QUANTIFYING MARKET RISK FOR LONG AND SHORT TRADERS

Pierre Giot[1,3] and Sébastien Laurent[2]

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Abstract

In this paper we quantify market risk for long and short traders using the Value-at-Risk methodology set in the framework of a non-symmetric Student density distribution. We suggest using an APARCH model based on the skewed Student distribution to fully take into account the fat left and right tails of the returns distribution, which are relevant to long and short traders respectively. The performances of a RiskMetrics, Student and skewed Student APARCH model are assessed on daily data for the CAC40, DAX, NASDAQ and NIKKEI stock indexes. It is shown that the newly introduced skewed Student APARCH market risk based model is a clear winner for traders having both long *and short* positions.

Keywords: Value-at-Risk, Skewed Student distribution, APARCH, long trader, short trader

JEL classification: C52, C53, G15

[1]Business School Department, University of Namur, Belgium and Center for Operations Research and Econometrics, UCL, Belgium; email: pierre.giot@fundp.ac.be

[2]Département des Sciences Economiques, Université de Liège, Belgium. This research was done when S. Laurent was visiting the Department of Quantitative Economics at Maastricht University. email: S.Laurent@ulg.ac.be

[3]Corresponding author

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1 Introduction

In recent years, the tremendous growth of trading activity and the well-publicized trading loss of well known financial institutions (see Jorion, 2000, for a brief history of these events) has led financial regulators and supervisory committee of banks to favor quantitative techniques which appraise the possible loss that these institutions can incur. To quantify market risk, Value-at-Risk has become one of the most sought-after techniques as it provides a simple answer to the following question: with a given probability (say α), what is my predicted financial loss over a given time horizon? The answer is the VaR at level α, which gives an amount in the currency of the traded assets (in dollar terms for example) and is thus easily understandable. In practice, the time horizon is usually one day (if a daily evaluation of profit and losses is required) or 10 days. Furthermore the VaR level is directly related to the amount of capital that the bank needs to put aside to cushion possible losses (see Jorion, 2000, for a discussion of the Basel Capital Accord). In practive, it turns out that the VaR has a simple statistical definition: the VaR at level α for a sample of returns is defined as the corresponding empirical quantile at $\alpha\%$. In other words, with probability $1 - \alpha$, the losses will be smaller than the dollar amount given by the VaR.

Most models in the literature focus on the computation of the VaR for negative returns (see van den Goorbergh and Vlaar, 1999 or Jorion, 2000). Indeed, it is assumed that traders or portfolio managers have long trading positions, i.e. they bought the traded asset and are concerned when the price of the asset falls. In this paper we focus on modelling VaR for portfolios defined on long *and short* trading positions. Thus we model VaR for traders having either bought the asset (long position) or short-sold it (short position).[1] In the first case, the risk comes from a drop in the price of the asset, while the trader loses money when the price increases in the second case (because he would have to buy back the asset at a higher price than the one he got when he sold it). Correspondingly, one focuses in the first case on the left side of the distribution of returns, and on the right side of the distribution in the second case.

Because the distribution of returns is often not symmetric (see Section 3), we show that 'usual' parametric VaR models of the RiskMetrics and ARCH class have a tough job in modelling correctly the left and right tails of the distribution of returns. This is also true for the so-called asymmetric GARCH models where the asymmetry refers to the relationship between the conditional variance and the lagged squared error term. To alleviate these problems, we introduce in this paper a skewed Student Asymmetric Power ARCH (APARCH) model (Ding, Granger, and Engle, 1993) to model the VaR for portfolios defined on long (long VaR) and short (short VaR) trading positions. We compare the performance of this new model with the ones of the RiskMetrics and

[1] An asset is short-sold by a trader when it is first borrowed and subsequently sold on the market. By doing this, the trader hopes that the price will fall, so that he can then buy the asset at a lower price and give it back to the lender. See Sharpe, Alexander, and Bailey (1999) for general information on trading procedures.

Student APARCH models and show that the new model brings about considerable improvements in correctly forecasting one-day-ahead VaR for long and short trading positions on daily stock indexes (French CAC40, German DAX, US NASDAQ and Japanese NIKKEI data).

