Maxima. This happens because Block Maxima needs many observations in order to be computed and furthermore, the block size has major effect in the estimation of the GEV parameters; in other words, we will prefer to use Peaks over Threshold in cases when the number of data is limited or insufficient.

Chapter 4: Modelling the Volatility of Financial Returns

4.1: Volatility Clustering and Financial Returns

As long ago as 1963, a French Mathematician, Benoit Mandelbrot, documented a weird phenomenon in a time series of financial returns: he found that financial market volatility came in 'clusters' where periods described as tranquil, of small returns were interspersed with volatile periods of large returns. Large returns follow large returns of either size and the technical term given to volatility clustering was 'autoregressive conditional heteroscedasticity'.

The estimation of the time varying volatility is thus very crucial and gives us a more realistic aspect of the properties of the financial returns and can capture the current volatility of a market, helping us estimate with more accuracy a Value-at –Risk model. Since the introduction of the Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle (1982) and the Generalized ARCH (GARCH) model by Bollerslev (1986), volatility modelling has become very popular in the finance literature.

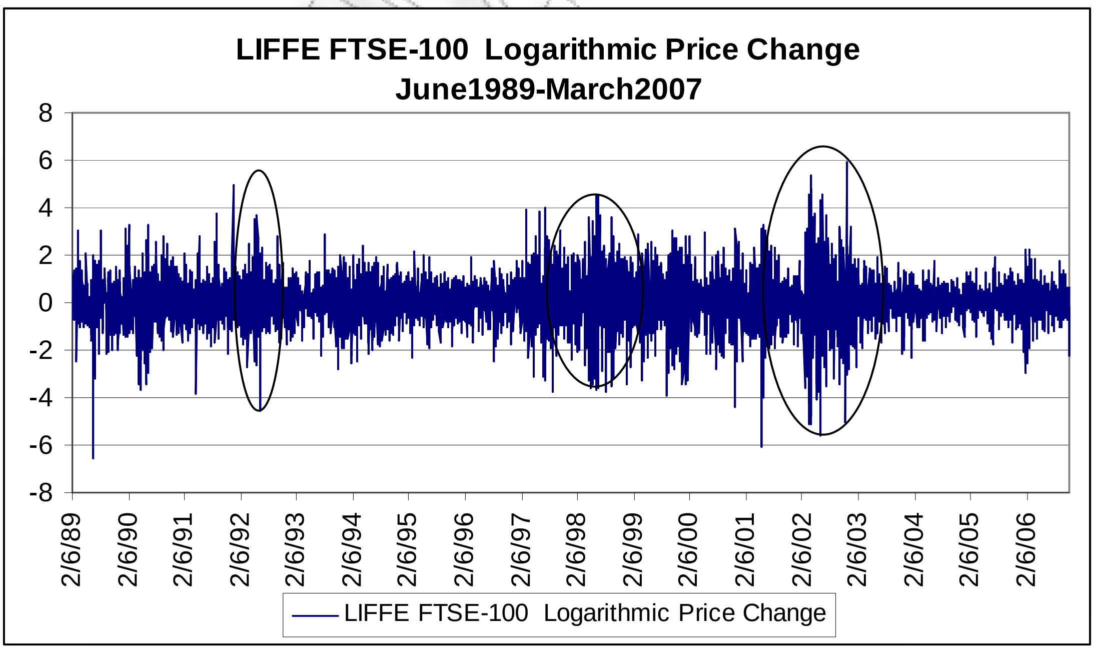


Diagram 4.a: Volatility Clustering in the LIFFE FTSE-100 index.

4.2: The simple GARCH (p,q) model

Let us define the daily asset log return as $y_{t+1} = \ln(\frac{S_{t+1}}{S_t})$. For short horizons such as daily, we can assume that the mean value of y_t is zero and that the innovations or news hitting the asset return are normally distributed, in other words:

$$y_{t+1} = \sigma_{t+1} \times h_{t+1} \quad \text{with } h_{t+1} \sim \text{i.i.d. N(0,1)}$$

Variance, as measured by squared returns, exhibits strong auto correlation so that if a recent period was of high variance, the tomorrow is likely to be a high variance day as well. An easy estimator for variance is:

$$\sigma_{t+1}^2 = \frac{1}{m}\sum_{\tau=1}^{m} y_{t+1-\tau}^2 = \sum_{\tau=1}^{m}\frac{1}{m} y_{t+1-\tau}^2 \ . \qquad (16)$$

However, this model puts equal weights on the past m observations, and yields unwarranted results, as an extreme return will cause variance to be very high for m periods and then it will decline sharply. The choice of m is crucial, but not clear.

A very popular approach to volatility modelling is the simple linear GARCH (p,q) model. The variance of the returns depends on its previous own lags and the previous lags of the squared errors, while the error term or innovation, is assumed to be normally distributed with $N(0,\sigma_t^2)$. The exact mathematical formula is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i h_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \ , \qquad (17)$$

$$a_i, \beta_j, \omega \geq 0, \qquad \sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \beta_j < 1$$

The above formulation corresponds to the GARCH (p,q) model where p is the number of the previous conditional variances, q is the number of the previous innovations. The basic idea of the model is that we have mean reversion to the long run variance ω and that the variance is not constant but changes, supporting this way the idea that financial returns are Heteroskedastic.

A special case of the general model is the GARCH (1,1) model which assumes that the conditional variance depends upon a constant, the previous conditional variance and the last period's squared error. In mathematical terms:

$$y_t = c + h_t \quad , \quad h_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^{\ 2} = \omega + \alpha h_{t-1}^2 + \beta \sigma_{t-1}^2, \qquad \alpha, \beta, \omega \geq 0 \quad , \quad \alpha + \beta < 1 \qquad (18)$$

(y_t is the return, α is the ARCH coefficient, β is the GARCH coefficient and ω is the long run variance.)

The GARCH (1,1) model is often called parsimonious, as we have only a small number of coefficients to estimate and is quite applicable in Finance because of its powerful and convenient characteristics. It fits the data well and gives emphasis to the latest information. The term *(α+β)* is called the persistence of the model. A high persistence implies that shocks which push variance away from its long run average will persist for a long time, but eventually the long horizon forecast will be the long run average variance σ^2.

We can make different assumptions about the distribution of the error terms. We can assume that they follow a t-Student Distribution or a Generalized Error Distribution or any other heavy tailed distribution.

The following diagrams depict the behaviour of the GARCH(1,1) model, using a moving estimation window of 1000 observations, for Nickel Cash 1993-2007.

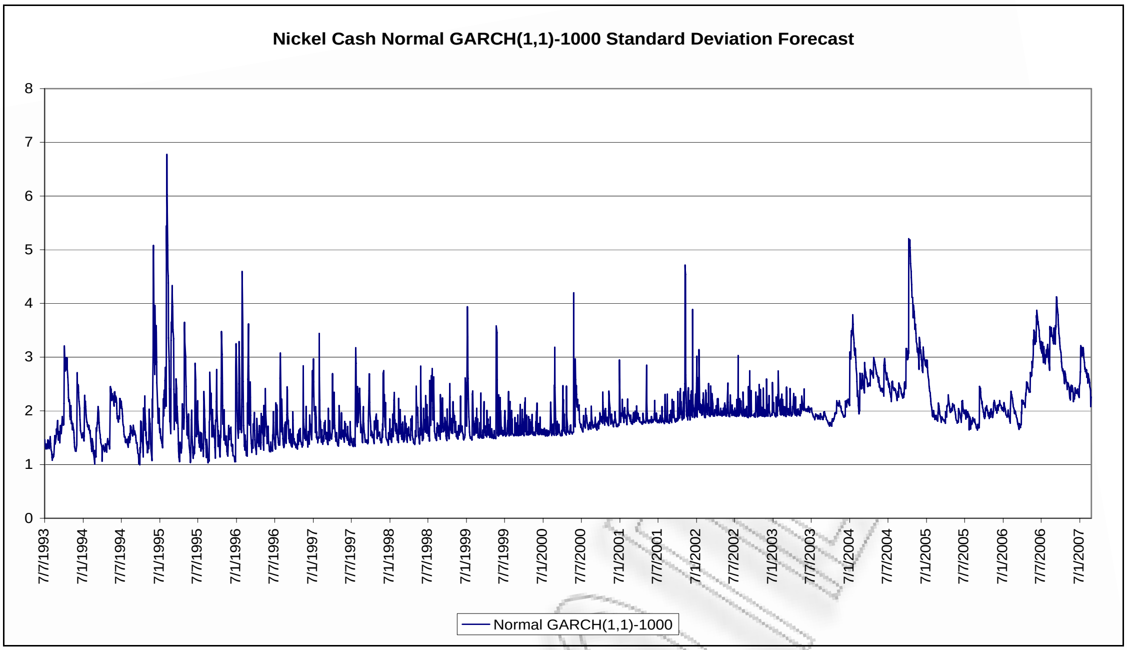


Diagram 4.b. GARCH(1,1)-1000 with Normal Innovations for Nickel Cash

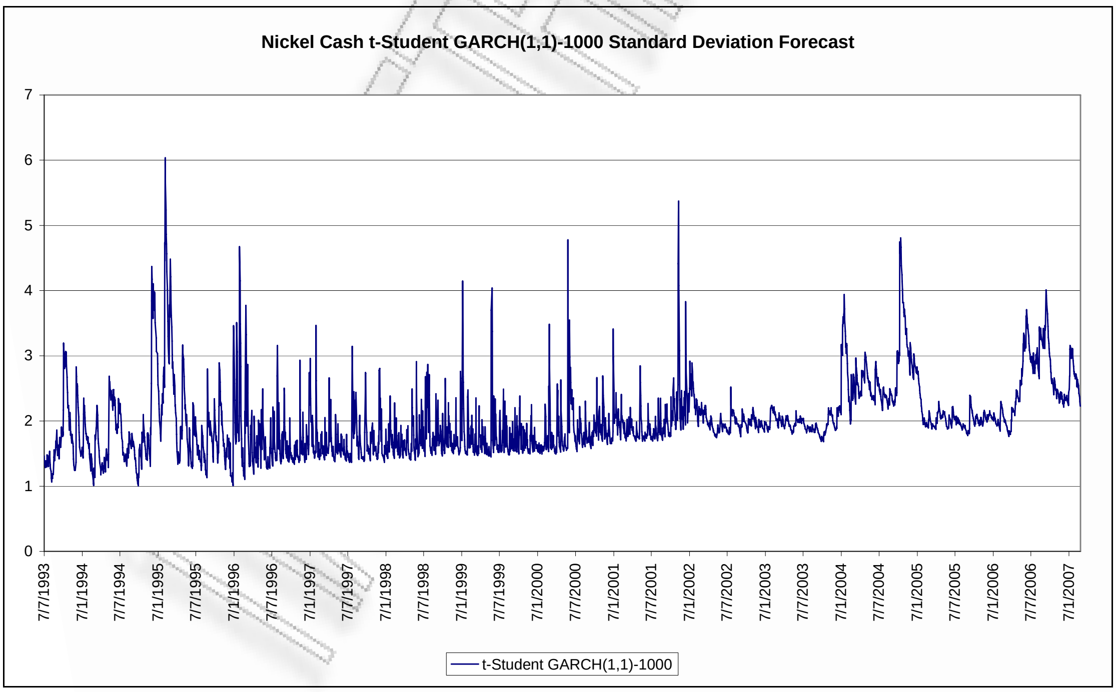


Diagram 4.c. GARCH(1,1)-1000 with t-Student Innovations for Nickel Cash

4.3: Exponential GARCH

Other types of GARCH models which have been proposed are the Integrated GARCH, the Non-Linear GARCH, the Threshold (or GJR) GARCH by Glosten et al. (1993) and the Exponential GARCH by Nelson (1991). These models take into account the leverage effect and are very popular in the Financial Econometrics field.

The **EGARCH (p,q)** is set in mathematical terms :

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left[\frac{|h_{t-i}|}{\sigma_{t-i}} - E\left\{ \frac{|h_{t-i}|}{\sigma_{t-i}} \right\} \right] h_{t-i}^2 + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^{p} L_i \left(\frac{h_{t-i}}{\sigma_{t-i}} \right)$$

(19)

Where:

$$E\{Z_{t-i}\} = E\left\{ \frac{|h_{t-i}|}{\sigma_{t-i}} \right\} = \begin{cases} \sqrt{\dfrac{2}{\pi}} & , Normally - Distributed \\ \sqrt{\dfrac{\nu-2}{\pi}} . \left(\dfrac{Gamma\left(\dfrac{\nu-1}{2}\right)}{Gamma\left(\dfrac{\nu}{2}\right)} \right) & , t - Student - Distributed \end{cases}$$

(20)

With ν > 2 degrees of freedom.
(L_i = leverage coefficient)

EGARCH models capture the most important stylized features of financial return volatility, namely time-series clustering, negative correlation with returns, lognormality and under certain specifications long memory, as Brandt & Jones (2006) state. This volatility framework has been advocated by Nelson (1991), Pagan & Schwert (1990) and Hentschel (1995) among others.

In contrast to the simple GARCH model, no restrictions need to be imposed on the model estimation since the logarithmic transformation ensures that the volatility forecasts are non-negative. Positive surprises (h_t >0) have the same effect on volatility as negative surprises (h_t <0) and therefore the model can capture asymmetric effects.

It will be very interesting to see if the Exponential GARCH is able to capture asymmetries in commodity markets and whether we have leverage effects in the metals markets other than the equity markets. The results of Backtesting will show if the particular model was superior to the simple linear GARCH model presented in the previous section.

The following diagrams depict the behaviour of the EGARCH(1,1) model, using a moving estimation window of 1000 observations, for Nickel Cash 1993-2007.

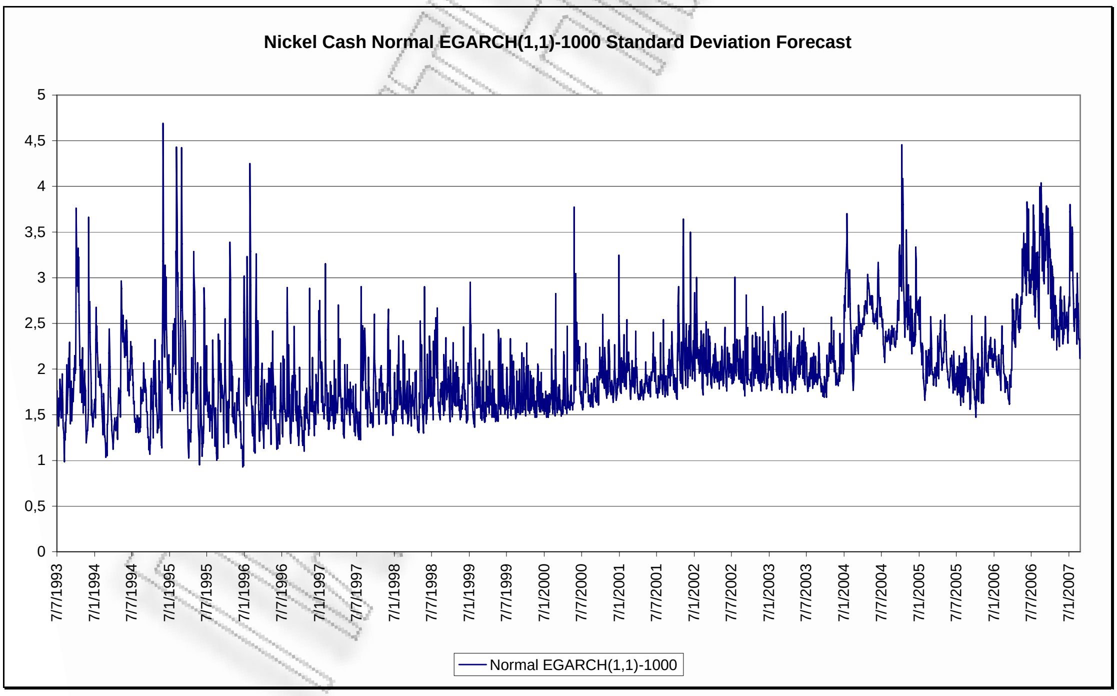


Diagram 4.d. EGARCH(1,1)-1000 with Normal Innovations for Nickel Cash

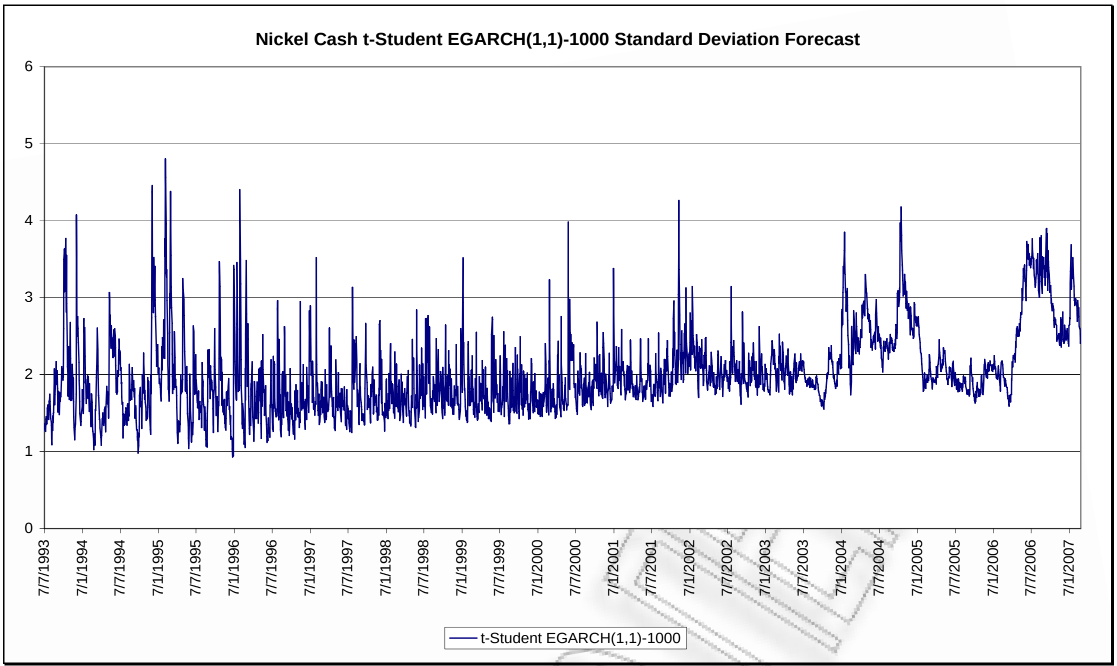


Diagram 4.e. EGARCH(1,1)-1000 with t-Student Innovations for Nickel Cash

4.4: Exponentially Weighted Moving Average (RiskMetrics)

A very popular model proposed by JP Morgan is ***the Exponential Weighted Moving Average or EWMA model.*** The variance is given by:

$$\sigma_{t+1}^2 = (1-\lambda)\sum_{\tau=1}^{\infty}\lambda^{\tau-1}R_{t+1-\tau}^2 = (1-\lambda)\sum_{\tau=2}^{\infty}\lambda^{\tau-1}R_{t+1-\tau}^2 + (1-\lambda)R_t^2 \quad \text{,For } 0<\lambda<1$$

$$\text{Or:} \quad \sigma_t^2 = (1-\lambda)\sum_{\tau=1}^{\infty}\lambda^{\tau-1}R_{t-\tau}^2 = \frac{1}{\lambda}(1-\lambda)\sum_{\tau=2}^{\infty}\lambda^{\tau-1}R_{t+1-\tau}^2$$

$$\text{Or:} \quad \sigma_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda)R_t^2 \qquad (21)$$

The model's forecast for tomorrow's volatility can be seen as a weighted average of today's volatility and today's squared return. The recent returns matter more for tomorrow's variance than distant returns as λ is less than one and therefore gets smaller when the lag τ gets bigger. Moreover there is only one parameter to estimate, λ. In RiskMetrics, λ is set as 0,94. We need to store a relatively small amount of data as (1-λ) = 0, 06 and $(1-\lambda)\sum_{\tau=1}^{100}\lambda^{\tau-1}$ =0,998 or 99,8% of the weight has been included, therefore we need to store about 100 daily lags of returns in order to calculate tomorrow's variance. One of the shortcomings of this model is that it does not allow for leverage effect and provides counterfactual longer horizon forecasts. Moreover, it ignores the fact that the long run average variance tends to be relatively stable over time.

The following diagram depicts the behaviour of the EWMA-100 model, using a moving estimation window of 100 observations, for Nickel Cash 1993-2007.

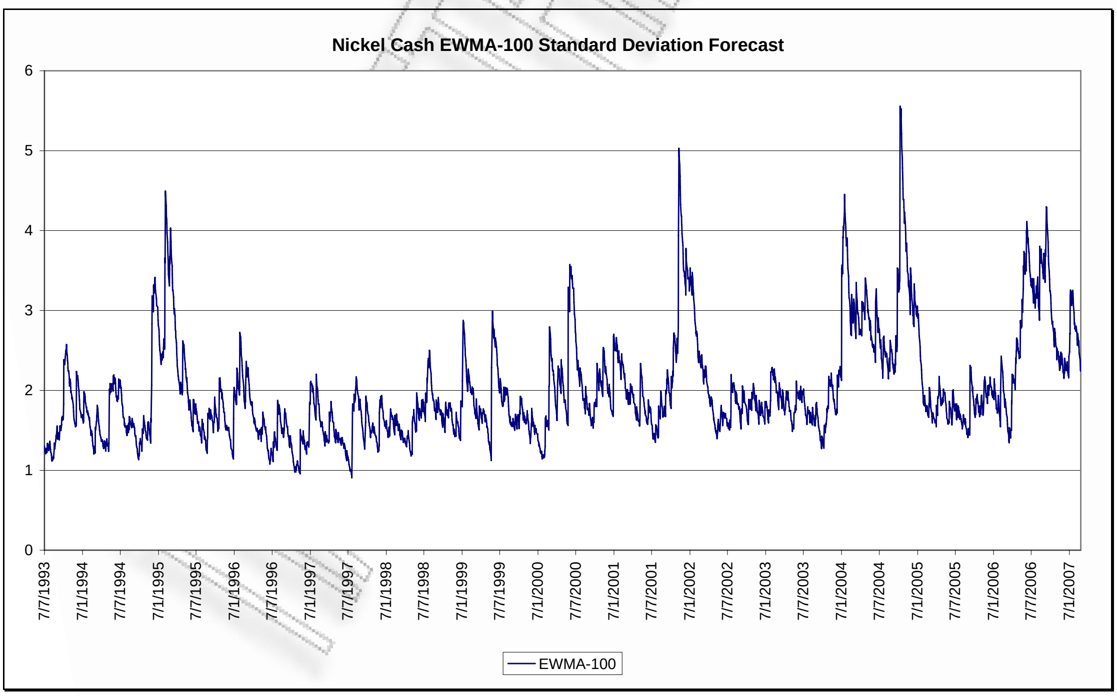


Diagram 4.f. EWMA-100 for Nickel Cash

4.5: Volatility modelling and Value-at-Risk

If we want to compute Value-at-Risk with a volatility model with **Normal Distribution**, we simply use the following formula:

$$VaR_{t+1}^{p} = -\sigma_{t+1}.\Phi_{p}^{-1} \qquad (22)$$

Where σ_{t+1} is the next day's standard deviation, forecasted by the volatility model and Φ_{p}^{-1} is the inverse cumulative density function of the standard normal distribution which calculates the number such that 100.p% of the probability mass is below Φ_{p}^{-1}.

In the case we assume that the errors are **t-Student distributed**, then the density of the standardized t(ν) will be:

$$f_{t(\nu)}(z;\nu) = \frac{\Gamma\left(\frac{(\nu+1)}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right).\sqrt{\pi(\nu-2)}}.\left(1+\frac{z^2}{(\nu-2)}\right)^{-\frac{(1+\nu)}{2}} \quad , \nu>2 \qquad (23)$$

Where: z denotes a r.v. with zero mean and unit standard deviation, Γ(.) denotes the gamma function and ν denotes the degrees of freedom.

Once we estimate ν, we can compute VaR:

$$R_{t+1} = \sigma_{t+1} z_{t+1} \quad \text{with } z_{t+1} \sim \text{t(v)} \quad \Rightarrow \quad VaR_{t+1}^{p} = -\sigma_{t+1} t^{-1}(\nu) \quad \Rightarrow$$

$$VaR_{t+1}^{p} = -\sigma_{t+1}\left(\sqrt{\frac{\nu-2}{\nu}}\right)t_{p}^{-1}(\nu) \qquad (24)$$

Where $t_{p}^{-1}(\nu)$ is the p-th quantile of the standardized t distribution.

Chapter 5: Backtesting Value-at-Risk Models

5.1. The Purpose of Backtesting

The objective of Backtesting a VaR model is to consider the ex- ante risk measure forecasts from our models and compare them with the ex- post realized portfolio returns. The VaR measure tells us that the actual return will only be worse than the VaR_{t+1} forecast *p*100%* of the time. If we observe a time series of past ex- ante VaR forecasts and past ex- post returns, we can define the *hit sequence* of VaR violations as:

$$I_{t+1} = \begin{cases} 1, if \ : R_{t+1} < -VaR_{t+1}^{p} \\ 0, if \ : R_{t+1} > -VaR_{t+1}^{p} \end{cases}$$

If I_{t+1}= 1 then the loss on that day was larger than the VaR forecast and we have a violation. If I_{t+1}= 0 then the loss on that day was smaller than the VaR forecast. If our VaR model is perfect then given all the information available to us at the time the VaR forecast is made, we should not be able to predict whether there will be a VaR violation, meaning that our forecast of a VaR violation should simply be 100*p% every day. The hit sequence of violations should be completely unpredictable and independently distributed over time.

In other words, the hit sequence I_{t+1} ~ *iid Bernoulli (p)* which is our null hypothesis. The Bernoulli Distribution Function is

$$f(I_{t+1}; p) = (1-p)^{1-I_{t+1}} \times p^{I_{t+1}} \qquad (25)$$

Thus if we assume that our experiment looks like a toss of a coin, we will either get heads or tails with probability 50%. The hit sequence will look like a coin toss experiment but instead the probability of getting heads will be 1% for $VaR^{0.01}$ or 5% for $VaR^{0.05}$.

5.2: Likelihood Ratio Test of Unconditional Coverage

Let's test if the fraction of violations obtained for a particular risk model, say π, is significantly different from the VaR coverage rate p. That will be the ***Unconditional Coverage Hypothesis.*** The likelihood of the iid Bernoulli (π) hit sequence is:

$$L(\pi)=\prod_{t=1}^{T}(1-\pi)^{1-I_{t+1}}\times\pi^{I_{t+1}}=(1-\pi)^{T_0}\times\pi^{T_1} \qquad (26)$$

T_0 and T_1 denote how many 0's and 1's we have in our sample. The fraction π can be estimated by $\frac{T_1}{T}$, the observed fraction of violations in the sequence. The likelihood function will become:

$$L(\pi)=\prod_{t=1}^{T}(1-\pi)^{1-I_{t+1}}\times\pi^{I_{t+1}}=(1-\pi)^{T_0}\times\pi^{T_1}=(1-\frac{T_1}{T})^{T_0}\times(\frac{T_1}{T})^{T_1}$$

(27)

Under the unconditional coverage null hypothesis that π = p, we get to the likelihood:

$$L(p)=\prod_{t=1}^{T}(1-p)^{1-I_{t+1}}\times p^{I_{t+1}}=(1-p)^{T_0}\times p^{T_1} \qquad (28)$$

Next we can check the unconditional coverage hypothesis by using the likelihood ratio test:

$$LR_{uc}=-2\ln[\frac{L(p)}{L(\pi)}] \qquad (29)$$

Asymptotically, as the number of observations T goes to infinity, the test will be chi-squared distributed with 1 degree of freedom:

$$LR_{uc} = -2\ln[\frac{L(p)}{L(\pi)}] = -2\ln[\frac{(1-p)^{T_0}\times p^{T_1}}{(1-\frac{T_1}{T})^{T_0}\times(\frac{T_1}{T})^{T_1}}] \sim \chi_1^2 \tag{30}$$

We choose a significance level for the test and then if the LR_{uc} is greater than the value we get from the tables of the chi-square distribution with 1 degree of freedom, we reject the VaR model at the significance level we have chosen. The choice of the significance level turns to weighting the costs of making two mistakes: Either falsely reject a correct model (Type I error) or falsely accept an incorrect model (Type II error). We can't minimize both errors, but we can keep one stable and minimize the other. Typically, in academic work researchers use three types of significance levels: 1%, 5%, 10%. In risk management the type II errors can be very costly for a financial institution, so we rather choose the 1and 5% significance levels.

5.3: Likelihood Ratio Test of Independence

If all the VaR violations happen around the same time, the unconditional coverage test would not be sufficient, in example if the $VaR^{0.05}$ gave us 5% violations all of which came in a period of 2 or three weeks, then the bankruptcy risk would be much higher than in the case where violations were scattered randomly through time. We would therefore reject VaR models which imply violations that are clustered in time, especially those that use historical simulation. So in the case we have clustered violations, we can predict that if today we have a violation, tomorrow is more than p*100% likely to have a violation. We should therefore increase the VaR in order to lower the conditional probability of a violation to the promised p. We need a test that will be able to reject the VaRs with clustered violations.

Let's assume that the hit sequence is dependent over time and that it can be described as a 1st order Markov sequence with transition probability matrix

$$\begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix}$$

Conditional on today being a non- violation ($I_t = 0$), then the probability of tomorrow being a violation ($I_{t+1} = 1$) is π_{01}. The probability of tomorrow being a violation given that today is also a violation, is $\pi_{11} = \Pr(I_t = 1 \text{ and } I_{t+1} = 1)$ .The 1st order Markov property refers to the fact that only today's outcome matters for tomorrow's outcome. The two probabilities π_{01}, π_{11} describe the whole process as we have only two possible outcomes 0 and 1. The likelihood function of this process is:

$$L(\Pi_1) = (1-\pi_{01})^{T_{00}} \times \pi_{01}^{T_{01}} \times (1-\pi_{11})^{T_{10}} \times \pi_{11}^{T_{11}} \tag{31}$$

where T_{ij} i,j =0,1 is the number of observations with a j following an i. The ML estimates

are: $$\pi_{01} = \frac{T_{01}}{T_{00} + T_{01}}$$

$$\pi_{01} = \frac{T_{01}}{T_{00} + T_{01}}$$

and $\pi_{00} = 1 - \pi_{01}$, $\pi_{10} = 1 - \pi_{11}$

Therefore the matrix of transition probabilities will be:

$$\Pi_1 = \begin{bmatrix} \pi_{00} & \pi_{01} \\ \pi_{10} & \pi_{11} \end{bmatrix} = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix} = \begin{bmatrix} \dfrac{T_{00}}{T_{00}+T_{01}} & \dfrac{T_{01}}{T_{00}+T_{01}} \\ \dfrac{T_{10}}{T_{10}+T_{11}} & \dfrac{T_{11}}{T_{10}+T_{11}} \end{bmatrix} \tag{32}$$

Therefore, we allow π_{01} to be different from π_{11}. If the hits are independent over time, then the probability of a violation tomorrow does not depend on today being a violation or not, so $\pi_{11} = \pi$. The transition matrix under independence will be:

$$\Pi = \begin{bmatrix} 1-\pi & \pi \\ 1-\pi & \pi \end{bmatrix}$$

Next we can ***test the independence hypothesis*** that $\pi_{11} = \pi_{01}$ with the likelihood ratio test:

$$LR_{ind} = -2\ln[\frac{L(\pi)}{L(\Pi_1)}] \sim \chi_1^2 \qquad (33)$$

where $L(\pi)$ is the likelihood under the alternative hypothesis from the LR_{uc} test.

5.4: Likelihood Ratio Test of Conditional Coverage

Another powerful test is the ***Conditional Coverage Test*** where we can test jointly for independence and correct coverage using the conditional coverage test:

$$LR_{cc} = -2\ln[\frac{L(p)}{L(\Pi_1)}] = LR_{uc} + LR_{ind} \sim \chi_2^2 \qquad (34)$$

The Conditional Coverage Test is the most powerful and trustworthy when compared with the previous tests and indicates which VaR models pass both unconditional coverage and independence. Therefore, we will emphasize on the p-values reported firstly by LR_{cc} and then by LR_{ind} and LR_{uc} in order to decide which VaR model yields the best forecasts.

(The above formulas and ideas were derived from Christoffersen (2003), p.184-189.)

Chapter 6: A Review of Previous Studies

The existing literature of Value-at-Risk is great and therefore effort has been done towards reviewing the most important and the most recent papers on EVT and VaR.

Neftci (2000) uses 3m, 2y, 5y, 7y US interest rates and the Deutsch Mark/US$, French Franc/US$, Yen/US$, British Pound/US$ exchange rates, covering a period of 5 years daily data, to get 1% VaR estimates for the left and the right tails of the empirical distributions. The author compares the normal distribution threshold estimates with the extreme distribution threshold estimates and finds that the extreme value method yields superior estimates for 1% VaR, from the Normal distribution method. The author uses the *mean excess function* as well to test the extreme value distribution towards the normal distribution. For both risk statistics, VaR and Mean Excess Function, the extreme distributions yield greater and more precise estimates than the normal distribution.

McNeil & Frey (2000) use the S&P 500 index (20 years of data), the DAX index (23 years of data), the BMW share price (23 years of data), the US$– British Pound exchange rate and the price of Gold (16 and 17 years of data respectively). The models they use are Conditional EVT (AR(1)-GARCH(1,1) with GPD innovations - two-stage model), Conditional Normal (AR(1)-GARCH(1,1) with Normal innovations), Conditional t (AR(1)-GARCH(1,1) with t-Student innovations) and Unconditional EVT to estimate Expected Shortfall and VaR at 95%, 99%, 99,5%. They use a moving window of 1000 observations and they find that the Conditional Approach in VaR estimates is better than the Unconditional Approach, the t-Student and GPD work well, with the latter being more preferable, as it can deal with tail asymmetries and that Expected Shortfall is a better risk measure, especially when it is combined with GARCH models and the innovation distribution is modelled using EVT.

Danielsson & de Vries (2000) use the S&P 500 for the period 1990-1996 and a stock portfolio consisting of JP Morgan, 3M, McDonalds, Intel, IBM, Xerox, and Exxon stocks for the period 1987-1996 and a combination of S&P 500 and the portfolio to test Extreme Value Theory with VaR. They make 10 day VaR calculations on a $ 100 million trading portfolio for risk levels: 5%, 1%, 0.5%, 0.1%, 0.05%, and 0.005% and use a moving Estimation Window of 1500 days. They use a Semi-parametric method for unconditional VaR evaluation. The largest risks are modelled parametrically, while smaller risks are captured by the non-parametric empirical distribution function. Moreover they test HS, EVT and RiskMetrics (GARCH with Normal Innovations) methods and find that Conditional Parametric methods such as GARCH with normal innovations underpredict VaR. HS performs better but suffers from high variance. Moreover, it is unable to address losses which are outside the sample. The EV estimator performs better than both RiskMetrics and HS far out in the tails.

Longin (2000) assumes Long and Short Positions in the US equity market: S&P500 (Jan 1962- Dec 1993). The minimal and the maximal returns are chosen for periods of 1week, 1month, 1quarter, 1semester and for holding periods of 1 day and 10 days. The models used are Unconditional EVT (Block Maxima) **vs.** Historical Distribution, Normal Distribution, GARCH (1,1) process, EWMA process. Moreover, he assumes Long, Short and Mixed Positions in S&P500 and SBF240 indexes and uses10-Day Returns from Jan 1976 to Dec 1993. The Minimal and Maximal returns are chosen for holding period of 10 days and tests the Unconditional EVT (Block Maxima) **vs.** Historical Distribution, Normal Distribution. The EVT method has more advantages than the other classical methods that do not account for rare events.

Danielsson (2001) tests the S&P 500 Index, Hang Seng Index, Microsoft Stock Prices, Amazon Stock Prices, Ringgit pound exchange rates, Pound dollar exchange rates, Clean US government bond price index, Gold Prices and Oil prices for the period 1990-1999. He uses moving 300, 1000, 2000 day estimation window with risk forecasts one day ahead. The models used for VaR estimation are Normal GARCH, t-Student GARCH, Historical Simulation and Extreme Value Theory (Unconditional EVT). The empirical properties of current risk forecasting models are found to be lacking in robustness while being excessively volatile. For regulatory use, VaR may give misleading information about risk and in some cases may increase both idiosyncratic and systematic risk. VaR may impose significant but unnecessary costs on the financial institution due to the misallocation of capital and excessive portfolio rebalancing.

Fernandez (2003) uses Daily data from the Chilean financial market: Index Price of Selective Stocks (IPSA) 1990-Nov 2002, Chilean Peso/us$ exchange rate 1988-2002, spot price of Copper 1998-2002, 1-year zero coupon bond 1993-2001. She tests the Conditional t, normal, EVT via GARCH (1,1) as in McNeil & Frey(2000) and unconditional EVT. The last 2 years of data were used for backtesting the 99% VaR estimates. She finds that the conditional t and EVT approaches yield better estimates.

Odening et al. (2003) provide an application of Extreme Value Theory to estimate Value at Risk to Hog Production in the German market. VaR is calculated on gross margin cash flows, associated with the various production activities. The data covers 7 years of weekly price quotations reported by hog producers and slaughter houses in East Germany. The author uses unconditional EVT, V-CM with Normal Distribution and Historical Simulation. The V-CM underestimates VaR for short horizons and HS and EVT give similar results, whereas V-CM and HS overestimate VaR for longer horizons, relative to EVT. There is no direct statistical proof that EVT is superior to V-CM and HS.

Giot & Laurent (2003) cope with market risk in commodity markets: the data they use are: Metals: *aluminium, copper* and *nickel* daily cash prices for the 3/1/1989 to 31/1/2002 period, Energy Commodities: *Brent* and *WTI Crude Oil* daily spot prices for the 20/5/1987 to 18/3/2002 period, Agricultural Commodities: *cocoa futures contracts*, daily prices for the nearest futures contract for the period 3/1/1994 to 31/1/2002. They use RiskMetrics, Student APARCH, Skewed Student APARCH, and Skewed Student ARCH to backtest the 5, 2.5, 1, 0.5 and 0.25% VaR with the last 5-year data. The Skewed Student APARCH performed best in all cases, followed by the Skewed Student ARCH.

Lambadiaris et al. (2003) assess the performance of historical and Monte Carlo Simulation in calculating VaR, using data from the Greek Stock Market and Bond Market. They find that while HS results in over-commitment of capital for linear stock portfolios, the results for non-linear bond portfolios are less clear.

Angelidis et al. (2004) evaluate the performance of an extensive family of ARCH models (GARCH, Exponential-GARCH, Threshold-GARCH) in calculating VaR one day ahead at 95% and 99% levels of perfectly diversified portfolios in stock indices for the period of July 9th 1987 to October 18th 2002, by using different distributions for the errors (Normal, t-Student, Generalized Error) and different rolling estimation windows (500, 1000, 1500, 2000 observations). Their findings show that leptokurtic distributions yield better VaR forecasts and the sample size plays an important role in the accuracy of the forecast.

Bali & Theodossiou (2004) propose a conditional technique for the estimation of VaR and Expected Shortfall risk statistics based on the skewed generalized t-Student distribution (SGT). They use daily returns on the S&P500 index from 1/4/1950 to 12/29/2000 (n=12,832 observations) and estimate a variety of GARCH models including Threshold GARCH and Exponential GARCH with different distributional assumptions for the errors (Normal, GED, SGT and others). They find that a variation of Threshold GARCH and the EGARCH yield the best overall performance.

Brooks et al. (2005) assess the performance of EVT with an unconditional model, a GARCH (1,1) model and a Bootstrapping Approach based on a combination of a GPD and the empirical Distribution of the returns (EVT).They estimate VaR for 1-day, 1-week, 1-month, 3-month investment horizons using data from the London Futures Market, with three Futures contracts traded on the LIFFE for the period 24/05/1991-3/09/1997. The 3 Models are compared with standard non parametric extreme value tail index estimation methods and a semi parametric (GPD) approach and they find that the proposed new semi- parametric approach (with GPD) generates more accurate VaRs than the other 2 methods (unconditional model, GARCH), but the modified Hill Estimator for small samples also performed well and that the choice between conditional and unconditional models appears to be of secondary concern.

Gencay & Selcuk (2004) test the relative performance of EVT and VaR in 10 emerging markets, using daily stock market data. The models for estimating VaR one period ahead in both tails are: V-CV Approach with Normal Distribution, V-CV Approach with t-Student Distribution, Historical Simulation (HS), Adaptive GPD and Non –Adaptive GPD. They use a Sliding Window of 500, 1000 and 1500 days and estimate VaR at 95%, 97,5%, 99%, 99,5%, 99,9%. They find that the GPD fits well the tails of the return distribution and left and right tails have different characteristics. At 99th and higher quantiles, the GPD model dominates others in terms of VaR Forecasting and GPD and EVT are indispensable part of risk management for VaR estimates in emerging markets.

Bekiros & Georgoutsos (2004) study extreme returns and the contagion effect between the foreign exchange and the stock market in Cyprus. They use daily returns of the US dollar/Cyprus pound exchange rate and the Cyprus Stock Exchange (CGI) general index for the period 4/1/96– 4/19/2002. They estimate VaR with BM and POT using RiskMetrics, GED, GARCH, HS and MA (60) for 8 levels of significance. The extreme value techniques give more accurate loss prediction results for heavy tailed distributed return series. The correlation of extreme returns between the Cyprus pound / USD exchange rate and the Cyprus General Index daily returns is quite low but clearly higher than the one that is based on the entire sample of observations.

Krehbiel & Adkins (2005) study the price risk in NYMEX energy complex using EVT. They use spot and Futures prices of Oil, Gasoline and Gas (10 price series) for different periods to estimate VaR and Expected Shortfall. They test Block Maxima and Peaks Over Threshold (POT) with: EWMA with Normal Innovations, AR(1)-GARCH(1,1) with Normal Innovations and AR(1)-GARCH(1,1) with GPD Innovations. The BackTesting is performed using 1000 observations and they find that for 7 of the 10 tails examined, the conditional EVT {AR(1),GARCH(1,1) model with GPD innovations} was statistically superior to the EWMA and AR(1),GARCH(1,1) models with normal innovations.

Harmantzis et al. (2005) use four exchange rates and six stock market indices for different periods and a Rolling Window of 126, 251 and 502 days to estimate VaR at 95% and 99% and Expected Shortfall. They study EVT with Block Maxima and POT, HS, Normal and Stable Paretian, all without filtering. At 95% c.l., the Normal and the POT give more accurate estimates and the effect of the rolling window cannot be predicted. At 99% c.l. the heavy tailed models give more accurate forecasts and the larger the window size, the more accurate the results. For ES, historical method and

POT give better estimates, the Normal underestimates ES and the stable paretian overestimates ES.

Bao, Lee & Saltoglou (2006) evaluate the predictive performance of Value-at-Risk Models in the stock markets of five Asian economies (Indonesia, Korea, Malaysia, Taiwan and Thailand), that suffered the 1997–1998 financial crisis. They use 3 out-of sample evaluation periods denoted as the *before crisis period, the crisis period and the after crisis period* respectively from 1/1/1988 to 31/12/1999. They test the following **filtered** models via GARCH (1,1): RiskMetrics, Normal, Historical Simulation, Monte Carlo, non parametrically estimated distribution of Hall(1999), EVT: GPD, GEV, Hill estimator and the **unfiltered** models: Historical Simulation, Monte Carlo, non parametrically estimated distribution of Hall(1999), EVT: GPD, GEV, Hill estimator, No Distribution: symmetric & asymmetric CaViaR. They find that RiskMetrics behaves well before and after the crisis, while some EVT models do better in the crisis period. Filtering is useful for EVT models. The assumption that RiskMetrics can be beaten during the crisis can't be rejected. CaViaR has shown some success in predicting VaR.

