ASML Stock Price Analysis

Project of Time Series Analysis for Economic and Financial Data

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Preface

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This project aims to conduct an in-depth time series analysis of the stock prices for **ASML Holding NV (ASML)**, a global leader in the manufacturing of lithography systems for the semiconductor industry. The primary objective is to explore the dynamics of historical prices, volatility, and underlying trends of the stock.

Data Source

We retrieve historical daily data using the `quantmod` R package, focusing on the **Adjusted Closing Price** to account for dividends and stock splits.

- **Ticker**: ASML
- **Source**: Yahoo Finance
- **Start Date**: 2000-01-01
- **End Date**: 2025-12-01

Data Loading

The dataset structure is shown below:

```
datatable(
  tail(asml, 100),
  rownames = FALSE,
  options = list(
    pageLength = 10,
    order = list(list(0, 'desc'))
  )
)
```

Show 10 entries Search:

Date	ASML.Open	ASML.High	ASML.Low	ASML.Close	ASML.Volume	ASML.Adjusted
2025-11-28	1040.400024414062	1060.280029296875	1035.43994140625	1060	939700	1060
2025-11-26	1040.670043945312	1055	1037.300048828125	1040.969970703125	1572400	1040.969970703125
2025-11-25	993.8300170898438	1006.880004882812	973.739990234375	1003.219970703125	1193000	1003.219970703125
2025-11-24	977.6199951171875	995.1400146484375	977.5900268554688	987.8200073242188	1628100	987.8200073242188
2025-11-21	963.3499755859375	978.5399780273438	946.1099853515625	966.5700073242188	2481800	966.5700073242188
2025-11-20	1042.22998046875	1050.949951171875	977	981.0399780273438	2055100	981.0399780273438
2025-11-19	1005.77001953125	1044.72998046875	1005	1039.329956054688	1587800	1039.329956054688
2025-11-18	1011.080017089844	1017.719970703125	993.989990234375	1004.059997558594	1414000	1004.059997558594
2025-11-17	1004.719970703125	1025	1004.27001953125	1020	1691500	1020
2025-11-14	989.2999877929688	1018.070007324219	981	1006.97998046875	1307800	1006.97998046875

Showing 1 to 10 of 100 entries

Previous 1 2 3 4 5 … 10 Next

1 Exploratory Data Analysis

1.1 Adjusted closing prices

Let us plot the adjusted closing prices...

```
fig_asml <- plot_ly(data = asml, x = ~Date, y = ~ASML.Adjusted,
  type = 'scatter', mode = 'lines', name = 'ASML Adjusted',
  line = list(color = 'darkblue', width = 1.5))

fig_asml <- layout(
  fig_asml,
  title = "ASML Stock Price Evolution",
  xaxis = list(
    title = "Date",
    rangeslider = list(visible = TRUE),
    rangeselector = list(
      buttons = list(
        list(count=1, label="1m", step="month", stepmode="backward"),
        list(count=6, label="6m", step="month", stepmode="backward"),
        list(count=1, label="YTD", step="year", stepmode="todate"),
        list(count=1, label="1y", step="year", stepmode="backward"),
        list(step="all")
      )
    )
  )
)

fig_asml
```

