# Value at Risk and Expected Shortfall for Microsoft (MSFT)

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### Introduction

This report estimates one-day Value at Risk (VaR) and Expected Shortfall (ES) for Microsoft (MSFT) using the variance-covariance (VCV, normal) and historical simulation (HS) approaches. We analyse unconditional risk over the sample and conditional risk on 22 Aug 2025 using EWMA(0.94) volatility. The objective is to compare parametric and non-parametric estimates and show how time-varying volatility affects tail risk.

### Method

Let  $r_t = \ln(P_t/P_{t-1})$ . Under VCV (normal):

$$VaR_{VCV} = -(\mu + \sigma q_{\alpha}), \qquad ES_{VCV} = \frac{\sigma \phi(q_{\alpha})}{\alpha},$$

where  $q_{\alpha} = \Phi^{-1}(\alpha)$  and  $\phi(\cdot)$ ,  $\Phi(\cdot)$  are the standard normal pdf and cdf. For HS, VaR<sub>HS</sub> is the empirical  $\alpha$ -quantile and

$$ES_{HS} = -\mathbb{E}[r_t \mid r_t \le -VaR_{HS}].$$

Conditional volatility is EWMA(0.94):  $\sigma_t^2=0.94\,\sigma_{t-1}^2+0.06\,r_{t-1}^2$ . Conditional VaR/ES at 22 Aug 2025 use  $\sigma_T$  and the last 500 standardised returns.

### Results

Table ?? reports unconditional one-day VaR and ES for MSFT (daily, simple returns). Risk grows monotonically with confidence. At 95%, VCV VaR is 2.8769% versus HS VaR of 2.6599%. By 99%, HS VaR (4.7845%) exceeds VCV (4.09297%), indicating a heavier extreme tail than the normal model. ES is consistently higher than VaR, and HS ES exceeds VCV ES across the grid.

Table 1: Unconditional VaR and ES for MSFT (daily, simple returns)

Confidence	VaR (VCV)	ES (VCV)	VaR (HS)	ES (HS)
90%	0.02234434	0.03072451	0.01809384	0.03170036
91%	0.02338856	0.03160211	0.01936284	0.03313952
92%	0.02452416	0.03256291	0.02075080	0.03480561
93%	0.02577428	0.03362793	0.02237411	0.03669804
94%	0.02717227	0.03482760	0.02455012	0.03890583
95%	0.02876900	0.03620839	0.02659900	0.04164943
96%	0.03064813	0.03784694	0.02943578	0.04501418
97%	0.03296299	0.03988841	0.03343547	0.04966853
98%	0.03604824	0.04262834	0.03887568	0.05671192
99%	0.04092970	0.04702989	0.04784450	0.07104446

Figure ?? illustrates MSFT's daily simple returns with the 95% and 99% unconditional VaR lines. The series exhibits clear volatility clustering: periods of calm with small fluctuations are followed by bursts of large losses and gains, especially during financial stress episodes such as 2008–2009 and 2020. The blue (HS) VaR lines lie consistently below the red (VCV) lines, implying that the historical distribution assigns greater probability to extreme losses than the normal model. Several return spikes exceed even the 99% VaR boundaries, demonstrating that both methods occasionally underpredict tail risk during turbulent periods. Overall, the figure visually confirms leptokurtosis and time-varying volatility in MSFT returns, validating the need for a conditional (EWMA) framework.