Kuester, Mittnik & Paolella (2006) construct a portfolio with a long position in the NASDAQ Composite Index from Feb 8, 1971 to June 22, 2001 (7681 obs.) and use a rolling window of 1000 observations. They test the **unconditional models**: Historical Simulation, Normal, t-Student, Skewed-t, EVT and the **conditional models** via Garch(1,1): Normal, t-Student, Skewed-t, EVT, Filtered HS, Mixed Normal, Mixed Generalized Exponential. All unconditional models produce clustered VaR violations. The conditional models lead to much more volatile VaR predictions. *Conditional skewed-t*, Mixed *GED*, *EVT* and *FHS* perform best.

Choudhary (2006) accomplished a research in daily foreign exchange returns (GBP/USD,CHF/USD, JPY/USD and AUD/USD) for the period Jan. 2nd 1982 – Dec. 31st 2004. He applied the V-CV method, the POT method and the Hill estimator method to calculate VaR and his target was to examine if the two EVT approaches can provide more accurate risk forecasts than the traditional V-CV approach. He concluded that the normal distribution might allow for large open trading positions that can be very dangerous. On the other hand, the EVT framework can provide more accurate results.

Angelidis and Degiannakis (2006) employed an empirical analysis of various traditional VaR approaches while they extended their study to the evaluation of the coherent alternative of VaR, namely the Expected Shortfall. In order to apply their study, they used equity data from the S & P 500 index, commodities (Gold) and exchange rates (US$ / British pound for 4th April 1988 – 5th April 2005). The authors tested the VaR and ES under the assumptions that the returns follow the normal distribution, the Generalized Error distribution (GED), the Student-t distribution and the skewed student-t distribution. Moreover, they used different statistical models for the estimation of the volatility such as the GARCH model, the I-GARCH model, the FI-GARCH model and others. What they found is that, the student-t and the skewed student-t distributions systematically overestimate the “true” risk while the returns incorporate some kind of asymmetry. Moreover, the normal-VaR (with various GARCH innovations) seems to perform well in the cases of exchange rates and equities while the GED-VaR performs well in the case of commodities. Concerning the ES forecasts, Angelidis and Degiannakis proposed that they are significantly higher than the VaR forecasts.

Chapter 7: Empirical Research

7.1: Application of EVT and VaR in Metal Commodities

As we can see from the literature review, most of the researchers test various models of VaR on equity markets, for example they assume long positions on stock indices or stocks, or construct portfolios of various instruments like stock, bonds, exchange rates, interest rates. Others have tested the performance of VaR models with portfolios consisting of Futures and Oil and Energy products like Brent Oil, Natural Gas, Copper and others. Little is the literature on industrial metals such as Copper, Tin, Nickel, Zinc and Aluminium. These commodities have different characteristics from equity as they have value because they are scarce in nature and fluctuations of prices are mainly caused by supply and demand imbalances that originate from the business cycle, political events and unexpected weather patterns. Moreover, such commodity markets are strongly shaped by storage limitations, convenience yield and seasonality effects and price volatility can stem from the behaviour of some market participants who engage in short term speculation, as Giot and Laurent (2003) state. So it is really interesting to test Extreme Value Theory and some selected Univariate Value-at-Risk models on various industrial metals such as the above mentioned. There are five main questions to answer:

1) Can the methods commonly applied to measure price risk for financial assets be successfully used to measure price risk exposure arising from positions in metal commodities?
2) Does Extreme Value Theory provide better VaR forecasts than traditional methods that assume normality of returns?
3) Which models of volatility can describe best the price risk in metal commodities?
4) Which methods provide the best VaR forecasts when we measure price risk in the contracts traded in the London Metal Exchange?
5) What are the expected likelihoods and magnitudes of extreme events for metal commodities?

7.2: Metals Markets

There are 12 major metal markets in the world, with the London Metal Exchange being the dominant one in futures contracts, serving that way as a benchmark for the pricing of copper, aluminium, tin, nickel and other base metals. On the other hand, the biggest market for physical exchange and delivery of the metals is the New York Metal Exchange (NYMEX). In the U.S. futures contracts on metals trade in the Commodity Exchange Market (COMEX) which is controlled by NYMEX. In Chicago however we can find the world's oldest commodity market, the Chicago Board of Trade (CBOT) founded in 1848. In Chicago one can find the Mid-America Commodity Exchange (MidAm), a market for the trading of contracts on precious metals. Other major markets that metals and futures contracts on metals are traded, can be found in Japan with the Tokyo Commodity Exchange (TOCOM) and Osaka Mercantile Exchange (OME) which was founded in 1997 after the merger of Osaka Textile Exchange and Kobe Rubber Exchange. In Australia we can find the Sydney Futures Exchange (SFE), in Shanghai the Shanghai Futures Exchange (SHME) and the Shanghai Gold Exchange (SGE) and in Dubai the Dubai Gold & Commodities Exchange (DGCX) which has been operating since 2005 and is characterized by the very sophisticated electronic trading platform. Lastly, in Iran there is the Tehran Metals Exchange (TME) which trades mostly gold and aluminium.

7.3: The London Metal Exchange (LME)

The London Metal Exchange was founded in 1877 and with 130 years of history is the world's premier non-ferrous metals market with liquid contracts and worldwide reputation. Trading is performed via open outcry market (ring trading), inter-office telephone market (OTC) and LME's Select (electronic trading platform). The London Metal Exchange provides the global forum for all those who wish to manage the risk of future price movements in non-ferrous metals and plastics. The Exchange has developed standardised contracts which assume that on falling due they will result in material either being delivered or received.

The world of metals and base metal trading has changed dramatically over the last century and new metals have been introduced as demand dictated. Copper and tin have traded on the LME since the beginning in 1877. The copper contract was upgraded to high grade copper in November 1981 and again to today's Grade-A contract in June 1986. Tin's present contract began trading in June 1989, following a brief cessation due to the collapse of the International Tin Council. Lead and zinc were officially introduced in 1920, but were traded unofficially before that. The lead contract has remained virtually unchanged, certainly since its reintroduction in October 1952 following the closure of the Exchange brought about by the Second World War. Zinc, on the other hand, has undergone a number of upgrades, most recently with the introduction of the special high grade contract in June 1986. Primary aluminium was introduced in December 1978 and today's high grade contract began trading in August 1987. Nickel commenced trading on the Exchange the year after primary aluminium, in April 1979, aluminium alloy in October 1992 and in May 1999, a silver contract was launched. An index contract -LMEX- based on the six primary metals traded on the exchange was introduced in 2000. In May 2005, the LME introduced the first ever Exchange traded plastics futures contracts for polypropylene and linear low density polyethylene, with the addition of regional contracts in 2007.

7.4: The LME contracts

Today the LME trades in eight metals, two plastics and one index comprising the six primary base metals. The LME's eight metals contracts are: *copper grade A*, *primary aluminium*, *standard lead*, *primary nickel*, *tin*, *special high grade zinc*, *aluminium alloy* and *North American Special Aluminium Alloy (NASAAC)*. The LME's plastics contracts are *polypropylene (PP)* and *linear low density polyethylene (LL)*.Unlike other commodity markets, which are usually based on monthly prompt dates, LME metal futures contracts run on a daily basis for a period of three months. The use of daily prompt dates is an important difference between the LME and other futures exchanges. After the 3-month date, the daily prompts for forward trading are reduced to weekly and then monthly contracts out to 15, 27 or 63 months forward.

The LME also offers traded options contracts based on each of these futures contracts, together with traded average price options contracts (TAPOs) based on the monthly average settlement price (MASP) for all metals futures contracts. The LME's plastics contracts are based on monthly prompt dates out to 15 months forward. All LME prices are quoted in US$ Dollars, but the LME permits contracts in U.K.Sterling £, Japanese yen ¥, and Euros € and provides official exchange rates from US Dollars for each of them. Trade is conducted in lots rather than tonnes, with each lot of aluminium, copper, lead and zinc amounting to 25 tonnes. Nickel is traded in 6 tonne lots, tin in 5 tonnes and aluminium alloy and NASAAC in 20 tonne lots. PP and LL are traded in 24.75 tonne lots. The contract for each metal sets out the shapes, weights and methods of strapping (metals) and packaging (plastics). The contract specifications are for the quality and shape which are most widely traded and demanded by industry.

Delivery against LME contracts is in the form of LME warrants, which are bearer documents of title enabling the holder to take possession of a specified parcel of metal at a specified LME approved warehouse. Each LME warrant is for one lot of metal, the tonnage of which is dependent on the contract specification. The front of the LME warrant displays information about the parcel of metal, including its brand, the exact tonnage, the shape and the location. Warrants are issued by the warehouse companies at the request of the owner of the metal once it is properly stored in an LME-approved warehouse and the warehouse company has ensured conformity with the LME's Special Contract Rules for that metal. These rules include, but are not limited to, the technical specification of the metal, its shape, weight and bundling. The metal must also be of a brand that is approved and listed by the LME.

(The above information was collected from the official website of the LME)

7.5: Description of the Dataset and Preliminary Data Analysis

We use daily logarithmic price changes: $R_t = 100* \ln\left(\frac{S_t}{S_{t-1}}\right)$ from **cash** and **3-month futures** prices from the following metals: **Aluminium**, **Nickel**, **Tin**, **Zinc**, **Copper**. All time series are quoted in US$ per tonne and the data spans from the 1st of June 1989 to 2nd of March 2007. Cash prices are the midpoint of the daily transaction price range (the product is delivered two days later in the cash price which has been agreed by the buyer and the seller). On the opposite, the nearby futures price series for each metal is constructed from the settlement price of the futures contract nearest delivery (the delivery, if any, will take place 3-months later in the price which has been agreed today by the buyer and the seller – marking to market is conducted and there exist margins). Descriptive statistics of the time series are provided in Table 7.a. For comparisons, we also analyze daily logarithmic price changes from **Gold Bullion** (US$ per troy ounce), **FTSE-100** (UK equity index) and **LIFFE FTSE-100** (UK futures equity index) for the same dates. We don't construct portfolios but analyze each time series separately; we assume long position on each contract and estimate VaR as a percent on each time series. The prices of metals (Aluminium, Nickel, Tin, Zinc, Copper) were downloaded from Bloomberg, whereas Gold Bullion, FTSE-100 and LIFFE FTSE-100 were downloaded from DataStream.

Table 7.a: Descriptive Statistics of the daily continuously compounded returns

Panel A: Daily Cash Logarithmic Price Changes 1st June 1989- 2nd March 2007							
Parameter	**Alumin.**	**Nickel**	**Tin**	**Zinc**	**Copper**	**Gold**	**FTSE-100**
N (# of obs.)	4403	4422	4419	4419	4419	4631	4630
Mean	0,00733	0,027906	0,005884	0,016403	0,019217	0,012645	0,023062
Maximum	8,22264	11,72604	11,17644	8,701138	17,19768	7,382031	5,902563
Minimum	-9,7826	-18,3585	-10,8277	-14,7157	-10,8463	-7,21783	-5,88533
St.Deviation	1,29596	2,079282	1,304073	1,583515	1,633042	0,836050	0,991342
Skewness	-0,27151	-0,17858	-0,28930	-0,65505	0,052103	-0,24446	-0,12528
Kurtosis	7,43827	7,487664	9,908094	9,551467	10,03757	11,81066	6,350336
Jarque-Bera* (p-value)	3667,90 (0,0000)	3734,138 (0,0000)	8848,412 (0,0000)	8218,991 (0,0000)	9121,234 (0,0000)	15025,06 (0,0000)	2177,555 (0,0000)

* Jarque-Bera Normality test statistic, p-value in brackets

Panel B: Daily 3-month Futures Logarithmic Price Changes 1st June 1989- 2nd March 2007						
Parameter	**Alumin.**	**Nickel**	**Tin**	**Zinc**	**Copper**	**LIFFE FTSE-100**
N (# of obs.)	4403	4422	4419	4419	4419	4630
Mean	0,007933	0,027220	0,005735	0,017450	0,019418	0,022431
Maximum	8,017648	11,48248	11,80672	7,364329	10,98360	5,950595
Minimum	-8,247160	-18,10605	-9,649783	-12,13802	-9,450249	-6,556740
St.Deviation	1,137124	1,932771	1,215349	1,357503	1,388228	1,075937
Skewness	-0,097971	-0,221237	-0,201089	-0,413746	-0,241927	-0,124208
Kurtosis	6,832630	7,762029	10,43788	8,304715	7,718669	5,816254
Jarque-Bera* (p-value)	2701,873 (0,0000)	4214,296 (0,0000)	10215,96 (0,0000)	5307,356 (0,0000)	4142,803 (0,0000)	1541,982 (0,0000)

* Jarque-Bera Normality test statistic, p-value in brackets

In Panel A we can see the descriptive statistics of the daily cash logarithmic price changes of Aluminium, Nickel, Tin, Zinc, Copper, Gold Bullion and the FTSE-100 index. In terms of the standard deviation reported, we can draw some conclusions about the volatility and the risk of fluctuations in the returns of each time series: Nickel is the most volatile of all the metals ($\sigma = 2{,}07$) followed by Copper, Zinc, Tin and Aluminium. The Gold and FTSE-100 time series are less volatile than the metals of LME as they have standard deviation less than 1, indicating that the equity market of UK and the gold market are safer markets than the London Metal Exchange. In terms of Skewness, which shows us how symmetric is the empirical distribution of returns only copper has a positive number and is closer to zero, opposite to the other time series which indicate negative skewness, meaning this way a higher probability for large negative returns. Kurtosis, which shows how fat is the distribution, is larger than 3 for all of the time series reported. Nickel has the larger minimum return (-18,35 %) opposite to FTSE-100 which has the smaller minimum (-5,88 %) and Copper has the larger maximum return (17,19 %) opposite to FTSE-100 (5,90 %). Finally, all time series are definitely non-normal, as the Normality assumption is rejected by the Jarque-Bera statistic.

In Panel B we can see the descriptive statistics of the daily 3-month futures logarithmic price changes of Aluminium, Nickel, Tin, Zinc, Copper and the LIFFE FTSE-100 index. In terms of the standard deviation reported, Nickel is the most volatile of all the metals (σ = 1,93) followed by Copper, Zinc, Tin and Aluminium. The LIFFE FTSE-100 time series is less volatile than the metals of LME indicating that the equity market of UK is safer than the London Metal Exchange. In terms of Skewness, all time series have negative numbers indicating negative skewness. Kurtosis, which shows the fatness of the distribution, is larger than 3 for all of the time series reported with the LIFFE FTSE-100 being closer to 3. Nickel has the larger minimum return (-18,1 %) opposite to LIFFE FTSE-100 which has the smaller minimum (-6,55 %) and Tin has the larger maximum return (11,8 %) opposite to LIFFE FTSE-100 (5,95 %). Finally, the Normality assumption is rejected by the Jarque-Bera statistic for all time series.

The preliminary data analysis indicates that we have to deal with time series which are definitely riskier and more volatile than Gold and Equity (FTSE-100). LME metals time series are negatively skewed and asymmetric, revealing a higher probability for negative extreme returns, leptokurtic and non-normal. The findings of the Jarque-Bera Normality test are in line with the Quantile-Quantile plots against the Normal Distribution and the histograms which can be found in Appendix I. Generally speaking, we have negatively skewed, leptokurtic and fat tailed empirical distributions for the cash and the 3-month futures time series and the deviations from the assumption of normality in the returns are clear.

In the Appendix I, besides the Histogram, the Q-Q plot, the returns plot and the closing prices for each time series, we report the statistics from the Augmented Dickey-Fuller unit root test and the Ljung – Box Q Statistic for Autocorrelation. The Dickey-Fuller test tests the null hypothesis that an autoregressive process is non-stationary. As we can see from the tables reported, all time series are stationary processes, as they have zero p-values. The Ljung-Box Q test is χ^2 distributed and tests the null hypothesis of no autocorrelation up to lag 20. Most of the time series exhibit significant autocorrelation for lags 2 to 20 (p-values < 0.05), with the only exception of the Aluminium 3-month series which reports p-values larger than 0.05 for almost all lags. These findings are inconsistent with the necessary condition of the extreme value theory that extremes are independent and identically distributed.

7.6: Computing Value-at-Risk and Methodology Description

In this study, we make Value-at-Risk forecasts at 95% and 99% levels with different methods including Peaks over Threshold and Block Maxima with different threshold levels and block sizes, Variance-Covariance with filters GARCH(1,1), EGARCH(1,1), EWMA (λ=0,94) under the Normal and the t-Student distributions and finally Historical Simulation. Our purpose is to investigate the empirical performance of these forecasts, compared to the actual portfolio returns, by using the 3 likelihood ratio tests of unconditional coverage, independence and conditional coverage.

In Extreme Value Theory there are several shortcomings in the estimation of the models that we have already mentioned, including the limited number of maxima in Block Maxima and the selection of the threshold in Peaks over Threshold method. In practice we will need a very large data set to compute Block Maxima as we need blocks with a lot of observations from which to choose the maximum and also we will need a large number of maxima to fit the Generalized Extreme Value Distribution. Moreover we will need an adequate number of forecasts for the Backtesting trials so that the LR tests will be asymptotically χ^2 distributed in order to take good results that we will trust. We can see that each stage of the estimation process needs too many observations and the same goes for Backtesting. Concerning the Peaks over Threshold method, we can use some tools from Statistics which include the Sample Mean Excess Function plot and the Hill plot, in order to determine the threshold u. The Sample Mean Excess Function gives us the sum of the excesses over the threshold u, divided by the number of data points which exceed the threshold u. If the empirical plot seems to follow a reasonably straight line with positive gradient above a certain value of u, then this is an indication that the excesses over this threshold follow the Generalized Pareto distribution with $\xi > 0$. The Hill estimator is a semi-parametric estimator for ξ, which governs the tail of the distribution and provides us with an alternative estimator other than the classic Maximum Likelihood Estimator for ξ. The Hill estimator can be used only in the cases where $\xi > 0$ (Frechet Distribution) and we can construct a Hill plot such that the estimated ξ is plotted as a function of the threshold.

Unfortunately we can't use the Sample Mean Excess Function and the Hill Plot to decide on the level of the threshold u, as we will need to have more than 1000 backtesting trials and the estimation of the models will be utilized via a moving estimation window. Therefore we will arbitrarily decide on the level of threshold u as in McNeil & Fray (2000). At this stage we must point that the Achilles' heel of the Extreme Value Theory is the choice of threshold u: there is a trade-off between bias and variance. If u is too large, then only very few observations will be left in the tail and the estimate of the tail parameter ξ will be uncertain. On the other hand, if u is set too small, the data to the right of the threshold may not conform sufficiently well to the Generalized Pareto Distribution to generate unbiased estimates of ξ.

In this study we used the method of the moving estimation window with 500 and 1000 observations which correspond to 2 and 4 years of trading data respectively. The estimation is made for the first 500 and 1000 observations respectively; we estimate the coefficients of each model and then we compute a VaR forecast for days 501 and 1001. Then we move one day front, by discarding the 1st observation and estimating the models with observations 2 up to 501 and 2 up to 1001 in order to compute VaR forecasts for days 502 and 1002 respectively. This method is continued until we reach at the point where we have a forecast for the 2nd of March 2007 with both windows of 500 and 1000 observations. This methodology is followed for V-CV with Normal GARCH(1,1), t-Student GARCH(1,1), Block Maxima and Peaks Over Threshold. Normal EGARCH(1,1) and t-Student EGARCH(1,1) are estimated with only one moving estimation window of 1000 observations, whereas in the estimation of Historical Simulation we follow Lambadiaris et al. (2003) and use two moving estimation windows of 100 and 252 observations. Finally, Exponentially Weighted Moving Average is estimated with a moving estimation window of 100 observations.

Concerning Block Maxima, we firstly multiplied each time series with -1, so as to model maximum losses from each block. Then we used 5 different ways of estimation: the 500 day window is estimated twice by dividing the 500 observations in 25 and 50 non- overlapping blocks of 20 and 10 observations respectively; in other words we use 20-day and 10-day maxima. The 1000 window is estimated three times by dividing the 1000 observations in 25, 50 and 100 non-overlapping blocks respectively; in other words we use 40-day, 20-day and 10-day maxima. In the bibliography, it is often argued that the researcher should use maxima that correspond to quarters, semesters or years so as to converge to the GEV distribution. However in this case we have limited data and we chose smaller blocks in order to utilize the moving estimation window method and in order to have an adequate number of forecasts for the Backtesting process. Moreover, we assume that the extremal index θ equals 1, which corresponds to full independence of the maxima (the VaR forecast is calculated via formula 10, page11). We expect that the Backtesting results will give us a sense of the convergence of the maxima in different block sizes and different lengths for the estimation windows.

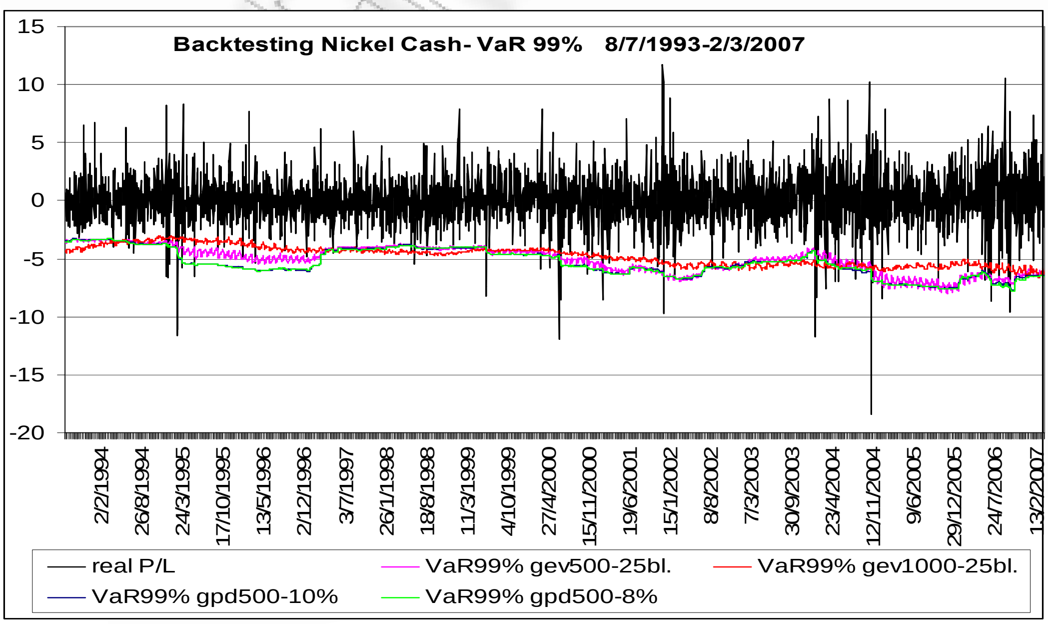
For the Peaks over Threshold method (VaR is computed via formula 15, p.14), we firstly multiplied each time series with -1, so as to model the negative extremes over a high threshold u and then we arbitrarily assumed that the 10%, the 8% and the 5% of the empirical distribution is extreme, extending the methodology of McNeil & Fray (2000). We expect that the Peaks over Threshold method will give us better results than Block Maxima as it handles better the existing data and we can’t discard extreme observations as in Block Maxima. Backtesting results should give us a sense of the convergence of the maxima in different threshold levels and different lengths for the estimation windows.

On Table 7.b. we can see the estimated coefficients and VaR calculations for Block Maxima and Peaks over Threshold for Nickel Cash on the last day of the dataset, on 2nd of March 2007. Diagram 7.a shows the behavior of the VaR forecasts at 99% level from some models of Block Maxima and Peaks over Threshold. (Fully estimated models and VaR calculations as well as VaR and Profit/Loss Diagrams for all the time series can be found in the DVD which accompanies the dissertation.)

Table 7.b: Nickel Cash VaR calculations on 2nd of March 2007

Panel A					
Method: Block Maxima	**ξ (kappa hat)**	**μ (mu hat)**	**σ (sigma hat)**	**VaR99%**	**VaR95%**
GEV500: 25 blocks of 20 obs.	-0,0356	3,4723	1,7973	-6,275	-3,426
GEV500: 50 blocks of 10 obs.	0,1945	2,4477	1,3547	-6,372	-3,413
GEV1000: 25 blocks of 40 obs.	0,3762	4,5252	1,6220	-6,288	-3,504
GEV1000: 50 blocks of 20 obs.	0,1381	3,4575	1,9184	-6,903	-3,409
GEV1000:100 blocks of 10 obs.	0,1859	2,4681	1,4840	-6,722	-3,523
Panel B					
Method: Peaks over Threshold	**ξ (kappa hat)**	**u (threshold)**	**σ (sigma hat)**	**VaR99%**	**VaR95%**
GPD500: 10%	-0,1016	2,4540	1,9502	-6,4581	-3,7593
GPD500: 8%	-0,1421	2,8444	2,0341	-6,5064	-3,7692
GPD1000: 10%	0,1741	2,5369	1,5449	-6,9127	-3,6750
GPD1000: 8%	0,2020	2,9039	1,5382	-6,8789	-3,6622
GPD1000: 5%	0,1699	3,6052	1,7949	-6,9275	-3,6052

Diagram 7.a: Backtesting Nickel Cash – Out of Sample VaR calculations



Chapter 8: Presentation of the Results

8.1: Copper Cash

In the APPENDIX II we can find Table 2 which contains the Backtesting results for Copper Cash. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3418 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), the models that pass the LR_{cc} test are Normal GARCH(1,1) 500 and 1000, t-Student GARCH(1,1) 500 and 1000, Historical Simulation 100 and 252, t-Student EGARCH(1,1) 1000 and all models of Peaks over Threshold method. The best method is t-Student EGARCH(1,1)-1000 (p-value = 0,68786) and t-Student GARCH(1,1)-500 & 1000 have the least violations of all models (30 violations, when the expected violations are 34). EWMA passes only the LR_{ind} test and is rejected by LR_{cc} test (p-value = 0,00064); the same goes for Normal EGARCH(1,1)-1000 (p-value = 0,00182). Block Maxima performs rather badly and only 2 models, GEV500-50bl. and GEV1000-100bl. pass the LR_{ind} test. Moreover, it is clear that t-Student models which are leptokurtic and fat-tailed, outperform the Normal distribution at 99% c.l., although Normal GARCH(1,1) showed good forecasting ability and passed the LR_{cc} test. Finally, only Peaks over Threshold did well with the GPD1000-10% model being the best among all (p-value = 0,4257, with 41 VaR violations) and Block Maxima models failed to pass the LR tests.

At 95% confidence level (Panel B), all GARCH(1,1) and EGARCH(1,1) models pass the LR_{cc} test, with t-Student GARCH(1,1)-500 (p-value = 0,64, VaR violations = 161) and t-Student EGARCH(1,1)-1000 (p-value = 0,64, VaR violations = 164) being the best among them. However, EWMA is the best model of all at the 95% cl.. (p-value = 0,897, VaR violations = 173). Historical Simulation and Peaks over Threshold pass only the LR_{uc} test at c.l. 5% and Block Maxima performs rather badly. It is clear that as we move to lower quantiles, the Normal Distribution models perform better and on the opposite, Extreme Value Theory methods can't model adequately the tails of the distribution.

8.2: Copper 3-Month

In the APPENDIX II we can find Table 3 which contains the Backtesting results for Copper 3-Month. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3418 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), the models that pass the LR_{cc} test are t-Student GARCH(1,1) 500 and 1000, Historical Simulation 100 and 252 and t-Student EGARCH(1,1) 1000. The best method is t-Student GARCH(1,1)-1000 (p-value = 0,70997) and together with t-Student EGARCH(1,1)-1000, have the least violations of all models (33 violations, when the expected violations are 34). EWMA is rejected by LR_{cc} test (p-value = 0,0000); the same goes for Normal GARCH(1,1)-500 & 1000 and Normal EGARCH(1,1)-1000 (p-value = 0,00023). Block Maxima performs badly and all models are rejected by the LR tests. Moreover, it is clear that t-Student models which are leptokurtic and fat-tailed, outperform the Normal distribution at 99% c.l. Finally, only Peaks over Threshold did well (at the significance level of 5%, almost all models pass the LR_{cc} test) and Block Maxima models failed to pass the LR tests.

At 95% confidence level (Panel B), EWMA is the best model of all (p-value = 0,062, VaR violations = 166) and it is very interesting that no other model passes the LR_{cc} test. Historical Simulation and Peaks over Threshold pass only the LR_{uc} test and Block Maxima performs rather badly. GARCH(1,1) and EGARCH(1,1) pass only the LR_{uc} test at s.l. of 5% . However, at s.l. 1% all GARCH and EGARCH models pass the LR_{cc} test.

8.3: Tin Cash

In the APPENDIX II we can find Table 4 which contains the Backtesting results for Tin Cash. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3418 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), the models that pass the LR_{cc} test are t-Student GARCH(1,1)-500 (p-value = 0,138, VaR violations = 34) & 1000 (p-value = 0,553, VaR violations = 32) and t-Student EGARCH(1,1) (p-value = 0,5537, VaR violations = 39). Normal GARCH & EGARCH don't perform well and pass only LR_{ind}. On the other hand Historical Simulation, Block Maxima and Peaks over Threshold are all rejected by LR_{cc} test and can't provide us with reliable VaR forecasts.

At 95% confidence level (Panel B), Normal GARCH(1,1)-500 (p-value = 0,394, VaR violations = 167), t-Student GARCH(1,1)-500 (p-value = 0,2647, VaR violations = 168) and Normal EGARCH(1,1)-1000 (p-value = 0,346, VaR violations = 161) have the best performance. On the other hand, the effect of the length of the estimation window is clear, as Normal GARCH(1,1)-1000, t-Student GARCH(1,1)-1000 and t-Student EGARCH(1,1)-1000 overestimate risk and prove very conservative (VaR violations = 145, 152 and 153 respectively). EWMA, Historical Simulation, GPD500-10% and GPD500-8% (Peaks over Threshold) pass only the LR_{uc} test. All the other models of Peaks over Threshold and Block Maxima underestimate risk and prove inadequate.

8.4: Tin 3-Month

In the APPENDIX II we can find Table 5 which contains the Backtesting results for Tin 3-Month. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3418 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), only t-Student models perform well, namely GARCH(1,1)-500 (p- value = 0,158, VaR violations = 39) & 1000 (p- value = 0,646, VaR violations = 34) and EGARCH(1,1)-1000 (p- value = 0,553, VaR violations = 32). Normal GARCH(1,1) and EGARCH(1,1) fail to provide us with good forecasts of VaR and the same results are derived for EWMA, which is rather reasonable as we know that as we model lower and lower quantiles, the Normal distribution underestimates risk. Historical Simulation, Block Maxima & Peaks over Threshold give us very bad VaR forecasts; they underestimate risk and all models are rejected by the LR tests.

At 95% confidence level (Panel B), the best model is Normal EGARCH(1,1) with 172 VaR violations. Normal GARCH(1,1). t-Student GARCH(1,1), EWMA and t-Student EGARCH pass the unconditional coverage LR test but fail to pass the test of independence and prove very conservative. On the other hand, Historical Simulation underestimates risk and fails to pass the LR_{cc} test. The methods of Extreme Value Theory fail to pass the LR tests. However Peaks over Threshold yields better VaR estimates and has fewer violations than Block Maxima. Moreover Peaks over Threshold is more conservative than Block Maxima under the criterion of Mean VaR.

8.5: Zinc Cash

In the APPENDIX II we can find Table 6 which contains the Backtesting results for Zinc Cash. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3418 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), the models that pass the LR_{cc} test are t-Student GARCH(1,1)-500 and 1000, Historical Simulation 100 and 252, t-Student EGARCH(1,1) 1000 and some models of Peaks over Threshold method (GPD500-

10%, GPD500-8%, GPD1000-8%). The best method is t-Student GARCH(1,1)-500 (p-value = 0,70997) and t-Student GARCH(1,1)-1000 has the least violations of all models (32 violations, when the expected violations are 34). EWMA is rejected by LR_{cc} test (p-value = 0,0000); the same happens with Normal EGARCH(1,1)-1000 (p-value = 0,0000). Block Maxima performs rather badly and it is clear that t-Student models which are leptokurtic and fat-tailed, outperform the Normal distribution at 99% c.l., although Normal GARCH(1,1) showed some good forecasting ability and passed the LR_{ind} test. Finally, Peaks over Threshold did well with the GPD500-10% model being the best (p-value = 0,0868, with 44 VaR violations) among all Extreme Value Theory models.

At 95% confidence level (Panel B), all models examined fail to pass the LR_{cc} test; t-Student GARCH(1,1)-500, EWMA, Peaks over Threshold (GPD500-10% & 8%), Historical Simulation 100 & 252 passed the unconditional coverage test. GARCH and EGARCH models overestimate risk and prove very conservative, contrary to Historical Simulation, Block Maxima & Peaks over Threshold. The best model for Zinc 3-Month was EWMA (164 VaR violations, p-value = 0,58573).

8.6: Zinc 3-Month

In the APPENDIX II we can find Table 7 which contains the Backtesting results for Zinc 3-Month. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3418 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), the models that pass the LR_{cc} test are t-Student GARCH(1,1)-500 & 1000, Historical Simulation 100 and 252, t-Student EGARCH(1,1) 1000 and some models of Peaks over Threshold method (GPD500-10% & GPD500-8%). The best method is t-Student GARCH(1,1)-1000 (p-value = 0,64965) with the least violations of all models (36 violations, when the expected violations are 34). EWMA is rejected by LR_{cc} test (p-value = 0,0000); the same happens with Normal EGARCH(1,1)-1000 (p-value = 0,00015). Block Maxima performs rather badly except from GEV500-25bl. & 50bl. (56 and 50 VaR violations respectively); t-Student models outperform the Normal distribution at 99% c.l. Finally, Peaks over Threshold did well with both GPD500-10% & 8% model being the best (p-value = 0,3586, with 42 VaR violations) among all Extreme Value Theory models.

At 95% confidence level (Panel B), all models examined fail to pass the LR_{cc} test; t-Student GARCH(1,1)-500, t-Student EGARCH(1,1)-500, EWMA & Historical Simulation 100 & 252 passed the unconditional coverage test. GARCH and EGARCH models overestimate risk and prove again very conservative as in Zinc Cash, contrary to Historical Simulation, Block Maxima & Peaks over Threshold. The best model for Zinc 3-Month was Historical Simulation 100 (177 VaR violations, p-value = 0,63402).

8.7: Nickel Cash

In the APPENDIX II we can find Table 8 which contains the Backtesting results for Nickel Cash. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3421 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), all models that we examined pass the LR_{ind} test except from Normal EGARCH(1,1,)-1000. The models that pass the LR_{cc} test are t-Student GARCH(1,1)-500 & 1000, Historical Simulation-252, t-Student EGARCH(1,1) 1000 and some models of Peaks over Threshold method (GPD500-10% & GPD500-8%). The best method for Nickel Cash is t-Student GARCH(1,1)-500 (p-value = 0,70942, 33 VaR violations) followed by t-Student GARCH(1,1)-1000 and t-Student EGARCH(1,1)-1000 (32 VaR violations for both models). It is interesting that Block Maxima yields better VaR forecasts for Nickel Cash, as well as Peaks over Threshold, contrary to all the other metals we have already examined.

At 95% confidence level (Panel B), we have many models that pass the LR_{cc} test. Surprisingly, Normal GARCH(1,1)-500 & 1000, t-Student GARCH(1,1)-500 & 1000, EWMA, Historical Simulation 100 & 252, Normal EGARCH(1,1)-1000 and t-Student EGARCH(1,1)-1000 pass all tests, with EWMA being the best of all models (p-value = 0,97908, 169 VaR violations). Block Maxima performed very well, just like at the 99% level and Peaks over Threshold gave the best model among the ones of EVT (p-value = 0,05248, 197 VaR violations).

8.8: Nickel 3-Month

In the APPENDIX II we can find Table 9 which contains the Backtesting results for Nickel 3-Month. The estimation period was 1/6/1989-7/7/1993 and the Backtesting period was 8/7/1993-2/3/2007, leaving us with 3421 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (171 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), t-Student GARCH(1,1)-500 & 1000, Historical Simulation-252 and all models of Peaks over Threshold method passed the LR_{cc} test. Block Maxima did well compared with previous metals and passed the LR_{ind} test (Block Maxima can't be rejected by the LR_{cc} test at 1% s.l.). The best model for Nickel 3-month is t-Student GARCH(1,1)-1000 (p-value = 0,66568, 36 VaR violations).

At 95% confidence level (Panel B), we have many models that pass the LR_{cc} test. Surprisingly, Normal GARCH(1,1)-500 & 1000, t-Student GARCH(1,1)-500 & 1000, EWMA, Historical Simulation 100 & 252, Normal EGARCH(1,1)-1000 and t-Student EGARCH(1,1)-1000 pass all tests, with t-Student GARCH(1,1)-500 being the best of all models (p-value = 0,94892, 167 VaR violations). Block Maxima performed poorly and Peaks over Threshold gave the best model among the ones of EVT (p-value = 0,0424, 194 VaR violations).

8.9: Aluminium Cash

In the APPENDIX II we can find Table 10 which contains the Backtesting results for Aluminium Cash. The estimation period was 1/6/1989-25/7/1993 and the Backtesting period was 26/7/1993-2/3/2007, leaving us with 3402 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (170 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), no model manages to pass the LR_{cc} test although two models, t-Student GARCH(1,1)-1000 and t-Student EGARCH(1,1)-1000 had the optimal number of VaR violations (34 VaR violations). Peaks over Threshold and Block Maxima delivered good results with the GPD1000 model being the best among the methods of EVT (41 VaR violations).

At 95% confidence level (Panel B), no model managed to pass the LR_{cc} and the GARCH(1,1) and EGARCH(1,1) proved very conservative and overestimated risk as we can see from the VaR violations of each model. EVT methods provided bad VaR forecasts and prove inadequate to model VaR for Aluminium Cash.

8.10: Aluminium 3-Month

In the APPENDIX II we can find Table 10 which contains the Backtesting results for Aluminium 3-Month. The estimation period was 1/6/1989-25/7/1993 and the Backtesting period was 26/7/1993-2/3/2007, leaving us with 3402 observations for the Backtesting process. The implied Failure Rates are 1% (34 VaR violations) and 5% (170 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), Block Maxima and Peaks over Threshold gave very good VaR forecasts and some models (GEV500-50bl., GPD500-10% & 8%) passed the LR_{cc} test. The best models for Aluminium 3- Month are t-Student GARCH(1,1)-1000, Historical Simulation 100 & 252 and t-Student EGARCH(1,1)-1000. The models that assume normality in the returns are not able to model the tails of the empirical distribution the confidence level of 99%.

At 95% confidence level (Panel B), no model managed to pass the LR_{cc} and the GARCH(1,1) and EGARCH(1,1) proved very conservative and overestimated risk as we can see from the VaR violations of each model. EVT methods provided bad VaR forecasts and prove inadequate to model VaR for Aluminium Cash, except from GPD1000-8% & 5% that pass the LR_{uc} test.

8.11: Gold Bullion

In the APPENDIX II we can find Table 1 which contains the Backtesting results for Gold Bullion. The estimation period was 1/6/1989-4/4/1993 and the Backtesting period was 5/4/1993-2/3/2007, leaving us with 3630 observations for the Backtesting process. The implied Failure Rates are 1% (36 VaR violations) and 5% (182 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), we can see that very few models have predictive ability with the t-Student GARCH(1,1)-500 & 1000 and t-Student EGARCH(1,1,)-1000 being the only ones that pass the LR_{cc} test. EWMA, Normal GARCH & EGARCH underestimate risk (72, 72, 73 and 76 VaR violations respectively) whereas EVT outperforms the Normal Distribution but fails to pass the LR_{cc} tests.

At 95% confidence level (Panel B), no model managed to pass the LR_{cc} although Normal GARCH(1,1)-500, t-Student GARCH(1,1)-500 & 1000 and t-Student EGARCH(1,1)-1000 reached the optimal number of VaR violations (182). Block Maxima and Peaks over Threshold yield very bad estimates with the only exception of GEV1000-100bl. that passed LR_{uc} and had the least VaR violations (207) of all EVT models.

8.12 FTSE-100

In the APPENDIX II we can find Table 12 which contains the Backtesting results for FTSE-100. The estimation period was 1/6/1989-5/4/1993 and the Backtesting period was 6/4/1993-2/3/2007, leaving us with 3629 observations for the Backtesting process. The implied Failure Rates are 1% (36 VaR violations) and 5% (181 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), Normal GARCH(1,1)-1000, t-Student GARCH(1,1)-1000, t-Student EGARCH(1,1,)-1000 and Historical Simulation 252 are the only ones that pass the LR_{cc} test. Moreover, Peaks over Threshold gave good results (4 models passed the LR_{ind} test); on the other hand, Block Maxima performed badly and underestimated risk in all cases.

At 95% confidence level (Panel B), Normal and t-Student GARCH(1,1), EWMA and Normal EGARCH(1,1) passed all LR tests and the best model of all was Normal GARCH(1,1)-500 (p-value = 0,46877, VaR violations = 193). Historical Simulation with the moving estimation window of 252 observations performed well and passed the LR_{uc} test (190 VaR violations), Peaks over Threshold did also well with the GPD1000-8% model yielding the least VaR violations (192). On the other hand, Block Maxima performed badly and was rejected by the LR tests.

8.13 LIFFE FTSE-100

In the APPENDIX II we can find Table 13 which contains the Backtesting results for FTSE-100. The estimation period was 1/6/1989-5/4/1993 and the Backtesting period was 6/4/1993-2/3/2007, leaving us with 3629 observations for the Backtesting process. The implied Failure Rates are 1% (36 VaR violations) and 5% (181 VaR violations) for confidence levels of 99% and 95% respectively.

At 99% confidence level (Panel A), the models that performed best are Normal GARCH(1,1)-1000, t-Student GARCH(1,1)- 500 & 1000, Historical Simulation 100 & 252, Normal EGARCH(1,1)-1000 and t-Student EGARCH(1,1)-1000, with t-Student GARCH(1,1)- 1000 being the best (p-value = 0,69637, VaR violations = 36).
Block Maxima was rejected by all the LR tests and Peaks over Threshold did better, managing to pass the LR_{uc} test for GEV1000.

At 95% confidence level (Panel B), Normal and t-Student GARCH(1,1) and Normal and t-Student EGARCH(1,1) passed all of the LR tests with the Normal GARCH(1,1)-1000 having the optimal number of VaR violations. Block Maxima failed to give good VaR forecasts and was rejected by all LR tests. Peaks over Threshold performed very well and was not rejected by the LR_{uc} test.

The following Tables present the best VaR model for each time series according to the LR_{cc} criterion.