While we focus exclusively on parametric models, other approaches are possible, such as Danielsson and de Vries (2000) who combine an historical simulation method (i.e. non parametric technique) for the interior of the distribution of returns with a fitted distribution based on extreme value theory for the most extreme returns. In this setting, normal and extreme events are thus modelled using two different methods. With the skewed Student APARCH model we aim to model left and right tail VaRs with a single parametric method for a wide range of values for α. As indicated in Christoffersen and Diebold (2000), volatility forecastability (such as featured by ARCH class models) decays quickly with the time horizon of the forecasts. An immediate consequence is that volatility forecastability is relevant for short time horizons (such as daily trading), but not for long time horizons on which portfolio managers usually focus. In this paper, we are consistent with these characteristics of volatility forecastability as we focus on daily returns and analyze VaR performance for daily trading portfolios made up of long and short positions.

The rest of the paper is organized in the following way. In Section 2, we describe the symmetric and asymmetric VaR models. These models are applied to daily stock indexes data in Section 3 where we assess their performances in quantifying the market risk for long and short traders.

2 VaR models for long and short traders

In this section we present parametric VaR models of the ARCH class. ARCH class models were first introduced by Engle (1982) with the ARCH model. Since then, numerous extensions have been put forward, see Engle (1995), Bera and Higgins (1993) or Palm (1996), but they all share the same goal, i.e. modelling the conditional variance as a function of past (squared) returns and associated characteristics. Because quantiles are direct functions of the variance in parametric models, ARCH class models immediately translate into conditional VaR models. As mentioned in the introduction, these conditional VaR models are important for characterizing short term risk for intradaily or daily trading positions. In the first sub-section we characterize the symmetric (RiskMetrics and Student APARCH) and asymmetric (skewed Student APARCH) volatility models, while we detail corresponding VaR results for negative and positive returns in the second sub-section. We stress that, by symmetric and asymmetric models, we mean a possible asymmetry in the distribution of the error term (i.e. whether it is skewed or not), and not the asymmetry in the relationship between the conditional variance and the lagged squared innovations (the APARCH model features this kind of 'conditional' asymmetry whatever the chosen error term).

2.1 Symmetric and asymmetric volatility models

To characterize the models, we consider a collection of daily returns, r_t, with $t = 1 \dots T$. Because daily returns are known to exhibit some serial autocorrelation[2], we fit an AR(p) structure on the r_t series for all specifications:

$$r_t = \rho_0 + \rho_1 r_{t-1} + \ldots + \rho_p r_{t-p} + e_t \tag{1}$$

We now consider several specifications for the the conditional variance of e_t.

2.1.1 RiskMetrics

In its most simple form, it can be shown that the basic RiskMetrics model is equivalent to a normal IGARCH model where the autoregressive parameter is set at a prespecified value λ and the coefficient of e^2_{i-1} is equal to $1 - \lambda$. In the RiskMetrics specification, $\lambda = 0.94$ and we then have:

$$e_t = \epsilon_t h_t \tag{2}$$

where ϵ_t is IID $N(0, 1)$ and h^2_t is defined as:

$$h^2_t = (1 - \lambda)e^2_{t-1} + \lambda h^2_{t-1} \tag{3}$$

2.1.2 Student APARCH

The APARCH(1,1) model (Ding, Granger, and Engle, 1993) is an extension of the GARCH(1,1) model of Bollerslev (1986) and specifies the conditional variance as

$$h^\delta_t = \omega + \alpha_1 \left(|e_{t-1}| - \alpha_n e_{t-1}\right)^\delta + \beta_1 h^\delta_{t-1} \tag{4}$$

where $\omega, \alpha_1, \alpha_n, \beta_1$ and δ are parameters to be estimated. δ ($\delta > 0$) plays the role of a Box-Cox transformation of h_t, while α_n ($-1 < \alpha_n < 1$), reflects the so-called leverage effect. A positive (resp. negative) value of α_n means that past negative (resp. positive) shocks have a deeper impact on current conditional volatility than past positive shocks (see Black, 1976; French, Schwert, and Stambaugh, 1987; Pagan and Schwert, 1990). Because the distribution of financial returns usually feature 'fat tails' (see Bauwens and Giot, 2001), we work with the Student APARCH (or t APARCH) where $e_t = \epsilon_t h_t$ and ϵ_t is IID $t(0, 1, \nu)$; h_t is defined as in (4).

