Integrated Risk Management for Multi-Asset Portfolios

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Executive Summary

This report presents an integrated risk management framework for assessing market and credit risk on a diversified portfolio of equities and corporate bonds. The model combines parametric and Monte Carlo simulation methods to compute Value at Risk (VaR) and Expected Shortfall (ES), while also simulating credit losses based on Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD). The model includes a backtest using Kupiec's Proportion of Failures (POF) test to evaluate the consistency of VaR predictions with actual return data.

Methodology

Market Risk

- Simulate daily returns using the t-distribution (`df = 3`) to reflect fat tails in financial data.
- Calculate 1-day 95% VaR and Expected Shortfall from simulated returns.
- Conduct Monte Carlo simulations (10,000 paths) based on user-defined volatility and expected return.

Credit Risk

- Simulate credit loss distribution using Bernoulli trials for default events.
- Loss = PD × LGD × EAD for each trial.
- Display histogram of losses and compute credit risk metrics.

Correlation Analysis

- Use historical stock prices for selected tickers.
- Calculate correlation matrix and visualize using `corrplot`.

Model Validation (Kupiec Test)

```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))
sim_var <- -0.0315  # replace with your VaR result
test_result <- kupiec_test(actual_returns, rep(abs(sim_var), length(actual_returns)))
kable(test_result, caption = "Kupiec Test Results for 95% VaR")
```

Table 1: Kupiec Test Results for 95% VaR

Breaches	LR_pof	p_value	Result
20	3.9757	0.0462	Fail

```r
if (!is.na(test_result$p_value)) {
  cat(ifelse(test_result$p_value > 0.05,
             "The Kupiec test indicates that the model's predicted risk levels are statistical
             "The Kupiec test failed, suggesting the model may be underestimating or overestima
}
```

The Kupiec test failed, suggesting the model may be underestimating or overestimating risk.

Visual Outputs

Simulated Returns Distribution

```
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)
```