Table 8.a. The Best VaR Models at confidence level of 99%

Time Series	model	p-value (LRcc)	Violations	Mean VaR (%)
Copper Cash	t-Student EGARCH(1,1)-1000	0,6878	32	-3,908
Copper 3-Months	t-Student GARCH(1,1)-1000	0,7099	33	-3,671
Tin Cash	t-Student EGARCH(1,1)-1000	0,55371	39	-3,803
Tin 3-Months	t-Student GARCH(1,1)-1000	0,64666	34	-3,585
Zinc Cash	t-Student GARCH(1,1)- 500	0,70997	33	-4,011
Zinc 3-Months	t-Student GARCH(1,1)-1000	0,64965	36	-3,626
Nickel Cash	t-Student GARCH(1,1)- 500	0,70942	33	-5,523
Nickel 3-Months	t-Student GARCH(1,1)-1000	0,66568	36	-5,119
Aluminium Cash	t-Student EGARCH(1,1)-1000	0,00713	34	-3,184
Aluminium 3-Months	Historical Simulation 100	0,66098	36	-2,947
Gold Bullion	t-Student GARCH(1,1)-500	0,67256	34	-2,375
FTSE-100	t-Student GARCH(1,1)-1000	0,46541	41	-2,312
LIFFE FTSE-100	t-Student GARCH(1,1)-1000	0,69637	36	-2,499

Table 8.b. The Best VaR Models at confidence level of 95%

Time Series	model	p-value (LRcc)	Violations	Mean VaR (%)
Copper Cash	EWMA (RiskMetrics)	0,8979	173	-2,414
Copper 3-Months	EWMA (RiskMetrics)	0,0628	166	-2,119
Tin Cash	Normal GARCH(1,1)-500	0,394	167	-2,051
Tin 3-Months	Normal EGARCH(1,1)-1000	0,0588	172	-1,869
Zinc Cash	EWMA (RiskMetrics)	0,02284	164	-2,271
Zinc 3-Months	Historical Simulation 252	0,02294	179	-1,902
Nickel Cash	EWMA (RiskMetrics)	0,97908	169	-3,312
Nickel 3-Months	t-Student GARCH(1,1)-500	0,94892	167	-3,058
Aluminium Cash	Historical Simulation 252	0,02381	185	-1,809
Aluminium 3-Months	t-Student EGARCH(1,1)-1000	0,02943	158	-1,705
Gold Bullion	t-Student GARCH(1,1)-500	0,03258	182	-1,251
FTSE-100	Normal GARCH(1,1)-500	0,46877	193	-1,53
LIFFE FTSE-100	Normal EGARCH(1,1)-1000	0,93044	186	-1,647

8.14 Stress Testing

It is very important for the risk manager to perform stress tests and scenario analysis so as to see how the various VaR models perform. Berkowitz (2000) proposes a coherent framework for stress testing and a useful general discussion on financial crises can be found in Kindleberger (2000). Moreover interesting experiments with simulated shocks can include the stock market crash of 1987 (Black Monday), terrorist attacks (9/11) and war events (invasion in Iraq by US troops). In the APPENDIX III we can find Tables III.1 to III.13 which show the performance of each VaR model against the 10 biggest negative returns of each time series. By comparing the VaR forecasts with the actual portfolio profit-loss, we will be able to study the expected likelihoods and magnitudes of extreme events in the metals market of London which correspond to real-life financial crises and distress which stems from various endogenous as well as exogenous sources. VaR forecasts in red colour mean that the corresponding VaR model was unable to predict the negative return. On the other hand, bold green VaR forecasts were able to cover the negative return and suggest that the corresponding VaR model has the ability to foresee and predict extreme returns. As we can see, the models that predicted most of the times the extreme negative returns were Normal GARCH, t-Student GARCH, EWMA, Historical Simulation, Normal EGARCH and finally t-Student EGARCH. The performance of Block Maxima and Peaks over Threshold is disappointing, as they are unable to predict extreme returns. In many cases no model was able to predict the forthcoming big negative return, especially in the Aluminium Cash and 3-Month time series.

A possible and reasonable explanation is that the Conditional Volatility models have a clear advantage over the Unconditional Extreme Value Theory and these findings come to confirm the results of the Backtesting which show that the GARCH(1,1) and EGARCH(1,1) models with t-Student distributed innovations are superior as they provide very good VaR forecasts and furthermore showed signs of good reaction to extreme returns.

Chapter 9: Conclusion

In this study we compared the predictive ability of eight Value-at-Risk methods including GARCH(1,1) with Normal and t-Student innovations, Exponential GARCH(1,1) with Normal and t-Student innovations, Exponentially Weighted Moving Average (EWMA), Block Maxima (GEV Distribution) and Peaks over Threshold (GP Distribution). We computed 1-day-ahead Value-at-Risk forecasts at 99% and 95% confidence levels and each model was estimated via the method of the moving estimation window by using two different lengths for each model. Block Maxima and Peaks over Threshold were estimated by using different assumptions about the block size and the level of the threshold u. The Value-at-Risk models were tested for the period 1/6/1989-2/3/2007 on cash and 3-month futures prices of Copper, Tin, Zinc, Nickel and Aluminium, metals that trade in the London Metal Exchange. We also analyzed equity market data (FTSE-100 & LIFFE FTSE-100) and Gold Bullion data for the same period, in order to compare the industrial metals market with equity and precious metals.

Block Maxima proved inadequate for VaR forecasting and was rejected by the likelihood ratio tests of unconditional coverage, independence and conditional coverage for almost all time series analyzed. The method exhibited some forecasting ability in the analysis of Nickel Cash, Nickel 3-month and Aluminium 3-month at 99% c.l. A possible explanation is that we should have selected larger blocks of observations so that the maxima would be independent and identically distributed in order to converge to the Generalized Extreme Value Distribution. On the other hand, we knew a priori that Block Maxima has a lot of flaws and that the data was limited, therefore we don't recommend the use of this method in cases we have limited data, because this will lead us to very bad forecasts. A risk manager will typically use the whole available dataset in order to make Value-at-Risk forecasts with the Block Maxima method and this is a possible reason for the failure of the method to provide us with reliable VaR estimates.

Peaks over Threshold had better performance and especially at the 99% confidence level gave us very good VaR estimates for Copper Cash, Copper 3-Month, Zinc Cash, Zinc 3-Month, Nickel Cash, Nickel 3-Month, Aluminium Cash, Aluminium 3-Month, FTSE-100 and LIFFE FTSE-100. The method however failed a lot of times to pass the LR_{cc} test, implying that the length of the estimation window was small, as we know that Extreme Value Theory methods need large datasets for the estimation process. Moreover, this study proved that the Peaks over Threshold method outperformes the Block Maxima and that it can handle the existing data more efficiently. Another issue is the i.i.d. assumption of the extreme observations, which seems unrealistic for typical financial data like the metals. It would be wise in future research to test the two-stage model of McNeil & Frey (2000) (Conditional EVT) by fitting a GARCH model with GPD innovations in the financial data.

Historical Simulation performed well in general and provided the best forecasts for Zinc 3-month and Aluminium cash at the 95% c.l. and Aluminium 3-month at the 99% c.l. Although the method provides forecasts with high variance, in some cases it can be very precise and forecast big negative returns in the case they come in clusters.

The models that assume time-varying volatility like GARCH, EGARCH and EWMA outperformed Extreme Value Theory and proved very important in predicting the Value-at-Risk measure. More specifically, at 99% c.l., t-Student GARCH(1,1) and t-Student EGARCH(1,1) were the best models for the metals of the London Metal Exchange, the FTSE-100 the LIFFE FTSE-100 and Gold Bullion. At 95% c.l., EWMA did very well in Copper Cash, Copper 3-month, Zinc Cash and Nickel Cash whereas Normal GARCH(1,1) & EGARCH(1,1) performed best in Tin Cash, Tin 3-month, FTSE-100 and LIFFE FTSE-100. The t-Student GARCH(1,1) and EGARCH (1,1) models were the best in Nickel 3-month, Aluminium 3-month and Gold Bullion.
As we can see from the results, Normal Distribution had better performance at 95% c.l. and t-Student Distribution proved best for the high quantile of 99%, because it is more leptokurtic and fat-tailed than the Normal Distribution. Moreover, Stress Testing proved that conditional volatility models and especially the t-Student GARCH(1,1) and EGARCH(1,1) can predict large negative returns.

Finally, the metals of the London Metal Exchange proved riskier than the equity of the FTSE-100 and LIFFE FTSE-100 and the Gold Bullion. In terms of mean VaR, the Nickel Cash and 3-Month time series are the riskier (Table 8.a: -5,523% and -5,119%

respectively) in contrast to Gold Bullion, LIFFE FTSE-100 and FTSE-100 (Table 8.b: -2,375%, -2,499% and -2,312% respectively). A possible and convincing explanation is that metals and generally the commodity markets are strongly shaped by limitations in storage, seasonality effects, output imbalances, short-term speculation of market participants and the convenience yield which can play a very important role in the particular case. Base metals are usually held for consumption by industries and therefore have high convenience yields, reflecting that way the market's expectations concerning the future availability of the metal. On the contrary, precious metals like gold and silver are held by investors as alternative investment tools and usually have zero convenience yields. Therefore it was not surprising that the t-Student distribution outperformed the other models in the analysis of the metals; the Normal Distribution fitted best the equity market, as we saw that the equity market was less turbulent than the metals market and was better approximated by the Normal Distribution. The conditional-variance models proved sufficient for short-term forecasting as they can take into account the heteroscedasticity exhibited by financial returns.

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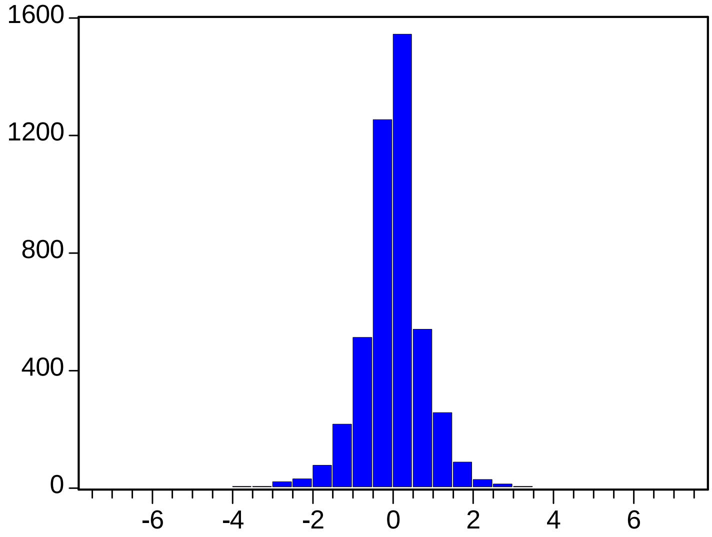
APPENDIX I -
Descriptive Statistics and Preliminary Data Analysis

1.) GOLD BULLION



Series: GOLD_BULLION	
Sample 1 4631	
Observations 4631	
Mean	0.012645
Median	0.000000
Maximum	7.382031
Minimum	-7.217834
Std. Dev.	0.836050
Skewness	-0.244466
Kurtosis	11.81066
Jarque-Bera	15025.06
Probability	0.000000

Diagram I.1: Histogram of the daily logarithmic price changes of Gold Bullion

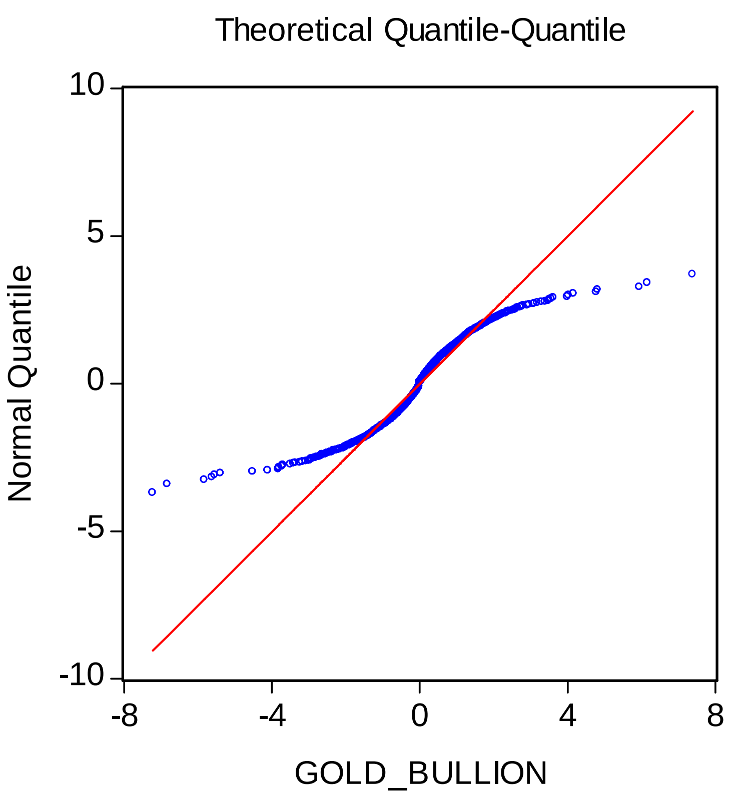


Diagram I.2: Q-Q Plot against the Normal Distribution of Gold Bullion

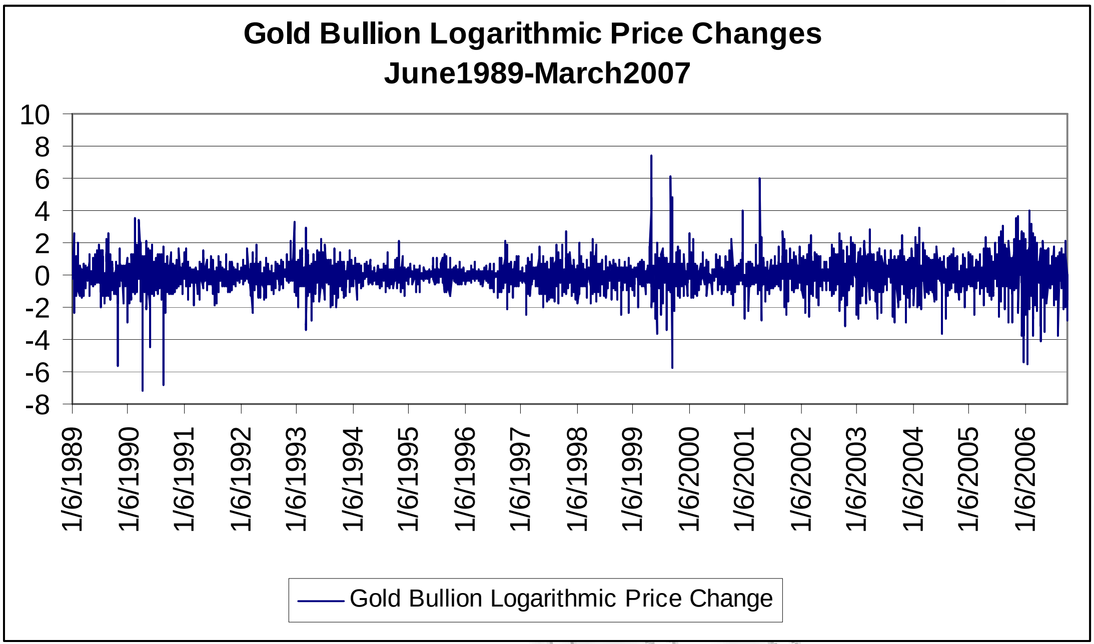


Diagram I.3: Daily Logarithmic price changes of Gold Bullion

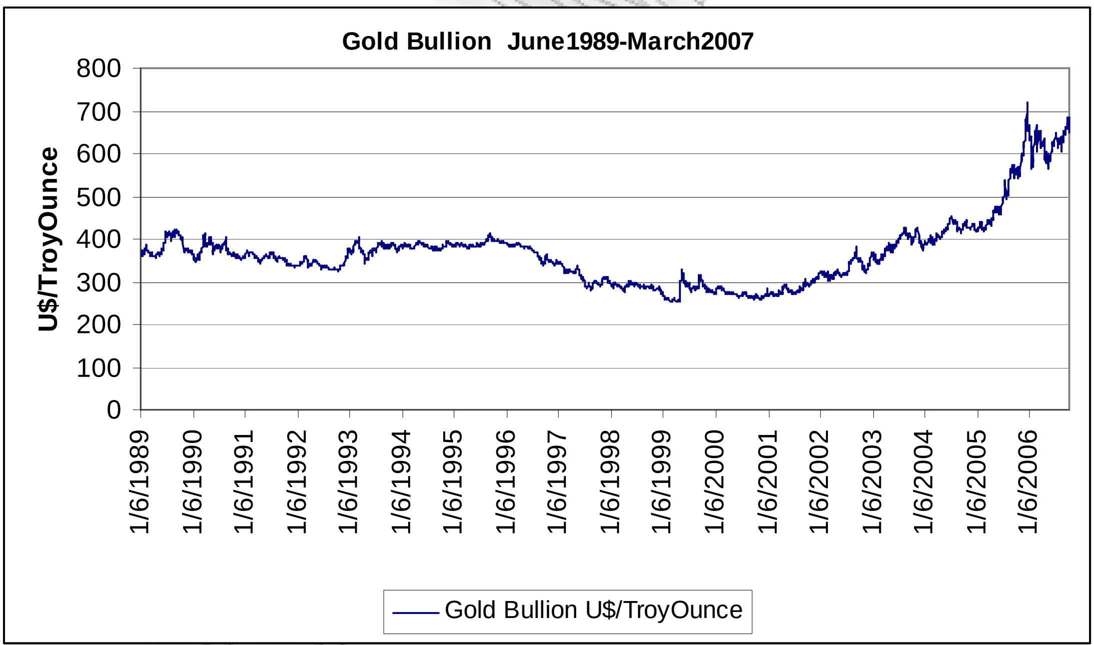


Diagram I.4: Closing Prices of Gold Bullion

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- GOLD BULLION
Included observations: 4631

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.004	0.004	0.0668	0.796
| |	| |	2	0.004	0.004	0.1454	0.930
| |	| |	3	0.012	0.012	0.8424	0.839
| |	| |	4	0.043	0.043	9.2617	0.055
| |	| |	5	0.031	0.031	13.722	0.017
| |	| |	6	-0.020	-0.021	15.671	0.016
| |	| |	7	-0.027	-0.029	19.169	0.008
| |	| |	8	0.015	0.013	20.271	0.009
| |	| |	9	0.018	0.016	21.804	0.010
| |	| |	10	-0.015	-0.014	22.845	0.011
| |	| |	11	-0.013	-0.010	23.627	0.014
| |	| |	12	-0.030	-0.030	27.764	0.006
| |	| |	13	-0.022	-0.025	30.060	0.005
| |	| |	14	-0.002	-0.002	30.084	0.007
| |	| |	15	-0.026	-0.022	33.221	0.004
| |	| |	16	-0.002	0.002	33.235	0.007
| |	| |	17	0.032	0.035	38.146	0.002
| |	| |	18	-0.007	-0.007	38.407	0.003
| |	| |	19	0.027	0.027	41.871	0.002
| |	| |	20	0.006	0.006	42.016	0.003

Table I.1: Autocorrelation Test (Ljung-Box Q Statistic)- Gold Bullion

Null Hypothesis: GOLD_BULLION has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-67.68252	0.0001
Test critical values:	1% level	-3.431580	
	5% level	-2.861968	
	10% level	-2.567041	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GOLD_BULLION)
Method: Least Squares
Date: 06/18/07 Time: 03:58
Sample (adjusted): 2 4631
Included observations: 4630 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GOLD_CASH(-1)	-0.996170	0.014718	-67.68252	0.0000
C	0.012597	0.012291	1.024889	0.3055

R-squared	0.497444	Mean dependent var	-0.000619
Adjusted R-squared	0.497335	S.D. dependent var	1.179461
S.E. of regression	0.836224	Akaike info criterion	2.480592
Sum squared resid	3236.227	Schwarz criterion	2.483374
Log likelihood	-5740.571	F-statistic	4580.924
Durbin-Watson stat	1.997062	Prob(F-statistic)	0.000000

Table I.2 Augmented Dickey-Fuller Test for Gold Bullion

2.) COPPER CASH

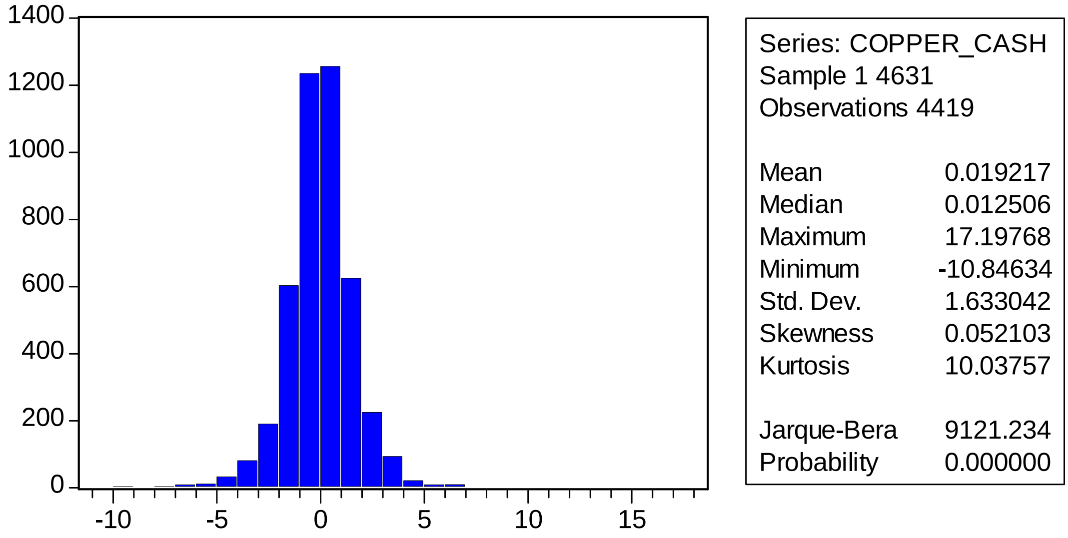


Diagram I.5: Histogram of the daily logarithmic price changes of Copper Cash

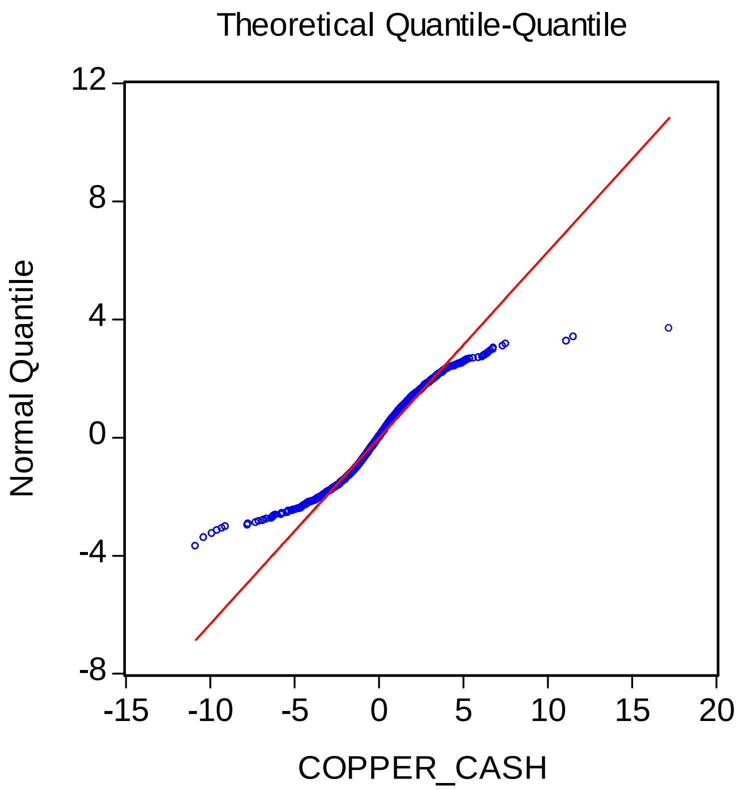


Diagram I.6: Q-Q Plot against the Normal Distribution of Copper Cash

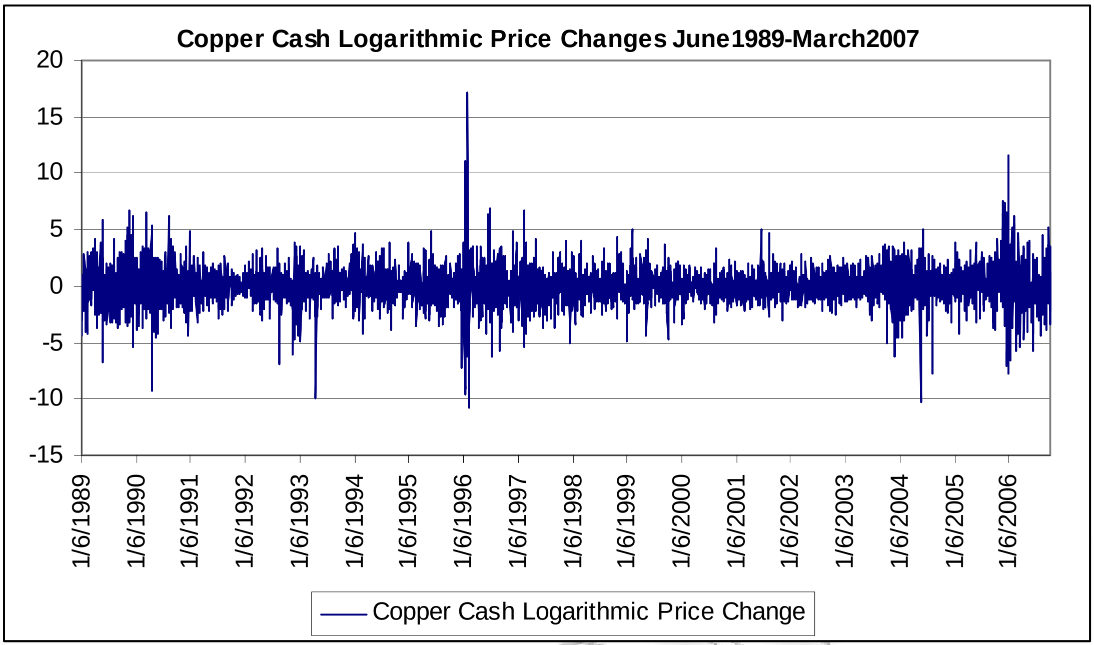


Diagram I.7: Daily Logarithmic price changes of Copper Cash

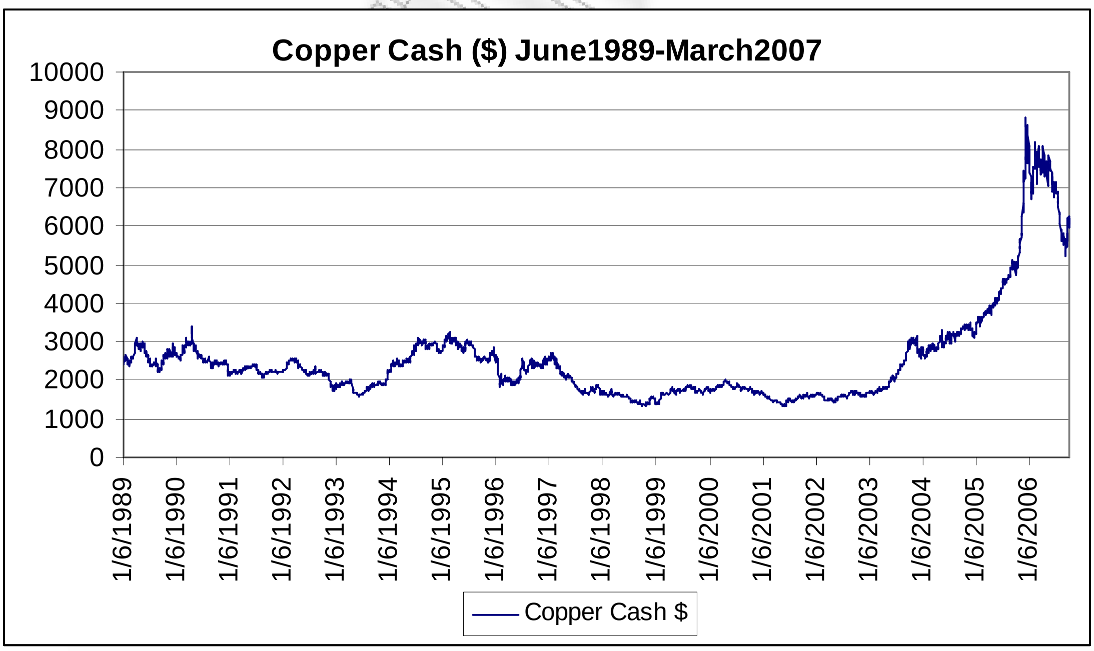


Diagram I.8: Closing Prices of Copper Cash

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC-COPPER CASH

Included observations: 4419

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.085	-0.085	32.062	0.000
*| |	*| |	2	-0.060	-0.068	48.070	0.000
| |	| |	3	0.029	0.018	51.852	0.000
| |	| |	4	-0.030	-0.030	55.865	0.000
| |	| |	5	0.032	0.030	60.446	0.000
| |	| |	6	0.024	0.026	62.996	0.000
| |	| |	7	0.004	0.014	63.080	0.000
| |	| |	8	0.001	0.004	63.085	0.000
| |	| |	9	0.007	0.009	63.302	0.000
| |	| |	10	0.012	0.014	63.989	0.000
| |	| |	11	0.021	0.024	65.994	0.000
| |	| |	12	0.019	0.024	67.624	0.000
| |	| |	13	-0.037	-0.032	73.743	0.000
| |	| |	14	-0.007	-0.011	73.936	0.000
| |	| |	15	0.027	0.020	77.125	0.000
| |	| |	16	-0.004	-0.001	77.204	0.000
| |	| |	17	0.002	0.000	77.225	0.000
| |	| |	18	0.003	0.002	77.268	0.000
| |	| |	19	-0.013	-0.010	78.002	0.000
| |	| |	20	0.029	0.027	81.853	0.000

Table I.3: Autocorrelation Test (Ljung-Box Q Statistic)- Copper Cash

Null Hypothesis: COPPER_CASH has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-72.42419	0.0001
Test critical values:	1% level	-3.431647	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

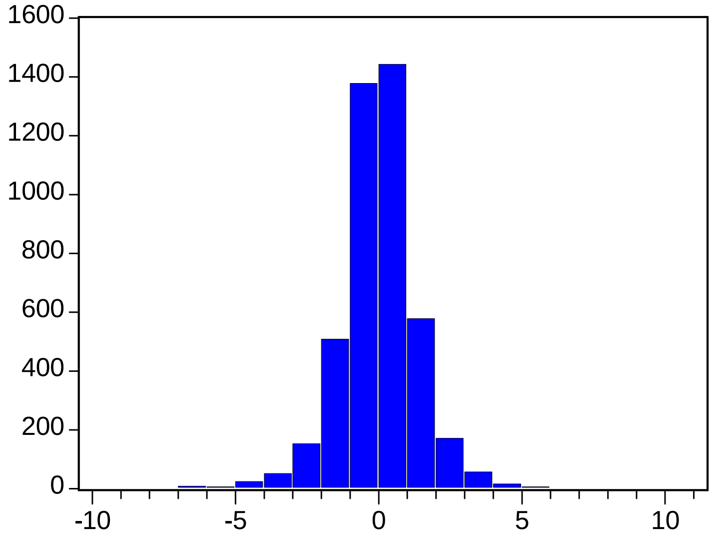
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(COPPER_CASH)
Method: Least Squares
Date: 06/18/07 Time: 03:50
Sample (adjusted): 2 4419
Included observations: 4418 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COPPER_CASH(-1)	-1.085185	0.014984	-72.42419	0.0000
C	0.021912	0.024466	0.895612	0.3705

R-squared	0.542917	Mean dependent var	0.000516
Adjusted R-squared	0.542813	S.D. dependent var	2.404882
S.E. of regression	1.626074	Akaike info criterion	3.810667
Sum squared resid	11676.43	Schwarz criterion	3.813562
Log likelihood	-8415.764	F-statistic	5245.263
Durbin-Watson stat	2.010787	Prob(F-statistic)	0.000000

Table I. 4 Augmented Dickey-Fuller Test for Copper Cash

3.) COPPER 3-MONTH



Series: COPPER_3MO	
Sample 1 4631	
Observations 4419	
Mean	0.019418
Median	0.012800
Maximum	10.98360
Minimum	-9.450249
Std. Dev.	1.388228
Skewness	-0.241927
Kurtosis	7.718669
Jarque-Bera	4142.803
Probability	0.000000

Diagram I.9: Histogram of the daily logarithmic price changes of Copper 3- Month

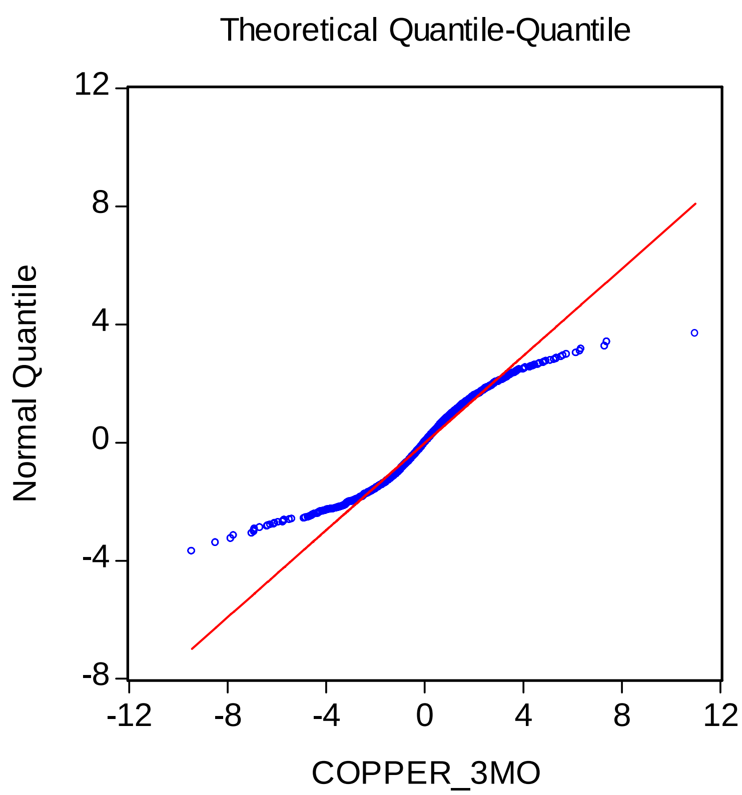


Diagram I.10: Q-Q Plot against the Normal Distribution of Copper 3-Month

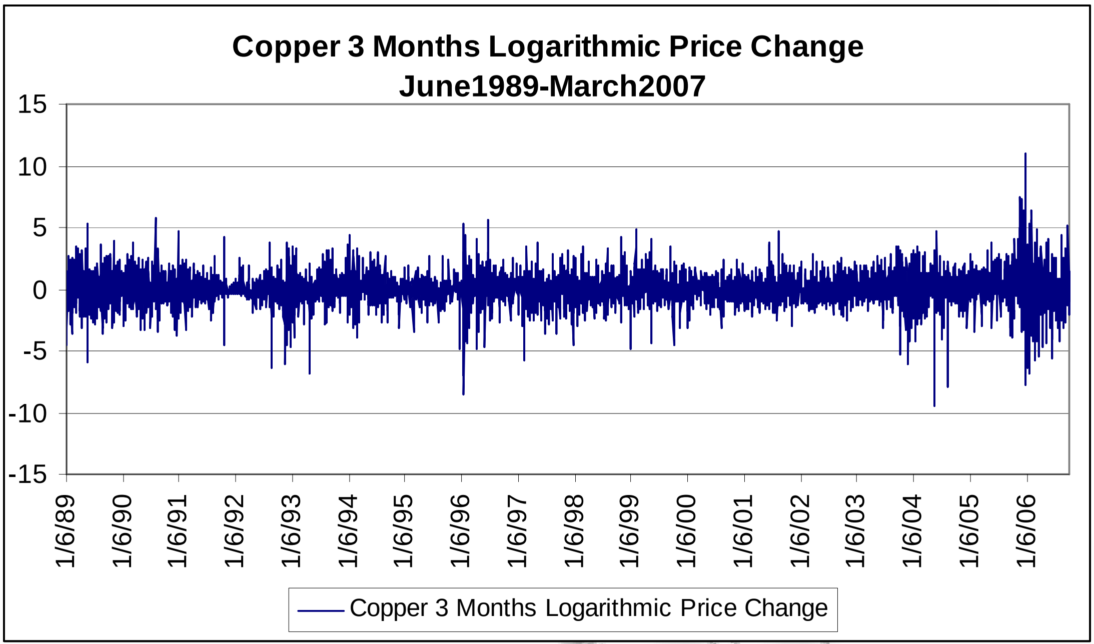


Diagram I.11: Daily Logarithmic price changes of Copper 3- Month

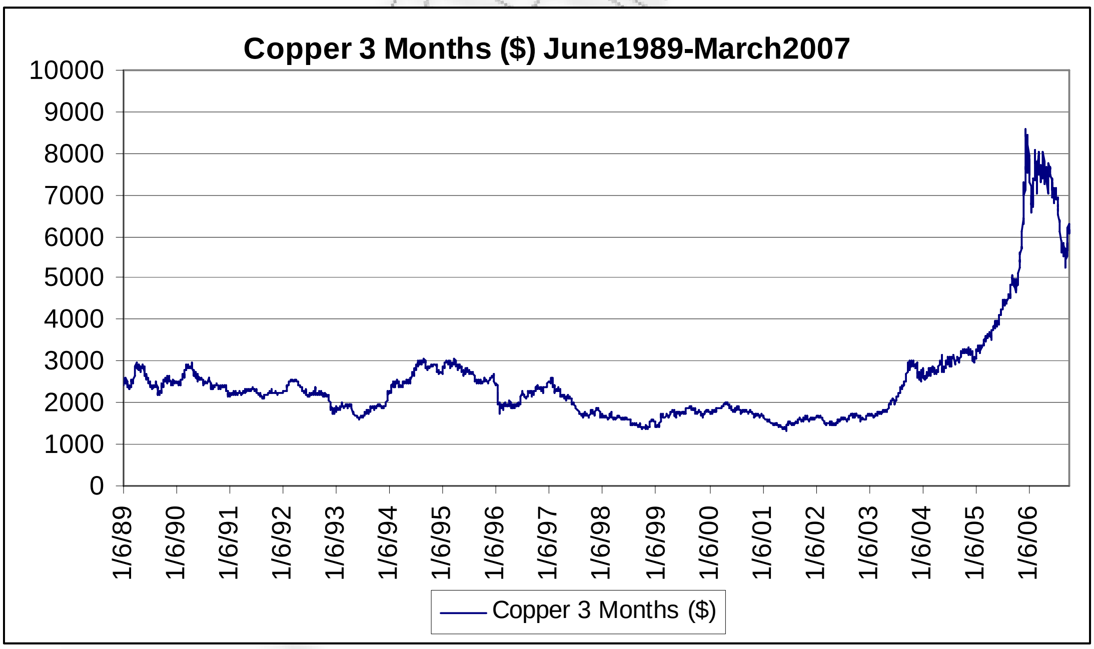


Diagram I.12: Closing Prices of Copper 3- Month

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC-COPPER 3- MONTH

Included observations: 4419

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.052	-0.052	12.183	0.000
		2	-0.039	-0.042	18.943	0.000
		3	0.013	0.008	19.647	0.000
		4	0.000	-0.000	19.648	0.001
		5	0.033	0.034	24.516	0.000
		6	0.018	0.022	26.028	0.000
		7	0.034	0.039	31.090	0.000
		8	-0.002	0.003	31.114	0.000
		9	-0.024	-0.021	33.570	0.000
		10	0.046	0.042	43.031	0.000
		11	0.018	0.019	44.390	0.000
		12	0.005	0.008	44.502	0.000
		13	0.010	0.010	44.937	0.000
		14	-0.009	-0.008	45.283	0.000
		15	0.002	-0.000	45.300	0.000
		16	0.017	0.015	46.580	0.000
		17	-0.019	-0.022	48.227	0.000
		18	0.010	0.007	48.687	0.000
		19	-0.002	-0.001	48.700	0.000
		20	0.026	0.026	51.785	0.000

Table I.5: Autocorrelation Test (Ljung-Box Q Statistic)- Copper 3- Month

Null Hypothesis: COPPER_3MO has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-70.12160	0.0001
Test critical values:	1% level	-3.431647	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(COPPER_3MO)
Method: Least Squares
Date: 06/18/07 Time: 03:48
Sample (adjusted): 2 4419
Included observations: 4418 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COPPER_3MO(-1)	-1.052496	0.015010	-70.12160	0.0000
C	0.021497	0.020837	1.031669	0.3023

R-squared	0.526842	Mean dependent var	0.000800
Adjusted R-squared	0.526735	S.D. dependent var	2.013076
S.E. of regression	1.384881	Akaike info criterion	3.489558
Sum squared resid	8469.422	Schwarz criterion	3.492452
Log likelihood	-7706.433	F-statistic	4917.039
Durbin-Watson stat	2.002780	Prob(F-statistic)	0.000000