[2]The serial autocorrelation found in daily returns is not necessarily at odds with the efficient market hypothesis. See Campbell, Lo, and MacKinlay (1997) for a detailed discussion.

2.1.3 Skewed Student APARCH

According to Lambert and Laurent (2001) who express the skewed Student density in terms of the mean and the variance[3], the innovation process ε is said to be (standardized) skewed Student distributed if:

$$f(\epsilon|\xi,\upsilon)=\begin{cases}\frac{2}{\xi+\frac{1}{\xi}}sg\left[\xi\left(s\epsilon+m\right)|\upsilon\right] & \text{if} \quad \epsilon<-\frac{m}{s}\\ \frac{2}{\xi+\frac{1}{\xi}}sg\left[\left(s\epsilon+m\right)/\xi|\upsilon\right] & \text{if} \quad \epsilon\geq-\frac{m}{s}\end{cases} \tag{5}$$

where $g(.|\upsilon)$ is the symmetric (unit variance) Student density and ξ is the asymmetry coefficient;[4] m and s^2 are respectively the mean and the variance of the non-standardized skewed Student. See Giot and Laurent (2001) for full analytical results and expressions for the quantile functions $st^*_{\alpha,\upsilon,\xi}$ of this student density. The conditional variance is modelled as in (4).

2.2 Quantifying market risk for long and short traders

Because the goal of our paper is to check the performance of the models on both the long and short sides of daily trading, we are particularly interested in comparing the Student APARCH model with the skewed Student APARCH model regarding their performance in forecasting one day ahead long and short VaR. As indicated in the introduction, the long side of the daily VaR is defined as the VaR level for traders having long positions in the relevant equity index: this is the 'usual' VaR where traders incur losses when negative returns are observed. Correspondingly, the short side of the daily VaR is the VaR level for traders having short positions, i.e. traders who incur losses when stock prices increase. How good a model is at predicting long VaR is thus related to its ability to model large negative returns, while its performance regarding the short side of the VaR is based on its ability to model large positive returns.

For the RiskMetrics model, the one-step-ahead VaR as computed in $t-1$ for long trading positions is given by $z_\alpha h_t$, for short trading positions it is equal to $z_{1-\alpha}h_t$, with z_α being the left quantile at $\alpha\%$ for the normal distribution and $z_{1-\alpha}$ is the right quantile at $\alpha\%$.[5] For the Student APARCH model, the VaR for long and short positions is given by $t_{\alpha,\upsilon}h_t$ and $t_{1-\alpha,\upsilon}h_t$, with $t_{\alpha,\upsilon}$ being the left quantile at $\alpha\%$ for the Student distribution with υ degrees of freedom and $t_{1-\alpha,\upsilon}$ is the right quantile at $\alpha\%$ for this same distribution. Because $z_\alpha=-z_{1-\alpha}$ for the normal distribution and $t_{\alpha,\upsilon}=-t_{1-\alpha,\upsilon}$ for the Student distribution, the forecasted long and short VaR will be equal in both cases. For the skewed Student APARCH model, the VaR for long and short

[3]See also Fernández and Steel (1998).

[4]The asymmetry coefficient $\xi>0$ is defined such that the ratio of probability masses above and below the mean is $\frac{\Pr(\epsilon\geq0|\xi)}{\Pr(\epsilon<0|\xi)}=\xi^2$.