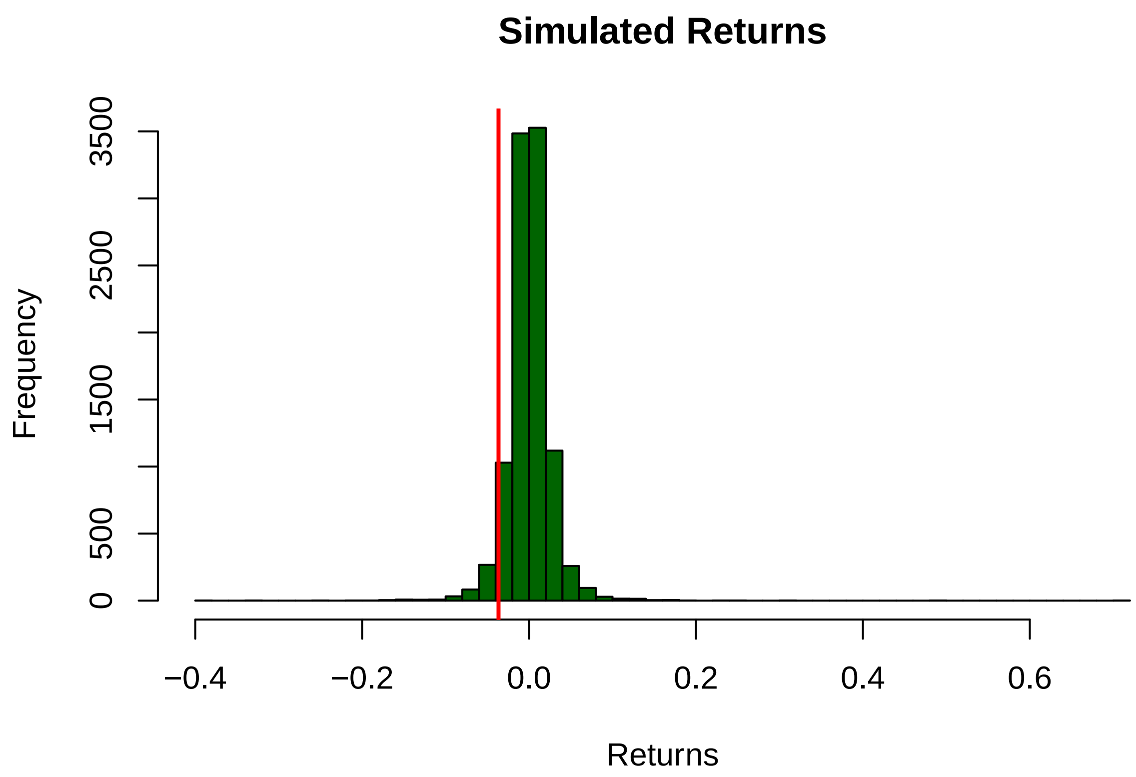

Figure 1: Simulated Daily Market Returns

```
if (es_val < -0.05) {
  cat("\nThe Expected Shortfall exceeds -5%, suggesting the portfolio is highly exposed to ext
} else {
  cat("\nThe Expected Shortfall is moderate, indicating limited exposure to tail events.\n")
}
```

```
##
## The Expected Shortfall exceeds -5%, suggesting the portfolio is highly exposed to extreme do
```

VaR Breaches Over Time

```
var_threshold <- -0.0315
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], c
```