Table I.6 Augmented Dickey-Fuller Test for Copper 3-Month

4.) TIN CASH

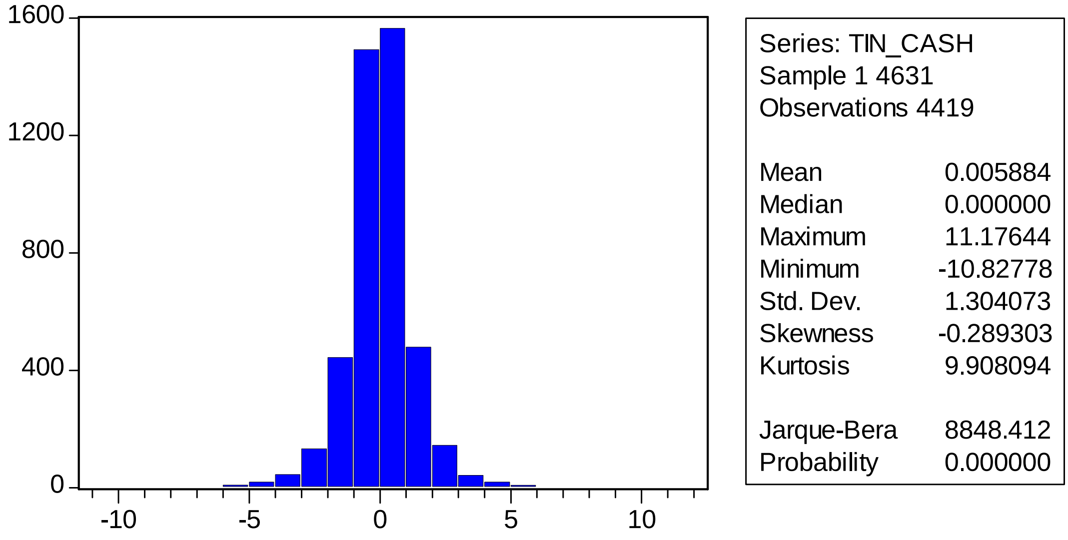


Diagram I.13: Histogram of the daily logarithmic price changes of Tin Cash

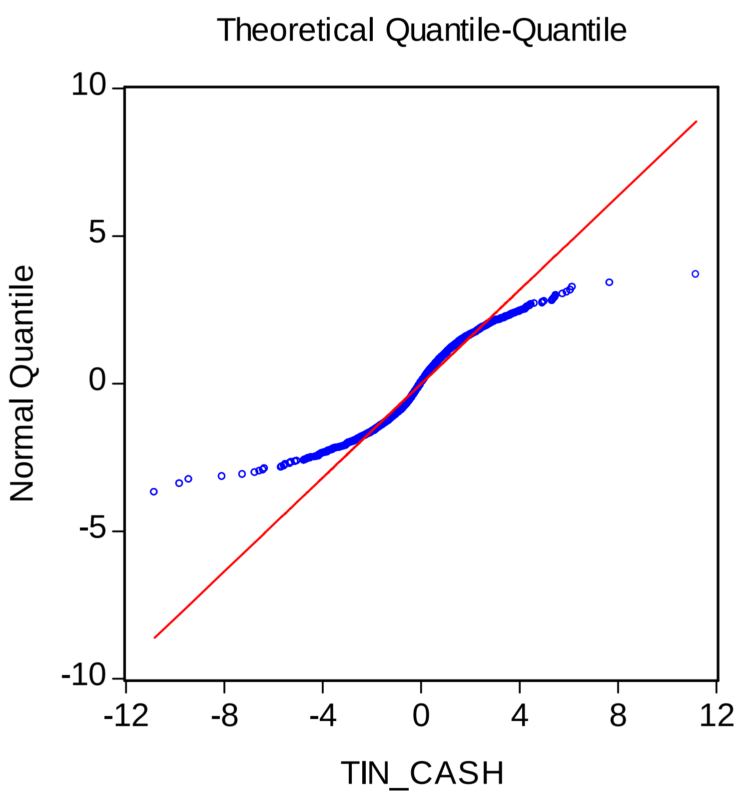


Diagram I.14: Q-Q Plot against the Normal Distribution of Tin Cash

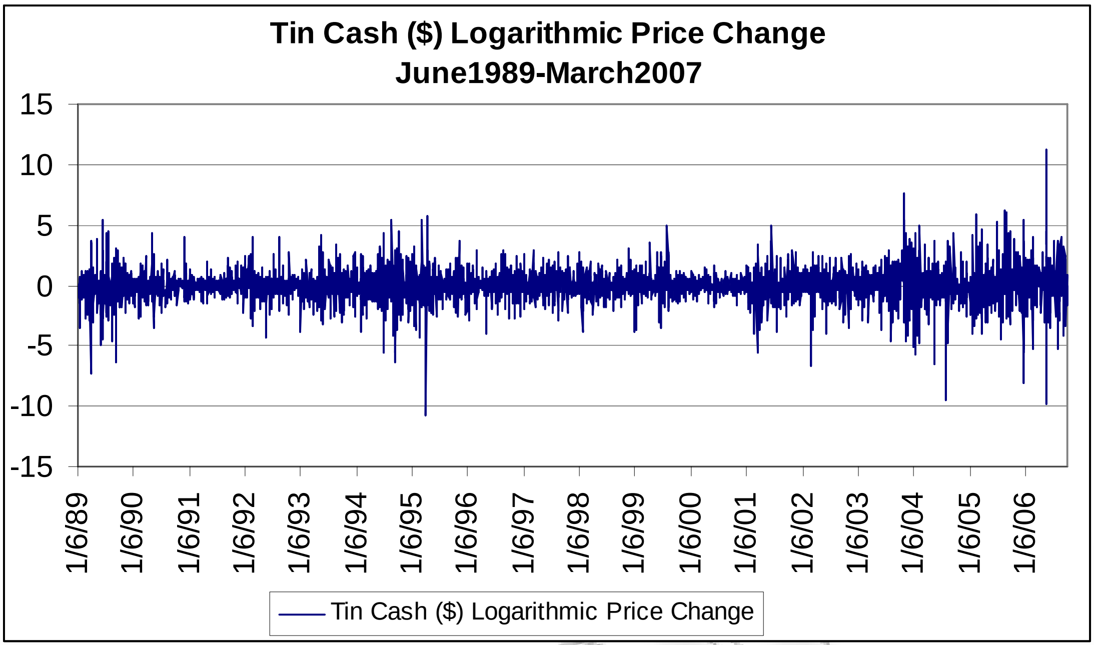


Diagram I.15: Daily Logarithmic price changes of Tin Cash

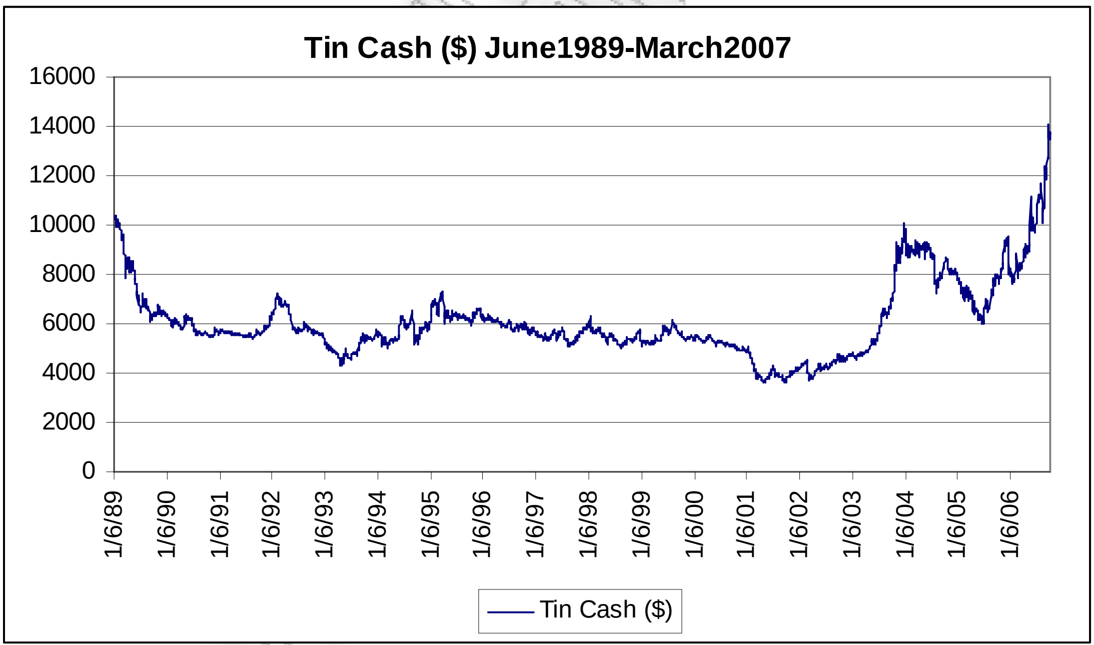


Diagram I.16: Closing Prices of Tin Cash

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC-TIN CASH

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>| |</td><td>| |</td><td>1</td><td>-0.023</td><td>-0.023</td><td>2.2518</td><td>0.133</td></tr>
<tr><td>*| |</td><td>*| |</td><td>2</td><td>-0.092</td><td>-0.093</td><td>39.649</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>-0.001</td><td>-0.005</td><td>39.651</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>0.019</td><td>0.010</td><td>41.176</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>-0.001</td><td>-0.001</td><td>41.181</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>0.045</td><td>0.048</td><td>49.962</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>0.017</td><td>0.020</td><td>51.301</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>0.021</td><td>0.030</td><td>53.183</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>9</td><td>0.006</td><td>0.011</td><td>53.339</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>0.006</td><td>0.010</td><td>53.522</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>11</td><td>-0.057</td><td>-0.056</td><td>67.677</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>12</td><td>0.026</td><td>0.022</td><td>70.711</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>13</td><td>0.014</td><td>0.003</td><td>71.551</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>14</td><td>-0.023</td><td>-0.022</td><td>73.946</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>15</td><td>-0.004</td><td>-0.003</td><td>74.016</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>16</td><td>0.029</td><td>0.023</td><td>77.818</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>17</td><td>-0.034</td><td>-0.030</td><td>82.891</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>18</td><td>0.001</td><td>0.005</td><td>82.900</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>19</td><td>0.025</td><td>0.021</td><td>85.701</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>20</td><td>-0.012</td><td>-0.010</td><td>86.288</td><td>0.000</td></tr>
</table>

Table I.7: Autocorrelation Test (Ljung-Box Q Statistic)- Tin Cash

Null Hypothesis: TIN_CASH has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-67.96897	0.0001
Test critical values:	1% level	-3.431647	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TIN_CASH)
Method: Least Squares
Date: 06/18/07 Time: 04:07
Sample (adjusted): 2 4419
Included observations: 4418 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIN_CASH(-1)	-1.022567	0.015045	-67.96897	0.0000
C	0.006075	0.019619	0.309638	0.7569

R-squared	0.511276	Mean dependent var	-6.28E-05
Adjusted R-squared	0.511166	S.D. dependent var	1.865121
S.E. of regression	1.304031	Akaike info criterion	3.369250
Sum squared resid	7509.395	Schwarz criterion	3.372145
Log likelihood	-7440.674	F-statistic	4619.781
Durbin-Watson stat	2.004075	Prob(F-statistic)	0.000000

Table I.8 Augmented Dickey-Fuller Test for Tin Cash

5.) TIN 3- MONTH

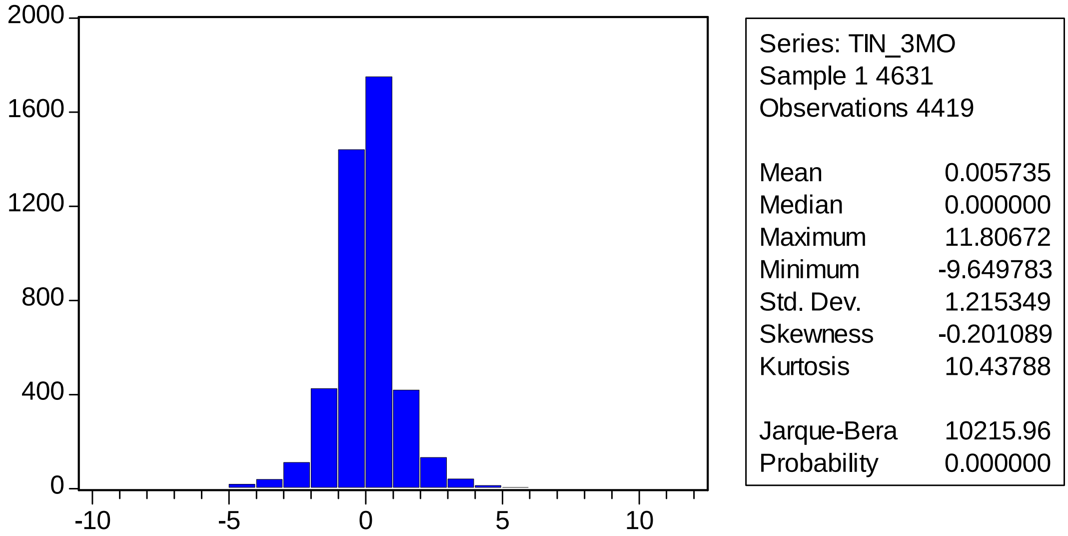


Diagram I.17: Histogram of the daily logarithmic price changes of Tin -3 Month

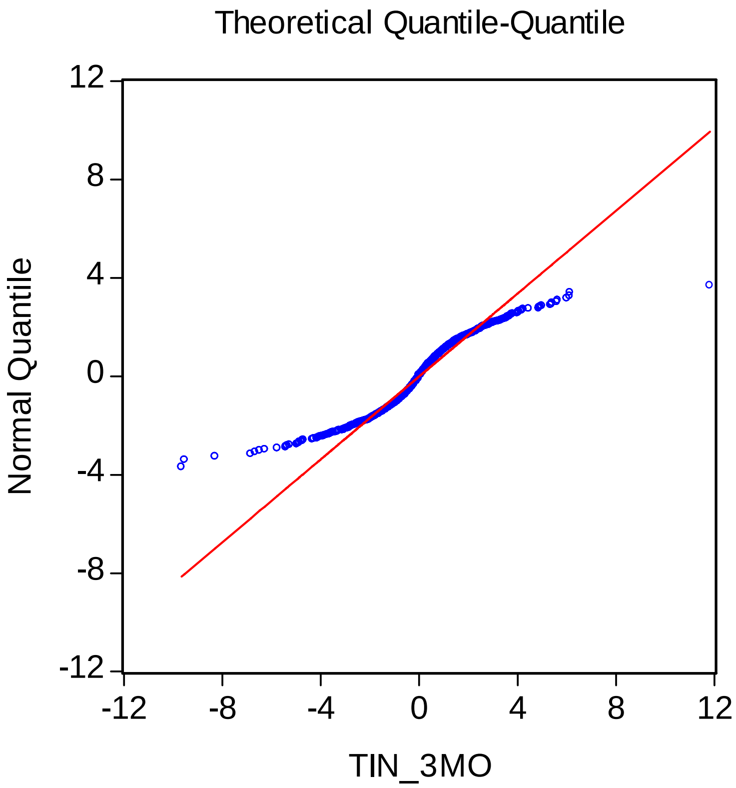


Diagram I.18: Q-Q Plot against the Normal Distribution of Tin-3 Month

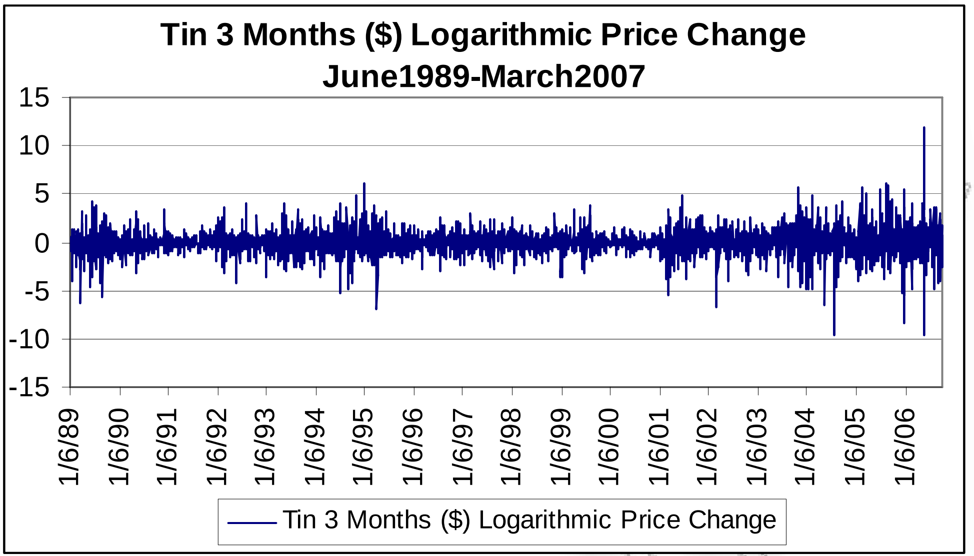


Diagram I.19: Daily Logarithmic price changes of Tin-3 Month

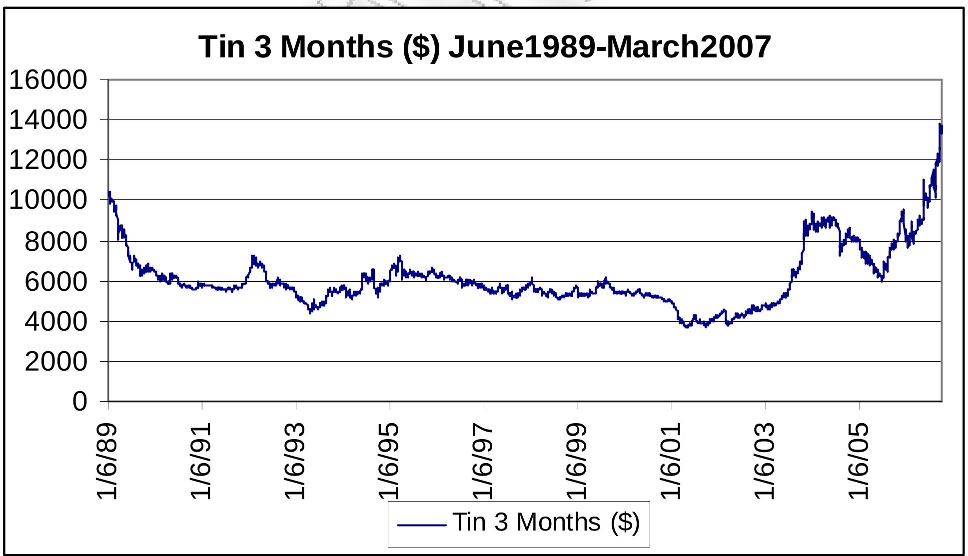


Diagram I.20: Closing Prices of Tin -3 Month

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC-TIN 3- MONTH

Included observations: 4419

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.004	-0.004	0.0612	0.805
*| |	*| |	2	-0.086	-0.086	32.691	0.000
| |	| |	3	-0.017	-0.018	33.940	0.000
| |	| |	4	0.034	0.026	39.005	0.000
| |	| |	5	0.002	-0.000	39.031	0.000
| |	| |	6	0.039	0.044	45.782	0.000
| |	| |	7	0.022	0.024	47.877	0.000
| |	| |	8	0.012	0.019	48.523	0.000
| |	| |	9	0.009	0.014	48.870	0.000
| |	| |	10	-0.002	-0.001	48.891	0.000
| |	| |	11	-0.044	-0.044	57.624	0.000
| |	| |	12	0.025	0.022	60.351	0.000
| |	| |	13	0.025	0.015	63.031	0.000
| |	| |	14	-0.038	-0.038	69.566	0.000
| |	| |	15	-0.003	0.002	69.617	0.000
| |	| |	16	0.040	0.033	76.746	0.000
| |	| |	17	-0.036	-0.035	82.437	0.000
| |	| |	18	-0.000	0.008	82.438	0.000
| |	| |	19	0.013	0.007	83.175	0.000
| |	| |	20	0.006	0.005	83.315	0.000

Table I.9: Autocorrelation Test (Ljung-Box Q Statistic)- Tin -3 Month

Null Hypothesis: TIN_3MO has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.69812	0.0001
Test critical values:	1% level	-3.431647	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TIN_3MO)
Method: Least Squares
Date: 06/18/07 Time: 04:05
Sample (adjusted): 2 4419
Included observations: 4418 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIN_3MO(-1)	-1.003722	0.015049	-66.69812	0.0000
C	0.005802	0.018289	0.317257	0.7511

R-squared	0.501841	Mean dependent var	-0.000125
Adjusted R-squared	0.501728	S.D. dependent var	1.722114
S.E. of regression	1.215612	Akaike info criterion	3.228825
Sum squared resid	6525.579	Schwarz criterion	3.231719
Log likelihood	-7130.475	F-statistic	4448.639
Durbin-Watson stat	2.000456	Prob(F-statistic)	0.000000

Table I.10 Augmented Dickey-Fuller Test for Tin-3 Month

6.) ZINC CASH

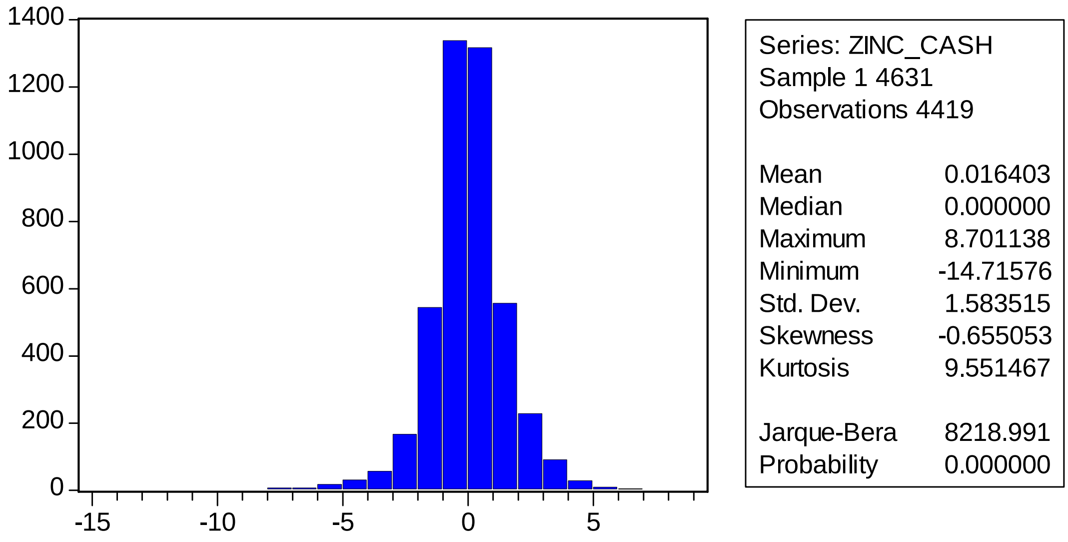


Diagram I.21: Histogram of the daily logarithmic price changes of Zinc Cash

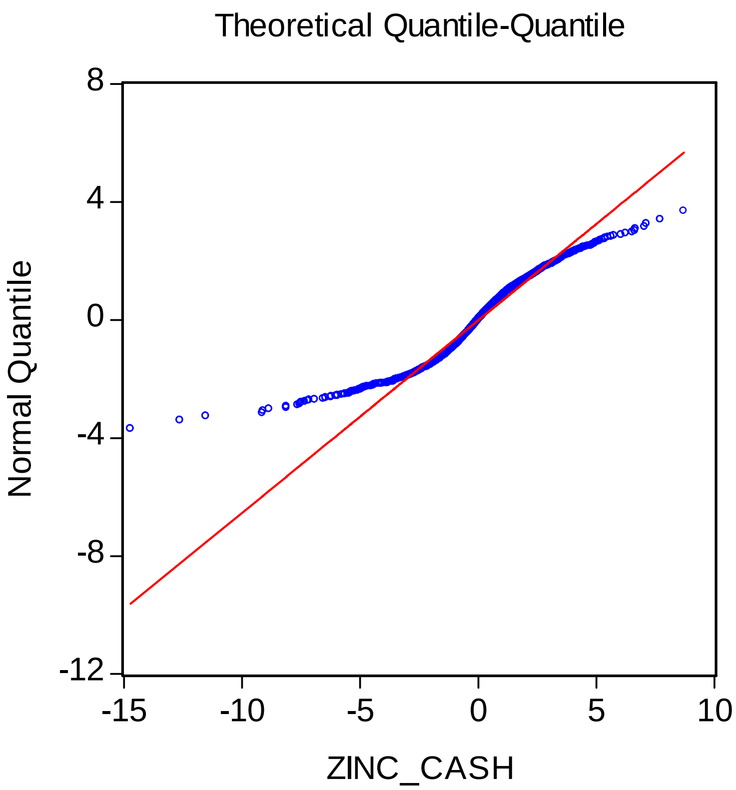


Diagram I.22: Q-Q Plot against the Normal Distribution of Zinc Cash

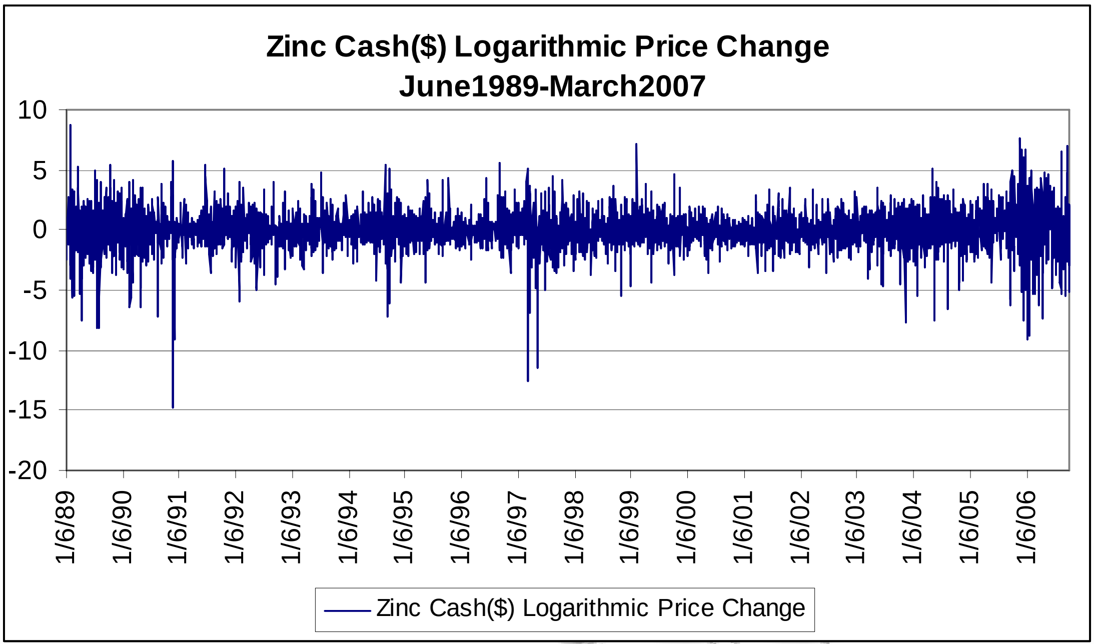


Diagram I.23: Daily Logarithmic price changes of Zinc Cash

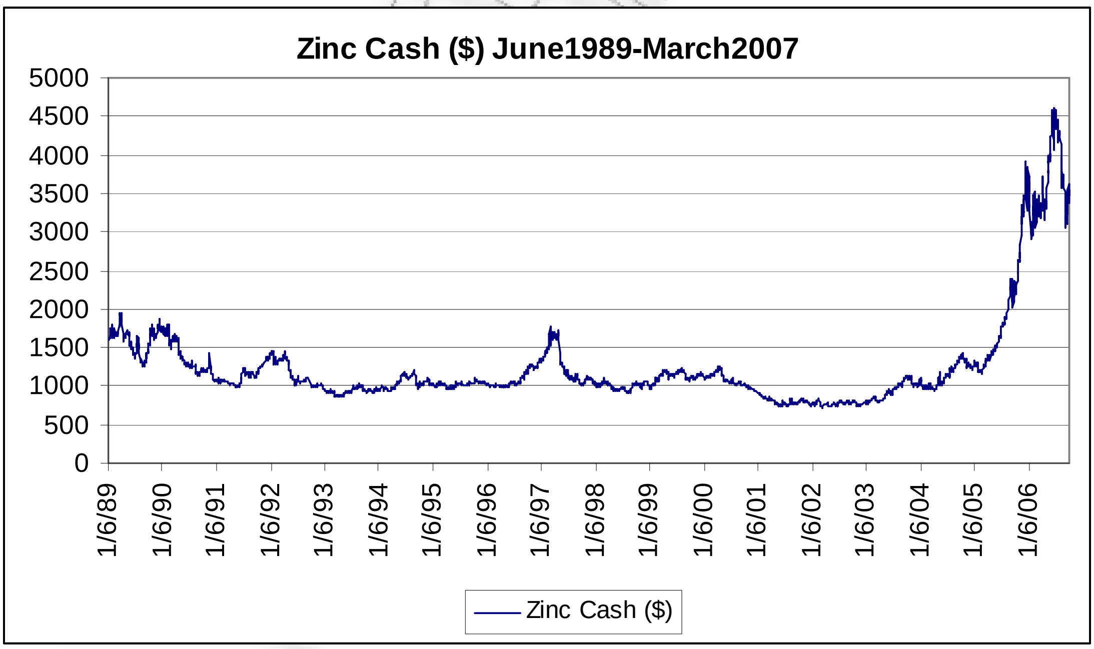


Diagram I.24: Closing Prices of Zinc Cash

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- ZINC CASH

Included observations: 4419

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.006	0.006	0.1837	0.668
*| |	*| |	2	-0.062	-0.062	16.950	0.000
| |	| |	3	-0.025	-0.024	19.722	0.000
| |	| |	4	0.024	0.020	22.232	0.000
| |	| |	5	0.054	0.051	35.162	0.000
| |	| |	6	-0.028	-0.026	38.552	0.000
| |	| |	7	0.008	0.015	38.812	0.000
| |	| |	8	-0.020	-0.021	40.519	0.000
| |	| |	9	0.005	0.003	40.643	0.000
| |	| |	10	0.038	0.035	47.122	0.000
| |	| |	11	-0.019	-0.017	48.682	0.000
| |	| |	12	-0.010	-0.007	49.137	0.000
| |	| |	13	0.018	0.020	50.528	0.000
| |	| |	14	0.020	0.015	52.252	0.000
| |	| |	15	0.008	0.008	52.548	0.000
| |	| |	16	-0.005	0.002	52.656	0.000
| |	| |	17	-0.031	-0.031	56.885	0.000
| |	| |	18	-0.002	-0.002	56.899	0.000
| |	| |	19	0.036	0.031	62.635	0.000
| |	| |	20	0.017	0.013	63.943	0.000

Table I.11: Autocorrelation Test (Ljung-Box Q Statistic)- Zinc Cash

Null Hypothesis: ZINC_CASH has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-65.96212	0.0001
Test critical values:	1% level	-3.431647	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ZINC_CASH)
Method: Least Squares
Date: 06/18/07 Time: 04:11
Sample (adjusted): 2 4419
Included observations: 4418 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ZINC_CASH(-1)	-0.993539	0.015062	-65.96212	0.0000
C	0.016855	0.023823	0.707518	0.4793

R-squared	0.496293	Mean dependent var	-0.000617
Adjusted R-squared	0.496179	S.D. dependent var	2.230749
S.E. of regression	1.583393	Akaike info criterion	3.757470
Sum squared resid	11071.50	Schwarz criterion	3.760364
Log likelihood	-8298.251	F-statistic	4351.002
Durbin-Watson stat	1.996218	Prob(F-statistic)	0.000000

Table I.12 Augmented Dickey-Fuller Test for Zinc Cash

7.) ZINC 3- MONTH

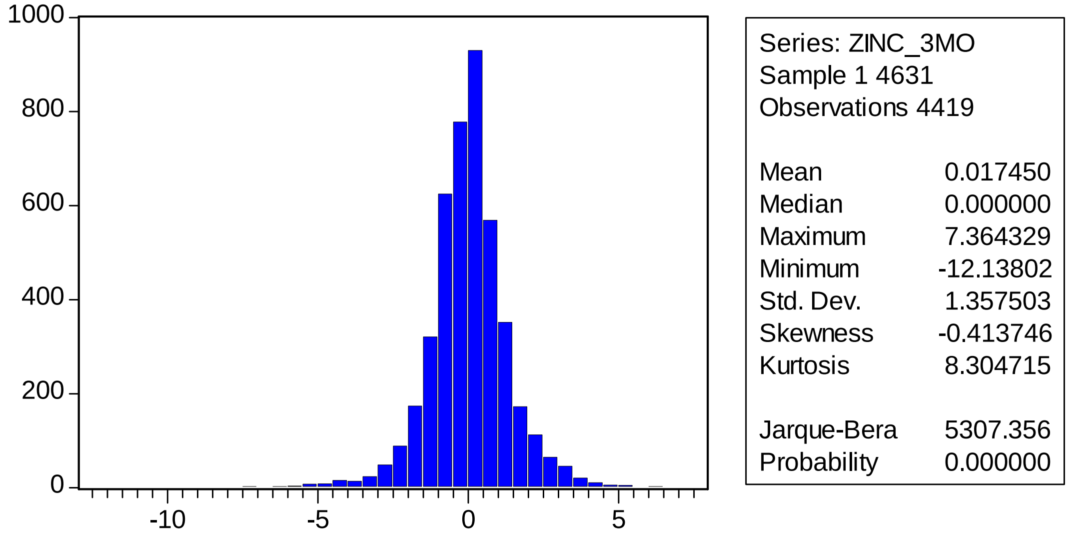


Diagram I.25: Histogram of the daily logarithmic price changes of Zinc-3 Month

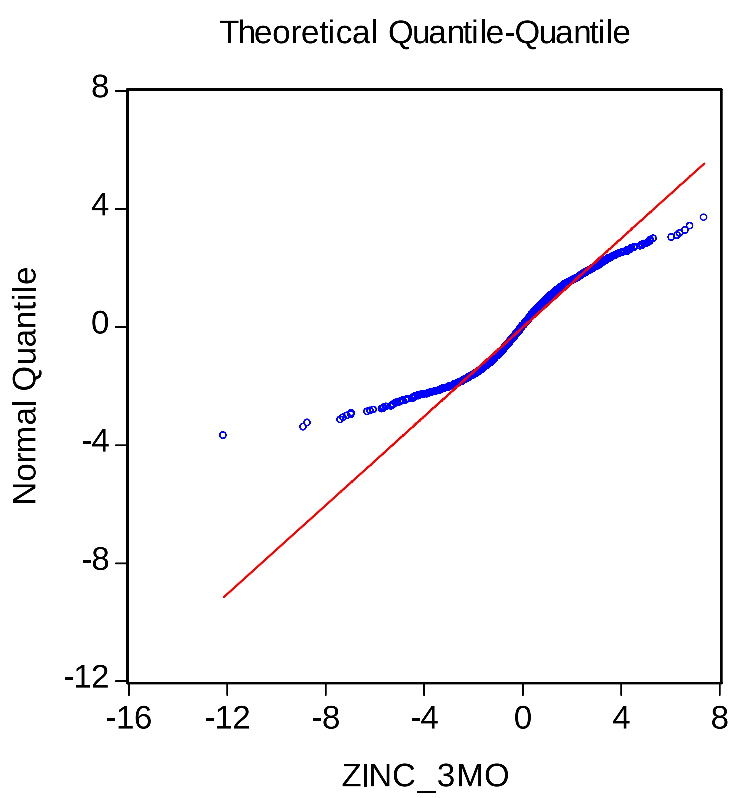


Diagram I.26: Q-Q Plot against the Normal Distribution of Zinc-3 Month

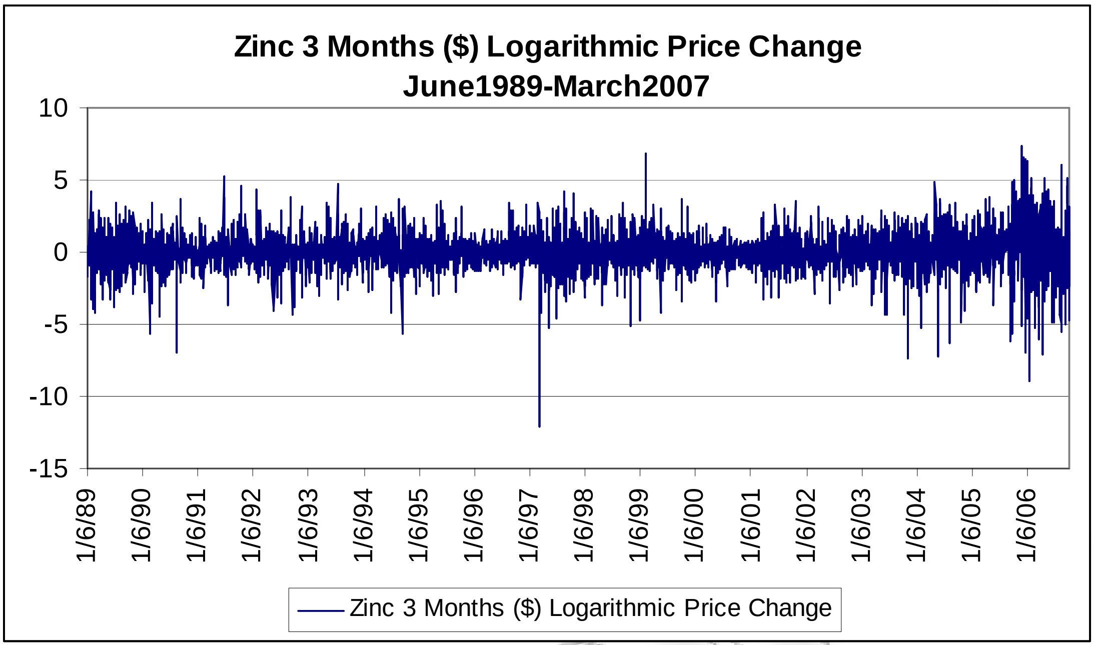


Diagram I.27: Daily Logarithmic price changes of Zinc Zinc-3 Month

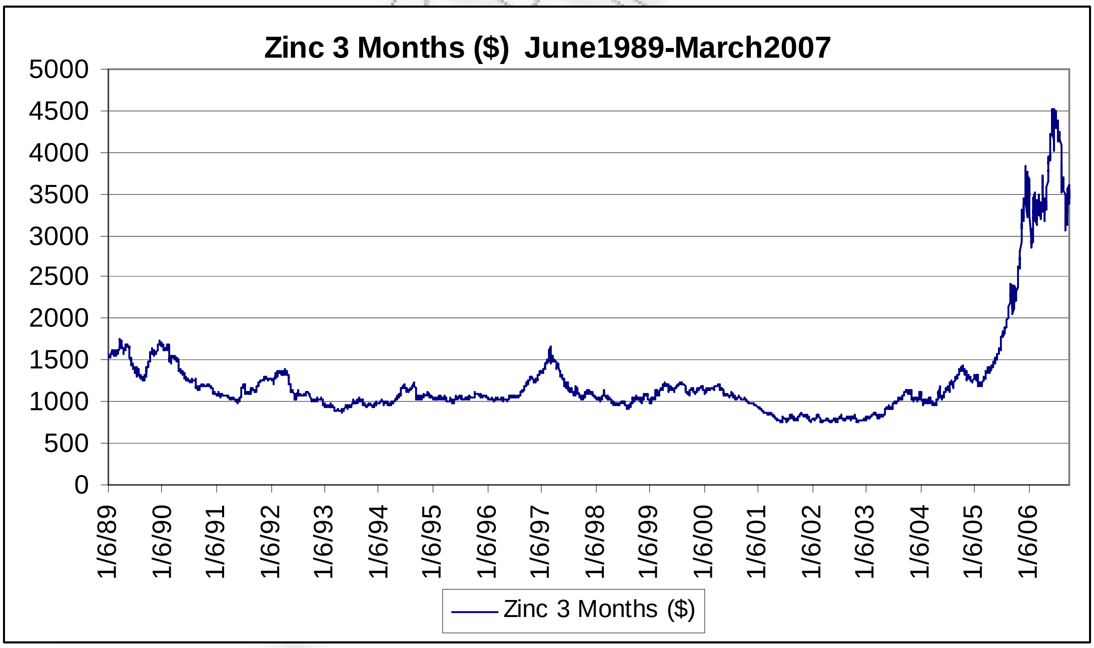


Diagram I.28: Closing Prices of Zinc-3 Month

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC-ZINC 3- MONTH

Included observations: 4419

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.004	-0.004	0.0751	0.784
| |	| |	2	-0.045	-0.045	9.0140	0.011
| |	| |	3	0.003	0.002	9.0482	0.029
| |	| |	4	0.009	0.007	9.3919	0.052
| |	| |	5	0.050	0.050	20.414	0.001
| |	| |	6	-0.034	-0.033	25.475	0.000
| |	| |	7	0.007	0.011	25.663	0.001
| |	| |	8	0.008	0.005	25.959	0.001
| |	| |	9	-0.020	-0.020	27.713	0.001
| |	| |	10	0.042	0.041	35.510	0.000
| |	| |	11	-0.017	-0.016	36.808	0.000
| |	| |	12	-0.026	-0.025	39.856	0.000
| |	| |	13	0.032	0.031	44.539	0.000
| |	| |	14	0.009	0.009	44.928	0.000
| |	| |	15	0.021	0.018	46.797	0.000
| |	| |	16	0.014	0.020	47.658	0.000
| |	| |	17	-0.025	-0.023	50.372	0.000
| |	| |	18	0.012	0.007	50.980	0.000
| |	| |	19	0.030	0.031	54.906	0.000
| |	| |	20	0.010	0.007	55.338	0.000

Table I.13: Autocorrelation Test (Ljung-Box Q Statistic)- Zinc-3 Month

Null Hypothesis: ZINC_3MO has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.64740	0.0001
Test critical values:	1% level	-3.431647	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ZINC_3MO)
Method: Least Squares
Date: 06/18/07 Time: 04:09
Sample (adjusted): 2 4419
Included observations: 4418 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ZINC_3MO(-1)	-1.004132	0.015066	-66.64740	0.0000
C	0.017910	0.020426	0.876799	0.3806

R-squared	0.501461	Mean dependent var	-0.000692
Adjusted R-squared	0.501348	S.D. dependent var	1.922473
S.E. of regression	1.357561	Akaike info criterion	3.449708
Sum squared resid	8138.559	Schwarz criterion	3.452603
Log likelihood	-7618.406	F-statistic	4441.876
Durbin-Watson stat	1.997416	Prob(F-statistic)	0.000000

Table I.14 Augmented Dickey-Fuller Test for Zinc-3 Month

8.) NICKEL CASH

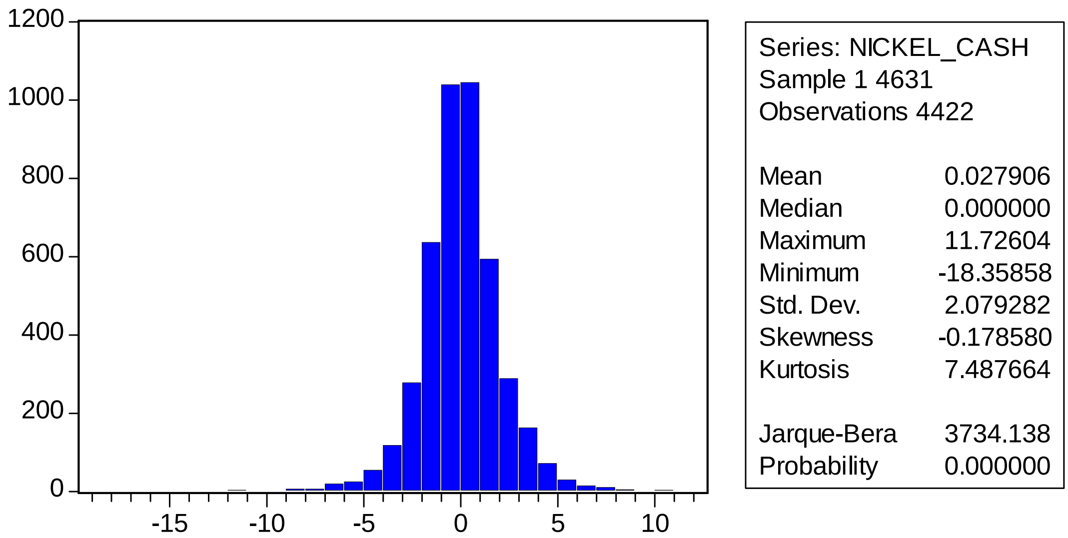


Diagram I.29: Histogram of the daily logarithmic price changes of Nickel Cash

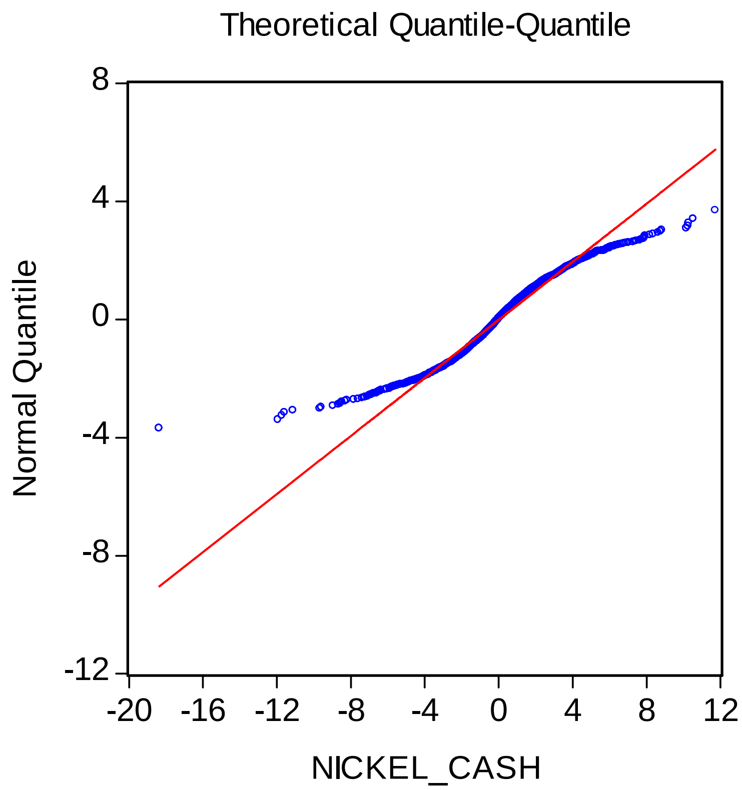


Diagram I.30: Q-Q Plot against the Normal Distribution of Nickel Cash

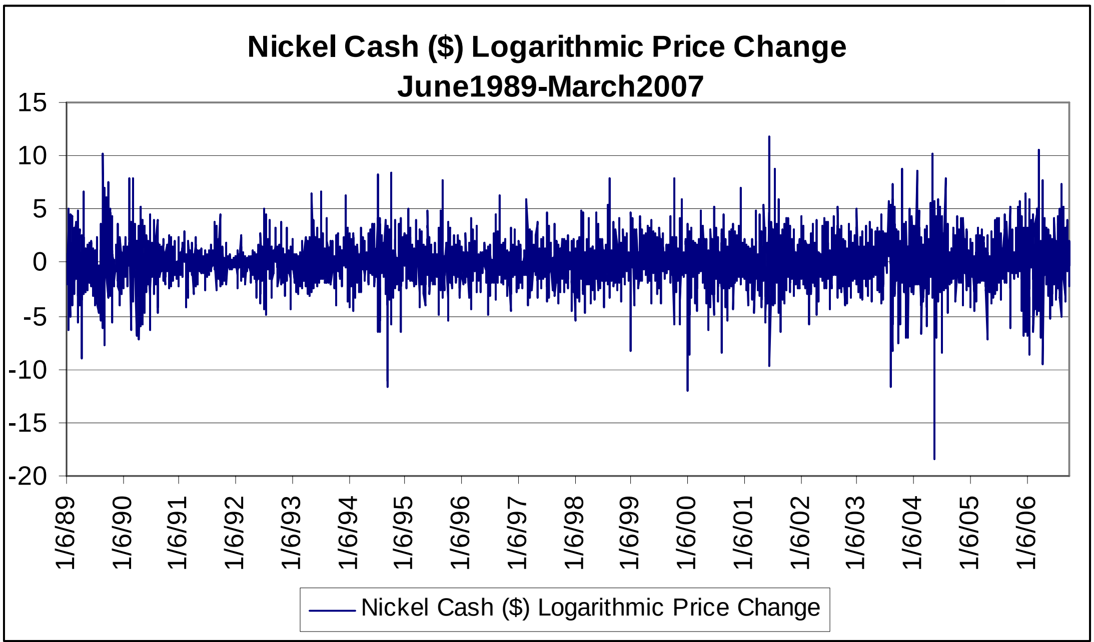


Diagram I.31: Daily Logarithmic price changes of Nickel Cash

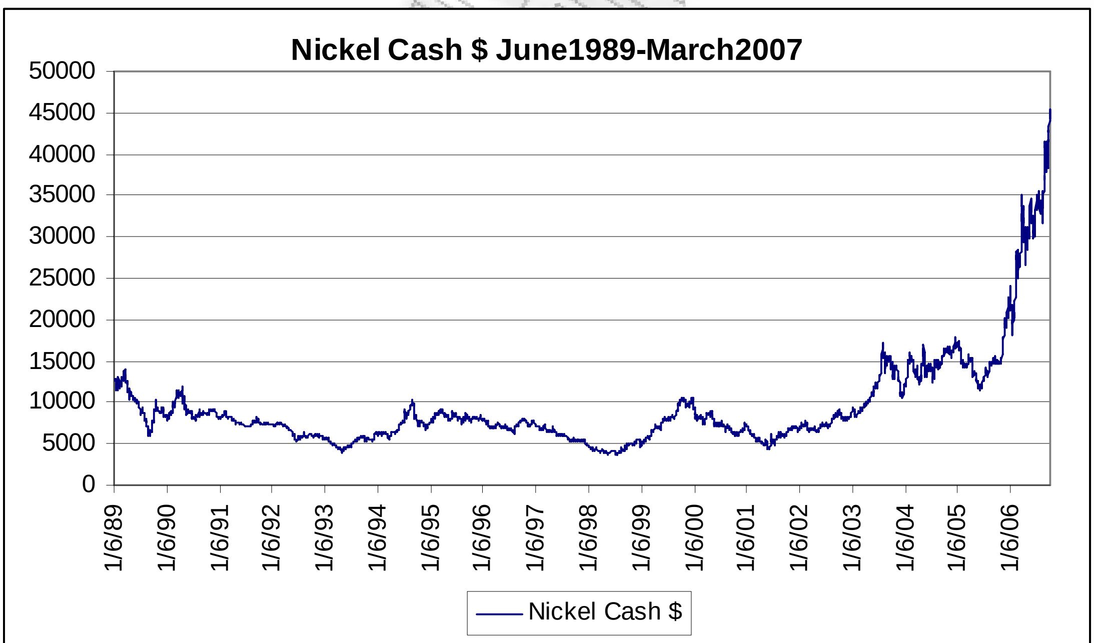


Diagram I.32: Closing Prices of Nickel Cash

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- NICKEL CASH

Included observations: 4422

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>| |</td><td>| |</td><td>1</td><td>0.007</td><td>0.007</td><td>0.2346</td><td>0.628</td></tr>
<tr><td>*| |</td><td>*| |</td><td>2</td><td>-0.063</td><td>-0.063</td><td>17.679</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>-0.021</td><td>-0.020</td><td>19.643</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>0.023</td><td>0.019</td><td>21.973</td><td>0.000</td></tr>
<tr><td>|* |</td><td>|* |</td><td>5</td><td>0.081</td><td>0.079</td><td>51.084</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>-0.018</td><td>-0.017</td><td>52.468</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>-0.002</td><td>0.009</td><td>52.478</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.006</td><td>-0.006</td><td>52.663</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>9</td><td>-0.000</td><td>-0.003</td><td>52.663</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>0.001</td><td>-0.005</td><td>52.669</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>11</td><td>0.021</td><td>0.023</td><td>54.600</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>12</td><td>-0.004</td><td>-0.005</td><td>54.671</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>13</td><td>-0.000</td><td>0.004</td><td>54.672</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>14</td><td>-0.022</td><td>-0.022</td><td>56.757</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>15</td><td>0.008</td><td>0.008</td><td>57.028</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>16</td><td>-0.005</td><td>-0.011</td><td>57.122</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>17</td><td>-0.016</td><td>-0.014</td><td>58.228</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>18</td><td>-0.004</td><td>-0.005</td><td>58.309</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>19</td><td>-0.015</td><td>-0.014</td><td>59.363</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>20</td><td>-0.011</td><td>-0.014</td><td>59.927</td><td>0.000</td></tr>
</table>