[5]All VaR expressions are reported for the residuals e_t, which is equivalent to reporting the VaR centered around the expected return based on (1).

positions is given by $st_{\alpha,\upsilon,\xi}h_t$ and $st_{1-\alpha,\upsilon,\xi}h_t$, with $st_{\alpha,\upsilon,\xi}$ being the left quantile at $\alpha\%$ for the skewed Student distribution with υ degrees of freedom and asymmetry coefficient ξ; $st_{1-\alpha,\upsilon,\xi}$ is the corresponding right quantile. If $\log(\xi)$ is smaller than zero (or $\xi < 1$), $|st_{\alpha,\upsilon,\xi}| > |st_{1-\alpha,\upsilon,\xi}|$ and the VaR for long traders will be larger (for the same conditional variance) than the VaR for short traders. When $\log(\xi)$ is positive, we have the opposite result.

3 Empirical application

3.1 Data

In this empirical application we consider daily data for a collection of 4 stock market indexes: the French CAC 40 stock index (CAC, 1/1/1990 - 21/12/2000), the German DAX stock index (DAX, 26/11/1990 - 21/12/2000), the U.S. NASDAQ stock index (NASDAQ, 11/10/1984 - 21/12/2000) and the Japanese NIKKEI stock index (NIKKEI, 4/1/1984 - 21/12/2000), where the numbers in parentheses are the start and end dates for the sample at hand and the first symbol inside the parentheses designates the short notation for the index that will be used in the tables and comments below.

For all price series p_t, daily returns are defined as $r_t = ln(p_t) - ln(p_{t-1})$. Descriptive characteristics for the returns series are given in Table 1. While the time spans for the four stock indexes are different, the four returns series share similar statistical properties as far as third and fourth moments are concerned. More specifically, the returns series are negatively skewed and the large returns (either positive or negative) lead to a large degree of kurtosis. The Ljung-Box Q-statistics of order 10 on the squared series indicate a high serial correlation in the second moment.

Descriptive graphs (level of index, daily returns, density of the daily returns and QQ-plot against the normal distribution) for the DAX and NASDAQ stock indexes are given in Figures 1 and 2. Similar graphs for the other stock indexes are available in Giot and Laurent (2001). Volatility clustering is immediately apparent from the graphs of daily returns. The density graphs and the QQ-plot against the normal distribution show that all returns distributions exhibit fat tails. Moreover, the QQ-plots indicate that fat tails are not symmetric.

3.2 Estimating the models

Table 2 presents the results for the (approximate quasi-maximum likelihood) estimation of the skewed Student APARCH model on the CAC, DAX, NASDAQ and NIKKEI data. An AR(3) was found to be sufficient to correct the serial correlation in the conditional mean. All the computations have been done using GAUSS. The model is particularly successful in taking into account the heteroskedasticity exhibited by the data as the Ljung-Box Q-statistic computed on the squared standardized residuals is never significant. The four stock market indexes feature relatively similar volatility specifications: (a) the autoregressive effect in the volatility specification is strong as β_1 is around 0.9, suggesting a strong memory effects; (b) α_n is positive and significant for all datasets, indicating a leverage effect for negative returns in the *conditional* variance specification; (c) $\log(\xi)$ is negative and significant for all datasets, which implies that the *asymmetry in the Student distribution* is needed to fully model the distribution of returns. These results indicate the need for a model featuring a negative leverage effect (conditional asymmetry) for the conditional variance combined with an asymmetric distribution for the underlying error term (unconditional asymmetry). The skewed Student APARCH model delivers such specifications and we study in Section 3.3 if this model improves on symmetric GARCH models when the VaR for long and short returns is needed.

3.3 In-sample VaR computation

In this section, we use the estimation results of Section 3.2 and the expressions of Section 2.2 to compute the one-day-ahead VaR for all models. All models are tested with a VaR level α which ranges from 5% to 0.25% and their performance is then assessed by computing the failure rate for the returns r_t. By definition, the failure rate is the number of times returns exceed (in absolute value) the forecasted VaR. If the VaR model is correctly specified, the failure rate should be equal to the prespecified VaR level. In our empirical application, we define a failure rate f_l for the long traders, which is equal to the percentage of negative returns smaller than one-step-ahead VaR for long positions. Correspondingly, we define f_s as the failure rate for short traders as the percentage of positive returns larger than the one-step-ahead VaR for short positions.