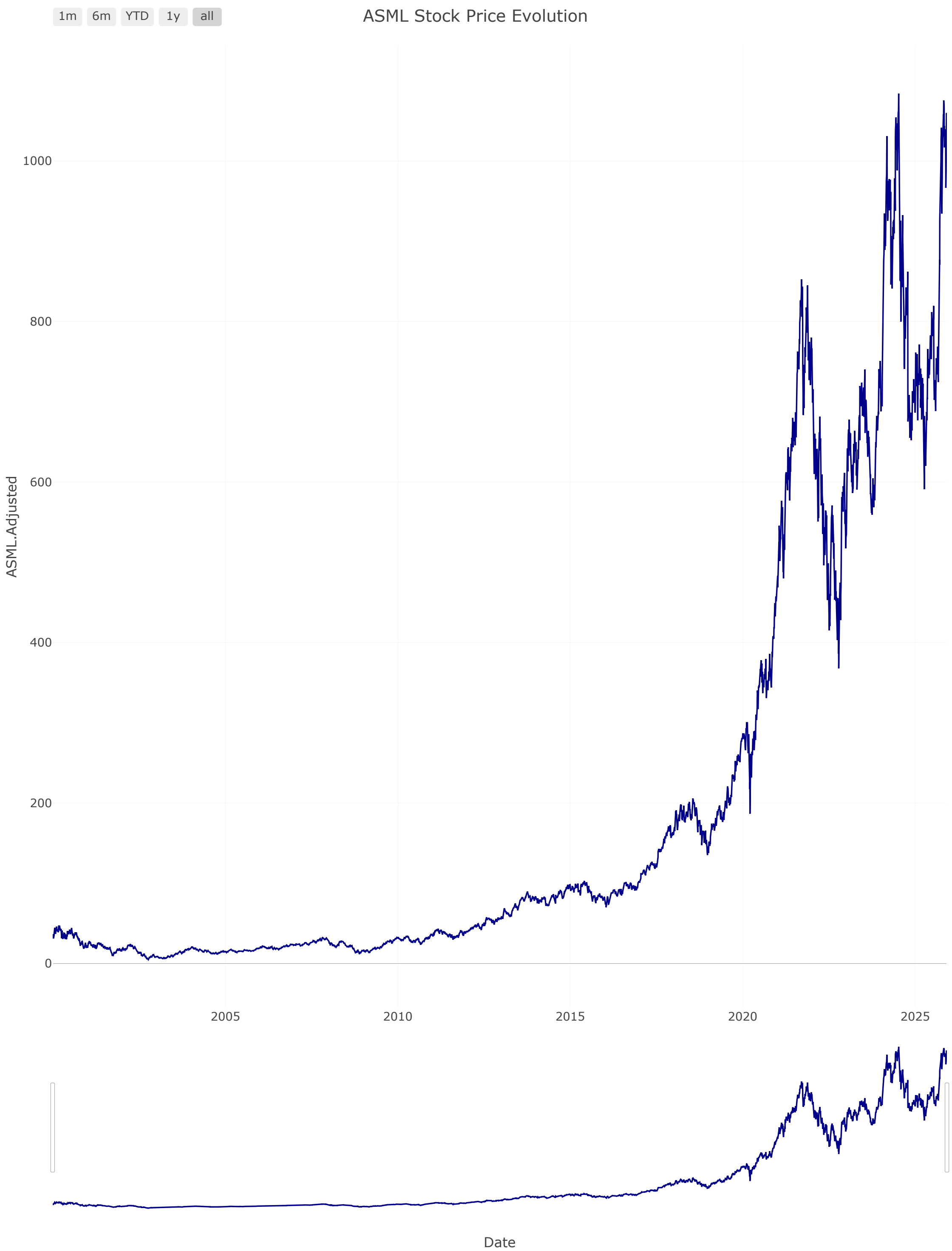

Figure 1.1: ASML Daily Adjusted Closing Prices

The graph clearly shows that the price series is **non-stationary**: the mean is not constant (it exhibits trends), and the variance appears to fluctuate depending on the price level. Consequently, standard statistical inference cannot be directly applied to prices.

1.2 Log returns

To obtain a stationary process, we transform prices into **log-returns**. Let P_t be the price at time t. The simple net return is defined as:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

However, in financial econometrics, **log-returns** (r_t) are preferred due to their time-additivity property. The log-return is defined as the natural logarithm of the gross return:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1})$$

We compute the log-returns for ASML in R:

```
log_ret_vec <- diff(log(asml$ASML.Adjusted))
log_ret_vec <- log_ret_vec[is.finite(log_ret_vec)]

log_returns <- data.frame(
  Date = asml$Date[-1],
  LogReturns = as.numeric(log_ret_vec)
)
```

Let's visualize the log-returns of ASML:

```
fig_log <- plot_ly(data = log_returns, x = ~Date, y = ~LogReturns, type = 'scatter',
  mode = 'lines', name = 'Log Returns', line = list(color = 'darkred', width = 1))

fig_log <- layout(
  fig_log,
  title = "ASML Log-Returns",
  xaxis = list(title = "Date"),
  yaxis = list(title = "Log Return"),
  shapes = list(
    list(
      type = "line",
      x0 = min(log_returns$Date),
      x1 = max(log_returns$Date),
      y0 = 0,
```

```
      y1 = 0,
      line = list(color = "black", width = 1)
    )
  )
)

fig_log
```