Figure 1 - MSFT Daily Simple Returns with Unconditional VaR Red = VCV (Normal); Blue = HS; solid = 99%, dashed = 95%

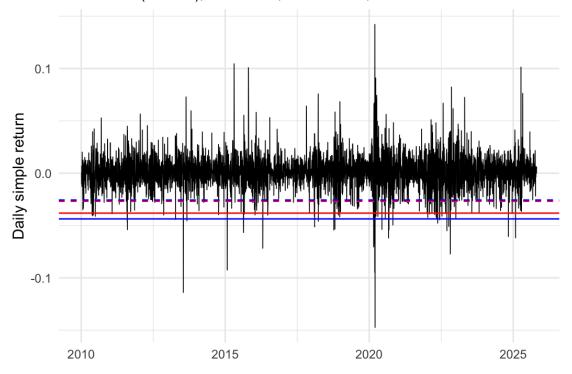


Figure 1: MSFT daily returns with unconditional VaR lines (Red = VCV, Blue = HS; solid = 99%, dashed = 95%).

Table ?? shows conditional one-day VaR and ES on 22 Aug 2025 using EWMA(0.94). These are below the unconditional figures at each confidence level, implying relatively subdued volatility at that date. At 95%, conditional VCV VaR and ES are 1.8697% and 2.3502%, while HS VaR and ES are 1.9915% and 3.0188%, respectively. HS estimates exceed VCV (especially ES), consistent with heavier empirical tails.

Table 2: Conditional VaR and ES for MSFT on 22 Aug 2025 (EWMA 0.94; daily, simple returns)

Confidence	VaR (VCV)	ES (VCV)	VaR (HS)	ES (HS)
90%	0.01453720	0.01996084	0.01399364	0.02347603
91%	0.01521386	0.02052794	0.01586047	0.02447826
92%	0.01594946	0.02114860	0.01645833	0.02552838
93%	0.01675891	0.02183636	0.01726701	0.02676907
94%	0.01766371	0.02261078	0.01834187	0.02829910
95%	0.01869661	0.02350173	0.01991488	0.03018831
96%	0.01991148	0.02455846	0.02245770	0.03199048
97%	0.02140699	0.02587145	0.02509336	0.03463847
98%	0.02339841	0.02763877	0.02723740	0.03873643
99%	0.02654502	0.03047004	0.03492866	0.04611230

# Conclusion

HS exceeds VCV across confidence levels, indicating fat tails in MSFT returns. Conditioning on EWMA volatility raises risk estimates during volatile periods and aligns exceedances with forecasts. Limitations include the normality assumption in VCV, finite HS samples for tail events, and fixed  $\lambda$  in EWMA.