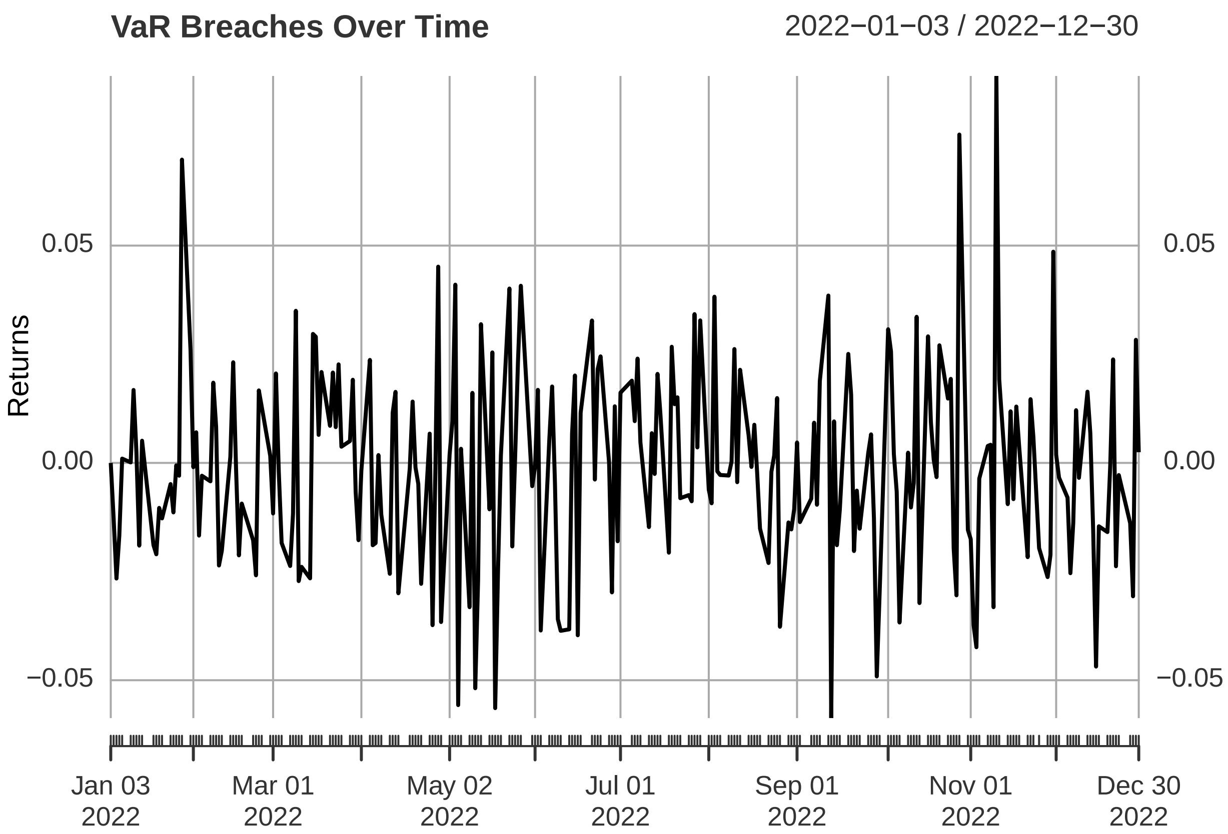

Figure 2: Actual Returns with 95% VaR Breaches

Credit Risk Simulation

```
set.seed(123)
pd <- 0.05
lgd <- 0.6
ead <- 100000
n <- 1000

losses <- rbinom(n, 1, pd) * lgd * ead
hist(losses, breaks = 20, col = "purple", main = "Credit Loss Distribution", xlab = "Loss Amou
```