Because the computation of the empirical failure rate defines a sequence of yes/no observations, it is possible to test $H_0 : f = \alpha$ against $H_1 : f \neq \alpha$, where f is the failure rate (estimated by $\widehat{f}$, the empirical failure rate).[6] At the 5% level and if T yes/no observations are available, a confidence interval for $\widehat{f}$ is given by $\left[\widehat{f} - 1.96\sqrt{\widehat{f}(1-\widehat{f})/T}, \widehat{f} + 1.96\sqrt{\widehat{f}(1-\widehat{f})/T}\right]$. In this paper these tests are successively applied to the failure rate f_l for long traders and then to f_s, the failure rate for short traders. In Table 3 we give summary results for the four stock indexes. These results indicate that:

- the VaR model based on the RiskMetrics method has a difficult job in modelling the market risk for large returns, with large positive returns being somewhat better handled than large negative returns;

- the symmetric Student APARCH model improves considerably on the performance of the Risk-

[6] In the literature on VaR models, this test is also called the Kupiec LR test, if the hypothesis is tested using a likelihood ratio test. See Kupiec (1995).

Metrics model but its performance is still not satisfactory for large positive returns;

- the skewed Student APARCH model improves on all other specifications for both negative and positive returns, thus for the market risk relevant for long and short traders. As indicated in Table 3, the skewed Student APARCH model correctly models nearly all VaR levels for long and short positions.

3.4 Out-of-sample VaR computation

The testing methodology in the previous subsection is equivalent to back-testing the model on the estimation sample. Therefore it can be argued that this should be favorable to the tested model. In a 'real life situation', VaR models are used to deliver out-of-sample forecasts, where the model is estimated on the known returns (up to time t for example) and the VaR forecast is made for period $[t+1, t+h]$, where h is the time horizon of the forecasts. In this subsection we implement this testing procedure for the long and short VaR with $h = 1$ day.

We use an iterative procedure where the skewed Student APARCH model is estimated to predict the one-day-ahead VaR. The first estimation sample is the complete sample for which the data is available less the last five years. The predicted one-day-ahead VaR (both for long and short positions) is then compared with the observed return and both results are recorded for later assessment using the statistical tests. At the second iteration, the estimation sample is augmented to include one more day, the model is *re-estimated* and the VaRs are forecasted and recorded. We iterate the procedure until all days (less the last one) have been included in the estimation sample. Corresponding failure rates are then computed by comparing the long and short forecasted VaR_{t+1} with the observed return e_{t+1} for all days in the five years period. We use the same statistical tests as in the subsection dealing with the in-sample VaR. Empirical results for the four stock indexes are given in the bottom rows of Table 3. Broadly speaking, these results are quite similar (although not as good) to those obtained for the in-sample testing procedure as the skewed Student APARCH model performs well for out-of-sample VaR prediction. Further results are available in Giot and Laurent (2001).

4 Conclusion

Over short-term time horizons, conditional VaR models are usually found to be good candidates for quantifying possible trading losses. In this paper, we extended this analysis by introducing a VaR model that could take into account losses arising from long and short trading positions. Because of the nature of long and short trading, this translates into bringing forward a statistical model that correctly models the left and right tails of the distribution of returns. The proposed model is the skewed Student APARCH model. As density distribution of returns are usually not symmetric, it is shown that models[7] that rely on symmetric distributions underperform with respect to the new model when the one-day-ahead VaR is to be forecasted. All models were applied to daily data for four stock indexes (CAC40, DAX, NASDAQ and NIKKEI), with an out-of-sample testing procedure confirming the results of the in-sample backtesting method: in all cases the skewed Student APARCH model succeeded in modelling adequately the VaR for long and short traders. Extended results, comments and suggestions for further work are available in Giot and Laurent (2001).

References

Bauwens, L., and P. Giot (2001): *Econometric modelling of stock market intraday activity.* Kluwer Academic Publishers.

Bera, A., and M. Higgins (1993): "ARCH models: properties, estimation and testing," *Journal of Economic Surveys.*

Black, F. (1976): "Studies of Stock Market Volatility Changes," *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, pp. 177–181.