### Appendix: R Code

Listing 1: R code for VaR and ES estimation

```
library("xts")
library("ggplot2")
setwd("/Users/haesoopyun/Documents/R/Year3")
data_raw <- read.csv("EFIM30057 Practical04 Data.csv", header = TRUE,</pre>
   stringsAsFactors = FALSE)
data_raw$date <- as.Date(data_raw$date, format = "%d/%m/%Y")</pre>
msft_prices <- xts(data_raw$msft, order.by = data_raw$date)</pre>
colnames(msft_prices) <- "msft"</pre>
msft_log_returns <- na.omit(diff(log(msft_prices)))</pre>
to_simple <- function(x) exp(x) - 1</pre>
conf_levels \leftarrow seq(0.90, 0.99, by = 0.01)
alpha <- 1 - conf_levels</pre>
z <- qnorm(alpha)</pre>
sigma_uncond <- sd(msft_log_returns$msft)</pre>
var_vcv_uncond_log <- -(sigma_uncond * z)</pre>
es_vcv_uncond_log <- sigma_uncond * dnorm(z) / alpha</pre>
returns_vec <- as.numeric(msft_log_returns$msft)</pre>
r_dm <- returns_vec - mean(returns_vec)</pre>
qs <- as.numeric(quantile(r_dm, probs = alpha, type = 1, names = FALSE))
var_hs_uncond_log <- -qs</pre>
es_hs_uncond_log <- sapply(qs, function(qa) -mean(r_dm[r_dm <= qa]))
results_uncond <- data.frame(</pre>
  Confidence = conf_levels,
  VaR_VCV = to_simple(var_vcv_uncond_log),
  ES_VCV = to_simple(es_vcv_uncond_log),
  VaR_HS = to_simple(var_hs_uncond_log),
  ES_HS = to_simple(es_hs_uncond_log)
get_val <- function(df, conf, col) df[[col]][which.min(abs(df$Confidence -</pre>
    conf))]
VaR95_vcv <- get_val(results_uncond, 0.95, "VaR_VCV")</pre>
VaR99_vcv <- get_val(results_uncond, 0.99, "VaR_VCV")</pre>
VaR95_hs <- get_val(results_uncond, 0.95, "VaR_HS")</pre>
VaR99_hs <- get_val(results_uncond, 0.99, "VaR_HS")</pre>
msft_simple_returns <- xts(to_simple(msft_log_returns$msft), order.by =</pre>
   index(msft_log_returns))
df_ret <- data.frame(Date = index(msft_simple_returns),</pre>
                      Return = as.numeric(msft_simple_returns$msft))
fig1 <- ggplot(df_ret, aes(x = Date, y = Return)) +
  geom_line(linewidth = 0.3, colour = "black") +
  geom_hline(yintercept = -VaR95_vcv, colour = "red", linetype = "dashed"
     ) +
```

```
geom_hline(yintercept = -VaR99_vcv, colour = "red", linetype = "solid")
  geom_hline(yintercept = -VaR95_hs, colour = "blue", linetype = "dashed"
  geom_hline(yintercept = -VaR99_hs, colour = "blue", linetype = "solid")
  labs(
    title = "Figure 1 - MSFT Daily Simple Returns with Unconditional VaR
       Lines",
    subtitle = "Red = VCV (Normal); Blue = HS; solid = 99%, dashed = 95%",
    x = NULL, y = "Daily simple return"
  theme_minimal()
print(fig1)
# Part b
target_date <- as.Date("2025-08-22")
lambda <- 0.94
conditional <- msft_log_returns</pre>
conditional$var_ewma <- NA</pre>
conditional$var_ewma[1] <- 0</pre>
Tn <- NROW(conditional)</pre>
for (i in 2:Tn) {
  conditional$var_ewma[i] <- lambda*conditional$var_ewma[i-1] + (1-lambda)</pre>
     *conditional $msft[i-1]^2
conditional$var_ewma[1:100] <- NA</pre>
conditional$sigma_ewma <- sqrt(conditional$var_ewma)</pre>
conditional <- na.omit(conditional)</pre>
idx_T <- max(which(index(conditional) <= target_date))</pre>
date_T <- index(conditional)[idx_T]</pre>
sigma_T <- as.numeric(conditional$sigma_ewma[idx_T])</pre>
z <- qnorm(alpha)</pre>
VaR_vcv_cond_log <- -sigma_T * z</pre>
ES_vcv_cond_log <- sigma_T * dnorm(z) / alpha
win <- 500L
window_r <- as.numeric(conditional$msft[(idx_T - win):(idx_T - 1)])</pre>
window_sig <- as.numeric(conditional$sigma_ewma[(idx_T - win):(idx_T - 1)</pre>
   ])
window_mu <- mean(window_r)</pre>
std_window <- (window_r - window_mu) / window_sig</pre>
VaR_hs_cond_log <- -sapply(alpha, function(a) {</pre>
  quantile(std_window, probs = a, type = 1, names = FALSE) * sigma_T
})
ES_hs_cond_log <- -sapply(alpha, function(a) {
  q_a <- quantile(std_window, probs = a, type = 1, names = FALSE)</pre>
  mean(std_window[std_window <= q_a]) * sigma_T</pre>
results_cond <- data.frame(</pre>
  Date = rep(date_T, length(conf_levels)),
  Confidence = conf_levels,
  VaR_VCV = to_simple(VaR_vcv_cond_log),
  ES_VCV = to_simple(ES_vcv_cond_log),
```

```
VaR_HS = to_simple(VaR_hs_cond_log),
ES_HS = to_simple(ES_hs_cond_log)
)
```