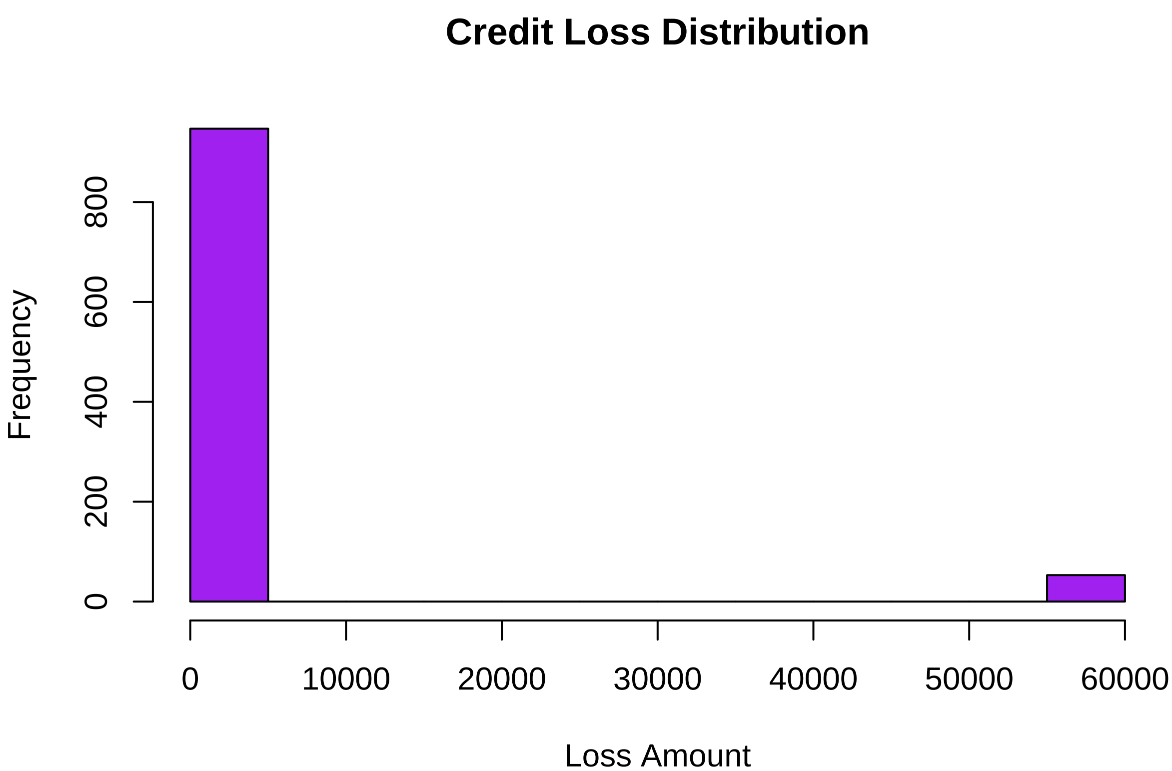

Figure 3: Simulated Credit Losses

```r
avg_loss <- mean(losses)
max_loss <- max(losses)
cat(paste("\nAverage Loss:", round(avg_loss, 2)))
```

```
##
## Average Loss: 3180
```

```r
cat(paste("\nMaximum Loss:", round(max_loss, 2)))
```

```
##
## Maximum Loss: 60000
```

Correlation Analysis

```r
tickers <- c("AAPL", "MSFT", "GOOG", "AMZN")
getSymbols(tickers, from = "2022-01-01", to = "2023-01-01")
```

```
## [1] "AAPL" "MSFT" "GOOG" "AMZN"
```

```r
prices <- do.call(merge, lapply(tickers, function(t) Cl(get(t))))
returns <- na.omit(ROC(prices))
corr_matrix <- cor(returns)
corrplot(corr_matrix, method = "color", type = "lower", tl.cex = 0.8)
```

Limitations & Extensions

- The model assumes i.i.d. returns; future work should explore GARCH models for volatility clustering.
- Current simulations use fixed volatilities — rolling VaR or EWMA could improve responsiveness.
- Historical simulation or filtered historical simulation could further improve tail risk modeling.
- The credit risk model does not incorporate macroeconomic covariates — an extension with logistic regression or machine learning could improve predictions.

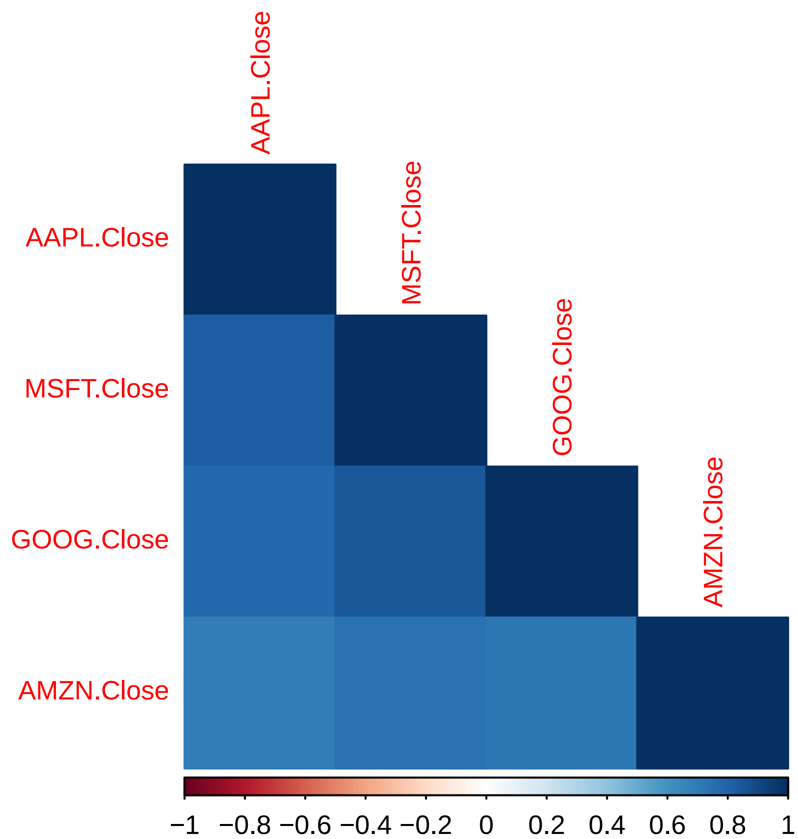

Figure 4: Correlation Matrix for Selected Tickers