Market Risk Simulation Report

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Executive Summary

This report analyzes market risk for a financial portfolio using Monte Carlo simulations and parametric methods. Simulated returns reflect fat-tailed behavior using the Student's t-distribution. Key risk measures such as Value at Risk (VaR) and Expected Shortfall (ES) are estimated and validated using Kupiec's backtest against actual returns from AAPL.

Methodology

- Generate 10,000 one-day return paths using the t-distribution (df = 3)
- Calculate 95% one-day VaR and ES
- Backtest simulated VaR using Kupiec's test with actual historical returns

Simulated Returns & Risk Metrics

```
sim_returns <- rt(10000, df = 3) * (0.25 / sqrt(252)) + 0.0002
hist(sim_returns, breaks = 40, col = 'darkgreen', main = "Simulated Returns", xlab = "Returns"

var_val <- quantile(sim_returns, 0.05)
es_val <- mean(sim_returns[sim_returns < var_val])
abline(v = var_val, col = "red", lwd = 2)
```

```
risk_metrics <- data.frame(
  Metric = c("VaR (95%)", "Expected Shortfall"),
  Value = round(c(var_val, es_val), 5)
)
kable(risk_metrics)
```

	Metric	Value
5%	VaR (95%)	-0.03676
	Expected Shortfall	-0.06146

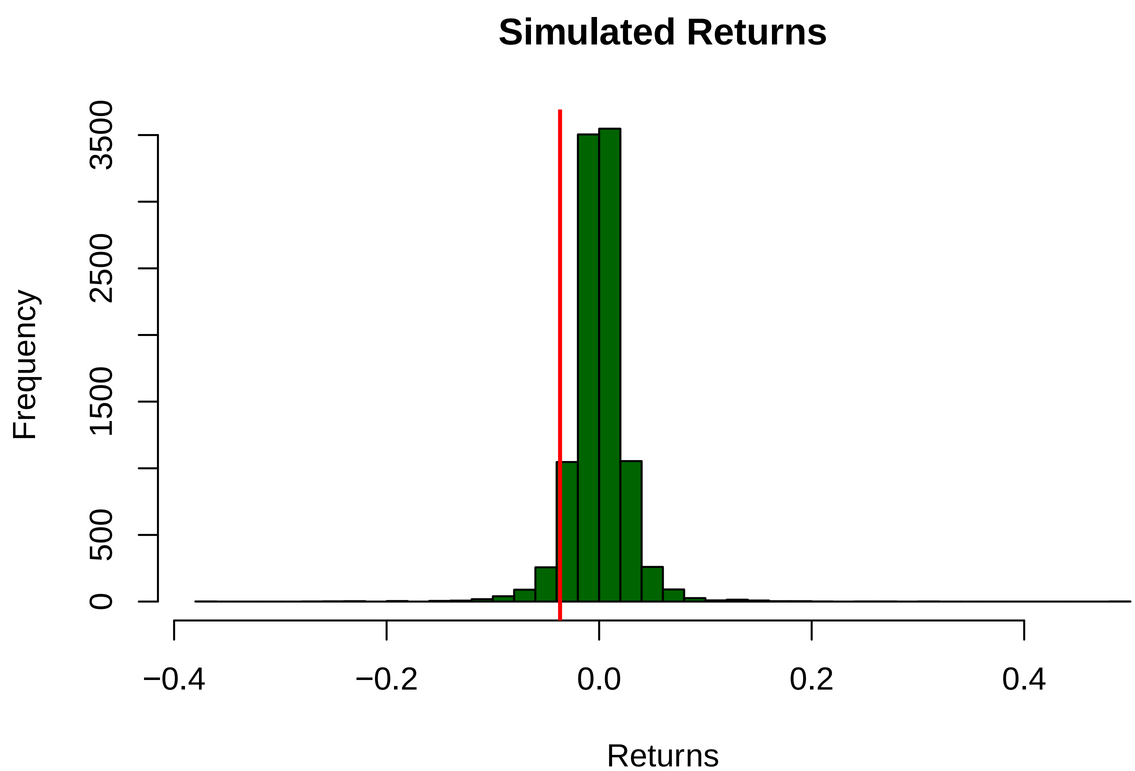

Figure 1: Simulated Daily Market Returns

```r
if (es_val < -0.05) {
  cat("\nThe Expected Shortfall exceeds -5%, suggesting high downside risk exposure.")
} else {
  cat("\nThe Expected Shortfall is moderate, indicating manageable tail risk.")
}
```

```
##
## The Expected Shortfall exceeds -5%, suggesting high downside risk exposure.
```

Kupiec Backtest

```r
kupiec_test <- function(actual_returns, var_series, alpha = 0.05) {
  n <- length(actual_returns)
  failures <- actual_returns < -var_series
  x <- sum(failures)
  pi_hat <- x / n

  if (pi_hat == 0 || pi_hat == 1) return(data.frame(
    Breaches = x,
    LR_pof = NA,
    p_value = NA,
    Result = "Test undefined (0% or 100% breach rate)"
  ))

  lr_pof <- -2 * (log((1 - alpha)^(n - x) * alpha^x) -
                  log((1 - pi_hat)^(n - x) * pi_hat^x))
  p_value <- 1 - pchisq(lr_pof, df = 1)

  data.frame(
    Breaches = x,
    LR_pof = round(lr_pof, 4),
    p_value = round(p_value, 4),
    Result = ifelse(p_value > 0.05, "Pass", "Fail")
  )
}

getSymbols("AAPL", from = "2022-01-01", to = "2023-01-01")
```