Table I.15: Autocorrelation Test (Ljung-Box Q Statistic)- Nickel Cash

Null Hypothesis: NICKEL_CASH has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-65.98822	0.0001
Test critical values:	1% level	-3.431646	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NICKEL_CASH)
Method: Least Squares
Date: 06/18/07 Time: 04:03
Sample (adjusted): 2 4422
Included observations: 4421 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NICKEL_CASH(-1)	-0.992717	0.015044	-65.98822	0.0000
C	0.028058	0.031279	0.897033	0.3698

R-squared	0.496321	Mean dependent var	-0.000166
Adjusted R-squared	0.496207	S.D. dependent var	2.929850
S.E. of regression	2.079560	Akaike info criterion	4.302642
Sum squared resid	19110.27	Schwarz criterion	4.305534
Log likelihood	-9508.990	F-statistic	4354.445
Durbin-Watson stat	1.998639	Prob(F-statistic)	0.000000

Table I.16 Augmented Dickey-Fuller Test for Nickel Cash

9.) NICKEL -3 MONTH

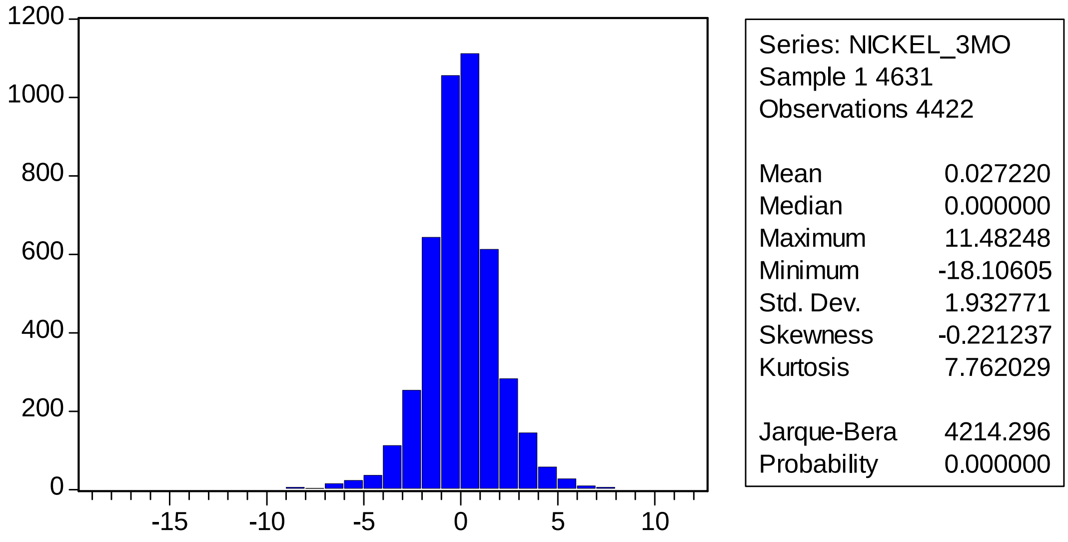


Diagram I.33: Histogram of the daily logarithmic price changes of Nickel -3 Month

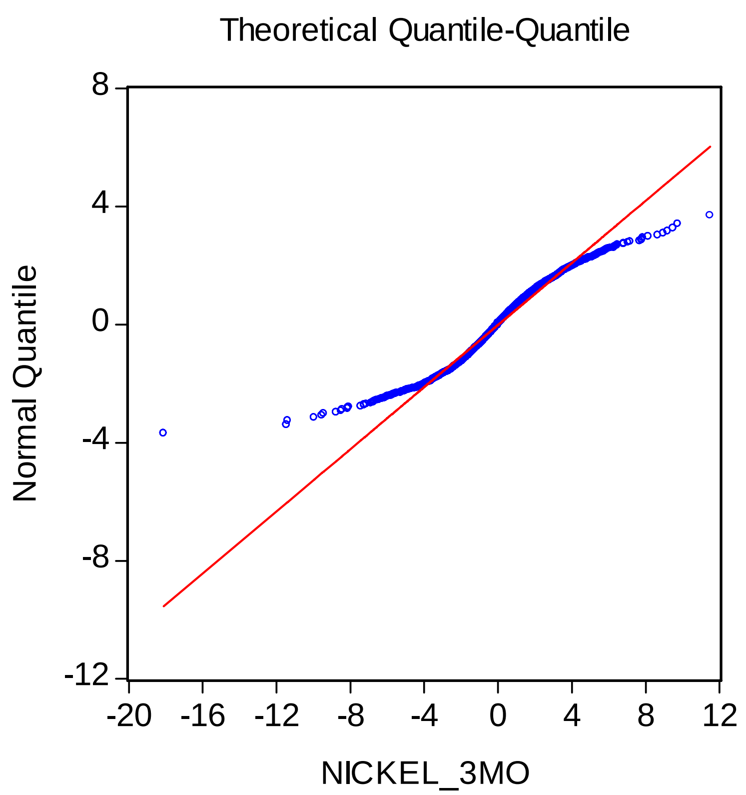


Diagram I.34: Q-Q Plot against the Normal Distribution of Nickel -3 Month

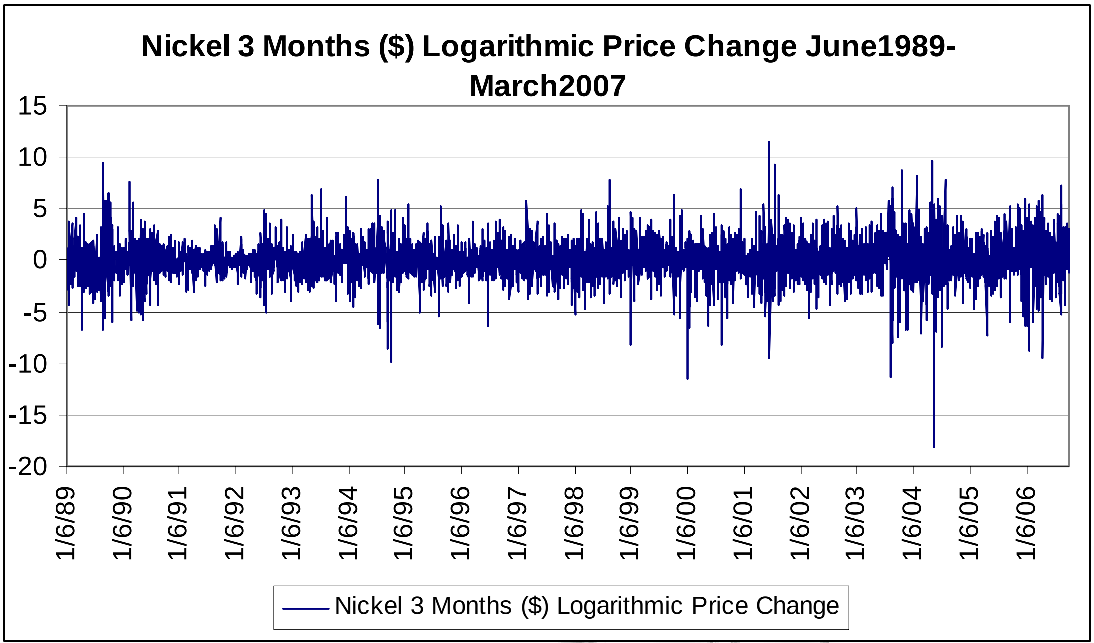


Diagram I.35: Daily Logarithmic price changes of Nickel -3 Month

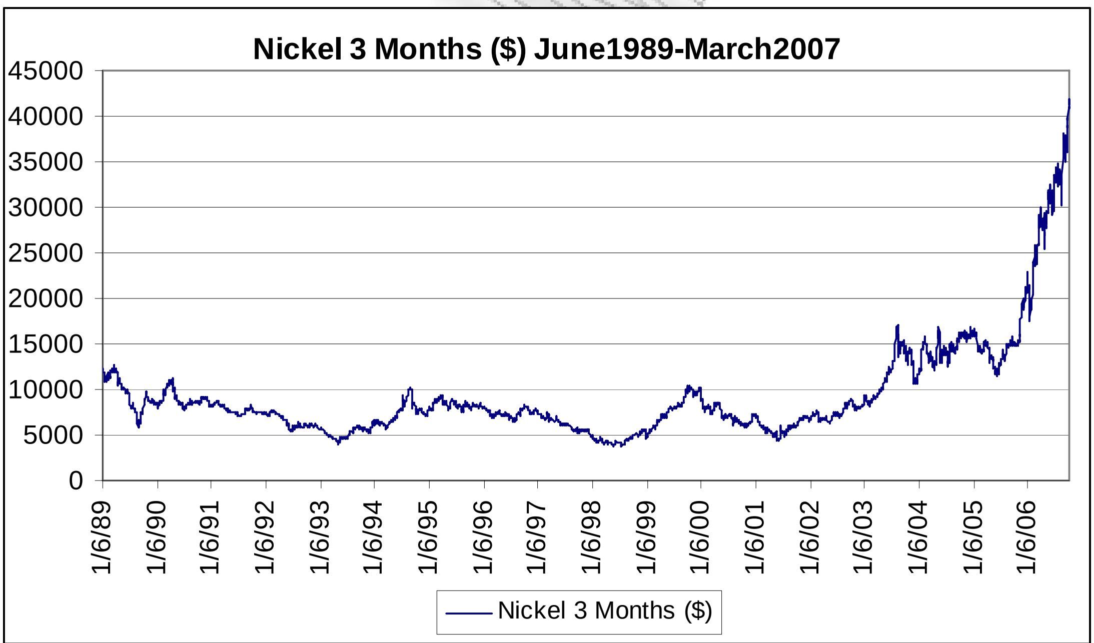


Diagram I.36: Closing Prices of Nickel -3 Month

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- NICKEL 3 MONTH

Included observations: 4422

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.012	0.012	0.6239	0.430
| |	| |	2	-0.054	-0.054	13.389	0.001
| |	| |	3	-0.010	-0.009	13.828	0.003
| |	| |	4	0.030	0.027	17.762	0.001
|* |	|* |	5	0.083	0.081	48.169	0.000
| |	| |	6	-0.023	-0.022	50.500	0.000
| |	| |	7	-0.007	0.002	50.728	0.000
| |	| |	8	0.004	0.002	50.807	0.000
| |	| |	9	0.005	-0.000	50.908	0.000
| |	| |	10	0.007	0.002	51.121	0.000
| |	| |	11	0.016	0.021	52.306	0.000
| |	| |	12	-0.016	-0.017	53.461	0.000
| |	| |	13	0.010	0.012	53.919	0.000
| |	| |	14	-0.019	-0.022	55.586	0.000
| |	| |	15	0.014	0.014	56.399	0.000
| |	| |	16	-0.021	-0.025	58.298	0.000
| |	| |	17	-0.014	-0.009	59.144	0.000
| |	| |	18	-0.004	-0.007	59.202	0.000
| |	| |	19	-0.009	-0.007	59.540	0.000
| |	| |	20	-0.006	-0.008	59.682	0.000

Table I.17: Autocorrelation Test (Ljung-Box Q Statistic)- Nickel -3 Month

Null Hypothesis: NICKEL_3MO has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-65.69591	0.0001
Test critical values:	1% level	-3.431646	
	5% level	-2.861998	
	10% level	-2.567057	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NICKEL_3MO)
Method: Least Squares
Date: 06/18/07 Time: 04:00
Sample (adjusted): 2 4422
Included observations: 4421 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NICKEL_3MO(-1)	-0.988125	0.015041	-65.69591	0.0000
C	0.027352	0.029072	0.940819	0.3468

R-squared	0.494101	Mean dependent var	0.000179
Adjusted R-squared	0.493987	S.D. dependent var	2.717149
S.E. of regression	1.932833	Akaike info criterion	4.156303
Sum squared resid	16508.69	Schwarz criterion	4.159195
Log likelihood	-9185.507	F-statistic	4315.953
Durbin-Watson stat	1.998234	Prob(F-statistic)	0.000000

Table I.18 Augmented Dickey-Fuller Test for Nickel -3 Month

10.) ALUMINIUM CASH

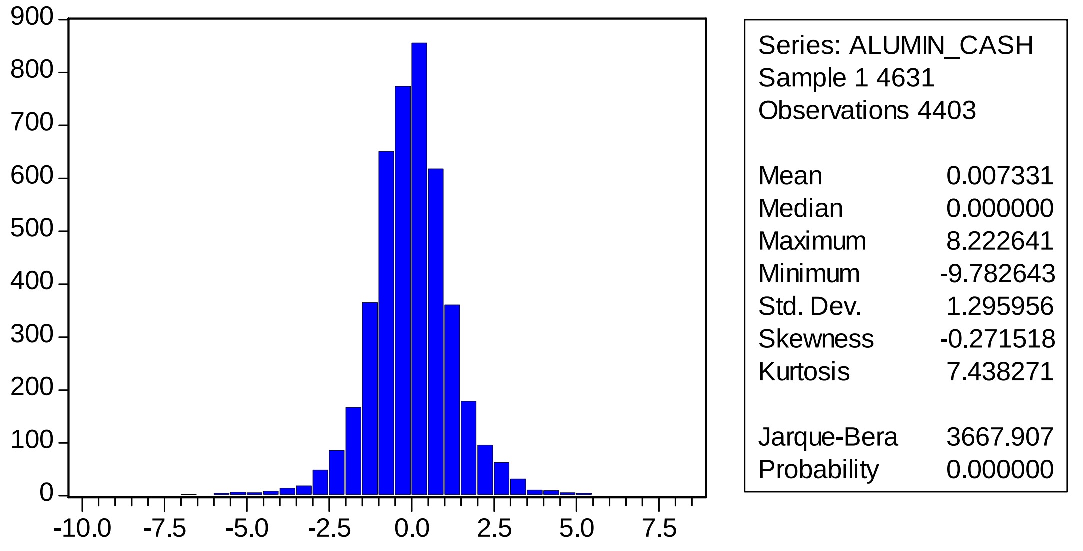


Diagram I.37: Histogram of the daily logarithmic price changes of Aluminium Cash

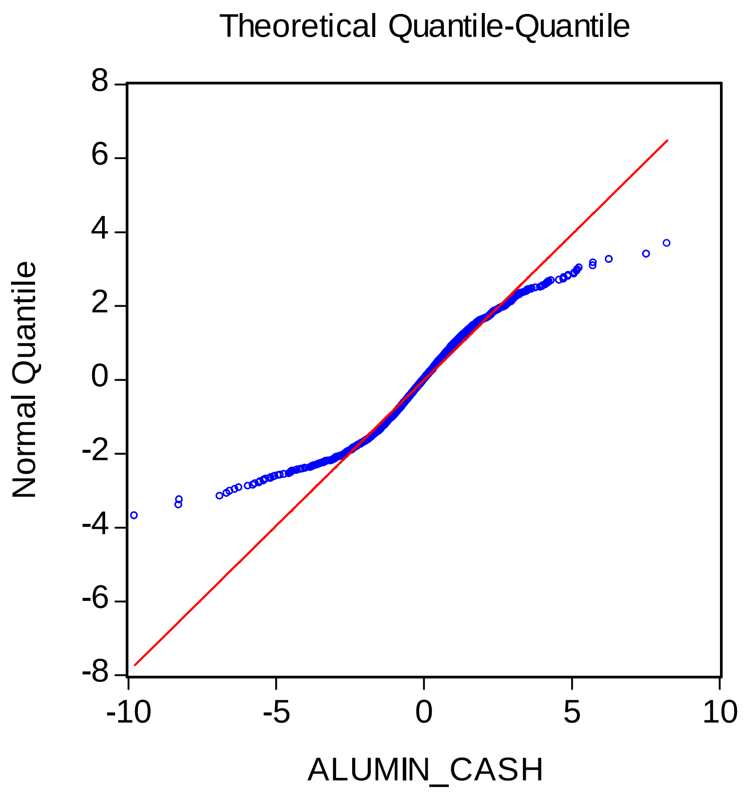


Diagram I.38: Q-Q Plot against the Normal Distribution of Aluminium Cash

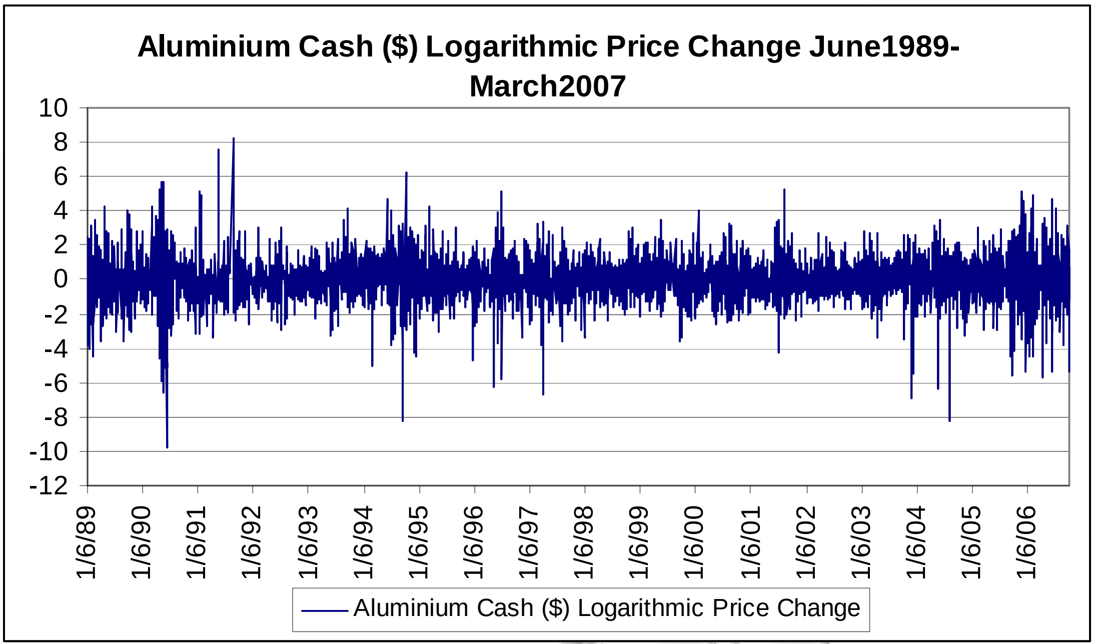


Diagram I.39: Daily Logarithmic price changes of Aluminium Cash

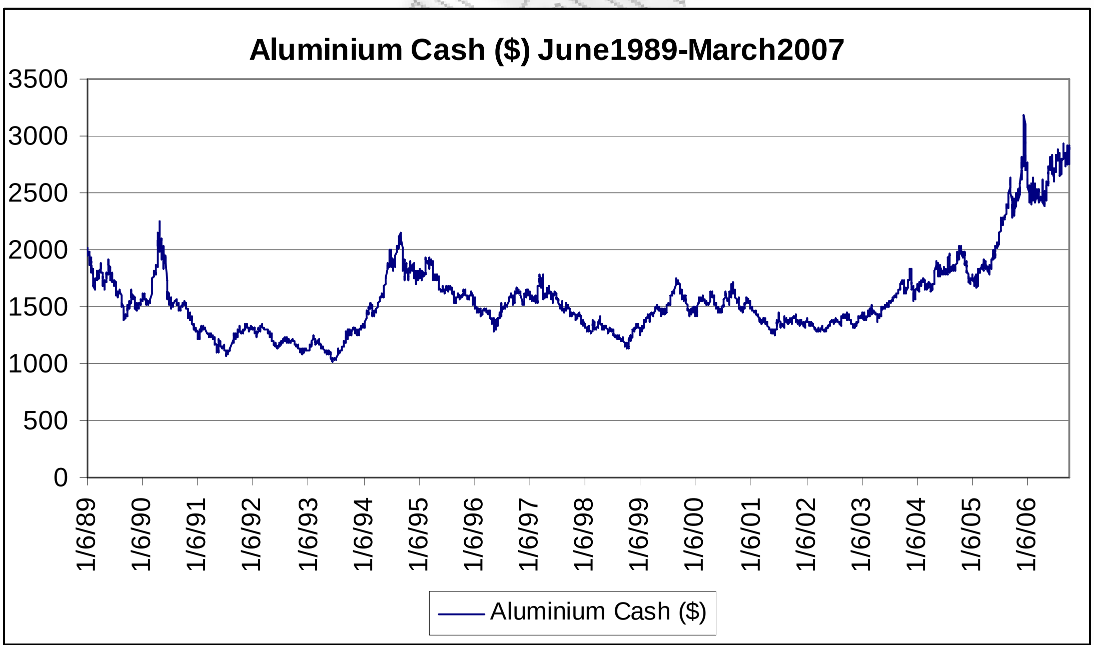


Diagram I.40: Closing Prices of Aluminium Cash

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- ALUMIN. CASH

Included observations: 4403

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.029	-0.029	3.5968	0.058
| |	| |	2	-0.055	-0.056	16.850	0.000
| |	| |	3	-0.002	-0.006	16.872	0.001
| |	| |	4	-0.000	-0.003	16.872	0.002
| |	| |	5	0.019	0.018	18.422	0.002
| |	| |	6	-0.001	0.000	18.424	0.005
| |	| |	7	0.004	0.006	18.500	0.010
| |	| |	8	0.012	0.013	19.164	0.014
| |	| |	9	-0.006	-0.005	19.320	0.023
| |	| |	10	0.015	0.015	20.250	0.027
| |	| |	11	0.041	0.041	27.572	0.004
| |	| |	12	-0.019	-0.015	29.210	0.004
| |	| |	13	-0.011	-0.007	29.701	0.005
| |	| |	14	-0.023	-0.026	32.137	0.004
| |	| |	15	0.019	0.016	33.805	0.004
| |	| |	16	-0.000	-0.004	33.806	0.006
| |	| |	17	-0.002	0.000	33.826	0.009
| |	| |	18	-0.011	-0.012	34.395	0.011
| |	| |	19	0.013	0.012	35.107	0.014
| |	| |	20	-0.009	-0.010	35.504	0.018

Table I.19: Autocorrelation Test (Ljung-Box Q Statistic)- Aluminium Cash

Null Hypothesis: ALUMIN_CASH has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-68.13530	0.0001
Test critical values:	1% level	-3.431652	
	5% level	-2.862000	
	10% level	-2.567058	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ALUMIN_CASH)
Method: Least Squares
Date: 06/18/07 Time: 03:44
Sample (adjusted): 2 4403
Included observations: 4402 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALUMIN_CASH(-1)	-1.028686	0.015098	-68.13530	0.0000
C	0.007864	0.019528	0.402736	0.6872

R-squared	0.513405	Mean dependent var	-0.000941
Adjusted R-squared	0.513294	S.D. dependent var	1.857078
S.E. of regression	1.295578	Akaike info criterion	3.356245
Sum squared resid	7385.494	Schwarz criterion	3.359148
Log likelihood	-7385.094	F-statistic	4642.420
Durbin-Watson stat	1.997592	Prob(F-statistic)	0.000000

Table I.20 Augmented Dickey-Fuller Test for Aluminium Cash

11.) ALUMINIUM 3 MONTH

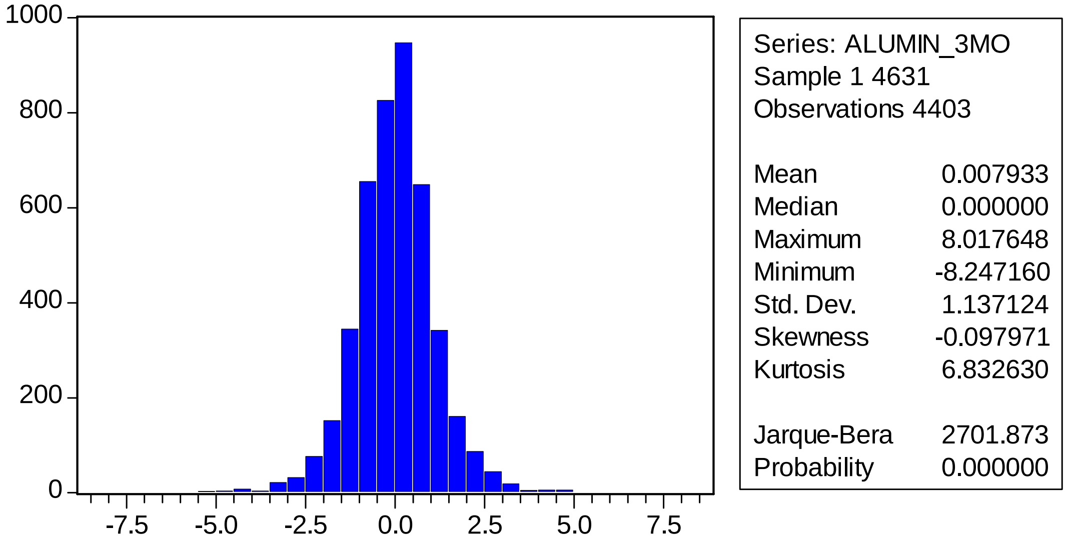


Diagram I.41: Histogram of the daily logarithmic price changes of Aluminium 3- Month

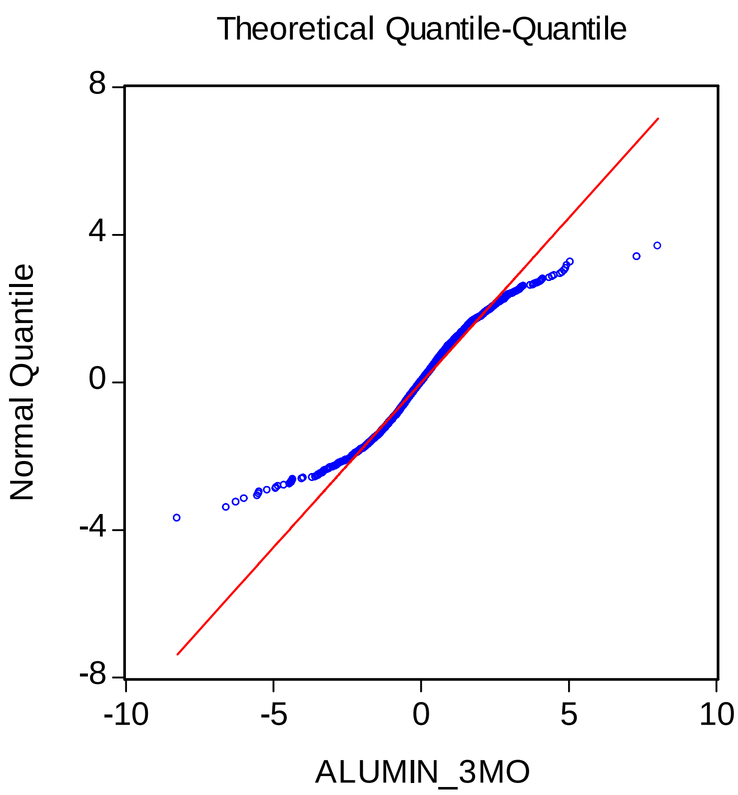


Diagram I.42: Q-Q Plot against the Normal Distribution of Aluminium 3- Month

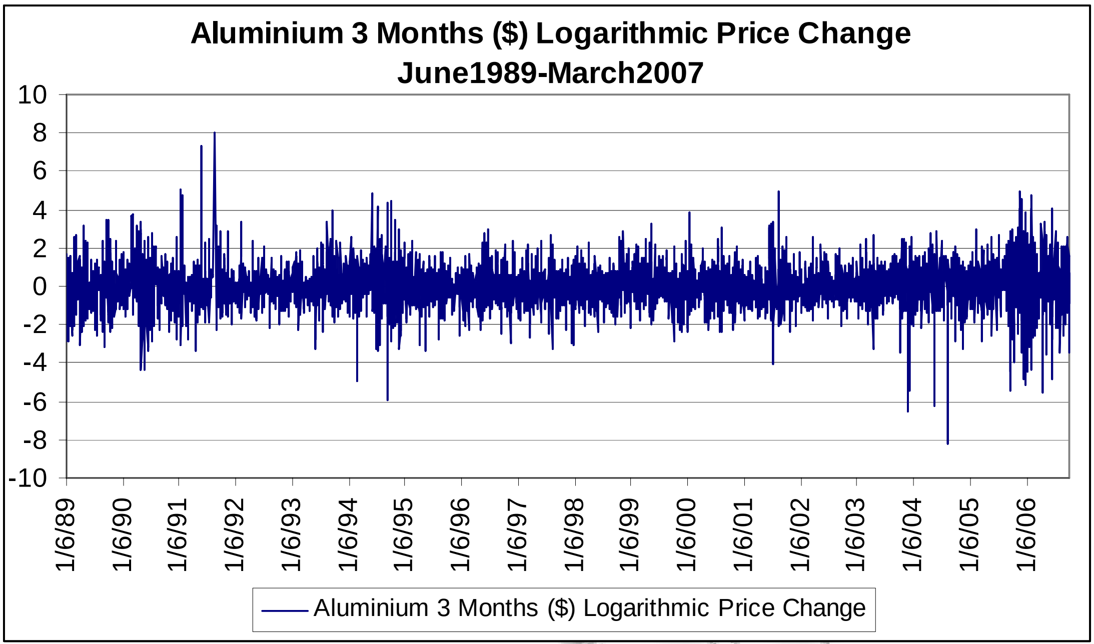


Diagram I.43: Daily Logarithmic price changes of Aluminium 3- Month

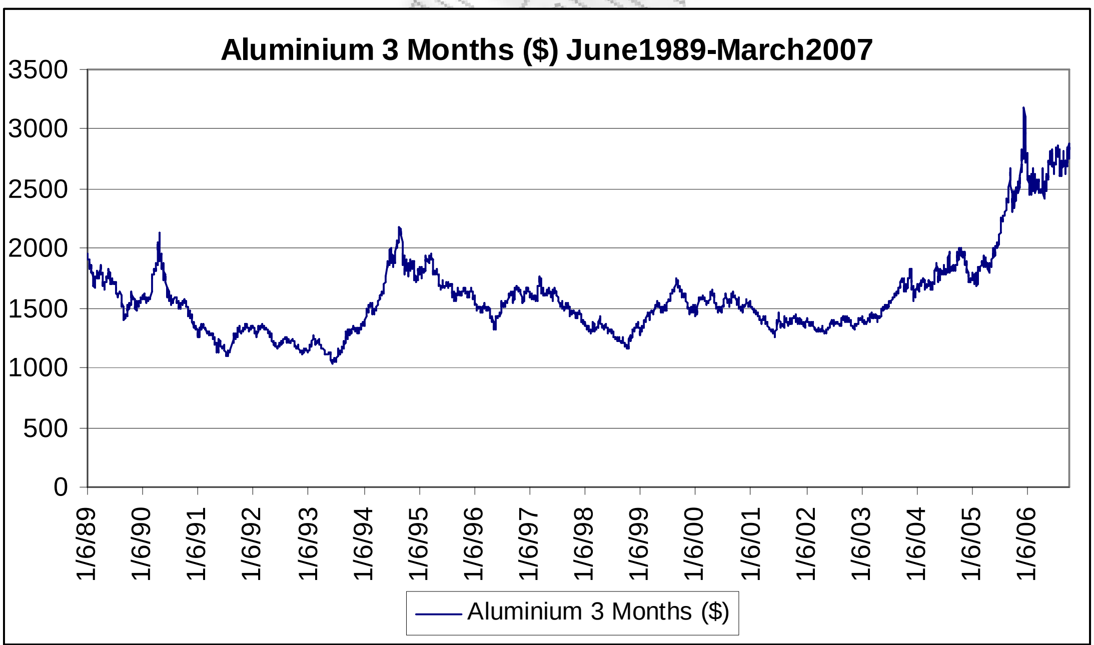


Diagram I.44: Closing Prices of Aluminium 3- Month

**AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC-
ALUMIINIUM 3 MONTH**

Included observations: 4403

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.005	-0.005	0.1049	0.746
| |	| |	2	-0.052	-0.052	12.055	0.002
| |	| |	3	0.019	0.019	13.706	0.003
| |	| |	4	-0.004	-0.007	13.790	0.008
| |	| |	5	0.013	0.015	14.591	0.012
| |	| |	6	0.004	0.003	14.655	0.023
| |	| |	7	0.010	0.012	15.092	0.035
| |	| |	8	0.005	0.005	15.217	0.055
| |	| |	9	-0.006	-0.005	15.380	0.081
| |	| |	10	0.010	0.010	15.783	0.106
| |	| |	11	0.010	0.009	16.184	0.134
| |	| |	12	-0.010	-0.009	16.607	0.165
| |	| |	13	-0.001	-0.001	16.611	0.218
| |	| |	14	-0.016	-0.017	17.719	0.220
| |	| |	15	0.026	0.026	20.714	0.146
| |	| |	16	-0.005	-0.007	20.830	0.185
| |	| |	17	-0.027	-0.023	23.945	0.121
| |	| |	18	-0.005	-0.007	24.039	0.154
| |	| |	19	0.009	0.008	24.410	0.181
| |	| |	20	0.003	0.002	24.439	0.224

Table I.21: Autocorrelation Test (Ljung-Box Q Statistic)- Aluminium 3 Month

Null Hypothesis: ALUMIN_3MO has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.59041	0.0001
Test critical values:	1% level	-3.431652	
	5% level	-2.862000	
	10% level	-2.567058	

*MacKinnon (1996) one-sided p-values.