Bollerslev, T. (1986): "Generalized autoregressive condtional heteroskedasticity," *Journal of Econometrics*, 31, 307–327.

Campbell, J., A. Lo, and A. MacKinlay (1997): *The Econometrics of Financial Markets.* Princeton University Press, Princeton.

Christoffersen, P., and F. Diebold (2000): "How relevant is volatility forecasting for financial risk management?," *Review of Economics and Statistics*, 82, 1–11.

Danielsson, J., and C. de Vries (2000): "Value-at-Risk and extreme returns," *Annales d'Economie et Statistique*, 3, 73–85.

Ding, Z., C. W. J. Granger, and R. F. Engle (1993): "A Long Memory Property of Stock Market Returns and a New Model," *Journal of Empirical Finance*, 1, 83–106.

Engle, R. (1982): "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation," *Econometrica*, 50, 987–1007.

——— (1995): *ARCH selected readings.* Oxford University Press, Oxford.

[7] We considered two symmetric volatility models: the RiskMetrics and Student APARCH models.

Fernández, C., and M. Steel (1998): "On Bayesian modelling of fat tails and skewness," *Journal of the American Statistical Association*, 93, 359–371.

French, K., G. Schwert, and R. Stambaugh (1987): "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 19, 3–29.

Giot, P., and S. Laurent (2001): "Value-at-Risk for long and short trading positions," CORE DP 2001/22, Maastricht University METEOR RM/01/005.

Jorion, P. (2000): *Value-at-Risk*. McGraw-Hill.

Kupiec, P. (1995): "Techniques for verifying the accuracy of risk measurement models," *Journal of Derivatives*, 2, 173–84.

Lambert, P., and S. Laurent (2001): "Modelling Financial Time Series Using GARCH-Type Models and a Skewed Student Density," Mimeo, Université de Liège.

Pagan, A., and G. Schwert (1990): "Alternative Models for Conditional Stock Volatility," *Journal of Econometrics*, 45, 267–290.

Palm, F. (1996): "GARCH Models of Volatility," *in Maddala, G.S., Rao, C.R., Handbook of Statistics*, pp. 209–240.

Sharpe, W., G. Alexander, and J. Bailey (1999): *Investments*. Prentice-Hall.

van den Goorbergh, R., and P. Vlaar (1999): "Value-at-Risk analysis of stock returns. Historical simulation, tail index estimation?," De Nederlandse Bank-Staff Report, 40.

Table 1: Descriptive statistics

	CAC	DAX	NASDAQ	NIKKEI
Annual mean	10.66	14.53	13.90	1.79
Annual s.d.	19.87	19.67	20.03	21.38
Skewness	-0.16	-0.39	-0.74	-0.14
Excess Kurtosis	2.09	4.15	11.25	10.15
Minimum	-7.57	-9.87	-12.04	-16.14
Maximum	6.83	7.29	9.96	12.43
$Q^2(10)$	444.8	428.7	3269.8	635.1

Descriptive statistics for the daily returns of the corresponding stock index expressed in %. All values are computed using PcGive. $Q^2(10)$ is the Ljung-Box Q-statistic of order 10 on the squared series.

Table 2: Skewed Student APARCH

	CAC	DAX	NASDAQ	NIKKEI
ω	0.032 (0.013)	0.013 (0.006)	0.016 (0.006)	0.024 (0.005)
α_1	0.056 (0.011)	0.081 (0.012)	0.128 (0.022)	0.105 (0.012)
α_n	0.501 (0.126)	0.248 (0.083)	0.291 (0.063)	0.493 (0.079)
β_1	0.915 (0.017)	0.926 (0.012)	0.887 (0.023)	0.897 (0.012)
υ	11.325 (2.793)	7.808 (1.441)	6.737 (0.708)	6.519 (0.703)
$\log(\xi)$	-0.067 (0.029)	-0.073 (0.029)	-0.185 (0.023)	-0.054 (0.023)
δ	1.378 (0.207)	1.133 (0.132)	1.122 (0.178)	1.185 (0.133)
$Q^2(10)$	9.5	0.7	12.7	13.3

Estimation results for the volatility specification of the skewed Student APARCH model. Robust standard errors are reported in parenthesis. $Q^2(10)$ is the Ljung-Box Q-statistic of order 10 computed on the squared standardized residuals.