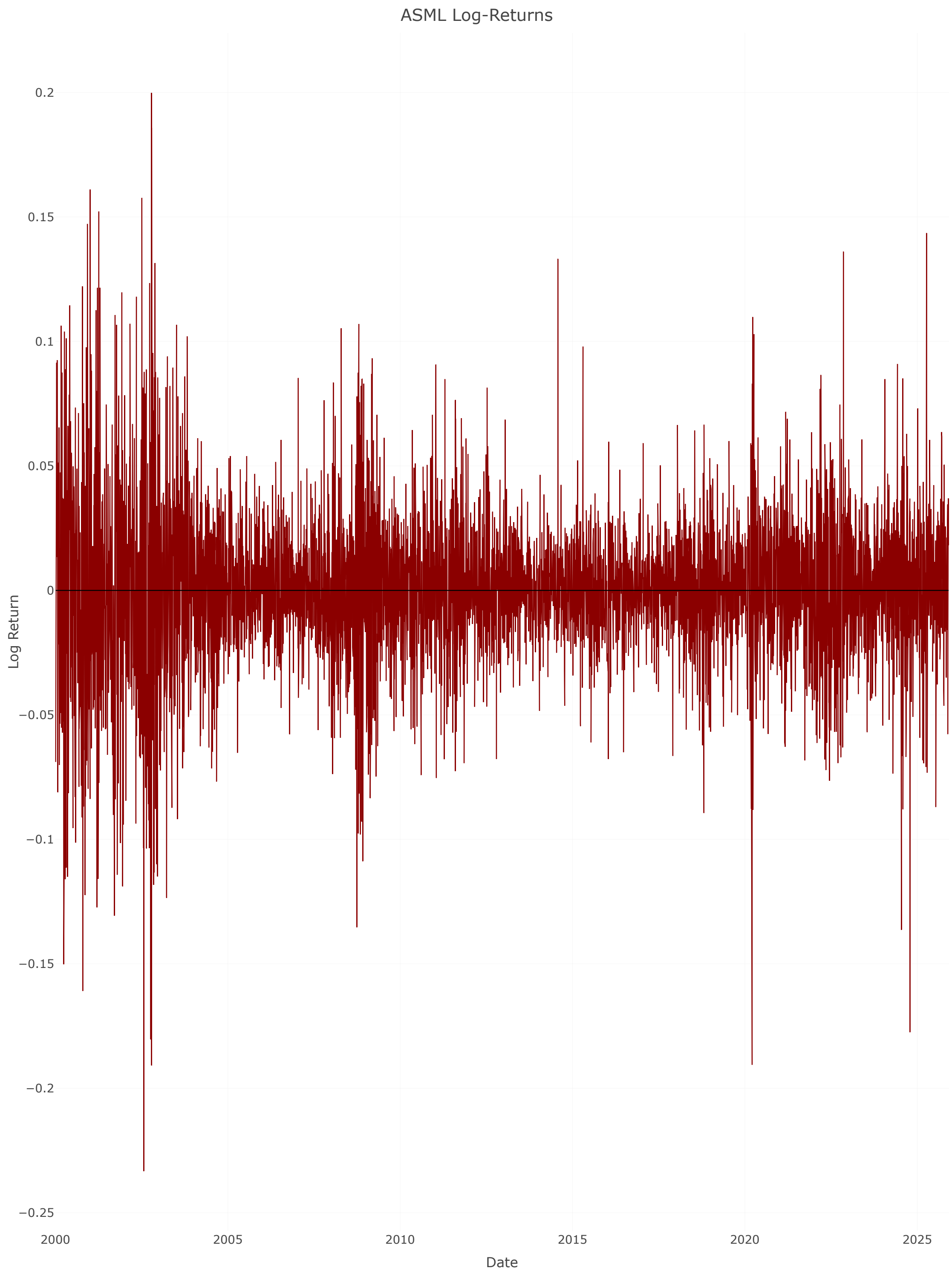

Figure 1.2: ASML Daily Log-Returns

Unlike prices, the log-returns oscillate around a constant mean (close to zero). This behavior suggests that the return series is **stationary**, satisfying the conditions for further econometric analysis.

1.3 Distribution analysis

We analyze the distribution of log-returns to check for deviations from normality (e.g., fat tails or asymmetry).