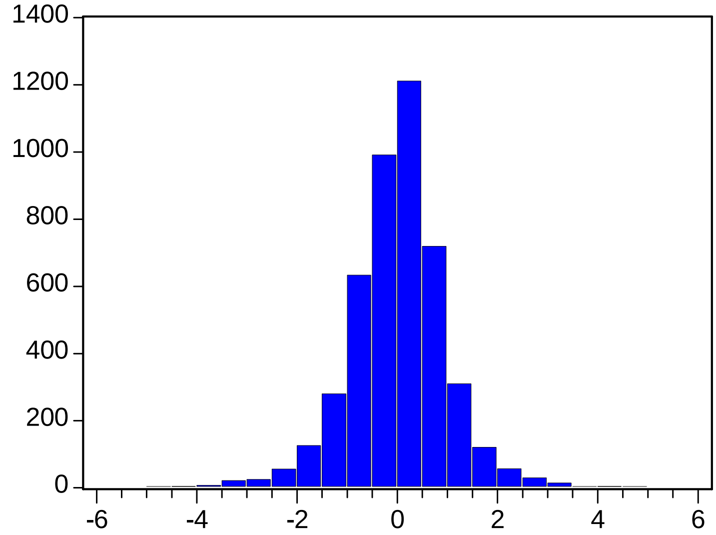
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ALUMIN_3MO)
Method: Least Squares
Date: 06/18/07 Time: 03:27
Sample (adjusted): 2 4403
Included observations: 4402 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ALUMIN_3MO(-1)	-1.004891	0.015091	-66.59041	0.0000
C	0.008165	0.017142	0.476332	0.6339

R-squared	0.501940	Mean dependent var	-0.000603
Adjusted R-squared	0.501827	S.D. dependent var	1.611331
S.E. of regression	1.137299	Akaike info criterion	3.095644
Sum squared resid	5691.178	Schwarz criterion	3.098547
Log likelihood	-6811.512	F-statistic	4434.282
Durbin-Watson stat	1.997375	Prob(F-statistic)	0.000000

Table I.22 Augmented Dickey-Fuller Test for Aluminium 3 Month

12.) FTSE-100



Series: FTSE_100	
Sample 1 4631	
Observations 4630	
Mean	0.023062
Median	0.006811
Maximum	5.902563
Minimum	-5.885338
Std. Dev.	0.991342
Skewness	-0.125286
Kurtosis	6.350336
Jarque-Bera	2177.555
Probability	0.000000

Diagram I.45: Histogram of the daily logarithmic price changes of FTSE-100

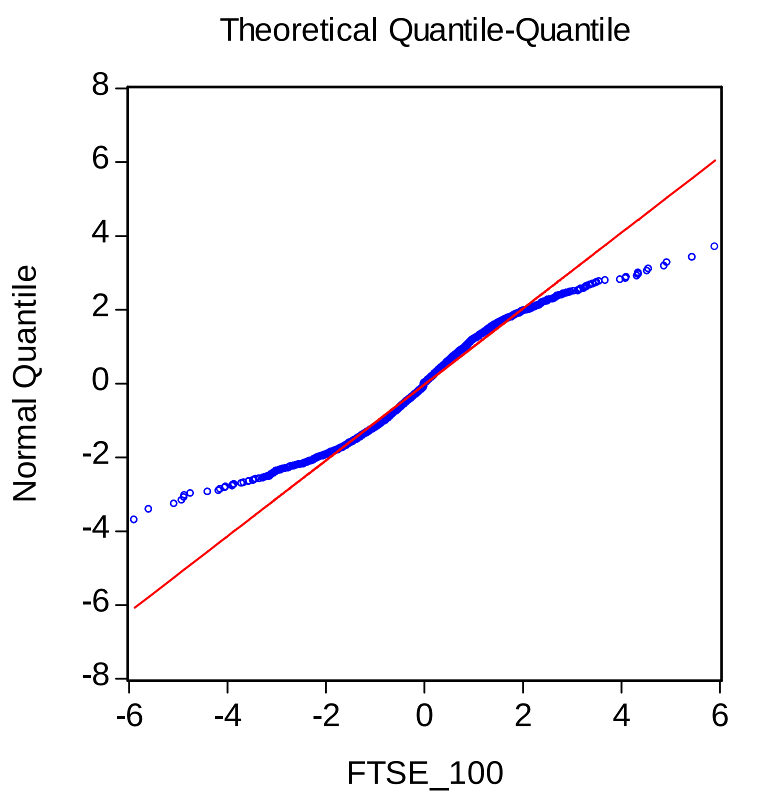


Diagram I.46: Q-Q Plot against the Normal Distribution of FTSE-100

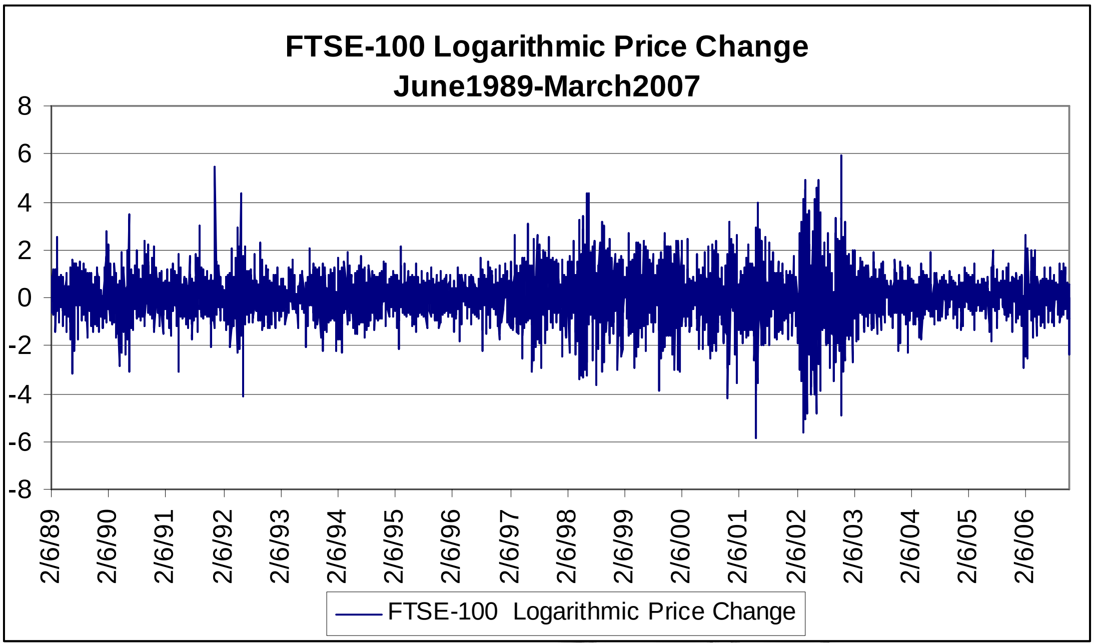


Diagram I.47: Daily Logarithmic price changes of FTSE-100

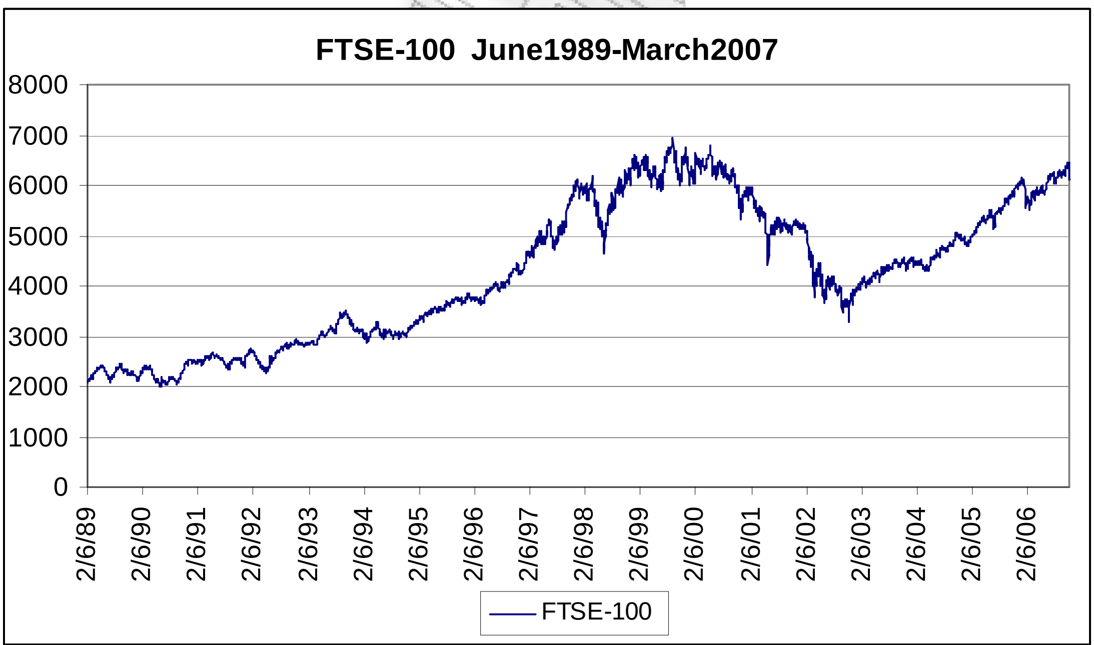


Diagram I.48: Closing Prices of FTSE-100

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- FTSE100

Included observations: 4630

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.009	0.009	0.3975	0.528
		2	-0.030	-0.030	4.4681	0.107
		3	-0.053	-0.053	17.511	0.001
		4	0.024	0.024	20.077	0.000
		5	-0.035	-0.039	25.883	0.000
		6	-0.032	-0.033	30.634	0.000
		7	-0.014	-0.013	31.510	0.000
		8	0.034	0.028	36.871	0.000
		9	0.025	0.022	39.704	0.000
		10	-0.023	-0.023	42.183	0.000
		11	0.003	0.007	42.229	0.000
		12	-0.009	-0.011	42.594	0.000
		13	0.036	0.034	48.559	0.000
		14	-0.010	-0.006	48.998	0.000
		15	0.026	0.028	52.132	0.000
		16	0.013	0.015	52.869	0.000
		17	-0.016	-0.020	54.092	0.000
		18	-0.054	-0.047	67.689	0.000
		19	-0.031	-0.029	72.208	0.000
		20	0.007	0.004	72.411	0.000

Table I.23 Autocorrelation Test (Ljung-Box Q Statistic) - FTSE-100

Null Hypothesis: FTSE_100 has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-67.39849	0.0001
Test critical values:	1% level	-3.431580	
	5% level	-2.861968	
	10% level	-2.567041	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FTSE_100)
Method: Least Squares
Date: 06/18/07 Time: 03:53
Sample (adjusted): 2 4630
Included observations: 4629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FTSE_100(-1)	-0.990738	0.014700	-67.39849	0.0000
C	0.022999	0.014576	1.577810	0.1147

R-squared	0.495395	Mean dependent var	0.000146
Adjusted R-squared	0.495286	S.D. dependent var	1.395575
S.E. of regression	0.991461	Akaike info criterion	2.821157
Sum squared resid	4548.316	Schwarz criterion	2.823940
Log likelihood	-6527.568	F-statistic	4542.557
Durbin-Watson stat	1.999007	Prob(F-statistic)	0.000000

Table I.24 Augmented Dickey-Fuller Test for FTSE-100

12.) LIFFE FTSE-100

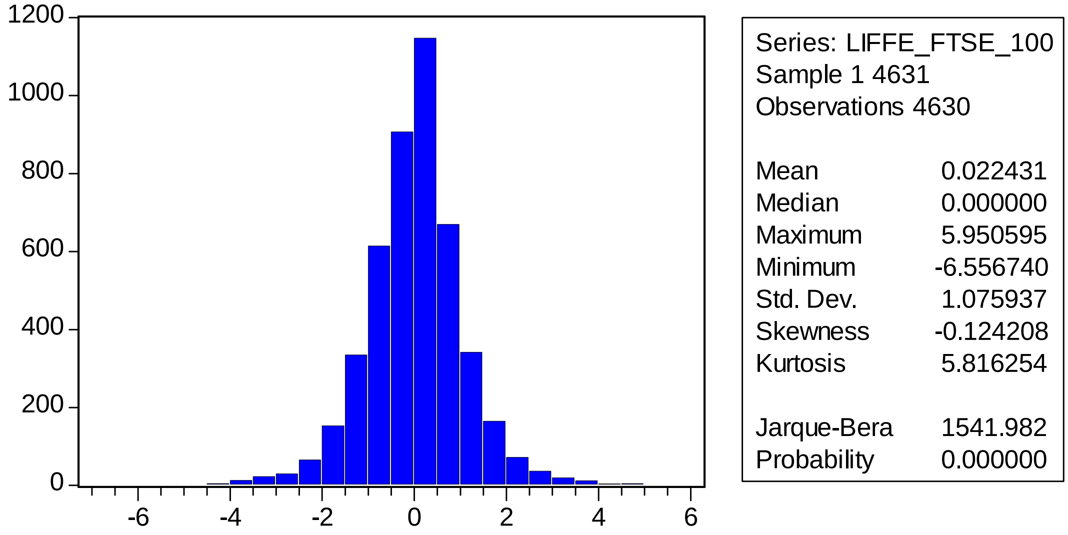


Diagram I.49: Histogram of the daily logarithmic price changes of LIFFE FTSE-100

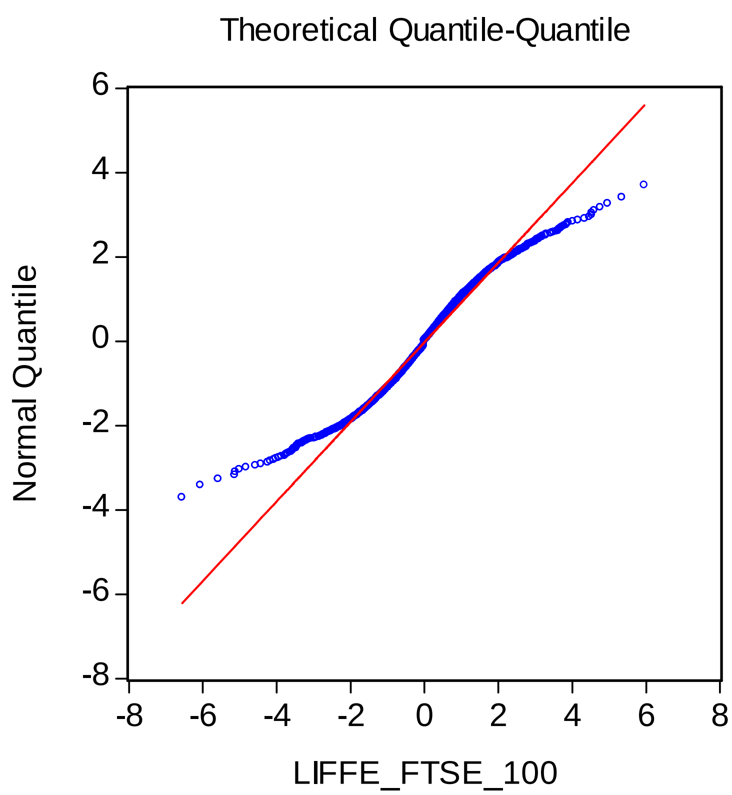


Diagram I.50: Q-Q Plot against the Normal Distribution of LIFFE FTSE-100

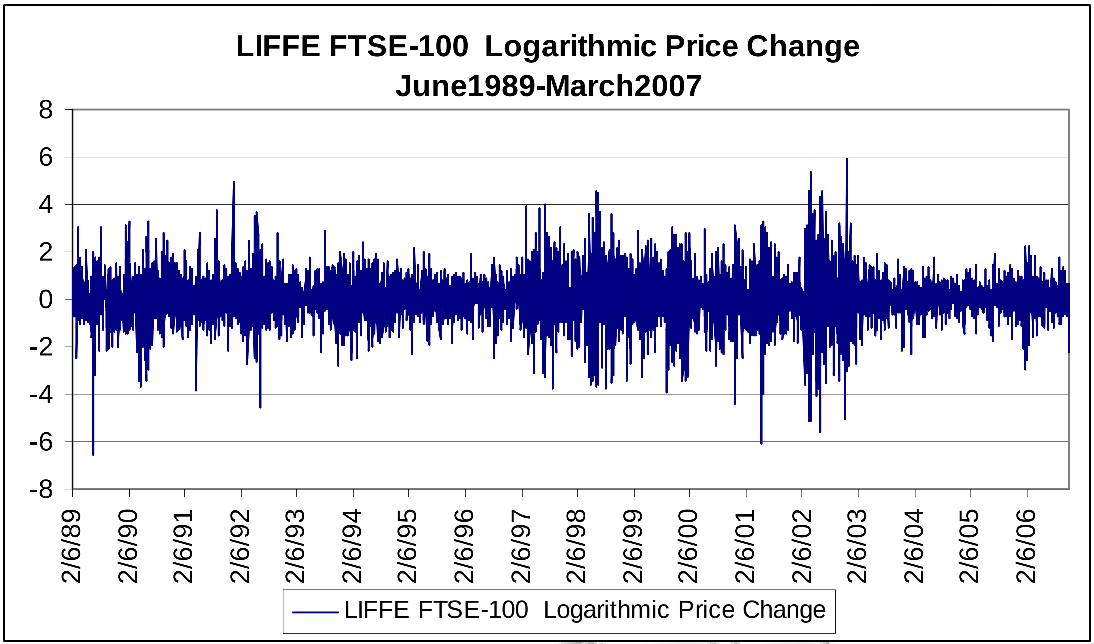


Diagram I.51: Daily Logarithmic price changes of LIFFE FTSE-100

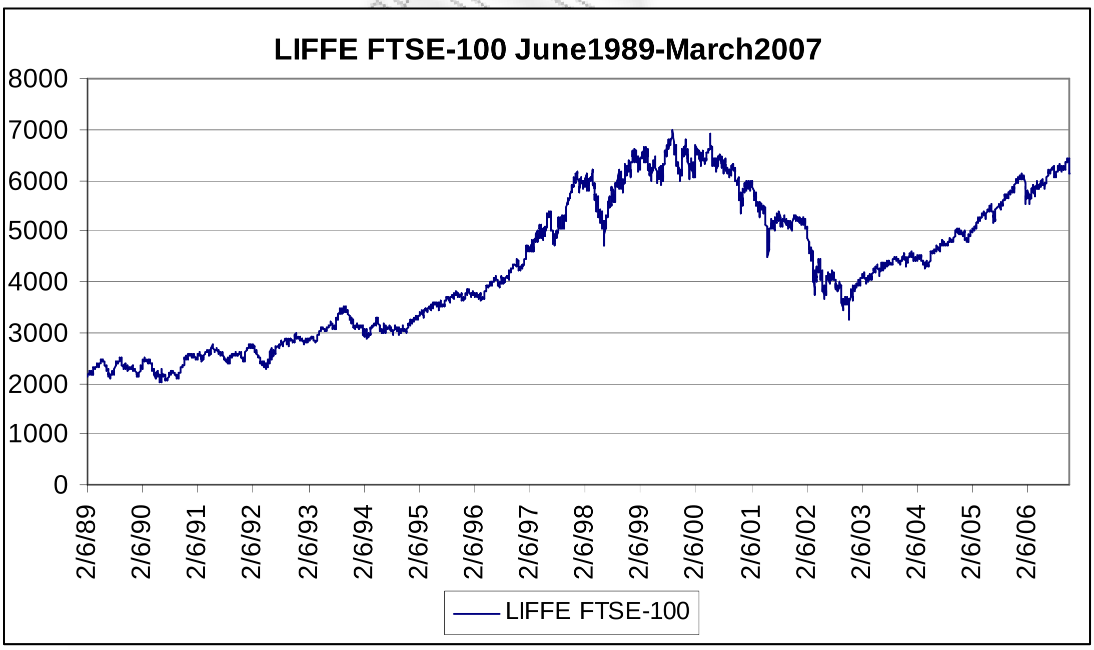


Diagram I.52: Closing Prices of LIFFE FTSE-100

AUTOCORRELATION TEST- LJUNG BOX Q STATISTIC- LIFFE FTSE100

Included observations: 4630

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.017	-0.017	1.3556	0.244
| |	| |	2	-0.027	-0.027	4.7049	0.095
*| |	*| |	3	-0.058	-0.059	20.406	0.000
| |	| |	4	0.022	0.019	22.665	0.000
| |	| |	5	-0.033	-0.035	27.610	0.000
| |	| |	6	-0.023	-0.027	30.052	0.000
| |	| |	7	-0.031	-0.032	34.611	0.000
| |	| |	8	0.034	0.027	39.824	0.000
| |	| |	9	0.012	0.010	40.530	0.000
| |	| |	10	-0.010	-0.012	41.009	0.000
| |	| |	11	-0.007	-0.004	41.231	0.000
| |	| |	12	-0.012	-0.015	41.854	0.000
| |	| |	13	0.029	0.028	45.889	0.000
| |	| |	14	-0.005	-0.003	45.986	0.000
| |	| |	15	0.015	0.017	46.976	0.000
| |	| |	16	0.018	0.021	48.496	0.000
| |	| |	17	-0.021	-0.024	50.631	0.000
| |	| |	18	-0.038	-0.035	57.422	0.000
| |	| |	19	-0.036	-0.036	63.334	0.000
| |	| |	20	0.011	0.008	63.939	0.000

Table I.25: Autocorrelation Test (Ljung-Box Q Statistic) – LIFFE FTSE-100

Null Hypothesis: LIFFE_FTSE_100 has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-69.19935	0.0001
Test critical values:	1% level	-3.431580	
	5% level	-2.861968	
	10% level	-2.567041	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LIFFE_FTSE_100)
Method: Least Squares
Date: 06/18/07 Time: 03:55
Sample (adjusted): 2 4630
Included observations: 4629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LIFFE_FTSE_100(-1)	-1.017105	0.014698	-69.19935	0.0000
C	0.022981	0.015818	1.452839	0.1463

R-squared	0.508579	Mean dependent var	0.000134
Adjusted R-squared	0.508473	S.D. dependent var	1.534686
S.E. of regression	1.075953	Akaike info criterion	2.984723
Sum squared resid	5356.563	Schwarz criterion	2.987505
Log likelihood	-6906.141	F-statistic	4788.550
Durbin-Watson stat	2.000777	Prob(F-statistic)	0.000000

Table I.26 Augmented Dickey-Fuller Test for LIFFE FTSE-100

APPENDIX II. BACKTESTING TABLES

TABLE II.1 - PANEL A: *GOLD BULLION VaR_99%*

Value-at-Risk 99% GOLD BULLION **significance level of the LR tests: 5%**
Backtesting Period: ***5 April 1993- 2 March 2007*****, N = 3630 backtesting trials, Expected Violations = 36**

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-1,789	-1,801	-2,375	-2,387	-1,781	-2,185	-2,175	-1,800	-2,439
StDev(VaR)	0,761	0,779	0,990	1,053	0,818	1,005	0,765	0,697	0,995
Min VaR	-9,083	-8,634	-11,398	-11,524	-5,859	-5,463	-4,103	-10,253	-12,000
Max VaR	-0,444	-0,451	-0,585	-0,610	-0,399	-0,558	-1,014	-0,555	-0,653
Violations	72	73	34	31	72	59	50	76	25
LRUC	27,57	28,98	0,15	0,82	27,57	12,06	4,67	33,36	3,99
LRUC p-value	0,00000	0,00000	**0,69817**	**0,36450**	0,00000	0,00052	0,03064	0,00000	0,04581
LRIND	11,18	16,34	0,64	0,53	11,18	5,67	4,43	15,48	0,35
LRIND p-value	0,00083	0,00005	**0,42265**	**0,46491**	0,00083	0,01725	0,03535	0,00008	**0,55596**
LRCC	38,75	45,32	0,79	1,36	38,75	17,73	9,10	48,83	4,34
LRCC p-value	0,00000	0,00000	**0,67256**	**0,50754**	0,00000	0,00014	0,01056	0,00000	**0,11446**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,993	-2,011	-1,929	-1,994	-2,021	-2,061	-2,073	-2,082	-2,077	-2,059
StDev(VaR)	0,543	0,546	0,437	0,415	0,402	0,558	0,568	0,394	0,396	0,384
Min VaR	-3,516	-3,664	-3,064	-3,042	-3,111	-3,727	-3,824	-3,211	-3,238	-3,178
Max VaR	-0,927	-0,959	-1,145	-1,265	-1,319	-1,013	-1,021	-1,401	-1,401	-1,424
Violations	65	61	73	66	63	57	53	59	58	57
LRUC	18,56	14,10	28,98	19,76	16,26	10,16	6,80	12,06	11,09	10,16
LRUC p-value	0,00002	0,00017	0,00000	0,00001	0,00006	0,00144	0,00914	0,00052	0,00087	0,00144
LRIND	4,46	2,63	5,55	7,13	4,84	6,12	3,87	5,67	3,06	3,21
LRIND p-value	0,03466	**0,10513**	0,01849	0,00758	0,02776	0,01336	0,04911	0,01725	**0,08047**	**0,07327**
LRCC	23,03	16,72	34,53	26,89	21,11	16,28	10,67	17,73	14,15	13,37
LRCC p-value	0,00001	0,00023	0,00000	0,00000	0,00003	0,00029	0,00483	0,00014	0,00085	0,00125

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.1 - PANEL B: *GOLD BULLION VaR_95%*

Value-at-Risk 95% GOLD BULLION , significance level of the LR tests: 5%
Backtesting Period: 5 April 1993- 2 March 2007, N = 3630 backtesting trials, Expected Violations = 182

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-1,265	-1,273	-1,251	-1,257	-1,259	-1,258	-1,231	-1,273	-1,266
StDev(VaR)	0,538	0,551	0,524	0,563	0,578	0,540	0,416	0,493	0,515
Min VaR	-6,422	-6,105	-5,908	-5,973	-4,143	-3,759	-2,663	-7,249	-6,219
Max VaR	-0,314	-0,319	-0,330	-0,365	-0,282	-0,381	-0,543	-0,393	-0,339
Violations	181	174	182	183	191	211	197	173	184
LRUC	0,00	0,33	0,00	0,01	0,51	4,81	1,36	0,43	0,04
LRIND	6,93	9,64	6,85	7,46	8,24	12,92	20,08	14,17	9,23
LRCC	6,93	9,97	6,85	7,47	8,76	17,73	21,44	14,60	9,26
LRUC p-value	**0,96961**	**0,56532**	**0,96964**	**0,90917**	**0,47299**	0,02834	**0,24400**	**0,51427**	**0,84933**
LRIND p-value	0,00847	0,00190	0,00888	0,00630	0,00410	0,00032	0,00001	0,00017	0,00239
LRCC p-value	0,03123	0,00683	0,03258	0,02382	0,01255	0,00014	0,00002	0,00068	0,00974

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,113	-1,106	-0,999	-1,061	-1,079	-1,197	-1,199	-1,167	-1,169	-1,172
StDev(VaR)	0,312	0,278	0,294	0,247	0,219	0,297	0,298	0,219	0,220	0,224
Min VaR	-1,851	-1,821	-1,813	-1,657	-1,684	-2,056	-2,062	-1,764	-1,763	-1,826
Max VaR	-0,523	-0,566	-0,541	-0,652	-0,706	-0,627	-0,632	-0,804	-0,806	-0,780
Violations	240	229	268	238	207	216	216	218	217	222
LRUC	18,14	12,15	38,13	16,97	3,63	6,52	6,52	7,28	6,90	8,91
LRIND	6,37	8,75	12,77	16,30	15,38	19,55	19,55	17,22	19,23	19,42
LRCC	24,51	20,91	50,91	33,27	19,00	26,07	26,07	24,50	26,13	28,33
LRUC p-value	0,00002	0,00049	0,00000	0,00004	**0,05676**	0,01064	0,01064	0,00697	0,00863	0,00284
LRIND p-value	0,01161	0,00309	0,00035	0,00005	0,00009	0,00001	0,00001	0,00003	0,00001	0,00001
LRCC p-value	0,00000	0,00003	0,00000	0,00000	0,00007	0,00000	0,00000	0,00000	0,00000	0,00000

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.2 - PANEL A: *COPPER CASH VaR_99%*

Value-at-Risk 99% COPPER CASH , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 34									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-3,488	-3,476	-3,992	-3,953	-3,414	-4,073	-4,117	-3,399	-3,908
StDev(VaR)	1,388	1,344	1,574	1,447	1,456	1,914	1,895	1,091	1,219
Min VaR	-18,209	-19,226	-21,282	-22,119	-14,403	-10,209	-9,041	-14,816	-16,965
Max VaR	-1,980	-1,668	-2,257	-2,278	-1,471	-1,618	-1,886	-1,897	-1,985
Violations	46	45	30	30	58	46	44	55	32
LRUC	3,73	3,15	0,54	0,54	13,87	3,73	2,61	10,81	0,14
LRIND	0,20	0,24	0,53	0,53	0,84	0,20	0,28	1,80	0,60
LRCC	3,93	3,39	1,07	1,07	14,71	3,93	2,89	12,61	0,75
LRUC p-value	**0,05359**	**0,07609**	**0,46303**	**0,46303**	0,00020	**0,05359**	**0,10600**	0,00101	**0,70483**
LRIND p-value	**0,65178**	**0,62462**	**0,46606**	**0,46606**	**0,35899**	**0,65178**	**0,59773**	**0,17983**	**0,43673**
LRCC p-value	**0,14022**	**0,18396**	**0,58571**	**0,58571**	0,00064	**0,14022**	**0,23560**	0,00182	**0,68786**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-3,651	-3,784	-3,507	-3,626	-3,780	-3,996	-3,982	-4,013	-3,995	-3,968
StDev(VaR)	0,953	1,030	0,643	0,693	0,734	1,256	1,258	0,911	0,916	0,910
Min VaR	-5,648	-5,973	-4,649	-4,801	-5,100	-6,359	-6,350	-5,259	-5,304	-5,442
Max VaR	-2,082	-2,136	-2,176	-2,286	-2,410	-2,166	-2,169	-2,416	-2,391	-2,304
Violations	54	50	72	62	51	44	44	41	44	45
LRUC	9,87	6,47	32,07	18,43	7,26	2,61	2,61	1,29	2,61	3,15
LRIND	6,45	1,55	5,32	7,68	0,07	2,28	2,28	0,42	0,28	0,24
LRCC	16,32	8,03	37,38	26,11	7,33	4,89	4,89	1,71	2,89	3,39
LRUC p-value	0,00168	0,01096	0,00000	0,00002	0,00704	**0,10600**	**0,10600**	**0,25566**	**0,10600**	**0,07609**
LRIND p-value	0,01109	**0,21271**	0,02113	0,00559	**0,79053**	**0,13144**	**0,13144**	**0,51902**	**0,59773**	**0,62462**
LRCC p-value	0,00029	0,01809	0,00000	0,00000	0,02556	**0,08680**	**0,08680**	**0,42572**	**0,23560**	**0,18396**

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05. VaR models that pass the LR tests have bold p-values.)

TABLE II.2 - PANEL B: *COPPER CASH VaR_95%*

Value-at-Risk 95% COPPER CASH , significance level of the LR tests: 5%
Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 171

Method:	Normal GARCH(1,1)		t-Student GARCH(1,1)		EWMA	Historical Simulation		Normal EGARCH(1,1)	t-Student EGARCH(1,1)	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,466	-2,458	-2,405	-2,396	-2,414	-2,371	-2,320	-2,404		-2,346
StDev(VaR)	0,982	0,950	0,903	0,855	1,029	1,016	0,740	0,772		0,693
Min VaR	-12,875	-13,594	-12,745	-12,585	-10,184	-5,935	-4,183	-10,476		-9,652
Max VaR	-1,400	-1,180	-1,475	-1,364	-1,040	-1,198	-1,381	-1,341		-1,227
Violations	148	151	161	154	173	185	190	156		164
LRUC	3,38	2,53	0,62	1,82	0,03	1,19	2,17	1,41		0,30
LRIND	0,03	0,27	0,28	0,00	0,19	5,90	6,27	3,10		0,59
LRCC	3,41	2,81	0,89	1,82	0,22	7,09	8,44	4,51		0,89
LRUC p-value	**0,06612**	**0,11138**	**0,43289**	**0,17767**	**0,86934**	**0,27455**	**0,14056**	**0,23558**		**0,58573**
LRIND p-value	**0,86476**	**0,60071**	**0,59913**	**0,98054**	**0,66440**	0,01514	0,01230	**0,07833**		**0,44202**
LRCC p-value	**0,18216**	**0,24556**	**0,64039**	**0,40301**	**0,89795**	0,02880	0,01471	**0,10508**		**0,64144**

Method:	Block Maxima (GEV distribution)					Peaks Over Threshold (GP distribution)				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,985	-2,089	-1,889	-1,948	-2,078	-2,244	-2,245	-2,232	-2,233	-2,244
StDev(VaR)	0,419	0,428	0,270	0,287	0,303	0,553	0,551	0,408	0,411	0,419
Min VaR	-3,210	-3,248	-2,475	-2,543	-2,624	-3,471	-3,478	-2,822	-2,837	-2,946
Max VaR	-1,392	-1,473	-1,410	-1,495	-1,574	-1,492	-1,498	-1,585	-1,582	-1,609
Violations	241	215	274	256	226	192	191	193	192	190
LRUC	27,00	11,11	55,79	38,95	17,05	2,64	2,40	2,89	2,64	2,17
LRIND	11,12	12,29	21,24	17,53	9,28	18,03	16,31	11,85	12,14	6,27
LRCC	38,11	23,40	77,03	56,48	26,34	20,67	18,71	14,74	14,78	8,44
LRUC p-value	0,00000	0,00086	0,00000	0,00000	0,00004	**0,10411**	**0,12125**	**0,08897**	**0,10411**	**0,14056**
LRIND p-value	0,00086	0,00046	0,00000	0,00003	0,00231	0,00002	0,00005	0,00058	0,00049	0,01230
LRCC p-value	0,00000	0,00001	0,00000	0,00000	0,00000	0,00003	0,00009	0,00063	0,00062	0,01471

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.3 - PANEL A: *COPPER 3-MONTH VaR_99%*

Value-at-Risk 99% COPPER 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 34										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-3,054	-3,054	-3,648	-3,671	-2,997	-3,676	-3,741	-2,997		-3,651
StDev(VaR)	1,100	1,103	1,380	1,281	1,214	1,609	1,561	0,914		1,128
Min VaR	-9,831	-10,200	-13,291	-13,923	-10,351	-8,653	-6,897	-10,307		-12,499
Max VaR	-1,501	-1,532	-1,532	-1,454	-1,166	-1,563	-1,864	-1,193		-1,251
Violations	49	54	38	33	62	46	41	60		33
LRUC	5,72	9,87	0,42	0,04	18,43	3,73	1,29	16,08		0,04
LRIND	1,66	0,02	0,59	0,64	7,68	2,01	2,71	0,70		0,95
LRCC	7,38	9,89	1,00	0,69	26,11	5,74	4,00	16,78		1,00
LRUC p-value	0,01675	0,00168	**0,51885**	**0,83833**	0,00002	**0,05359**	**0,25566**	0,00006		**0,83833**
LRIND p-value	**0,19746**	**0,87495**	**0,44391**	**0,42247**	0,00559	**0,15582**	**0,09977**	**0,40197**		**0,32882**
LRCC p-value	0,02493	0,00710	**0,60582**	**0,70997**	0,00000	**0,05671**	**0,13524**	0,00023		**0,60799**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-3,318	-3,449	-3,179	-3,234	-3,349	-3,644	-3,627	-3,580	-3,571	-3,548
StDev(VaR)	0,779	0,856	0,471	0,477	0,516	1,010	1,024	0,674	0,686	0,700
Min VaR	-5,346	-5,954	-4,566	-4,696	-4,978	-5,897	-5,892	-5,128	-5,143	-5,326
Max VaR	-2,017	-2,055	-2,156	-2,204	-2,297	-2,095	-2,091	-2,319	-2,316	-2,220
Violations	53	51	68	60	52	42	41	42	44	46
LRUC	8,96	7,26	26,25	16,08	8,09	1,68	1,29	1,68	2,61	3,73
LRIND	10,39	11,09	12,71	11,85	15,00	5,90	6,15	5,90	5,41	8,68
LRCC	19,36	18,35	38,96	27,93	23,09	7,58	7,44	7,58	8,03	12,41
LRUC p-value	0,00276	0,00704	0,00000	0,00006	0,00444	**0,19433**	**0,25566**	**0,19433**	**0,10600**	**0,05359**
LRIND p-value	0,00126	0,00087	0,00036	0,00058	0,00011	0,01516	0,01312	0,01516	0,01997	0,00321
LRCC p-value	0,00006	0,00010	0,00000	0,00000	0,00001	0,02257	0,02418	0,02257	0,01806	0,00202

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.3 - PANEL B: *COPPER 3-MONTH VaR_95%*

Value-at-Risk 95% COPPER 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 171										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,160	-2,159	-2,110	-2,120	-2,119	-2,106	-2,103	-2,119		-2,095
StDev(VaR)	0,778	0,780	0,720	0,736	0,858	0,895	0,646	0,646		0,620
Min VaR	-6,951	-7,212	-6,888	-7,216	-7,319	-5,601	-4,236	-7,288		-6,623
Max VaR	-1,061	-1,083	-0,871	-0,828	-0,824	-0,976	-1,320	-0,844		-0,712
Violations	155	156	162	156	166	180	188	158		158
LRUC	1,61	1,41	0,50	1,41	0,15	0,50	1,75	1,05		1,05
LRIND	6,03	5,83	7,79	7,46	5,38	6,93	13,36	5,44		7,02
LRCC	7,64	7,24	8,28	8,87	5,53	7,44	15,10	6,50		8,07
LRUC p-value	**0,20517**	**0,23558**	**0,48121**	**0,23558**	**0,69926**	**0,47875**	**0,18627**	**0,30542**		**0,30542**
LRIND p-value	0,01404	0,01572	0,00526	0,00630	0,02031	0,00846	0,00026	0,01963		0,00808
LRCC p-value	0,02194	0,02678	0,01590	0,01185	**0,06285**	0,02429	0,00053	0,03887		0,01771

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,735	-1,800	-1,633	-1,684	-1,773	-1,998	-2,000	-1,943	-1,944	-1,949
StDev(VaR)	0,303	0,296	0,216	0,174	0,179	0,394	0,396	0,247	0,250	0,237
Min VaR	-2,774	-2,868	-2,154	-2,196	-2,318	-3,219	-3,213	-2,760	-2,757	-2,623
Max VaR	-1,186	-1,280	-1,103	-1,344	-1,407	-1,449	-1,443	-1,521	-1,519	-1,563
Violations	254	236	266	254	238	190	191	192	192	196
LRUC	37,24	23,45	47,98	37,24	24,84	2,17	2,40	2,64	2,64	3,71
LRIND	10,42	11,02	14,17	16,54	15,20	16,66	16,31	15,96	15,96	14,62
LRCC	47,66	34,47	62,15	53,78	40,04	18,83	18,71	18,60	18,60	18,33
LRUC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	**0,14056**	**0,12125**	**0,10411**	**0,10411**	**0,05400**
LRIND p-value	0,00125	0,00090	0,00017	0,00005	0,00010	0,00004	0,00005	0,00006	0,00006	0,00013
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00008	0,00009	0,00009	0,00009	0,00010

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.4 - PANEL A: *TIN CASH VaR_99%*

Value-at-Risk 99% TIN CASH , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 34									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-2,901	-2,934	-3,761	-3,833	-2,894	-3,778	-3,584	-2,866	-3,803
StDev(VaR)	1,141	1,156	1,626	1,724	1,252	1,692	1,150	1,060	1,573
Min VaR	-16,413	-13,519	-20,814	-19,446	-9,188	-7,987	-5,660	-11,780	-17,088
Max VaR	-1,049	-1,117	-1,672	-1,654	-0,847	-1,228	-1,513	-1,056	-1,378
Violations	62	60	34	32	77	51	47	70	39
LRUC	18,43	16,08	0,00	0,14	39,98	7,26	4,35	29,10	0,66
LRIND	2,25	2,52	3,95	1,04	6,86	7,23	8,38	1,37	0,53
LRCC	20,68	18,60	3,95	1,18	46,84	14,49	12,72	30,47	1,18
LRUC p-value	0,00002	0,00006	**0,97529**	**0,70483**	0,00000	0,00704	0,03705	0,00000	**0,41773**
LRIND p-value	**0,13327**	**0,11255**	0,04679	**0,30755**	0,00882	0,00718	0,00380	**0,24170**	**0,46850**
LRCC p-value	0,00003	0,00009	**0,13848**	**0,55303**	0,00000	0,00071	0,00173	0,00000	**0,55371**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-3,288	-3,382	-3,103	-3,170	-3,262	-3,524	-3,512	-3,428	-3,409	-3,416
StDev(VaR)	0,848	0,875	0,651	0,615	0,625	0,919	0,917	0,675	0,668	0,680
Min VaR	-5,008	-5,117	-4,965	-4,809	-4,868	-5,181	-5,117	-4,963	-4,936	-4,924
Max VaR	-1,690	-1,750	-1,990	-2,109	-2,111	-1,959	-1,962	-2,344	-2,344	-2,376
Violations	61	58	75	73	63	52	53	58	59	56
LRUC	17,24	13,87	36,73	33,59	19,65	8,09	8,96	13,87	14,96	11,80
LRIND	19,76	26,19	21,38	18,30	18,79	24,75	24,14	21,31	20,78	17,69
LRCC	37,00	40,06	58,11	51,89	38,44	32,84	33,10	35,18	35,74	29,49
LRUC p-value	0,00003	0,00020	0,00000	0,00000	0,00001	0,00444	0,00276	0,00020	0,00011	0,00059
LRIND p-value	0,00001	0,00000	0,00000	0,00002	0,00001	0,00000	0,00000	0,00000	0,00001	0,00003
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.4 - PANEL B: *TIN CASH VaR_95%*

Value-at-Risk 95% TIN CASH , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 171										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,051	-2,074	-2,052	-2,073	-2,046	-2,032	-2,007	-2,027		-2,053
StDev(VaR)	0,807	0,817	0,855	0,890	0,885	0,741	0,590	0,749		0,802
Min VaR	-11,605	-9,558	-10,788	-10,079	-6,496	-4,183	-3,609	-8,329		-8,856
Max VaR	-0,742	-0,790	-0,872	-0,941	-0,599	-0,690	-0,792	-0,747		-0,784
Violations	167	145	168	152	170	192	198	161		153
LRUC	0,09	4,35	0,05	2,28	0,00	2,64	4,31	0,62		2,04
LRIND	1,77	2,24	2,61	5,08	11,12	20,20	17,91	1,51		6,45
LRCC	1,86	6,59	2,66	7,36	11,13	22,84	22,22	2,12		8,49
LRUC p-value	**0,75870**	0,03710	**0,81948**	**0,13092**	**0,94364**	**0,10411**	0,03781	**0,43289**		**0,15296**
LRIND p-value	**0,18358**	**0,13438**	**0,10644**	0,02421	0,00085	0,00001	0,00002	**0,21973**		0,01113
LRCC p-value	**0,39400**	0,03712	**0,26470**	0,02521	0,00384	0,00001	0,00001	**0,34625**		0,01435

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,755	-1,786	-1,592	-1,643	-1,692	-1,965	-1,964	-1,875	-1,876	-1,870
StDev(VaR)	0,432	0,453	0,363	0,308	0,319	0,482	0,482	0,342	0,342	0,338
Min VaR	-2,788	-2,856	-2,754	-2,489	-2,609	-2,948	-2,954	-2,745	-2,744	-2,737
Max VaR	-0,891	-0,973	-1,058	-1,136	-1,175	-1,102	-1,099	-1,350	-1,350	-1,332
Violations	248	233	304	280	262	191	193	206	206	210
LRUC	32,33	21,44	89,51	61,99	44,27	2,40	2,89	7,14	7,14	8,80
LRIND	15,24	18,74	16,59	18,90	15,46	18,40	19,81	7,00	7,00	7,48
LRCC	47,57	40,18	106,10	80,89	59,73	20,81	22,70	14,14	14,14	16,29
LRUC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	**0,12125**	**0,08897**	0,00753	0,00753	0,00300
LRIND p-value	0,00009	0,00001	0,00005	0,00001	0,00008	0,00002	0,00001	0,00816	0,00816	0,00623
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00003	0,00001	0,00085	0,00085	0,00029

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.5 - PANEL A: *TIN -3 MONTH VaR_99%*

Value-at-Risk 99% TIN 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 34									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-2,680	-2,704	-3,491	-3,585	-2,691	-3,484	-3,322	-2,644	-3,581
StDev(VaR)	1,088	1,067	1,558	1,569	1,196	1,580	1,056	0,961	1,479
Min VaR	-18,503	-14,289	-20,215	-19,733	-9,201	-8,061	-5,406	-10,938	-16,829
Max VaR	-1,006	-1,337	-1,411	-1,730	-0,753	-0,978	-1,406	-1,219	-1,570
Violations	64	69	39	34	72	47	45	68	32
LRUC	20,91	27,66	0,66	0,00	32,07	4,35	3,15	26,25	0,14
LRIND	2,01	1,47	3,03	0,87	8,13	12,60	9,00	3,59	1,04
LRCC	22,92	29,13	3,69	0,87	40,19	16,95	12,15	29,84	1,18
LRUC p-value	0,00000	0,00000	**0,41773**	**0,97529**	0,00000	0,03705	**0,07609**	0,00000	**0,70483**
LRIND p-value	**0,15647**	**0,22583**	**0,08178**	**0,35070**	0,00437	0,00039	0,00269	**0,05800**	**0,30755**
LRCC p-value	0,00001	0,00000	**0,15835**	**0,64666**	0,00000	0,00021	0,00230	0,00000	**0,55303**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-3,006	-3,123	-2,836	-2,889	-2,996	-3,250	-3,244	-3,131	-3,139	-3,148
StDev(VaR)	0,822	0,854	0,648	0,612	0,634	0,904	0,899	0,659	0,672	0,680
Min VaR	-4,814	-4,971	-4,796	-4,613	-4,692	-5,049	-5,088	-4,826	-4,820	-4,751
Max VaR	-1,609	-1,649	-1,914	-1,999	-1,984	-1,789	-1,813	-2,246	-2,230	-2,251
Violations	59	58	73	70	61	50	51	54	54	55
LRUC	14,96	13,87	33,59	29,10	17,24	6,47	7,26	9,87	9,87	10,81
LRIND	16,31	16,76	22,39	23,97	24,41	20,76	20,22	23,55	23,55	22,97
LRCC	31,27	30,63	55,98	53,07	41,65	27,24	27,48	33,42	33,42	33,78
LRUC p-value	0,00011	0,00020	0,00000	0,00000	0,00003	0,01096	0,00704	0,00168	0,00168	0,00101
LRIND p-value	0,00005	0,00004	0,00000	0,00000	0,00000	0,00001	0,00001	0,00000	0,00000	0,00000
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.5 - PANEL B: *TIN -3 MONTH VaR_95%*

Value-at-Risk 95% TIN 3MO , significance level of the LR tests: 5%
Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 171

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-1,895	-1,912	-1,891	-1,919	-1,903	-1,877	-1,850	-1,869		-1,910
StDev(VaR)	0,769	0,755	0,805	0,814	0,846	0,693	0,573	0,680		0,752
Min VaR	-13,083	-10,103	-10,477	-10,227	-6,505	-4,061	-3,564	-7,734		-8,722
Max VaR	-0,711	-0,946	-0,731	-0,900	-0,532	-0,556	-0,665	-0,862		-0,826
Violations	162	156	164	158	171	198	192	172		158
LRUC	0,50	1,41	0,30	1,05	0,00	4,31	2,64	0,01		1,05
LRIND	9,56	7,46	10,90	8,75	14,83	15,89	18,03	5,66		5,44
LRCC	10,05	8,87	11,20	9,80	14,83	20,20	20,67	5,67		6,50
LRUC p-value	**0,48121**	**0,23558**	**0,58573**	**0,30542**	**0,99374**	0,03781	0,10411	**0,93127**		**0,30542**
LRIND p-value	0,00199	0,00630	0,00096	0,00310	0,00012	0,00007	0,00002	0,01736		0,01963
LRCC p-value	0,00656	0,01185	0,00370	0,00745	0,00060	0,00004	0,00003	**0,05880**		0,03887

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,605	-1,660	-1,434	-1,500	-1,568	-1,816	-1,816	-1,721	-1,722	-1,718
StDev(VaR)	0,415	0,447	0,342	0,295	0,317	0,468	0,468	0,327	0,329	0,333
Min VaR	-2,610	-2,721	-2,682	-2,390	-2,485	-2,794	-2,801	-2,636	-2,629	-2,615
Max VaR	-0,833	-0,884	-0,949	-1,054	-1,055	-0,994	-0,997	-1,241	-1,236	-1,226
Violations	246	233	301	277	248	192	191	204	204	205
LRUC	30,76	21,44	85,83	58,85	32,33	2,64	2,40	6,37	6,37	6,75
LRIND	21,31	18,74	22,48	20,04	18,69	24,84	25,29	15,78	15,78	15,44
LRCC	52,08	40,18	108,32	78,89	51,02	27,48	27,69	22,15	22,15	22,19
LRUC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	**0,10411**	**0,12125**	0,01160	0,01160	0,00937
LRIND p-value	0,00000	0,00001	0,00000	0,00001	0,00002	0,00000	0,00000	0,00007	0,00007	0,00009
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00002	0,00002	0,00002

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.6 - PANEL A: *ZINC CASH VaR_99%*

Value-at-Risk 99% ZINC CASH , significance level of the LR tests: 5%
Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 34