[1] "AAPL"

```r
actual_returns <- dailyReturn(Cl(AAPL))
test_result <- kupiec_test(actual_returns, rep(abs(var_val), length(actual_returns)))
kable(test_result, caption = "Kupiec Test Results for Simulated VaR")
```

Table 2: Kupiec Test Results for Simulated VaR

Breaches	LR_pof	p_value	Result
14	0.1703	0.6799	Pass

```
if (!is.na(test_result$p_value)) {
  cat(ifelse(test_result$p_value > 0.05,
             "The model passes Kupiec's test, suggesting statistically consistent risk predicti
             "The model fails Kupiec's test, indicating a potential underestimation of tail ris
}
```

The model passes Kupiec's test, suggesting statistically consistent risk prediction.

Breaches Visualization

```
var_threshold <- var_val
plot(actual_returns, type = "l", col = "black", ylab = "Returns", main = "VaR Breaches Over Ti
abline(h = var_threshold, col = "red", lwd = 2)
points(which(actual_returns < var_threshold), actual_returns[actual_returns < var_threshold], 
```

Conclusion

This analysis demonstrates how simulated VaR and ES can be used to assess market risk exposure. The backtest with historical AAPL returns provides insight into the calibration of the model. Future improvements can include dynamic volatility models (e.g., GARCH) or filtered historical simulation for robustness.

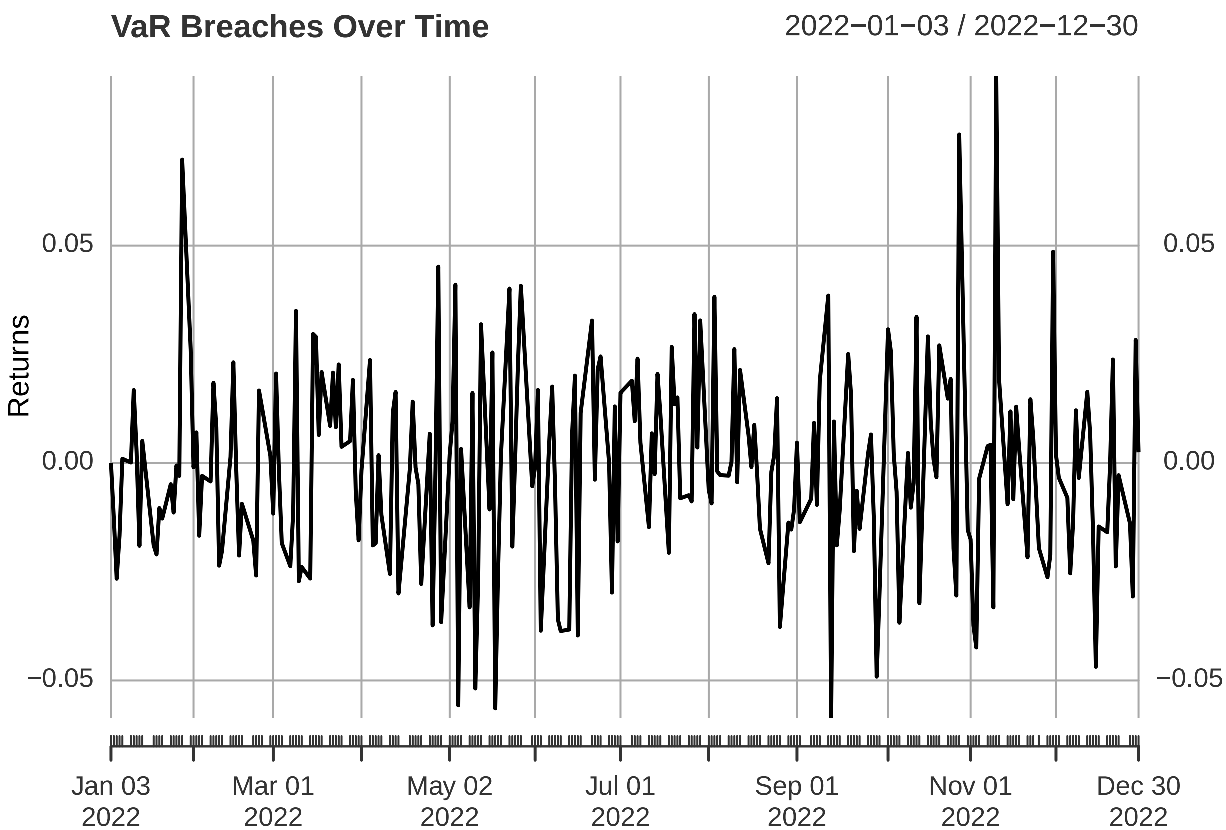

Figure 2: Actual Returns with Simulated VaR Breaches