Table 3: VaR results for all indexes

VaR for long positions				
	CAC	DAX	NASDAQ	NIKKEI
RiskMetrics (in-sample)	0	0	0	0
Student APARCH (in-sample)	100	100	40	100
Skewed Student APARCH (in-sample)	100	100	100	80
Skewed Student APARCH (out-of-sample)	60	100	80	80
VaR for short positions				
	CAC	DAX	NASDAQ	NIKKEI
RiskMetrics (in-sample)	20	40	60	20
Student APARCH (in-sample)	60	60	0	60
Skewed Student APARCH (in-sample)	100	80	100	100
Skewed Student APARCH (out-of-sample)	80	80	60	100

Number of times (out of 100) that the null hypothesis $f_l = \alpha$ (i.e. failure rate for the long trading positions is equal to α, top of the table) is not rejected and $f_s = \alpha$ (i.e. failure rate for the short trading positions is equal to α, bottom of the table) is not rejected for the combined five possible values of α.

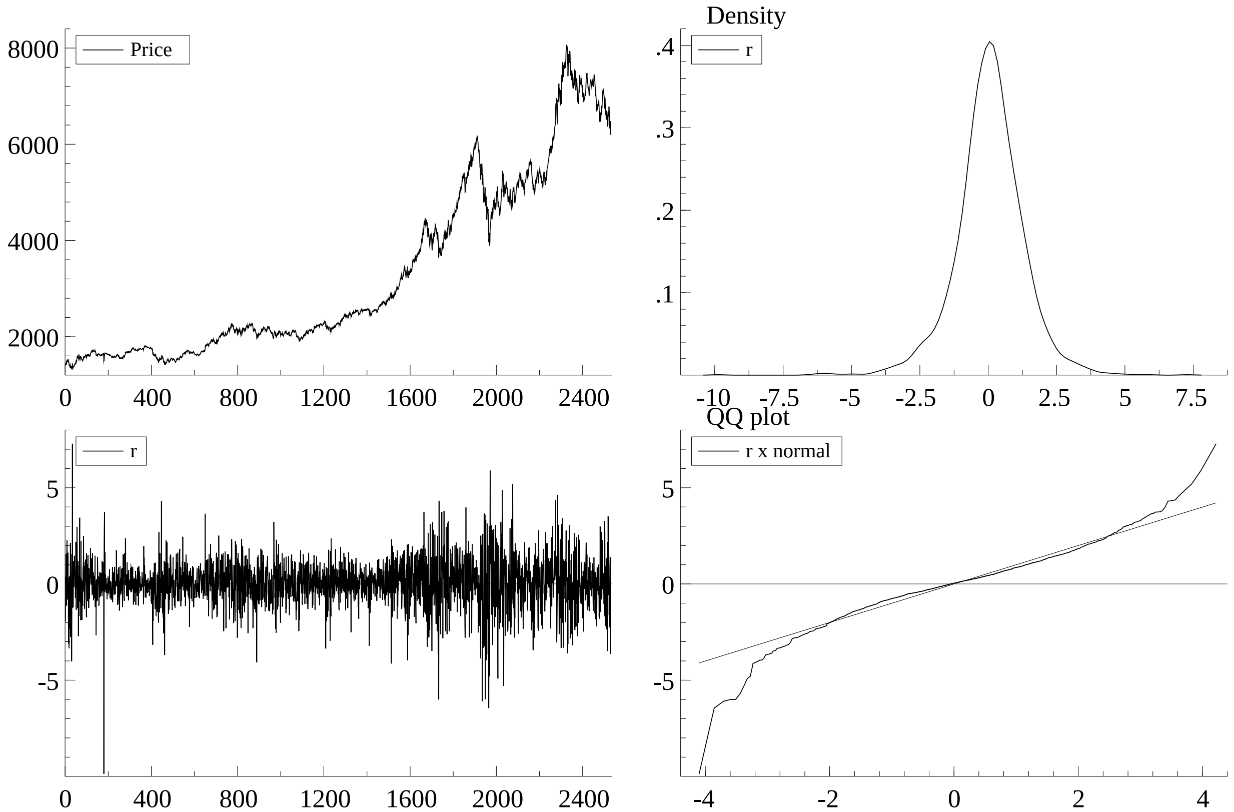

Figure 1: DAX stock index in level, daily returns, daily returns density and QQ-plot against the normal distribution. The time period is 26/11/1990 - 21/12/2000.

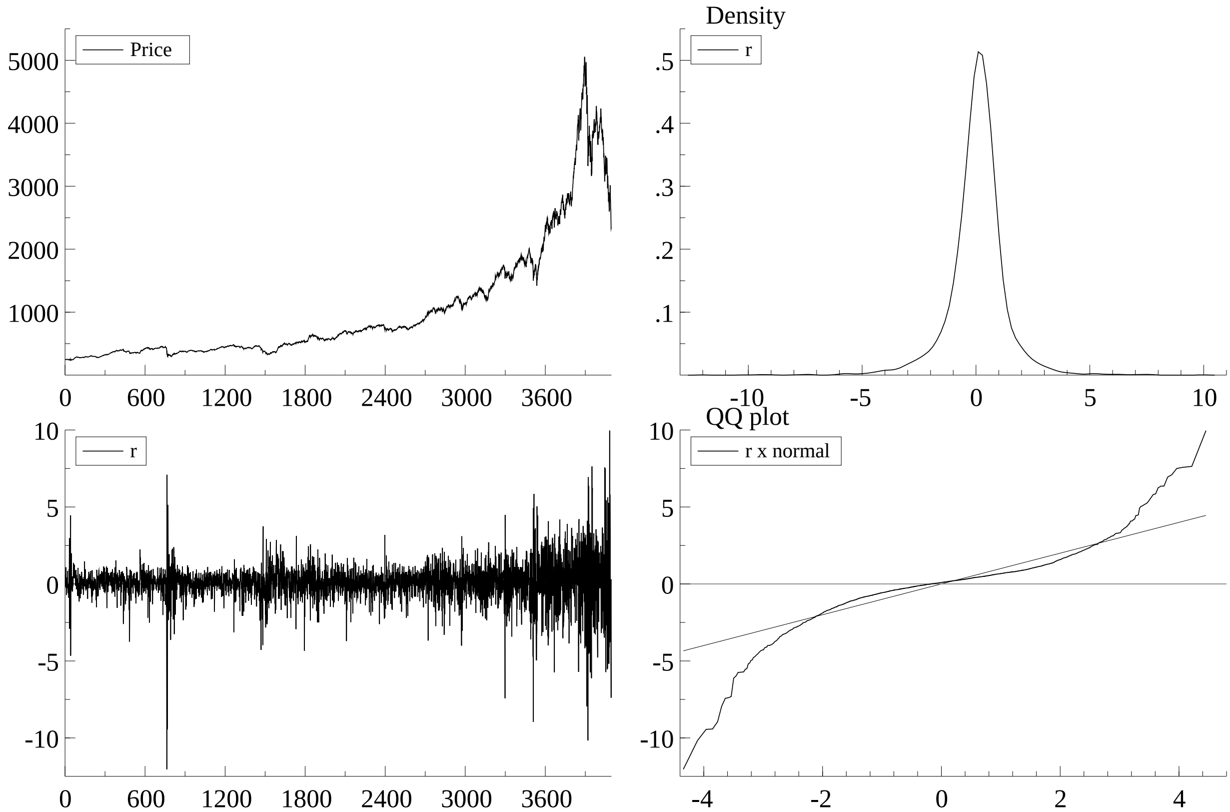

Figure 2: NASDAQ stock index in level, daily returns, daily returns density and QQ-plot against the normal distribution. The time period is 11/10/1984 - 21/12/2000.