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-3,237	-3,291	-4,011	-4,096	-3,212	-4,067	-4,014	-3,274		-4,070
StDev(VaR)	1,173	1,109	1,509	1,386	1,372	2,083	1,501	1,047		1,231
Min VaR	-15,273	-12,203	-17,111	-15,054	-10,258	-12,069	-7,543	-10,558		-10,858
Max VaR	-1,457	-1,435	-1,713	-1,631	-1,345	-1,591	-1,646	-1,363		-1,788
Violations	64	58	33	32	62	46	41	57		37
LRUC	20,91	13,87	0,04	0,14	18,43	3,73	1,29	12,82		0,23
LRIND	2,01	2,80	0,64	0,60	4,68	2,01	0,42	5,74		0,65
LRCC	22,92	16,67	0,69	0,75	23,11	5,74	1,71	18,55		0,88
LRUC p-value	0,00000	0,00020	**0,83833**	**0,70483**	0,00002	**0,05359**	**0,25566**	0,00034		**0,63237**
LRIND p-value	**0,15647**	**0,09420**	**0,42247**	**0,43673**	0,03054	**0,15582**	**0,51902**	0,01660		**0,41981**
LRCC p-value	0,00001	0,00024	**0,70997**	**0,68786**	0,00001	**0,05671**	**0,42572**	0,00009		**0,64413**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-3,516	-3,638	-3,494	-3,541	-3,654	-3,760	-3,768	-3,810	-3,812	-3,830
StDev(VaR)	0,737	0,863	0,522	0,529	0,579	0,937	0,954	0,674	0,680	0,699
Min VaR	-5,459	-6,372	-5,513	-5,306	-5,490	-6,486	-6,608	-5,728	-5,712	-6,032
Max VaR	-2,237	-2,342	-2,590	-2,644	-2,665	-2,356	-2,344	-2,704	-2,699	-2,778
Violations	55	48	62	60	54	44	45	47	46	47
LRUC	10,81	5,01	18,43	16,08	9,87	2,61	3,15	4,35	3,73	4,35
LRIND	14,57	4,54	7,68	16,44	14,86	2,28	2,14	4,75	2,01	4,75
LRCC	25,39	9,55	26,11	32,52	24,73	4,89	5,29	9,10	5,74	9,10
LRUC p-value	0,00101	0,02514	0,00002	0,00006	0,00168	**0,10600**	**0,07609**	0,03705	**0,05359**	0,03705
LRIND p-value	0,00013	0,03310	0,00559	0,00005	0,00012	**0,13144**	**0,14329**	0,02933	**0,15582**	0,02933
LRCC p-value	0,00000	0,00842	0,00000	0,00000	0,00000	**0,08680**	**0,07105**	0,01059	**0,05671**	0,01059

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.6 - PANEL B: *ZINC CASH VaR_95%*

Value-at-Risk 95% ZINC CASH , significance level of the LR tests: 5%
Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 171

Method:	Normal GARCH(1,1)		t-Student GARCH(1,1)		EWMA	Historical Simulation		Normal EGARCH(1,1)	t-Student EGARCH(1,1)
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-2,289	-2,327	-2,272	-2,278	-2,271	-2,142	-2,094	-2,315	-2,267
StDev(VaR)	0,829	0,784	0,834	0,798	0,970	0,918	0,708	0,740	0,716
Min VaR	-10,799	-8,628	-8,868	-7,802	-7,253	-5,783	-5,061	-7,465	-6,502
Max VaR	-1,030	-1,015	-1,083	-0,977	-0,951	-1,159	-1,258	-0,964	-1,071
Violations	150	138	152	141	164	180	182	144	146
LRUC	2,80	7,12	2,28	5,84	0,30	0,50	0,74	4,70	4,01
LRIND	8,98	8,36	11,31	9,10	7,26	12,83	13,90	11,38	10,99
LRCC	11,78	15,47	13,60	14,94	7,56	13,33	14,64	16,08	15,00
LRUC p-value	**0,09419**	0,00764	**0,13092**	0,01566	**0,58573**	**0,47875**	**0,38844**	0,03020	0,04527
LRIND p-value	0,00273	0,00384	0,00077	0,00255	0,00704	0,00034	0,00019	0,00074	0,00092
LRCC p-value	0,00277	0,00044	0,00112	0,00057	0,02284	0,00127	0,00066	0,00032	0,00055

Method:	Block Maxima (GEV distribution)					Peaks Over Threshold (GP distribution)				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,856	-1,948	-1,792	-1,826	-1,915	-2,043	-2,047	-2,013	-2,014	-2,001
StDev(VaR)	0,260	0,343	0,200	0,179	0,213	0,445	0,447	0,277	0,278	0,258
Min VaR	-2,909	-3,400	-2,565	-2,621	-2,781	-3,894	-3,893	-3,161	-3,149	-2,956
Max VaR	-1,403	-1,397	-1,453	-1,527	-1,602	-1,410	-1,406	-1,652	-1,653	-1,637
Violations	245	213	259	250	230	192	191	199	200	204
LRUC	29,99	10,16	41,57	33,93	19,50	2,64	2,40	4,63	4,96	6,37
LRIND	19,86	22,10	17,00	16,75	16,58	19,81	20,14	19,38	19,06	21,47
LRCC	49,86	32,26	58,57	50,68	36,08	22,45	22,54	24,01	24,02	27,84
LRUC p-value	0,00000	0,00144	0,00000	0,00000	0,00001	**0,10411**	**0,12125**	0,03142	0,02598	0,01160
LRIND p-value	0,00001	0,00000	0,00004	0,00004	0,00005	0,00001	0,00001	0,00001	0,00001	0,00000
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00001	0,00001	0,00001	0,00001	0,00000

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.7 - PANEL A: *ZINC 3- MONTH VaR_99%*

Value-at-Risk 99% ZINC 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 34									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-2,960	-2,977	-3,617	-3,626	-2,931	-3,701	-3,552	-2,970	-3,639
StDev(VaR)	1,133	1,080	1,362	1,266	1,283	1,776	1,292	0,965	1,091
Min VaR	-18,830	-13,859	-14,483	-11,570	-10,026	-8,806	-7,100	-8,625	-10,640
Max VaR	-1,055	-1,313	-1,443	-1,573	-1,128	-1,224	-1,328	-1,340	-1,770
Violations	62	63	38	36	65	43	39	59	39
LRUC	18,43	19,65	0,42	0,10	22,20	2,13	0,66	14,96	0,66
LRIND	0,58	4,48	0,85	0,77	6,90	0,32	0,53	2,66	0,53
LRCC	19,01	24,14	1,27	0,86	29,10	2,45	1,18	17,62	1,18
LRUC p-value	0,00002	0,00001	**0,51885**	**0,75642**	0,00000	**0,14490**	**0,41773**	0,00011	**0,41773**
LRIND p-value	**0,44727**	0,03421	**0,35529**	**0,38133**	0,00860	**0,57115**	**0,46850**	**0,10308**	**0,46850**
LRCC p-value	0,00007	0,00001	**0,52977**	**0,64965**	0,00000	**0,29436**	**0,55371**	0,00015	**0,55371**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-3,217	-3,277	-3,142	-3,110	-3,185	-3,317	-3,316	-3,257	-3,247	-3,269
StDev(VaR)	0,823	0,851	0,477	0,462	0,490	0,922	0,933	0,568	0,572	0,615
Min VaR	-6,031	-6,148	-5,302	-5,097	-5,259	-6,314	-6,456	-5,559	-5,542	-5,899
Max VaR	-1,758	-1,923	-2,282	-2,341	-2,463	-2,029	-1,974	-2,503	-2,538	-2,581
Violations	56	50	63	64	61	42	42	51	54	54
LRUC	11,80	6,47	19,65	20,91	17,24	1,68	1,68	7,26	9,87	9,87
LRIND	1,00	0,09	7,41	10,49	7,95	0,37	0,37	3,96	6,45	6,45
LRCC	12,79	6,56	27,07	31,40	25,19	2,05	2,05	11,22	16,32	16,32
LRUC p-value	0,00059	0,01096	0,00001	0,00000	0,00003	**0,19433**	**0,19433**	0,00704	0,00168	0,00168
LRIND p-value	**0,31848**	**0,76249**	0,00647	0,00120	0,00481	**0,54490**	**0,54490**	0,04669	0,01109	0,01109
LRCC p-value	0,00167	0,03756	0,00000	0,00000	0,00000	**0,35861**	**0,35861**	0,00366	0,00029	0,00029

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.7 - PANEL B: *ZINC 3- MONTH VaR_95%*

Value-at-Risk 95% ZINC 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3418 backtesting trials, Expected Violations = 171										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,093	-2,105	-2,064	-2,068	-2,072	-1,939	-1,902	-2,100		-2,058
StDev(VaR)	0,801	0,764	0,791	0,774	0,907	0,881	0,708	0,682		0,682
Min VaR	-13,314	-9,799	-8,240	-6,928	-7,089	-5,628	-4,978	-6,098		-6,372
Max VaR	-0,746	-0,928	-0,864	-0,942	-0,798	-0,854	-1,025	-0,947		-1,007
Violations	145	143	154	139	154	177	179	141		149
LRUC	4,35	5,06	1,82	6,68	1,82	0,23	0,40	5,84		3,08
LRIND	14,62	19,41	16,03	18,43	14,16	15,19	7,15	20,08		13,61
LRCC	18,96	24,47	17,84	25,11	15,98	15,41	7,55	25,92		16,70
LRUC p-value	0,03710	0,02443	**0,17767**	0,00977	**0,17767**	**0,63402**	**0,52802**	0,01566		**0,07917**
LRIND p-value	0,00013	0,00001	0,00006	0,00002	0,00017	0,00010	0,00749	0,00001		0,00022
LRCC p-value	0,00008	0,00000	0,00013	0,00000	0,00034	0,00045	0,02294	0,00000		0,00024

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,693	-1,766	-1,558	-1,609	-1,698	-1,860	-1,861	-1,794	-1,793	-1,778
StDev(VaR)	0,353	0,368	0,218	0,194	0,212	0,464	0,464	0,252	0,254	0,228
Min VaR	-3,210	-3,265	-2,345	-2,464	-2,626	-3,760	-3,752	-3,009	-3,007	-2,744
Max VaR	-1,055	-1,148	-1,209	-1,270	-1,360	-1,201	-1,193	-1,470	-1,477	-1,481
Violations	248	228	284	274	240	201	200	215	215	220
LRUC	32,33	18,26	66,27	55,79	26,27	5,29	4,96	11,11	11,11	13,67
LRIND	23,97	24,18	12,87	11,85	13,88	24,61	25,01	21,39	21,39	19,68
LRCC	56,30	42,44	79,14	67,64	40,15	29,91	29,96	32,50	32,50	33,35
LRUC p-value	0,00000	0,00002	0,00000	0,00000	0,00000	0,02139	0,02598	0,00086	0,00086	0,00022
LRIND p-value	0,00000	0,00000	0,00033	0,00058	0,00020	0,00000	0,00000	0,00000	0,00000	0,00001
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.8 - PANEL A: *NICKEL CASH VaR_99%*

Value-at-Risk 99% NICKEL CASH , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3421 backtesting trials, Expected Violations = 34										
Method:	Normal GARCH(1,1)		t-Student GARCH(1,1)		EWMA	Historical Simulation		Normal EGARCH(1,1)	t-Student EGARCH(1,1)	
Window Length:	500	1000	500	1000	100	100	252	1000		1000
E(VaR)	-4,648	-4,606	-5,523	-5,525	-4,684	-5,727	-5,350	-4,606		-5,558
StDev(VaR)	1,382	1,340	1,574	1,540	1,547	2,475	1,398	1,150		1,410
Min VaR	-15,639	-15,757	-18,635	-17,179	-12,924	-13,410	-8,458	-10,909		-13,725
Max VaR	-2,263	-2,314	-2,642	-2,791	-2,112	-2,415	-3,065	-2,161		-2,576
Violations	58	61	33	32	60	47	42	65		32
LRUC	13,83	17,19	0,04	0,15	16,04	4,33	1,67	22,14		0,15
LRIND	0,00	2,22	0,64	0,60	2,52	1,89	0,37	14,34		1,04
LRCC	13,83	19,41	0,69	0,75	18,56	6,22	2,04	36,49		1,19
LRUC p-value	0,00020	0,00003	**0,83433**	**0,70104**	0,00006	0,03754	**0,19617**	0,00000		**0,70104**
LRIND p-value	**0,98640**	**0,13667**	**0,42267**	**0,43694**	**0,11230**	**0,16874**	**0,54442**	0,00015		**0,30726**
LRCC p-value	0,00099	0,00006	**0,70942**	**0,68670**	0,00009	0,04461	**0,36094**	0,00000		**0,55161**

Method:	Block Maxima (GEV distribution)					Peaks Over Threshold (GP distribution)				
Window Length:	25bl.-500	50bl.-500	25bl.-1000	50bl.-1000	100bl.-1000	10%thr.-500	8%thr.-500	10%thr.-1000	8%thr.-1000	5%thr.-1000
E(VaR)	-5,086	-5,166	-4,753	-4,947	-5,033	-5,352	-5,367	-5,262	-5,249	-5,204
StDev(VaR)	1,135	1,134	0,840	0,795	0,766	1,172	1,174	0,739	0,730	0,686
Min VaR	-7,968	-7,788	-6,620	-6,916	-6,820	-7,726	-7,824	-6,976	-6,905	-6,927
Max VaR	-3,242	-3,213	-3,067	-3,482	-3,520	-3,292	-3,295	-3,627	-3,587	-3,696
Violations	52	48	63	56	53	43	44	47	47	49
LRUC	8,06	4,99	19,60	11,76	8,93	2,11	2,60	4,33	4,33	5,70
LRIND	1,35	1,78	2,13	3,11	3,60	2,42	2,28	1,89	1,89	1,66
LRCC	9,41	6,77	21,74	14,87	12,53	4,53	4,87	6,22	6,22	7,36
LRUC p-value	0,00452	0,02550	0,00001	0,00061	0,00281	**0,14639**	**0,10717**	0,03754	0,03754	0,01700
LRIND p-value	**0,24488**	**0,18260**	**0,14424**	**0,07791**	**0,05769**	**0,12004**	**0,13122**	**0,16874**	**0,16874**	**0,19715**
LRCC p-value	0,00903	0,03394	0,00002	0,00059	0,00190	**0,10402**	**0,08745**	0,04461	0,04461	0,02523

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.8 - PANEL B: *NICKEL CASH VaR_95%*

Value-at-Risk 95% NICKEL CASH , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3421 backtesting trials, Expected Violations = 171									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-3,286	-3,257	-3,240	-3,225	-3,312	-3,140	-3,053	-3,257	-3,234
StDev(VaR)	0,977	0,948	0,902	0,909	1,094	1,008	0,632	0,813	0,847
Min VaR	-11,058	-11,141	-10,585	-9,774	-9,138	-6,663	-5,306	-7,713	-7,809
Max VaR	-1,600	-1,636	-1,369	-1,588	-1,493	-1,757	-1,957	-1,528	-1,466
Violations	164	167	166	171	169	184	185	160	166
LRUC	0,31	0,10	0,16	0,00	0,03	1,01	1,17	0,77	0,16
LRIND	0,53	0,69	0,63	0,33	0,02	0,47	2,46	0,04	0,63
LRCC	0,84	0,79	0,79	0,33	0,04	1,48	3,62	0,80	0,79
LRUC p-value	**0,57772**	**0,74979**	**0,69061**	**0,99687**	**0,87200**	**0,31532**	**0,27983**	**0,38107**	**0,69061**
LRIND p-value	**0,46830**	**0,40764**	**0,42729**	**0,56627**	**0,89833**	**0,49258**	**0,11710**	**0,85154**	**0,42729**
LRCC p-value	**0,65839**	**0,67457**	**0,67415**	**0,84833**	**0,97908**	**0,47732**	**0,16336**	**0,66955**	**0,67415**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-2,844	-2,874	-2,752	-2,744	-2,804	-3,000	-3,002	-2,929	-2,929	-2,951
StDev(VaR)	0,408	0,400	0,395	0,336	0,342	0,444	0,440	0,356	0,355	0,383
Min VaR	-3,952	-3,891	-3,635	-3,518	-3,734	-3,840	-3,847	-3,711	-3,698	-3,645
Max VaR	-1,972	-1,877	-1,906	-2,047	-2,100	-2,069	-2,083	-2,254	-2,255	-2,205
Violations	223	222	231	227	214	199	197	197	199	197
LRUC	15,22	14,66	20,03	17,55	10,55	4,58	3,96	3,96	4,58	3,96
LRIND	2,13	1,54	1,33	3,27	1,65	1,73	1,94	2,80	3,50	2,80
LRCC	17,36	16,21	21,35	20,82	12,20	6,30	5,89	6,76	8,08	6,76
LRUC p-value	0,00010	0,00013	0,00001	0,00003	0,00116	0,03239	0,04661	0,04661	0,03239	0,04661
LRIND p-value	**0,14399**	**0,21434**	**0,24930**	**0,07060**	**0,19838**	**0,18892**	**0,16420**	**0,09426**	**0,06126**	**0,09426**
LRCC p-value	0,00017	0,00030	0,00002	0,00003	0,00224	0,04277	**0,05248**	0,03406	0,01759	0,03406

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.9 - PANEL A: *NICKEL 3- MONTH VaR_99%*

Value-at-Risk 99% NICKEL 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3421 backtesting trials, Expected Violations = 34									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-4,377	-4,333	-5,199	-5,119	-4,417	-5,414	-5,045	-4,338	-5,138
StDev(VaR)	1,283	1,230	1,459	1,355	1,432	2,315	1,351	1,090	1,290
Min VaR	-14,866	-13,224	-16,658	-13,670	-12,665	-13,266	-8,419	-12,127	-12,848
Max VaR	-2,342	-2,183	-2,749	-2,599	-2,001	-2,391	-2,943	-2,160	-2,506
Violations	60	65	37	36	56	47	43	65	36
LRUC	16,04	22,14	0,22	0,09	11,76	4,33	2,11	22,14	0,09
LRIND	2,52	0,05	0,81	0,72	3,11	4,75	0,32	1,89	7,57
LRCC	18,56	22,19	1,03	0,81	14,87	9,08	2,43	24,04	7,66
LRUC p-value	0,00006	0,00000	**0,63609**	**0,76038**	0,00061	0,03754	**0,14639**	0,00000	**0,76038**
LRIND p-value	**0,11230**	**0,82374**	**0,36838**	**0,39586**	**0,07791**	0,02926	**0,57065**	**0,16867**	0,00593
LRCC p-value	0,00009	0,00002	**0,59660**	**0,66568**	0,00059	0,01068	**0,29655**	0,00001	0,02167

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-4,844	-4,918	-4,507	-4,671	-4,744	-5,030	-5,047	-4,880	-4,896	-4,894
StDev(VaR)	1,124	1,124	0,782	0,816	0,801	1,161	1,170	0,809	0,802	0,757
Min VaR	-7,831	-7,601	-6,438	-6,653	-6,555	-7,481	-7,516	-6,660	-6,603	-6,593
Max VaR	-3,135	-3,139	-3,065	-3,294	-3,299	-3,212	-3,204	-3,352	-3,297	-3,365
Violations	50	48	56	50	49	46	46	45	45	45
LRUC	6,44	4,99	11,76	6,44	5,70	3,70	3,70	3,13	3,13	3,13
LRIND	1,56	1,78	3,11	1,56	1,66	2,02	2,02	2,14	2,14	2,14
LRCC	8,00	6,77	14,87	8,00	7,36	5,72	5,72	5,27	5,27	5,27
LRUC p-value	0,01113	0,02550	0,00061	0,01113	0,01700	**0,05427**	**0,05427**	**0,07699**	**0,07699**	**0,07699**
LRIND p-value	**0,21237**	**0,18260**	**0,07791**	**0,21237**	**0,19715**	**0,15556**	**0,15556**	**0,14306**	**0,14306**	**0,14306**
LRCC p-value	0,01832	0,03394	0,00059	0,01832	0,02523	**0,05723**	**0,05723**	**0,07164**	**0,07164**	**0,07164**

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.9 - PANEL B: *NICKEL 3- MONTH VaR_95%*

Value-at-Risk 95% NICKEL 3MO , significance level of the LR tests: 5% Backtesting Period: 8 July 1993- 2 March 2007, N = 3421 backtesting trials, Expected Violations = 171									
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-3,094	-3,064	-3,058	-3,017	-3,123	-2,940	-2,827	-3,067	-3,024
StDev(VaR)	0,907	0,870	0,820	0,799	1,012	0,965	0,636	0,771	0,758
Min VaR	-10,511	-9,350	-8,634	-7,777	-8,954	-6,347	-5,034	-8,574	-7,310
Max VaR	-1,656	-1,543	-1,425	-1,556	-1,415	-1,523	-1,734	-1,527	-1,426
Violations	166	161	167	163	167	184	189	156	163
LRUC	0,16	0,63	0,10	0,40	0,10	1,01	1,92	1,43	0,40
LRIND	0,00	0,39	0,00	0,48	0,09	2,58	1,24	0,20	0,48
LRCC	0,16	1,02	0,10	0,88	0,20	3,59	3,16	1,64	0,88
LRUC p-value	**0,69061**	**0,42609**	**0,74979**	**0,52459**	**0,74979**	**0,31532**	**0,16582**	**0,23105**	**0,52459**
LRIND p-value	**0,98375**	**0,53397**	**0,95515**	**0,48964**	**0,75849**	**0,10824**	**0,26522**	**0,65370**	**0,48964**
LRCC p-value	**0,92365**	**0,60041**	**0,94892**	**0,64334**	**0,90654**	**0,16630**	**0,20580**	**0,44138**	**0,64334**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-2,653	-2,694	-2,521	-2,554	-2,619	-2,781	-2,781	-2,710	-2,711	-2,717
StDev(VaR)	0,429	0,429	0,398	0,356	0,366	0,473	0,472	0,390	0,389	0,405
Min VaR	-3,820	-3,773	-3,421	-3,377	-3,558	-3,729	-3,725	-3,562	-3,556	-3,512
Max VaR	-1,873	-1,768	-1,868	-1,943	-1,990	-1,991	-1,991	-2,149	-2,135	-2,156
Violations	220	211	229	224	208	197	195	195	196	194
LRUC	13,58	9,17	18,77	15,79	7,88	3,96	3,38	3,38	3,67	3,11
LRIND	5,45	7,28	2,19	7,07	4,21	6,21	5,31	4,12	3,96	3,21
LRCC	19,02	16,45	20,96	22,86	12,09	10,17	8,69	7,51	7,63	6,32
LRUC p-value	0,00023	0,00246	0,00001	0,00007	0,00499	0,04661	**0,06583**	**0,06583**	**0,05552**	**0,07769**
LRIND p-value	0,01960	0,00697	**0,13864**	0,00784	0,04029	0,01268	0,02121	0,04232	0,04653	**0,07325**
LRCC p-value	0,00007	0,00027	0,00003	0,00001	0,00237	0,00618	0,01295	0,02345	0,02205	0,04240

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.10 - PANEL A: *ALUMINIUM CASH VaR_99%*

Value-at-Risk 99% ALUMINIUM CASH , significance level of the LR tests: 5% Backtesting Period: 26 July 1993- 2 March 2007, N = 3402 backtesting trials, Expected Violations = 34										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,772	-2,813	-3,119	-3,174	-2,748	-3,381	-3,236	-2,797		-3,184
StDev(VaR)	0,779	0,779	0,879	0,858	0,925	1,434	1,134	0,672		0,823
Min VaR	-7,120	-6,794	-7,926	-7,804	-6,965	-7,315	-6,358	-6,894		-8,302
Max VaR	-1,557	-1,821	-1,807	-2,003	-1,359	-1,376	-1,686	-1,653		-1,769
Violations	51	47	32	34	52	43	47	46		34
LRUC	7,42	4,47	0,12	0,00	8,26	2,21	4,47	3,84		0,00
LRIND	9,91	9,85	9,93	9,89	9,93	9,08	9,85	9,84		9,89
LRCC	17,34	14,32	10,06	9,89	18,20	11,29	14,32	13,67		9,89
LRUC p-value	0,00644	0,03448	**0,72516**	**0,99725**	0,00405	**0,13715**	0,03448	**0,05009**		**0,99725**
LRIND p-value	0,00164	0,00170	0,00162	0,00166	0,00162	0,00259	0,00170	0,00171		0,00166
LRCC p-value	0,00017	0,00078	0,00655	0,00713	0,00011	0,00354	0,00078	0,00107		0,00713

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-2,963	-3,039	-2,825	-2,941	-3,034	-3,080	-3,081	-3,133	-3,141	-3,143
StDev(VaR)	0,644	0,670	0,390	0,392	0,411	0,714	0,720	0,492	0,486	0,546
Min VaR	-4,610	-4,799	-4,170	-4,084	-4,236	-4,859	-4,937	-4,284	-4,297	-4,430
Max VaR	-1,979	-1,994	-2,170	-2,253	-2,331	-2,023	-2,011	-2,413	-2,432	-2,363
Violations	50	46	53	49	43	44	44	41	41	41
LRUC	6,62	3,84	9,14	5,86	2,21	2,71	2,71	1,36	1,36	1,36
LRIND	9,89	9,84	8,35	9,88	9,82	9,82	9,82	9,81	9,81	9,81
LRCC	16,52	13,67	17,50	15,74	12,02	12,53	12,53	11,17	11,17	11,17
LRUC p-value	0,01006	**0,05009**	0,00250	0,01545	**0,13715**	**0,09992**	**0,09992**	**0,24395**	**0,24395**	**0,24395**
LRIND p-value	0,00166	0,00171	0,00385	0,00168	0,00173	0,00173	0,00173	0,00173	0,00173	0,00173
LRCC p-value	0,00026	0,00107	0,00016	0,00038	0,00245	0,00190	0,00190	0,00375	0,00375	0,00375

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.10 - PANEL B: *ALUMINIUM CASH VaR_95%*

Value-at-Risk 95% ALUMINIUM CASH , significance level of the LR tests: 5% Backtesting Period: 26 July 1993- 2 March 2007, N = 3402 backtesting trials, Expected Violations = 170										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-1,960	-1,989	-1,914	-1,920	-1,943	-1,849	-1,809	-1,977		-1,920
StDev(VaR)	0,551	0,551	0,513	0,493	0,654	0,633	0,470	0,475		0,442
Min VaR	-5,034	-4,803	-4,721	-4,518	-4,925	-4,481	-3,674	-4,875		-4,606
Max VaR	-1,101	-1,287	-1,174	-1,140	-0,961	-0,938	-1,118	-1,169		-1,007
Violations	148	136	153	152	155	192	185	141		156
LRUC	3,16	7,70	1,87	2,10	1,45	2,85	1,34	5,55		1,26
LRIND	6,55	6,79	6,71	6,67	6,79	5,70	6,14	6,97		6,28
LRCC	9,70	14,50	8,58	8,77	8,24	8,56	7,48	12,52		7,54
LRUC p-value	**0,07569**	0,00551	**0,17147**	**0,14736**	**0,22814**	**0,09112**	**0,24748**	0,01848		**0,26091**
LRIND p-value	0,01052	0,00915	0,00959	0,00979	0,00916	0,01693	0,01323	0,00830		0,01223
LRCC p-value	0,00783	0,00071	0,01371	0,01245	0,01621	0,01386	0,02381	0,00191		0,02305

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,653	-1,718	-1,583	-1,627	-1,708	-1,750	-1,752	-1,754	-1,755	-1,752
StDev(VaR)	0,230	0,237	0,166	0,124	0,124	0,299	0,302	0,168	0,169	0,142
Min VaR	-2,632	-2,527	-2,060	-2,033	-2,099	-2,834	-2,826	-2,229	-2,228	-2,255
Max VaR	-1,135	-1,240	-1,260	-1,390	-1,474	-1,270	-1,263	-1,486	-1,487	-1,502
Violations	230	209	251	229	207	200	199	197	196	197
LRUC	20,10	8,76	35,55	19,46	7,90	5,25	4,91	4,27	3,97	4,27
LRIND	5,42	5,51	5,82	5,27	5,50	5,71	5,75	5,60	5,60	5,60
LRCC	25,52	14,27	41,38	24,73	13,40	10,96	10,66	9,87	9,57	9,87
LRUC p-value	0,00001	0,00309	0,00000	0,00001	0,00493	0,02195	0,02666	0,03878	0,04644	0,03878
LRIND p-value	0,01990	0,01888	0,01582	0,02168	0,01904	0,01687	0,01647	0,01800	0,01796	0,01800
LRCC p-value	0,00000	0,00080	0,00000	0,00000	0,00123	0,00417	0,00483	0,00720	0,00837	0,00720

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.11 - PANEL A: *ALUMINIUM 3- MONTH VaR_99%*

Value-at-Risk 99% ALUMINIUM 3MO , significance level of the LR tests: 5% Backtesting Period: 26 July 1993- 2 March 2007, N = 3402 backtesting trials, Expected Violations = 34										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,480	-2,517	-2,734	-2,763	-2,469	-2,947	-2,851	-2,489		-2,766
StDev(VaR)	0,697	0,738	0,798	0,783	0,855	1,242	1,037	0,647		0,730
Min VaR	-6,546	-6,615	-7,411	-7,051	-6,704	-7,252	-6,242	-6,561		-8,088
Max VaR	-1,171	-1,604	-1,594	-1,496	-1,116	-1,386	-1,679	-1,539		-1,562
Violations	58	52	39	36	60	36	41	52		38
LRUC	14,10	8,26	0,70	0,11	16,33	0,11	1,36	8,26		0,45
LRIND	8,13	8,41	9,82	0,77	8,78	0,71	0,41	8,41		0,86
LRCC	22,22	16,67	10,52	0,88	25,11	0,83	1,77	16,67		1,31
LRUC p-value	0,00017	0,00405	**0,40172**	**0,73538**	0,00005	**0,73538**	**0,24395**	0,00405		**0,50084**
LRIND p-value	0,00436	0,00373	0,00172	**0,38020**	0,00304	**0,39818**	**0,52148**	0,00373		**0,35415**
LRCC p-value	0,00001	0,00024	0,00518	**0,64265**	0,00000	**0,66098**	**0,41301**	0,00024		**0,51901**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-2,594	-2,638	-2,479	-2,537	-2,591	-2,669	-2,671	-2,671	-2,660	-2,671
StDev(VaR)	0,582	0,612	0,306	0,314	0,347	0,664	0,670	0,417	0,414	0,438
Min VaR	-4,436	-4,654	-3,945	-3,862	-4,030	-4,728	-4,853	-4,141	-4,153	-4,292
Max VaR	-1,889	-1,880	-2,064	-2,120	-2,147	-1,828	-1,833	-2,209	-2,220	-2,221
Violations	50	46	51	52	48	46	46	46	46	47
LRUC	6,62	3,84	7,42	8,26	5,15	3,84	3,84	3,84	3,84	4,47
LRIND	1,54	2,00	3,94	3,75	4,52	2,00	2,00	4,94	4,94	4,73
LRCC	8,16	5,84	11,36	12,02	9,66	5,84	5,84	8,78	8,78	9,20
LRUC p-value	0,01006	**0,05009**	0,00644	0,00405	0,02330	**0,05009**	**0,05009**	**0,05009**	**0,05009**	0,03448
LRIND p-value	**0,21452**	**0,15719**	0,04729	**0,05270**	0,03354	**0,15719**	**0,15719**	0,02624	0,02624	0,02972
LRCC p-value	0,01687	**0,05395**	0,00342	0,00246	0,00797	**0,05395**	**0,05395**	0,01241	0,01241	0,01007

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.11 - PANEL B: *ALUMINIUM 3- MONTH VaR_95%*

Value-at-Risk 95% ALUMINIUM 3MO , significance level of the LR tests: 5%
Backtesting Period: 26 July 1993- 2 March 2007, N = 3402 backtesting trials, Expected Violations = 170

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-1,754	-1,780	-1,712	-1,711	-1,746	-1,662	-1,634	-1,760	-1,705
StDev(VaR)	0,493	0,522	0,471	0,459	0,604	0,599	0,447	0,457	0,398
Min VaR	-4,629	-4,677	-4,582	-4,264	-4,740	-4,431	-3,509	-4,639	-4,602
Max VaR	-0,828	-1,134	-0,985	-0,925	-0,789	-0,916	-1,067	-1,088	-0,889
Violations	151	142	157	156	166	192	190	145	158
LRUC	2,34	5,16	1,09	1,26	0,10	2,85	2,37	4,10	0,93
LRIND	6,43	7,84	6,53	6,59	7,03	5,79	5,87	6,80	6,12
LRCC	8,77	13,00	7,61	7,86	7,13	8,64	8,24	10,89	7,05
LRUC p-value	**0,12589**	0,02305	**0,29673**	**0,26091**	**0,74611**	**0,09112**	**0,12408**	0,04301	**0,33561**
LRIND p-value	0,01125	0,00512	0,01063	0,01025	0,00802	0,01613	0,01537	0,00913	0,01333
LRCC p-value	0,01248	0,00150	0,02221	0,01969	0,02825	0,01328	0,01625	0,00431	0,02943

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,513	-1,550	-1,497	-1,488	-1,534	-1,585	-1,585	-1,585	-1,585	-1,574
StDev(VaR)	0,190	0,217	0,134	0,080	0,093	0,283	0,286	0,140	0,143	0,139
Min VaR	-2,432	-2,431	-1,802	-1,842	-1,970	-2,667	-2,691	-2,062	-2,072	-2,037
Max VaR	-1,100	-1,143	-1,167	-1,311	-1,360	-1,150	-1,153	-1,395	-1,393	-1,389
Violations	226	208	234	226	208	199	200	188	189	195
LRUC	17,61	8,33	22,73	17,61	8,33	4,91	5,25	1,92	2,14	3,67
LRIND	6,46	5,63	6,28	7,09	5,94	6,61	6,53	5,97	5,92	6,39
LRCC	24,07	13,95	29,01	24,69	14,26	11,53	11,78	7,89	8,06	10,06
LRUC p-value	0,00003	0,00391	0,00000	0,00003	0,00391	0,02666	0,02195	**0,16584**	**0,14378**	**0,05535**
LRIND p-value	0,01101	0,01770	0,01221	0,00777	0,01483	0,01012	0,01063	0,01454	0,01496	0,01149
LRCC p-value	0,00001	0,00093	0,00000	0,00000	0,00080	0,00314	0,00277	0,01934	0,01779	0,00654

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.12 - PANEL A: *FTSE-100 VaR_99%*

Value-at-Risk 99% FTSE-100 , significance level of the LR tests: 5% Backtesting Period: 6 April 1993- 2 March 2007, N = 3629 backtesting trials, Expected Violations = 36										
Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-2,164	-2,188	-2,269	-2,312	-2,140	-2,364	-2,501	-2,164		-2,260
StDev(VaR)	0,969	0,904	1,005	0,964	1,021	1,066	1,019	0,845		0,940
Min VaR	-8,281	-7,597	-8,409	-8,771	-6,954	-5,332	-5,071	-7,156		-8,096
Max VaR	-0,997	-0,929	-1,072	-1,094	-0,969	-0,958	-1,258	-0,632		-0,626
Violations	60	49	51	41	67	51	49	50		45
LRUC	13,07	4,05	5,35	0,59	21,01	5,35	4,05	4,68		1,96
LRIND	0,00	1,34	1,45	0,94	0,41	1,60	1,82	1,40		1,13
LRCC	13,07	5,39	6,80	1,53	21,42	6,95	5,88	6,08		3,09
LRUC p-value	0,00030	0,04411	0,02073	**0,44141**	0,00000	0,02073	0,04411	0,03051		**0,16130**
LRIND p-value	**0,99350**	**0,24679**	**0,22790**	**0,33304**	**0,52005**	**0,20522**	**0,17691**	**0,23721**		**0,28776**
LRCC p-value	0,00145	**0,06742**	0,03332	**0,46541**	0,00002	0,03090	**0,05298**	0,04789		**0,21310**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-2,330	-2,425	-2,277	-2,388	-2,511	-2,542	-2,561	-2,687	-2,692	-2,730
StDev(VaR)	0,775	0,847	0,563	0,602	0,660	0,940	0,972	0,765	0,771	0,855
Min VaR	-4,114	-4,426	-3,445	-3,494	-3,710	-4,491	-4,662	-3,872	-3,865	-4,058
Max VaR	-1,294	-1,333	-1,506	-1,527	-1,563	-1,310	-1,308	-1,663	-1,645	-1,633
Violations	69	63	78	72	64	51	51	54	54	51
LRUC	23,55	16,28	36,43	27,59	17,41	5,35	5,35	7,59	7,59	5,35
LRIND	6,42	4,84	17,07	19,69	14,95	1,60	1,60	3,70	3,70	4,24
LRCC	29,97	21,12	53,50	47,28	32,36	6,95	6,95	11,29	11,29	9,58
LRUC p-value	0,00000	0,00005	0,00000	0,00000	0,00003	0,02073	0,02073	0,00587	0,00587	0,02073
LRIND p-value	0,01131	0,02779	0,00004	0,00001	0,00011	**0,20522**	**0,20522**	**0,05453**	**0,05453**	0,03959
LRCC p-value	0,00000	0,00003	0,00000	0,00000	0,00000	0,03090	0,03090	0,00354	0,00354	0,00829

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.12 - PANEL B: *FTSE-100 VaR_95%*

Value-at-Risk 95% FTSE-100 , significance level of the LR tests: 5%
Backtesting Period: 6 April 1993- 2 March 2007, N = 3629 backtesting trials, Expected Violations = 181

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-1,530	-1,547	-1,523	-1,540	-1,513	-1,559	-1,581	-1,530	-1,478
StDev(VaR)	0,685	0,639	0,689	0,649	0,722	0,782	0,655	0,597	0,602
Min VaR	-5,855	-5,372	-5,808	-5,543	-4,917	-4,568	-3,423	-5,060	-5,410
Max VaR	-0,705	-0,657	-0,743	-0,708	-0,685	-0,554	-0,792	-0,447	-0,429
Violations	193	188	197	190	207	205	190	195	219
LRUC	0,76	0,25	1,37	0,42	3,63	3,09	0,42	1,04	7,69
LRIND	0,76	1,85	1,05	1,65	1,00	11,67	12,51	0,63	0,05
LRCC	1,52	2,10	2,42	2,07	4,63	14,77	12,93	1,68	7,75
LRUC p-value	**0,38370**	**0,61983**	**0,24244**	**0,51798**	**0,05676**	**0,07861**	**0,51798**	**0,30761**	0,00554
LRIND p-value	**0,38444**	**0,17375**	**0,30510**	**0,19864**	**0,31799**	0,00063	0,00040	**0,42566**	**0,81999**
LRCC p-value	**0,46877**	**0,35056**	**0,29848**	**0,35518**	**0,09892**	0,00062	0,00156	**0,43268**	0,02079

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,373	-1,445	-1,273	-1,346	-1,444	-1,609	-1,617	-1,628	-1,628	-1,604
StDev(VaR)	0,433	0,464	0,306	0,340	0,361	0,578	0,591	0,426	0,425	0,390
Min VaR	-2,320	-2,477	-1,965	-2,021	-2,234	-2,793	-2,831	-2,338	-2,336	-2,237
Max VaR	-0,816	-0,842	-0,900	-0,939	-0,966	-0,863	-0,859	-1,092	-1,094	-1,086
Violations	264	238	296	266	240	193	194	193	192	196
LRUC	34,88	16,97	64,46	36,49	18,14	0,76	0,89	0,76	0,63	1,20
LRIND	8,86	12,39	8,26	12,02	10,33	13,51	15,15	17,55	17,91	14,51
LRCC	43,74	29,36	72,72	48,51	28,46	14,27	16,04	18,31	18,54	15,70
LRUC p-value	0,00000	0,00004	0,00000	0,00000	0,00002	**0,38370**	**0,34428**	**0,38370**	**0,42583**	**0,27368**
LRIND p-value	0,00291	0,00043	0,00406	0,00053	0,00131	0,00024	0,00010	0,00003	0,00002	0,00014
LRCC p-value	0,00000	0,00000	0,00000	0,00000	0,00000	0,00080	0,00033	0,00011	0,00009	0,00039

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.13 - PANEL A: *LIFFE FTSE-100 VaR_99%*

Value-at-Risk 99% LIFFE FTSE-100 , significance level of the LR tests: 5%
Backtesting Period: 6 April 1993- 2 March 2007, N = 3629 backtesting trials, Expected Violations = 36

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**	**1000**
E(VaR)	-2,331	-2,351	-2,461	-2,499	-2,285	-2,525	-2,708	-2,330	-2,445
StDev(VaR)	0,988	0,916	1,071	1,014	1,039	1,046	1,003	0,872	1,009
Min VaR	-7,958	-7,388	-8,251	-8,013	-7,014	-5,354	-5,111	-6,898	-8,328
Max VaR	-0,952	-1,021	-1,082	-1,040	-0,898	-1,113	-1,275	-0,903	-0,626
Violations	55	51	46	36	63	47	49	48	43
LR_{UC}	8,41	5,35	2,42	0,00	16,28	2,92	4,05	3,47	1,18
LR_{IND}	0,03	0,10	1,18	0,72	0,63	0,22	1,34	1,29	1,03
LR_{CC}	8,45	5,45	3,60	0,72	16,91	3,14	5,39	4,75	2,21
LR_{UC} p-value	0,00372	0,02073	**0,11984**	**0,96136**	0,00005	**0,08744**	0,04411	**0,06266**	**0,27672**
LR_{IND} p-value	**0,85748**	**0,74850**	**0,27712**	**0,39568**	**0,42785**	**0,64140**	**0,24679**	**0,25663**	**0,30986**
LR_{CC} p-value	0,01465	**0,06548**	**0,16525**	**0,69637**	0,00021	**0,20828**	**0,06742**	**0,09291**	**0,33049**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-2,536	-2,612	-2,493	-2,619	-2,743	-2,718	-2,742	-2,899	-2,909	-2,962
StDev(VaR)	0,748	0,804	0,518	0,505	0,559	0,875	0,902	0,641	0,648	0,707
Min VaR	-4,181	-4,379	-3,575	-3,601	-3,759	-4,451	-4,591	-3,894	-3,924	-4,031
Max VaR	-1,313	-1,339	-1,593	-1,607	-1,688	-1,349	-1,354	-1,857	-1,893	-1,890
Violations	66	62	69	63	55	56	55	47	47	46
LR_{UC}	19,78	15,18	23,55	16,28	8,41	9,27	8,41	2,92	2,92	2,42
LR_{IND}	14,17	11,76	17,59	16,12	15,08	6,35	6,59	13,84	13,84	14,10
LR_{CC}	33,94	26,94	41,14	32,40	23,50	15,63	15,01	16,76	16,76	16,52
LR_{UC} p-value	0,00001	0,00010	0,00000	0,00005	0,00372	0,00232	0,00372	**0,08744**	**0,08744**	**0,11984**
LR_{IND} p-value	0,00017	0,00061	0,00003	0,00006	0,00010	0,01172	0,01023	0,00020	0,00020	0,00017
LR_{CC} p-value	0,00000	0,00000	0,00000	0,00000	0,00001	0,00040	0,00055	0,00023	0,00023	0,00026

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

TABLE II.13 - PANEL B: *LIFFE FTSE-100 VaR_95%*

Value-at-Risk 95% LIFFE FTSE-100 , significance level of the LR tests: 5%
Backtesting Period: 6 April 1993- 2 March 2007, N = 3629 backtesting trials, Expected Violations = 181

Method:	**Normal GARCH(1,1)**		**t-Student GARCH(1,1)**		**EWMA**	**Historical Simulation**		**Normal EGARCH(1,1)**	**t-Student EGARCH(1,1)**	
Window Length:	**500**	**1000**	**500**	**1000**	**100**	**100**	**252**	**1000**		**1000**
E(VaR)	-1,648	-1,662	-1,634	-1,649	-1,616	-1,652	-1,684	-1,647		-1,598
StDev(VaR)	0,699	0,648	0,705	0,668	0,735	0,765	0,650	0,616		0,642
Min VaR	-5,627	-5,224	-5,576	-5,327	-4,959	-4,200	-3,416	-4,877		-5,462
Max VaR	-0,673	-0,722	-0,703	-0,643	-0,635	-0,647	-0,785	-0,638		-0,407
Violations	195	182	197	187	211	205	190	186		202
LRUC	1,04	0,00	1,37	0,18	4,82	3,09	0,42	0,12		2,37
LRIND	0,24	2,52	0,17	1,95	3,63	7,12	9,01	0,03		0,29
LRCC	1,28	2,52	1,54	2,13	8,46	10,21	9,42	0,14		2,66
LRUC p-value	**0,30761**	**0,96660**	**0,24244**	**0,67397**	0,02806	**0,07861**	**0,51798**	**0,72995**		**0,12393**
LRIND p-value	**0,62642**	**0,11263**	**0,67815**	**0,16218**	**0,05661**	0,00762	0,00269	**0,87429**		**0,58741**
LRCC p-value	**0,52786**	**0,28385**	**0,46335**	**0,34459**	0,01456	0,00606	0,00899	**0,93044**		**0,26430**

Method:	**Block Maxima (GEV distribution)**					**Peaks Over Threshold (GP distribution)**				
Window Length:	**25bl.-500**	**50bl.-500**	**25bl.-1000**	**50bl.-1000**	**100bl.-1000**	**10%thr.-500**	**8%thr.-500**	**10%thr.-1000**	**8%thr.-1000**	**5%thr.-1000**
E(VaR)	-1,517	-1,567	-1,408	-1,484	-1,582	-1,740	-1,749	-1,768	-1,770	-1,739
StDev(VaR)	0,444	0,451	0,244	0,287	0,309	0,571	0,581	0,362	0,364	0,325
Min VaR	-2,680	-2,643	-2,096	-2,154	-2,219	-2,711	-2,740	-2,342	-2,356	-2,309
Max VaR	-0,803	-0,822	-0,914	-0,933	-0,971	-0,880	-0,880	-1,089	-1,093	-1,085
Violations	240	229	268	238	207	189	190	174	175	182
LRUC	18,14	12,15	38,13	16,97	3,63	0,33	0,42	0,33	0,24	0,00
LRIND	6,37	8,75	12,77	16,30	15,38	6,19	6,00	17,52	17,23	17,09
LRCC	24,51	20,91	50,91	33,27	19,00	6,52	6,41	17,85	17,47	17,09
LRUC p-value	0,00002	0,00049	0,00000	0,00004	**0,05676**	**0,56777**	**0,51798**	**0,56788**	**0,62126**	**0,96660**
LRIND p-value	0,01161	0,00309	0,00035	0,00005	0,00009	0,01285	0,01434	0,00003	0,00003	0,00004
LRCC p-value	0,00000	0,00003	0,00000	0,00000	0,00007	0,03845	0,04049	0,00013	0,00016	0,00019

(Critical Value for ***LRUC*** and ***LRIND*** : 3.8414 , Critical Value for ***LRCC*** : 5.9914, VaR model is rejected if the p-value is less than 0.05.
VaR models that pass the LR tests have bold p-values.)