1.3.1 Graphical representation

1.3.1.1 Histogram

The graphical representation using a histogram of the frequency distribution of returns observed over a given sample period provides an initial indication of the characteristics of the probability distribution that generated them.

```
mu_ret <- mean(log_returns$LogReturns)
sd_ret <- sd(log_returns$LogReturns)

t_fit_fGarch <- stdFit(log_returns$LogReturns * 100)
t_params <- t_fit_fGarch$par

fig_dist <- plot_ly(data = log_returns, x = ~LogReturns,
  type = "histogram", name = "Log Returns", histnorm = "probability density",
  marker = list(color = "lightgray", line = list(color = "gray", width = 1)),
  opacity = 0.7)

x_seq <- seq(min(log_returns$LogReturns), max(log_returns$LogReturns), length.out = 500)

y_norm <- dnorm(x_seq, mean = mu_ret, sd = sd_ret)
y_t <- dstd(
  x_seq,
  mean = t_params["mean"]/100,
  sd = t_params["sd"]/100,
  nu = t_params["nu"]
)

fig_dist <- fig_dist %>%
  add_lines(
    x = x_seq,
    y = y_norm,
    name = "Normal Distribution",
    line = list(color = "#E74C3C", width = 2, dash = "dash"),
```

```
    inherit = FALSE
  ) %>%

  add_lines(
    x = x_seq,
    y = y_t,
    name = "Student-t",
    line = list(color = "#2E86C1", width = 2),
    inherit = FALSE
  ) %>%

  layout(
    title = "Distribution of ASML Log-Returns",
    xaxis = list(title = "Log Return"),
    yaxis = list(title = "Density"),
    legend = list(x = 0.8, y = 0.9),
    hovermode = "x unified"
  )

fig_dist
```