APPENDIX III: Stress testing – $VaR_{99\%}$ forecasts against the 10 biggest negative returns

Table III.1.: Gold Bullion VaR99% against the 10 biggest negative returns

Date	8/2/2000	13/6/2006	19/5/2006	11/9/2006	24/5/2006	5/1/2007	15/5/2006	24/7/2006	8/12/2004	1/11/1999
real P/L	**-5,819**	**-5,542**	**-5,383**	**-4,109**	**-3,820**	**-3,809**	**-3,796**	**-3,723**	**-3,701**	**-3,695**
n-garch500	**-7,858**	-4,015	-3,239	-3,665	**-3,930**	-2,109	-3,029	**-4,427**	-2,164	-2,645
n-garch1000	**-6,324**	-3,902	-3,096	-3,594	**-3,844**	-2,202	-2,901	-3,543	-1,953	-3,218
t-garch500	**-8,600**	-5,037	-4,038	**-4,285**	**-4,823**	-2,693	**-3,804**	**-5,504**	-2,094	**-3,798**
t-garch1000	**-8,237**	-4,630	-3,763	-4,096	**-4,681**	-2,492	-3,533	**-5,017**	-2,205	**-4,082**
EWMA100	-4,332	-4,200	-3,573	-3,324	**-4,600**	-1,980	-3,354	**-4,462**	-1,591	**-3,926**
HS100	-3,551	-4,602	-3,377	**-5,463**	**-4,590**	-3,802	-2,949	**-5,463**	-1,889	-2,348
HS252	-2,669	-3,779	-2,931	-3,820	-2,958	**-4,103**	-2,545	**-3,820**	-2,632	-2,341
gev500-25	-2,214	-2,748	-2,574	-3,234	-2,588	-3,246	-2,440	-2,964	-2,445	-1,920
gev500-50	-2,163	-2,800	-2,553	-3,251	-2,606	-3,283	-2,370	-2,982	-2,437	-1,911
gev1000-25	-1,962	-2,504	-2,608	-2,786	-2,546	-2,846	-2,549	-2,619	-2,366	-1,854
gev1000-50	-1,936	-2,631	-2,530	-2,835	-2,526	-2,990	-2,508	-2,743	-2,274	-1,759
gev1000-100	-1,917	-2,652	-2,518	-2,873	-2,543	-2,955	-2,448	-2,755	-2,277	-1,753
gpd500-10%	-2,266	-2,946	-2,509	-3,529	-2,730	-3,634	-2,383	-3,269	-2,472	-1,980
gpd500-8%	-2,268	-3,008	-2,532	-3,582	-2,756	-3,681	-2,394	-3,343	-2,469	-1,969
gpd1000-10%	-2,051	-2,721	-2,506	-3,026	-2,623	-3,161	-2,441	-2,922	-2,307	-1,850
gpd1000-8%	-2,045	-2,725	-2,538	-3,040	-2,652	-3,180	-2,473	-2,919	-2,317	-1,846
gpd1000-5%	-1,994	-2,799	-2,600	-2,987	-2,696	-3,126	-2,543	-2,984	-2,371	-1,821
n-egarch1000	**-7,041**	-3,230	-3,653	-2,666	-3,685	-2,274	**-3,972**	-3,121	-1,951	-2,820
t-egarch1000	**-9,003**	-2,880	-3,831	**-4,716**	**-4,060**	-2,743	-3,360	**-4,070**	-2,315	**-4,247**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.2.: Copper Cash VaR99% against the 10 biggest negative returns

Date	**1/7/1996**	**13/10/2004**	**17/9/1993**	**11/6/1996**	**6/6/1996**	**24/5/2006**	**4/1/2005**	**20/5/1996**	**19/5/2006**	**13/6/2006**
real P/L	**-10,846**	**-10,358**	**-9,875**	**-9,571**	**-9,078**	**-7,765**	**-7,737**	**-7,272**	**-7,094**	**-6,649**
n-garch500	**-16,775**	-3,409	-3,035	**-11,661**	-5,312	**-10,215**	-2,951	-3,706	-5,969	**-8,353**
n-garch1000	**-18,115**	-3,322	-2,969	**-12,028**	-5,470	**-9,948**	-3,269	-4,336	-7,043	**-9,120**
t-garch500	**-19,330**	-3,444	-3,170	**-12,788**	-6,119	**-11,952**	-3,540	-4,156	-6,324	**-9,236**
t-garch1000	**-20,490**	-3,447	-3,143	**-12,860**	-6,122	**-10,720**	-3,571	-4,935	**-7,099**	**-9,101**
EWMA100	**-13,419**	-3,471	-2,613	-9,338	-5,431	**-10,064**	-3,313	-3,600	**-7,235**	**-9,079**
HS100	-9,324	-3,806	-4,641	-8,175	-5,833	-5,502	**-7,391**	-3,437	-3,858	**-7,430**
HS252	-7,251	-5,139	-4,863	-4,378	-3,629	-3,908	-6,149	-3,481	-3,800	-6,297
gev500-25	-4,054	-3,212	-3,537	-3,590	-3,607	-4,475	-3,727	-3,305	-4,289	-4,520
gev500-50	-4,163	-3,551	-3,625	-3,905	-3,723	-4,480	-3,888	-3,278	-4,342	-4,694
gev1000-25	-3,562	-2,530	-4,221	-3,581	-3,666	-3,632	-2,811	-3,685	-3,387	-3,487
gev1000-50	-3,997	-2,707	-4,232	-3,749	-3,698	-3,676	-2,852	-3,606	-3,589	-3,796
gev1000-100	-4,143	-2,957	-4,380	-3,956	-3,857	-3,722	-3,065	-3,694	-3,763	-4,076
gpd500-10%	-4,992	-3,797	-3,804	-4,031	-3,691	-4,591	-4,389	-3,281	-4,335	-5,059
gpd500-8%	-5,076	-3,822	-3,808	-3,993	-3,661	-4,543	-4,479	-3,286	-4,354	-5,046
gpd1000-10%	-4,688	-3,097	-4,522	-4,157	-3,995	-4,055	-3,428	-3,831	-3,924	-4,413
gpd1000-8%	-4,652	-3,041	-4,520	-4,064	-3,899	-4,068	-3,364	-3,783	-3,928	-4,409
gpd1000-5%	-4,675	-3,137	-4,430	-4,028	-3,875	-4,061	-3,415	-3,671	-3,934	-4,403
n-egarch1000	**-11,299**	-3,359	-3,441	-7,993	-5,560	**-10,998**	-3,640	-4,573	-5,839	-5,433
t-egarch1000	**-13,897**	-3,807	-3,672	-9,042	-6,130	**-10,112**	-2,668	-5,092	**-7,313**	**-11,104**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.3.: Copper 3-Month VaR99% against the 10 biggest negative returns

Date	**13/10/2004**	**14/6/1996**	**4/1/2005**	**24/5/2006**	**6/6/1996**	**13/6/2006**	**19/5/2006**	**17/9/1993**	**11/6/1996**	**8/6/2006**
real P/L	**-9,450**	**-8,469**	**-7,856**	**-7,739**	**-7,004**	**-6,909**	**-6,908**	**-6,882**	**-6,677**	**-6,360**
n-garch500	-3,019	-7,465	-2,758	**-8,904**	-4,365	**-8,478**	-5,904	-2,250	**-7,055**	**-8,332**
n-garch1000	-2,998	-7,813	-3,632	**-8,703**	-5,637	-6,863	-6,396	-2,300	**-7,811**	**-8,456**
t-garch500	-3,091	-3,769	-3,449	**-10,241**	-6,316	**-9,066**	-6,769	-3,037	**-9,741**	**-8,700**
t-garch1000	-4,010	**-10,802**	-3,348	**-9,587**	**-7,516**	**-9,067**	-6,860	-2,534	**-10,600**	**-8,896**
EWMA100	-3,046	-7,076	-3,061	**-9,659**	-4,627	**-8,875**	**-6,974**	-2,085	-6,432	**-8,821**
HS100	-3,542	-6,841	-6,757	-5,452	-5,569	**-7,323**	-3,845	-4,303	-6,629	**-7,323**
HS252	-5,349	-6,226	-5,682	-3,688	-4,002	-6,312	-3,463	-4,660	-4,867	-3,990
gev500-25	-3,124	-2,835	-3,686	-4,405	-3,143	-4,410	-4,187	-3,245	-2,937	-4,309
gev500-50	-3,477	-3,031	-3,942	-4,424	-3,237	-4,625	-4,235	-3,398	-3,165	-4,634
gev1000-25	-2,442	-3,306	-2,740	-3,558	-3,373	-3,334	-3,289	-3,588	-3,330	-3,376
gev1000-50	-2,636	-3,212	-2,865	-3,583	-3,279	-3,649	-3,468	-3,599	-3,230	-3,534
gev1000-100	-2,854	-3,376	-3,032	-3,674	-3,381	-3,981	-3,652	-3,636	-3,377	-3,843
gpd500-10%	-3,762	-3,837	-4,211	-4,470	-3,291	-4,954	-4,229	-3,559	-3,573	-4,773
gpd500-8%	-3,735	-3,824	-4,243	-4,410	-3,268	-4,957	-4,143	-3,555	-3,551	-4,727
gpd1000-10%	-3,042	-3,866	-3,352	-4,015	-3,632	-4,293	-3,886	-3,684	-3,754	-4,198
gpd1000-8%	-2,976	-3,894	-3,266	-3,930	-3,624	-4,328	-3,797	-3,682	-3,768	-4,186
gpd1000-5%	-2,988	-3,874	-3,301	-3,916	-3,598	-4,204	-3,845	-3,630	-3,738	-4,100
n-egarch1000	-3,182	-6,078	-3,587	**-10,307**	-6,407	**-7,232**	-6,767	-2,379	**-6,687**	**-7,713**
t-egarch1000	-3,086	**-8,790**	-3,437	**-8,390**	-6,444	-5,717	-5,697	-2,590	**-9,449**	**-8,240**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.4.: Tin Cash VaR99% against the 10 biggest negative returns

Date	1/9/1995	17/10/2006	23/12/2004	19/5/2006	23/7/2002	13/10/2004	8/2/1995	11/6/2004	6/8/2001	14/2/1995
real P/L	-10,828	-9,801	-9,425	-8,071	-6,746	-6,550	-6,401	-5,671	-5,642	-5,549
n-garch500	-5,135	**-16,343**	-3,538	-4,391	-1,621	-2,337	-4,878	-4,118	-3,134	**-6,279**
n-garch1000	-4,628	**-11,135**	-3,344	-4,462	-1,676	-2,265	-5,105	-4,868	-3,057	**-6,508**
t-garch500	-6,388	**-16,650**	-5,162	-6,297	-1,978	-2,803	**-6,620**	-5,344	-3,283	**-8,364**
t-garch1000	-6,835	**-15,648**	-4,519	-6,655	-1,983	-2,570	**-7,176**	**-5,914**	-3,477	**-7,832**
EWMA100	-4,515	-7,525	-3,097	-4,274	-1,561	-2,430	-4,845	-4,989	-3,119	**-5,828**
HS100	-4,430	-4,179	-5,340	-4,285	-1,674	-5,387	-4,824	-4,864	-3,161	**-5,953**
HS252	-5,488	-5,320	-5,095	-4,053	-3,887	-4,719	-3,822	-4,616	-2,041	-4,136
gev500-25	-4,057	-4,116	-4,375	-4,529	-2,674	-3,724	-3,305	-3,889	-1,932	-3,389
gev500-50	-3,957	-4,392	-4,203	-4,765	-3,092	-3,922	-3,261	-3,972	-2,150	-3,412
gev1000-25	-3,195	-4,180	-4,085	-4,373	-2,249	-3,806	-2,688	-3,238	-2,086	-2,683
gev1000-50	-3,342	-4,272	-3,854	-4,224	-2,407	-3,541	-2,762	-3,249	-2,274	-2,868
gev1000-100	-3,389	-4,332	-3,840	-4,330	-2,538	-3,694	-2,875	-3,549	-2,323	-2,925
gpd500-10%	-4,154	-4,741	-4,450	-4,830	-3,053	-4,224	-3,502	-4,248	-2,240	-3,766
gpd500-8%	-4,193	-4,656	-4,519	-4,793	-2,951	-4,291	-3,436	-4,293	-2,269	-3,650
gpd1000-10%	-3,586	-4,633	-4,099	-4,527	-2,728	-3,941	-2,980	-3,673	-2,494	-3,115
gpd1000-8%	-3,582	-4,617	-4,141	-4,488	-2,718	-3,973	-3,000	-3,711	-2,496	-3,129
gpd1000-5%	-3,583	-4,615	-4,367	-4,491	-2,725	-4,150	-3,031	-3,855	-2,488	-3,157
n-egarch1000	-4,279	-9,516	-2,737	-4,779	-1,964	-2,394	-4,367	-4,619	-2,715	-5,306
t-egarch1000	-6,120	**-13,331**	-3,590	-6,592	-2,120	-2,771	**-6,430**	**-5,757**	-3,257	**-7,681**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.5.: Tin 3-Month VaR99% against the 10 biggest negative returns

Date	23/12/2004	17/10/2006	19/5/2006	31/8/1995	23/7/2002	13/10/2004	6/8/2001	24/5/2006	15/5/2006	29/11/1994
real P/L	-9,650	-9,531	-8,289	-6,846	-6,661	-6,472	-5,420	-5,407	-5,354	-5,264
n-garch500	-3,470	**-18,503**	-4,331	-4,043	-1,580	-2,382	-2,755	**-8,356**	-3,325	-2,288
n-garch1000	-3,061	**-12,452**	-4,306	-4,167	-1,613	-2,330	-2,464	**-7,626**	-2,967	-2,402
t-garch500	-6,022	**-16,688**	-6,044	-5,097	-2,223	-2,785	-3,435	**-10,922**	-4,111	-2,998
t-garch1000	-4,920	**-16,451**	-6,427	-5,927	-2,165	-2,541	-3,659	**-11,494**	-4,032	-4,026
EWMA100	-2,918	-7,660	-4,212	-3,989	-1,525	-2,385	-2,900	**-6,628**	-3,273	-2,996
HS100	-5,157	-3,940	-4,301	-3,142	-1,659	-4,871	-2,924	**-6,821**	-3,496	-2,399
HS252	-4,862	-5,346	-3,738	-4,327	-3,814	-4,849	-1,937	-4,089	-3,366	-2,809
gev500-25	-4,210	-3,908	-4,335	-3,496	-2,599	-3,623	-1,803	-4,373	-4,242	-2,772
gev500-50	-4,067	-4,245	-4,576	-3,513	-3,072	-3,781	-2,050	-4,684	-4,424	-2,762
gev1000-25	-4,004	-3,888	-4,244	-2,834	-2,124	-3,712	-2,016	-4,353	-4,192	-2,383
gev1000-50	-3,742	-4,106	-4,099	-2,966	-2,305	-3,449	-2,155	-4,244	-3,956	-2,430
gev1000-100	-3,731	-4,192	-4,208	-3,100	-2,471	-3,578	-2,219	-4,364	-4,082	-2,524
gpd500-10%	-4,332	-4,573	-4,709	-3,550	-2,927	-4,026	-2,162	-4,885	-4,567	-2,882
gpd500-8%	-4,350	-4,522	-4,661	-3,494	-2,884	-4,140	-2,129	-4,829	-4,539	-2,968
gpd1000-10%	-3,926	-4,471	-4,383	-3,136	-2,657	-3,764	-2,387	-4,542	-4,302	-2,596
gpd1000-8%	-3,934	-4,437	-4,370	-3,181	-2,613	-3,767	-2,379	-4,521	-4,309	-2,617
gpd1000-5%	-4,160	-4,387	-4,309	-3,069	-2,596	-3,968	-2,395	-4,459	-4,263	-2,674
n-egarch1000	-2,632	**-10,266**	-4,815	-4,412	-1,858	-2,340	-2,361	-4,392	-3,218	-2,347
t-egarch1000	-4,004	**-13,860**	-6,072	-5,708	-2,343	-2,625	-3,495	**-9,938**	-4,201	-3,920

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.6.: Zinc Cash VaR99% against the 10 biggest negative returns

Date	29/7/1997	30/9/1997	8/6/2006	13/6/2006	5/4/2004	15/5/2006	13/10/2004	11/9/2006	7/2/1995	12/8/1997
real P/L	**-12,618**	**-11,519**	**-9,101**	**-8,852**	**-7,633**	**-7,547**	**-7,500**	**-7,329**	**-7,209**	**-6,920**
n-garch500	-5,620	-6,779	-7,096	-8,764	-2,946	**-7,775**	-3,702	-6,197	-2,816	-4,510
n-garch1000	-5,129	-6,023	-7,386	-8,518	-3,169	-7,516	-3,804	-5,991	-3,327	-5,461
t-garch500	-7,899	-8,438	-8,661	**-10,605**	-3,900	**-9,426**	-4,371	-7,154	-3,708	**-7,365**
t-garch1000	-7,521	-7,727	-8,892	**-10,114**	-3,863	**-8,731**	-4,511	-7,225	-4,293	**-8,496**
EWMA100	-4,803	-5,993	-8,411	**-9,212**	-3,373	**-8,009**	-4,207	-6,450	-3,953	**-7,325**
HS100	-2,628	-9,769	-6,879	-8,324	-4,629	-5,993	-4,296	**-8,977**	-3,728	**-8,070**
HS252	-2,365	-4,941	-5,760	-6,203	-4,454	-5,082	-4,699	**-7,521**	-2,989	-2,365
gev500-25	-2,237	-3,124	-4,325	-4,520	-3,146	-4,324	-3,785	-5,055	-3,219	-2,653
gev500-50	-2,391	-3,380	-4,825	-5,471	-3,148	-4,830	-3,937	-5,669	-3,095	-2,849
gev1000-25	-2,757	-2,993	-3,980	-4,455	-2,876	-4,166	-3,285	-4,548	-3,609	-2,888
gev1000-50	-2,792	-3,307	-4,119	-4,286	-2,926	-4,084	-3,262	-4,561	-3,666	-2,966
gev1000-100	-2,900	-3,378	-4,258	-4,552	-2,913	-4,211	-3,320	-4,783	-3,730	-3,128
gpd500-10%	-2,356	-3,543	-5,317	-5,651	-3,183	-4,872	-3,814	-6,300	-3,172	-2,709
gpd500-8%	-2,344	-3,517	-5,379	-5,733	-3,180	-4,888	-3,820	-6,342	-3,209	-2,693
gpd1000-10%	-3,103	-3,621	-4,576	-4,773	-2,955	-4,285	-3,334	-5,278	-3,999	-3,298
gpd1000-8%	-3,126	-3,528	-4,593	-4,796	-2,958	-4,304	-3,310	-5,329	-4,028	-3,303
gpd1000-5%	-3,099	-3,575	-4,685	-4,875	-2,953	-4,383	-3,352	-5,555	-4,032	-3,248
n-egarch1000	-4,673	-5,175	-6,426	-7,782	-3,099	**-7,714**	-4,385	-6,121	-3,421	-5,666
t-egarch1000	-6,724	-7,160	-7,311	-7,568	-3,487	**-9,270**	-4,938	-7,196	-4,331	**-7,726**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.7.: Zinc 3-Month VaR99% against the 10 biggest negative returns

Date	29/7/1997	13/6/2006	8/6/2006	5/4/2004	13/10/2004	11/9/2006	15/5/2006	4/1/2005	10/2/2006	17/8/2006
real P/L	**-12,138**	**-8,884**	**-8,729**	**-7,383**	**-7,265**	**-7,104**	**-6,929**	**-6,293**	**-6,169**	**-6,031**
n-garch500	-2,598	-8,586	-7,024	-2,879	-3,577	-6,073	**-7,362**	-3,266	-3,493	-5,438
n-garch1000	-2,609	-8,443	-7,470	-3,132	-3,761	-5,870	**-7,210**	-3,593	-3,226	-5,390
t-garch500	-3,866	**-10,360**	-8,579	-3,538	-4,220	-6,968	**-8,861**	-3,905	-4,201	**-6,567**
t-garch1000	-3,413	**-10,006**	**-8,926**	-3,571	-4,423	**-7,788**	**-8,355**	-4,251	-3,765	**-6,540**
EWMA100	-3,107	**-8,926**	-8,175	-3,276	-4,041	-6,242	**-7,612**	-3,469	-3,429	**-6,095**
HS100	-2,507	-7,829	-6,549	-4,342	-4,100	**-8,806**	-5,909	-5,287	-3,063	**-8,806**
HS252	-1,609	-6,159	-5,638	-4,312	-4,358	-6,913	-5,115	-5,215	-4,122	**-6,913**
gev500-25	-1,976	-4,952	-4,522	-2,970	-3,566	-5,226	-4,564	-3,760	-4,250	-5,050
gev500-50	-1,976	-5,260	-4,616	-2,979	-3,738	-5,490	-4,672	-3,948	-4,225	-5,236
gev1000-25	-2,322	-4,261	-3,942	-2,723	-3,099	-4,473	-3,998	-3,197	-3,473	-4,240
gev1000-50	-2,522	-4,086	-3,893	-2,715	-3,088	-4,326	-3,872	-3,163	-3,466	-4,349
gev1000-100	-2,533	-4,370	-4,052	-2,708	-3,166	-4,602	-4,044	-3,287	-3,559	-4,473
gpd500-10%	-2,029	-5,489	-5,157	-3,035	-3,613	-6,145	-4,701	-3,876	-4,354	-5,954
gpd500-8%	-1,974	-5,536	-5,200	-3,038	-3,614	-6,178	-4,702	-3,831	-4,337	-5,972
gpd1000-10%	-2,589	-4,567	-4,388	-2,756	-3,196	-5,116	-4,081	-3,352	-3,628	-4,978
gpd1000-8%	-2,606	-4,596	-4,424	-2,785	-3,158	-5,118	-4,138	-3,309	-3,639	-5,031
gpd1000-5%	-2,604	-4,725	-4,558	-2,728	-3,106	-5,300	-4,231	-3,275	-3,678	-5,172
n-egarch1000	-3,219	-7,552	-6,352	-2,991	-4,279	-6,382	**-6,995**	-3,790	-4,126	**-6,172**
t-egarch1000	-4,244	-7,512	-8,139	-3,499	-4,826	-6,988	**-8,932**	-4,272	-4,543	**-6,798**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.8.: Nickel Cash VaR99% against the 10 biggest negative returns

Date	13/10/2004	30/5/2000	6/1/2004	8/2/1995	6/2/1995	14/11/2001	15/9/2006	13/6/2006	7/6/2000	3/1/2001
real P/L	-18,359	-11,930	-11,711	-11,583	-11,129	-9,666	-9,579	-8,662	-8,556	-8,498
n-garch500	-7,280	-4,048	-4,364	-10,559	-4,351	**-11,903**	-8,320	-7,870	-4,355	-4,479
n-garch1000	-7,140	-3,730	-4,881	-11,168	-4,853	**-10,776**	-8,292	-7,665	-3,955	-4,220
t-garch500	-8,121	-4,941	-4,455	**-12,039**	-5,120	**-16,472**	**-10,137**	**-8,764**	-5,112	-5,521
t-garch1000	-7,804	-4,441	-5,683	**-12,723**	-7,243	**-14,357**	-9,291	-8,410	-4,974	-5,196
EWMA100	-7,828	-3,636	-4,948	-8,364	-5,858	**-10,645**	-8,639	-8,139	-6,948	-4,038
HS100	-6,383	-5,819	-3,683	-8,857	-6,570	-5,229	-7,837	-6,805	**-8,898**	-5,656
HS252	-7,576	-5,738	-3,750	-6,534	-5,471	-5,390	-6,834	-6,770	-5,738	-6,342
gev500-25	-6,074	-4,525	-4,444	-3,936	-3,632	-6,292	-7,008	-6,601	-4,855	-5,427
gev500-50	-5,959	-4,457	-4,353	-4,266	-3,984	-6,299	-6,986	-6,600	-4,949	-5,692
gev1000-25	-5,724	-4,349	-5,269	-3,238	-3,267	-5,420	-6,050	-5,662	-4,561	-4,841
gev1000-50	-6,010	-4,285	-5,514	-3,786	-3,572	-5,296	-6,538	-6,148	-4,436	-4,747
gev1000-100	-5,889	-4,247	-5,421	-3,865	-3,735	-5,361	-6,530	-6,105	-4,494	-4,903
gpd500-10%	-6,174	-4,668	-4,337	-4,506	-4,107	-6,155	-7,410	-6,878	-5,147	-5,970
gpd500-8%	-6,054	-4,734	-4,331	-4,520	-4,130	-6,211	-7,492	-7,010	-5,186	-5,850
gpd1000-10%	-6,014	-4,372	-5,483	-4,070	-3,851	-5,481	-6,754	-6,382	-4,626	-5,083
gpd1000-8%	-5,911	-4,420	-5,600	-4,026	-3,822	-5,462	-6,703	-6,337	-4,658	-4,913
gpd1000-5%	-5,850	-4,340	-5,456	-4,130	-3,955	-5,490	-6,642	-6,192	-4,526	-4,924
n-egarch1000	-6,642	-3,796	-4,654	-7,321	-4,521	-7,758	-7,432	-6,528	-4,124	-4,737
t-egarch1000	-7,931	-4,470	-5,630	-10,210	-5,875	**-10,086**	**-9,611**	-8,559	-4,894	-5,655

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.9.: Nickel 3-Month VaR99% against the 10 biggest negative returns

Date	13/10/2004	30/5/2000	6/1/2004	28/2/1995	15/9/2006	14/11/2001	13/6/2006	8/2/1995	2/12/2004	3/1/2001
real P/L	-18,106	-11,453	-11,384	-9,953	-9,531	-9,431	-8,763	-8,493	-8,426	-8,129
n-garch500	-7,061	-3,981	-4,192	-4,074	-6,788	**-10,705**	-7,336	-6,692	-6,661	-4,284
n-garch1000	-6,858	-3,684	-4,432	-3,675	-6,813	-9,205	-7,104	-7,065	-6,456	-4,111
t-garch500	-7,836	-4,855	-4,268	-4,546	-7,452	**-14,375**	-8,071	-7,621	-6,620	-4,717
t-garch1000	-7,906	-4,145	-5,358	-5,847	-7,685	**-12,597**	-7,806	-7,304	-7,013	-4,969
EWMA100	-7,575	-3,230	-4,886	-5,723	-7,052	**-10,104**	-7,528	-5,977	-6,707	-3,661
HS100	-6,431	-5,390	-3,419	-7,540	-7,563	-5,170	-6,321	-6,390	**-12,615**	-5,434
HS252	-7,415	-5,204	-3,503	-6,189	-6,275	-5,439	-6,275	-5,977	-8,069	-6,418
gev500-25	-5,958	-4,418	-4,129	-3,728	-6,591	-5,945	-6,481	-3,670	-6,332	-5,189
gev500-50	-5,860	-4,313	-4,000	-4,175	-6,471	-5,970	-6,426	-3,949	-6,773	-5,403
gev1000-25	-5,476	-4,200	-4,967	-3,229	-5,717	-5,205	-5,498	-3,150	-5,561	-4,650
gev1000-50	-5,785	-4,107	-5,207	-3,433	-6,275	-5,105	-6,024	-3,522	-5,818	-4,617
gev1000-100	-5,672	-4,091	-5,152	-3,672	-6,236	-5,155	-5,896	-3,579	-5,964	-4,684
gpd500-10%	-6,056	-4,543	-4,034	-4,441	-6,861	-5,817	-6,684	-4,143	-6,893	-5,588
gpd500-8%	-5,995	-4,591	-3,988	-4,426	-6,934	-5,977	-6,780	-4,139	-6,795	-5,587
gpd1000-10%	-5,778	-4,157	-5,153	-3,852	-6,413	-5,245	-6,166	-3,747	-6,101	-4,785
gpd1000-8%	-5,823	-4,218	-5,204	-3,780	-6,430	-5,248	-6,241	-3,689	-6,114	-4,697
gpd1000-5%	-5,743	-4,171	-5,110	-3,830	-6,379	-5,217	-6,134	-3,770	-5,929	-4,793
n-egarch1000	-6,383	-3,804	-4,532	-3,494	-6,434	-6,930	-6,362	-5,129	-5,148	-4,337
t-egarch1000	-8,077	-4,226	-5,327	-4,807	-8,245	-9,060	-7,933	-6,208	-6,592	-5,257

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.10.: Aluminium Cash VaR99% against the 10 biggest negative returns

Date	8/2/1995	4/1/2005	21/4/2004	27/8/1997	13/10/2004	1/10/1996	29/11/1996	11/9/2006	15/2/2006	10/5/2004
real P/L	-8,290	-8,255	-6,893	-6,653	-6,375	-6,244	-5,769	-5,701	-5,558	-5,519
n-garch500	-3,940	-2,504	-2,405	-3,960	-2,882	-2,607	-3,911	-3,477	-3,146	-4,006
n-garch1000	-3,600	-2,477	-2,573	-4,109	-2,834	-2,426	-3,788	-3,381	-3,315	-3,828
t-garch500	-4,598	-2,767	-2,492	-4,494	-2,981	-3,228	-4,442	-3,761	-3,563	-3,717
t-garch1000	-4,546	-2,703	-2,702	-4,470	-2,999	-2,773	-4,348	-3,595	-3,554	-3,926
EWMA100	-4,053	-2,522	-2,689	-3,982	-2,923	-2,140	-4,014	-3,511	-3,854	-4,129
HS100	-3,943	-4,320	-2,584	-3,603	-2,121	-3,706	-4,987	-5,177	-3,724	**-5,661**
HS252	-3,798	-5,497	-2,392	-3,840	-4,410	-2,688	-3,709	-5,021	-2,966	-3,489
gev500-25	-2,631	-2,792	-2,059	-3,406	-2,766	-3,406	-3,884	-4,227	-3,855	-2,291
gev500-50	-2,840	-3,098	-2,100	-3,404	-2,884	-3,539	-3,897	-4,443	-3,951	-2,559
gev1000-25	-2,779	-2,494	-2,247	-3,348	-2,412	-2,818	-2,962	-3,388	-2,945	-2,401
gev1000-50	-2,745	-2,559	-2,339	-3,484	-2,626	-3,009	-3,241	-3,582	-2,969	-2,489
gev1000-100	-2,860	-2,734	-2,410	-3,492	-2,712	-3,067	-3,280	-3,658	-3,045	-2,615
gpd500-10%	-2,843	-3,077	-2,122	-3,330	-2,809	-3,812	-3,976	-4,643	-3,891	-2,435
gpd500-8%	-2,838	-3,101	-2,103	-3,288	-2,801	-3,787	-3,958	-4,719	-3,915	-2,434
gpd1000-10%	-2,830	-2,730	-2,438	-3,561	-2,659	-3,266	-3,404	-3,955	-3,003	-2,598
gpd1000-8%	-2,857	-2,746	-2,459	-3,555	-2,690	-3,257	-3,388	-3,942	-2,993	-2,620
gpd1000-5%	-2,873	-2,647	-2,378	-3,679	-2,584	-3,305	-3,455	-4,120	-2,899	-2,491
n-egarch1000	-3,181	-2,899	-2,746	-4,170	-2,998	-2,559	-3,695	-3,825	-3,471	-2,781
t-egarch1000	-3,831	-3,033	-2,890	-4,718	-3,123	-2,953	-4,334	-3,913	-3,516	-2,973

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.11.: Aluminium 3-Month VaR99% against the 10 biggest negative returns

Date	4/1/2005	21/4/2004	13/10/2004	8/2/1995	11/9/2006	10/5/2004	15/2/2006	19/5/2006	27/7/1994	10/11/2006
real P/L	-8,247	-6,581	-6,257	-5,984	-5,535	-5,491	-5,465	-5,194	-4,910	-4,888
n-garch500	-2,376	-2,215	-2,740	-3,781	-3,473	-3,873	-3,034	-4,941	-2,167	-4,388
n-garch1000	-2,352	-2,411	-2,668	-3,475	-3,344	-3,925	-3,208	**-5,578**	-2,372	-4,028
t-garch500	-2,595	-2,309	-2,800	-4,508	-3,701	-3,439	-3,198	**-5,733**	-2,503	-4,724
t-garch1000	-2,507	-2,534	-2,764	-4,486	-3,535	-3,646	-3,078	**-5,613**	-2,738	-4,383
EWMA100	-2,399	-2,587	-2,767	-3,837	-3,456	-3,981	-3,900	**-5,705**	-2,257	-4,008
HS100	-4,057	-2,572	-2,135	-3,430	-5,011	-5,470	-3,646	-5,146	-1,759	**-4,957**
HS252	-5,468	-2,021	-4,340	-3,384	-4,824	-3,417	-2,885	-4,436	-2,336	**-5,186**
gev500-25	-2,628	-1,960	-2,558	-2,555	-4,089	-2,179	-3,786	-3,586	-1,972	-4,182
gev500-50	-2,867	-2,004	-2,721	-2,708	-4,284	-2,387	-3,777	-3,758	-2,026	-4,283
gev1000-25	-2,418	-2,159	-2,327	-2,450	-3,229	-2,284	-2,771	-2,945	-2,258	-3,196
gev1000-50	-2,410	-2,206	-2,404	-2,519	-3,395	-2,329	-2,836	-3,099	-2,381	-3,621
gev1000-100	-2,518	-2,244	-2,519	-2,638	-3,491	-2,417	-2,893	-3,143	-2,567	-3,692
gpd500-10%	-2,864	-1,937	-2,673	-2,736	-4,531	-2,275	-3,762	-3,872	-2,052	-4,545
gpd500-8%	-2,723	-1,948	-2,580	-2,704	-4,602	-2,255	-3,753	-3,849	-2,057	-4,653
gpd1000-10%	-2,504	-2,239	-2,450	-2,637	-3,830	-2,378	-2,821	-3,298	-2,796	-3,997
gpd1000-8%	-2,441	-2,252	-2,377	-2,625	-3,882	-2,377	-2,770	-3,290	-2,810	-4,019
gpd1000-5%	-2,413	-2,250	-2,413	-2,615	-4,006	-2,332	-2,855	-3,281	-2,754	-4,209
n-egarch1000	-2,638	-2,414	-2,837	-3,404	-3,663	-2,733	-3,297	-3,692	-2,458	-4,275
t-egarch1000	-2,855	-2,559	-2,991	-4,158	-3,954	-2,828	-3,309	-4,262	-2,898	-4,657

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.12.: FTSE-100 VaR99% against the 10 biggest negative returns

Date	11/9/2001	15/7/2002	22/7/2002	12/3/2003	1/8/2002	30/9/2002	19/7/2002	11/7/2002	22/3/2001	18/9/2002
real P/L	-5,885	-5,589	-5,076	-4,918	-4,866	-4,863	-4,741	-4,396	-4,164	-4,049
n-garch500	-3,019	-5,213	**-7,492**	-3,279	**-6,304**	**-5,373**	**-6,657**	**-4,629**	-3,149	-3,946
n-garch1000	-2,950	-4,980	**-6,909**	-3,211	**-6,071**	**-4,945**	**-6,215**	**-4,474**	-3,183	-3,889
t-garch500	-3,169	-5,334	**-7,628**	-3,380	**-6,426**	**-5,464**	**-6,793**	**-4,737**	-3,325	-4,032
t-garch1000	-3,066	-5,222	**-7,221**	-3,345	**-6,491**	**-5,222**	**-6,514**	**-4,725**	-3,368	**-4,132**
EWMA100	-2,770	-4,697	**-6,189**	-3,486	**-6,577**	**-5,295**	**-5,743**	-4,276	-3,128	**-4,863**
HS100	-3,085	-3,923	**-5,165**	-3,660	**-5,332**	**-5,332**	**-4,992**	-3,231	-2,749	**-5,332**
HS252	-2,944	-3,868	-4,734	-4,866	**-5,069**	**-4,864**	**-4,385**	-3,550	-3,003	**-4,864**
gev500-25	-2,848	-2,937	-3,133	-3,718	-3,105	-3,348	-3,136	-2,902	-2,764	-3,509
gev500-50	-2,963	-3,140	-3,434	-4,067	-3,487	-3,872	-3,383	-3,031	-2,751	-3,629
gev1000-25	-2,953	-2,972	-2,918	-2,983	-2,901	-2,957	-2,972	-2,972	-2,871	-2,942
gev1000-50	-2,884	-2,969	-3,057	-3,250	-3,071	-3,234	-3,068	-2,958	-2,842	-3,180
gev1000-100	-2,976	-3,125	-3,250	-3,537	-3,284	-3,444	-3,250	-3,105	-2,891	-3,265
gpd500-10%	-3,038	-3,434	-3,740	-4,380	-3,892	-4,253	-3,607	-3,320	-2,857	**-4,182**
gpd500-8%	-3,063	-3,408	-3,690	-4,517	-3,846	-4,341	-3,580	-3,279	-2,883	**-4,233**
gpd1000-10%	-3,098	-3,320	-3,462	-3,792	-3,542	-3,719	-3,395	-3,292	-2,988	-3,656
gpd1000-8%	-3,131	-3,373	-3,515	-3,746	-3,593	-3,708	-3,447	-3,343	-3,043	-3,672
gpd1000-5%	-3,123	-3,336	-3,484	-3,928	-3,576	-3,818	-3,407	-3,302	-3,033	-3,734
n-egarch1000	-3,392	-5,006	**-6,200**	-3,907	**-4,947**	-4,563	**-5,200**	**-4,500**	-3,530	**-4,209**
t-egarch1000	-3,677	**-5,643**	**-6,978**	-3,837	**-5,600**	**-5,061**	**-5,832**	**-5,000**	-3,829	**-4,695**

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.

Table III.13.: LIFFE FTSE-100 VaR99% against the 10 biggest negative returns

Date	11/9/2001	30/9/2002	15/7/2002	22/7/2002	12/3/2003	1/8/2002	22/3/2001	11/7/2002	19/7/2002	28/8/2002
real P/L	-6,062	-5,576	-5,132	-5,113	-5,007	-4,822	-4,414	-4,237	-4,163	-4,075
n-garch500	-2,925	-5,475	-4,996	**-6,898**	-3,239	**-6,709**	-2,780	**-4,370**	**-6,413**	-3,678
n-garch1000	-2,960	-5,042	-4,854	**-6,496**	-3,186	**-6,442**	-2,909	**-4,321**	**-6,070**	-3,879
t-garch500	-3,108	**-5,652**	**-5,258**	**-7,195**	-3,456	**-6,994**	-2,933	**-4,617**	**-6,747**	-3,898
t-garch1000	-3,099	-5,427	**-5,233**	**-6,920**	-3,383	**-7,034**	-3,061	**-4,661**	**-6,542**	**-4,368**
EWMA100	-2,753	-5,402	-4,574	**-5,925**	-3,418	**-6,656**	-2,679	-4,135	**-5,600**	**-5,373**
HS100	-2,525	-5,123	-3,899	-4,685	-3,472	**-5,123**	-2,541	-3,334	**-4,685**	**-5,123**
HS252	-2,563	-4,810	-4,005	-4,235	**-5,107**	**-5,095**	-3,241	-3,556	**-4,232**	**-5,107**
gev500-25	-2,898	-3,153	-2,938	-3,126	-3,647	-2,917	-2,945	-2,799	-3,136	-3,082
gev500-50	-3,022	-3,740	-3,085	-3,278	-4,047	-3,377	-2,948	-2,973	-3,268	-3,585
gev1000-25	-3,170	-2,954	-3,111	-3,047	-3,077	-3,017	-3,214	-3,154	-3,091	-3,171
gev1000-50	-3,055	-3,273	-3,116	-3,220	-3,332	-3,162	-3,146	-3,097	-3,231	-3,192
gev1000-100	-3,166	-3,495	-3,267	-3,354	-3,600	-3,389	-3,183	-3,283	-3,372	-3,444
gpd500-10%	-3,074	-4,126	-3,279	-3,549	-4,298	-3,728	-3,023	-3,158	-3,439	-3,879
gpd500-8%	-3,093	-4,196	-3,266	-3,528	-4,402	-3,713	-3,048	-3,142	-3,418	-3,878
gpd1000-10%	-3,270	-3,747	-3,446	-3,545	-3,809	-3,629	-3,258	-3,426	-3,500	-3,612
gpd1000-8%	-3,311	-3,764	-3,439	-3,542	-3,837	-3,636	-3,303	-3,418	-3,492	-3,612
gpd1000-5%	-3,361	-3,862	-3,519	-3,646	-3,921	-3,724	-3,377	-3,492	-3,583	-3,686
n-egarch1000	-3,416	-4,777	-5,113	**-5,950**	-3,846	**-5,289**	-3,518	**-4,414**	**-5,203**	-3,657
t-egarch1000	-3,823	-5,527	**-5,977**	**-7,005**	-3,958	**-4,893**	-3,920	**-5,316**	**-6,066**	-3,168

- ✓ VaR Forecasts in red colour: the VaR model can't forecast the corresponding extreme return.
- ✓ VaR Forecasts in bold green colour: the VaR model successfully forecasts the corresponding extreme return.