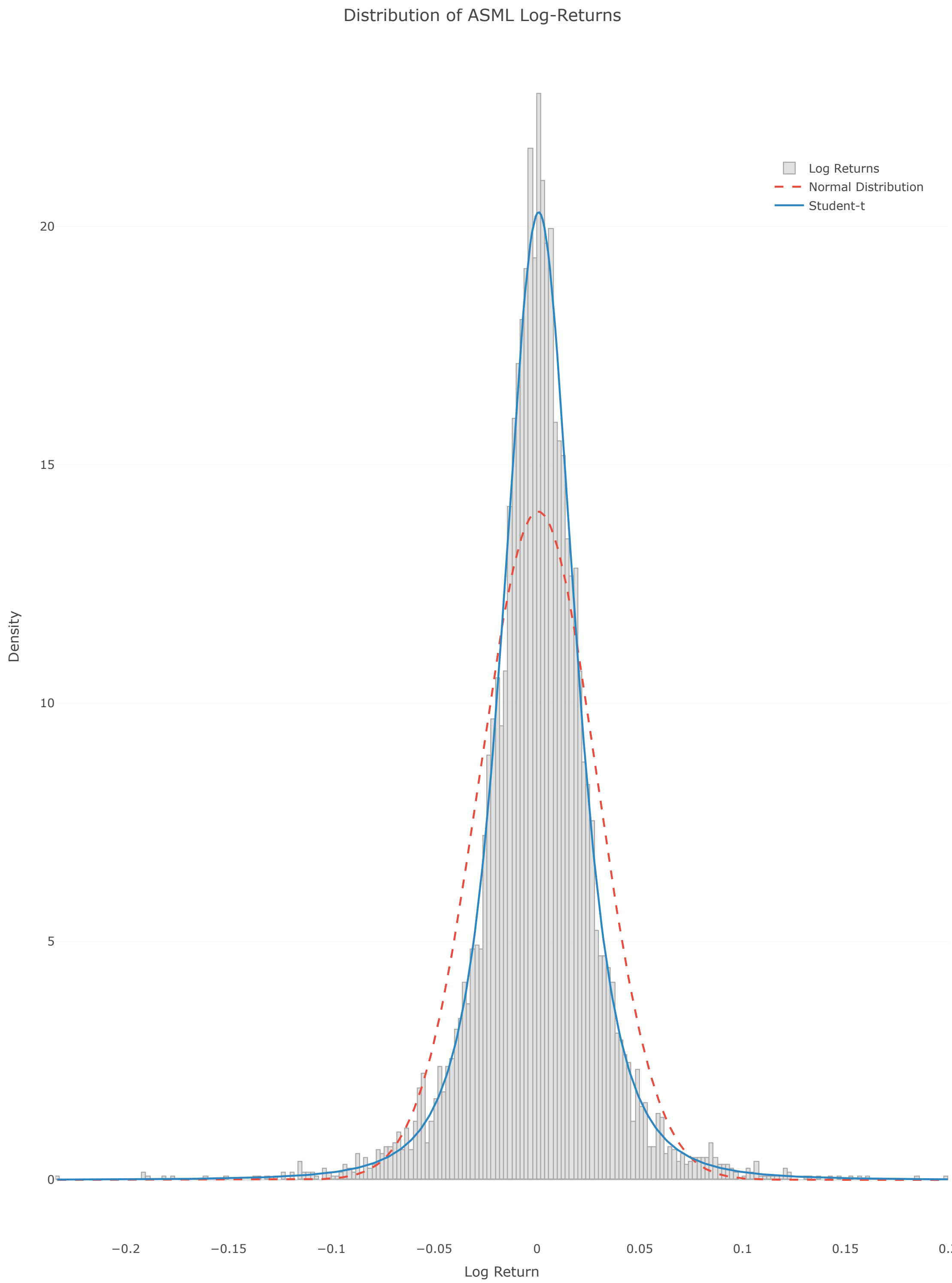

Figure 1.3: Histogram of ASML Log-Returns

The histogram indicates that the distribution of log-returns is closer to a Student-t distribution than to a Normal distribution.

1.3.1.2 Q-Q plot

```
vec_ret <- log_returns$LogReturns

qq_vals <- qqnorm(vec_ret, plot.it = FALSE)
qq_data <- data.frame(
  Theoretical = qq_vals$x,
  Sample = qq_vals$y
)

y <- quantile(vec_ret, c(0.25, 0.75), names = FALSE)
x <- qnorm(c(0.25, 0.75))
slope <- diff(y)/diff(x)
int <- y[1L] - slope * x[1L]

fig_qq <- plot_ly(data = qq_data, x = ~Theoretical, y = ~Sample, type = 'scatter',
  mode = 'markers', marker = list(size = 3, color = '#2E86C1', opacity = 0.6),
  name = "Returns")

fig_qq <- fig_qq %>%
  add_lines(
    x = ~Theoretical,
    y = ~Theoretical * slope + int,
    line = list(color = "#E74C3C", width = 2, dash = "dash"),
    name = "Normal Reference",
    inherit = FALSE
    ) %>%

    layout(
      title = "Q-Q Plot: Normal vs Empirical",
      xaxis = list(title = "Theoretical Quantiles (Normal)"),
      yaxis = list(title = "Sample Quantiles (ASML)")
    )

fig_qq
```

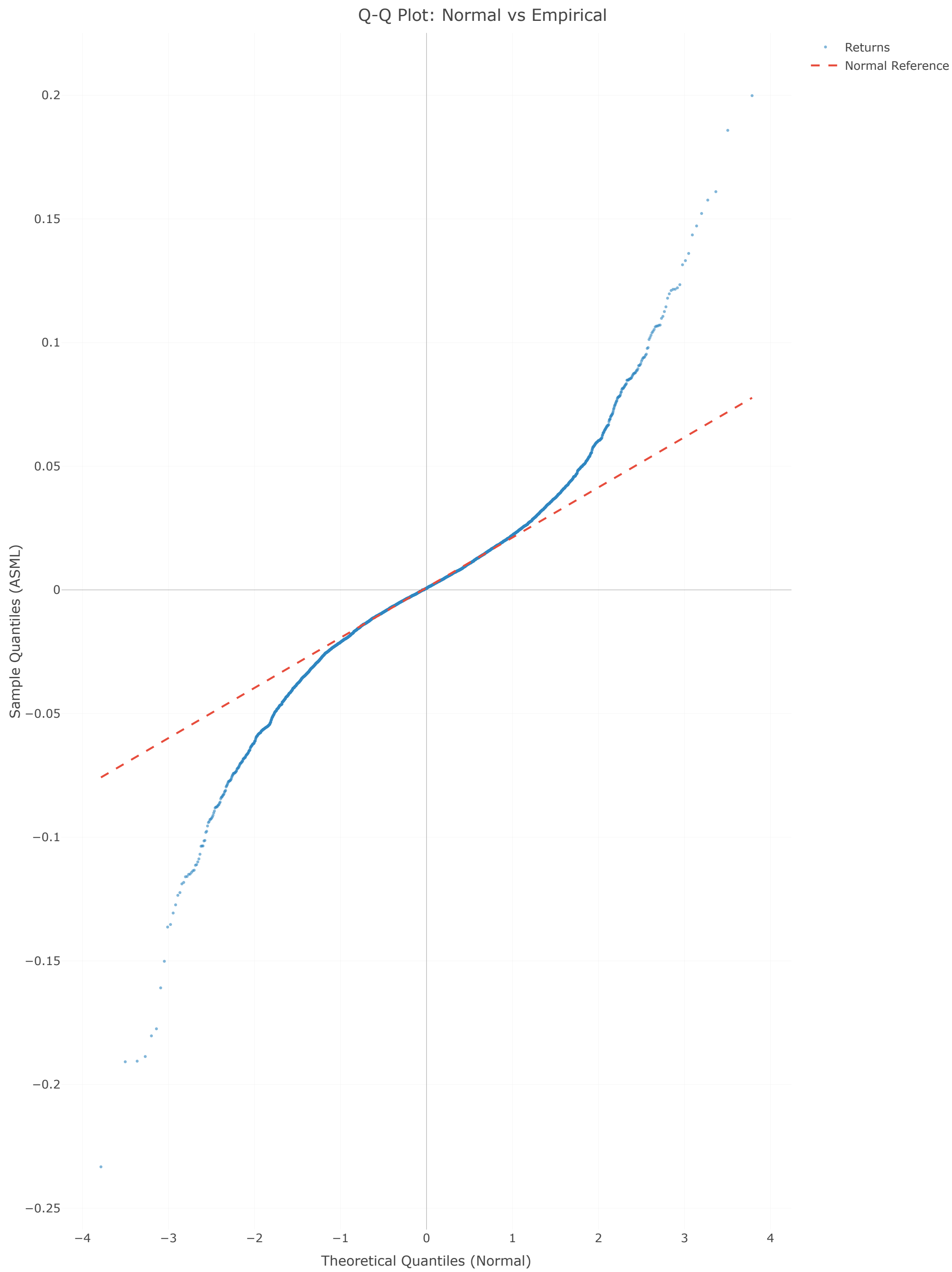

Figure 1.4: Q-Q Plot of ASML Log-Returns

The **Q-Q plot** confirms the findings from the histogram. While the central observations (the body of the distribution) align well with the theoretical normal line (in red), the extreme values at both ends deviate significantly, forming an '*S-shape*'. This provides clear visual evidence of fat tails (leptokurtosis), reinforcing the stylized fact that extreme market movements occur more frequently than predicted by a Gaussian model.

1.3.2 Synthetic indicators

```
desc_stats <- data.frame(
  Metric = c("Mean", "Std. Dev.", "Skewness", "Kurtosis"),
  Value = c(
    mean(log_returns$LogReturns),
    sd(log_returns$LogReturns),
    skewness(log_returns$LogReturns),
    kurtosis(log_returns$LogReturns)
  )
)

datatable(
  desc_stats,
  options = list(dom = 't', paging = FALSE),
  rownames = FALSE
  ) %>% formatRound('Value', digits = 5)
```

Metric	Value
Mean	0.00052
Std. Dev.	0.02846
Skewness	-0.17892
Kurtosis	8.67665

As we can see, the distribution has a mean close to zero, slight negative skewness, and significant leptokurtosis (fat tails). These characteristics align with the well-known **stylized facts** of financial log-returns, indicating a departure from normality.

1.3.3 Test of normality

To formally test the normality hypothesis, we employ the **Jarque-Bera test**, which is based on skewness and kurtosis matching a normal distribution.

$$H_0 : \text{The data is normally distributed (Skewness=0, Kurtosis=3)}$$
$$H_1 : \text{The data is not normally distributed}$$

```r
jb_test <- jarque.bera.test(log_returns$LogReturns)

jb_res <- data.frame(
  Test = "Jarque-Bera",
  Statistic = round(jb_test$statistic, 2),
  P_Value = ifelse(jb_test$p.value < 0.001, "< 0.001", round(jb_test$p.value, 4)),
  Result = ifelse(jb_test$p.value < 0.05, "Reject H0", "Fail to Reject H0")
)
datatable(jb_res, options = list(dom = 't'), rownames = FALSE)
```

Test	Statistic	P_Value	Result
Jarque-Bera	8783.67	< 0.001	Reject H0

Since the p-value is virtually zero (<0.001), we strongly reject the null hypothesis of normality. This confirms that ASML returns are not normally distributed.

2 Return analysis

3 Volatility analysis