

Project 2 – Rolling Correlation and Portfolio Risk in Cryptocurrencies

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1. Objective

To analyze time-varying dependence between Bitcoin and selected altcoins using rolling correlations, and to evaluate the implications for portfolio risk, volatility, and Value-at-Risk (VaR).

This project bridges univariate volatility modeling (Project 1) and multivariate conditional dependence modeling (Project 3).

2. Libraries & Setup

```
library(quantmod)
library(xts)
library(tidyverse)
library(zoo)
library(PerformanceAnalytics)
```

3. Data Download and Preparation

```
get_crypto_data <- function(symbol, start_date = "2025-01-01") {
  tryCatch({
    data <- getSymbols(
      paste0(symbol, "-USD"),
      src = "yahoo",
      from = start_date,
      auto.assign = FALSE
    )
    Cl(data)
  }, error = function(e) {
    message(paste("Downloading error:", symbol))
    return(NULL)
  })
}

btc  <- get_crypto_data("BTC")
eth  <- get_crypto_data("ETH")
link <- get_crypto_data("LINK")
zec  <- get_crypto_data("ZEC")

prices <- na.omit(merge(btc, eth, link, zec))
colnames(prices) <- c("BTC", "ETH", "LINK", "ZEC")

head(prices)
```

```
##          BTC      ETH      LINK      ZEC
## 2025-01-01 94419.76 3353.504 21.67484 58.11317
## 2025-01-02 96886.88 3451.393 22.04044 59.39714
## 2025-01-03 98107.43 3605.010 23.39836 60.91785
## 2025-01-04 98236.23 3657.707 23.61336 59.18812
```

```
## 2025-01-05 98314.96 3634.104 23.63523 58.53623
## 2025-01-06 102078.09 3688.611 23.81981 60.16333
```

4. Log Returns

```
returns <- na.omit(diff(log(prices)))
summary(returns)
```

```
##      Index          BTC          ETH
##  Min.   :2025-01-02  Min.   :-0.0908227  Min.   :-0.1607306
##  1st Qu.:2025-03-31  1st Qu.:-0.0125000  1st Qu.:-0.0235762
##  Median :2025-06-27  Median :-0.0002815  Median : 0.0001428
##  Mean   :2025-06-27  Mean   :-0.0001982  Mean   :-0.0003402
##  3rd Qu.:2025-09-23  3rd Qu.: 0.0116691  3rd Qu.: 0.0195359
##  Max.   :2025-12-21  Max.   : 0.0912150  Max.   : 0.1972001
##      LINK          ZEC
##  Min.   :-0.237734  Min.   :-0.222889
##  1st Qu.:-0.028336  1st Qu.:-0.029082
##  Median :-0.001650  Median : 0.003598
##  Mean   :-0.001559  Mean   : 0.005770
##  3rd Qu.: 0.026852  3rd Qu.: 0.034111
##  Max.   : 0.163347  Max.   : 0.477598
```

5. Rolling Correlation Analysis

Rolling correlations capture short-term dependence dynamics that are not observable in static correlation measures.

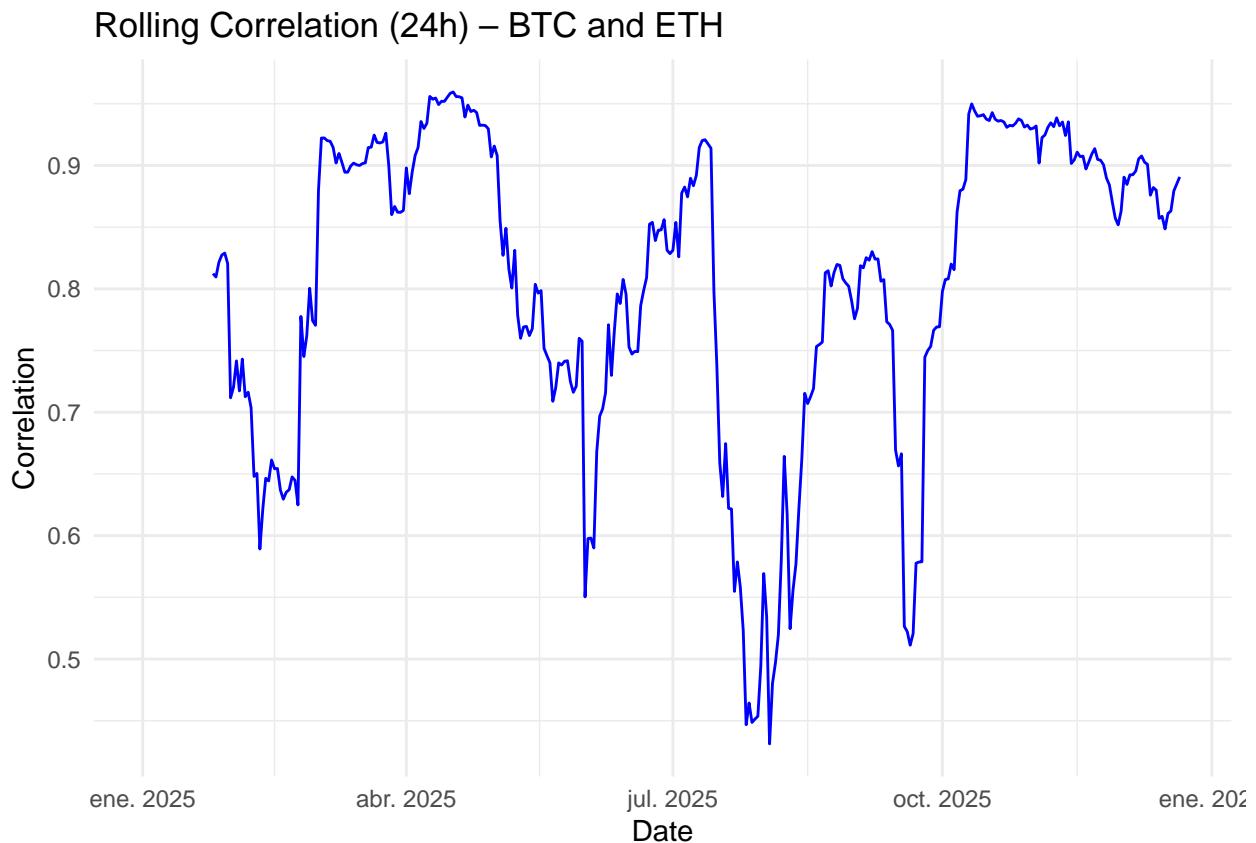
5.1 BTC–ETH Rolling Correlation

```
roll_corr_btc_eth <- rollapply(
  data = returns[, c("BTC", "ETH")],
  width = 24,
  FUN = function(x) cor(x[,1], x[,2]),
  by.column = FALSE,
  align = "right",
  fill = NA
)

roll_corr_df <- data.frame(
  Date = index(returns),
  BTC_ETH = roll_corr_btc_eth
)

ggplot(roll_corr_df, aes(x = Date, y = BTC_ETH)) +
  geom_line(color = "blue") +
  labs(
```

```
    title = "Rolling Correlation (24h) - BTC and ETH",
    y = "Correlation",
    x = "Date"
) +
theme_minimal()
```



5.2 Comparison Across Altcoins

```
roll_corr_matrix <- rollapply(
  returns,
  width = 24,
  FUN = function(x) cor(x)[1, ],
  by.column = FALSE,
  align = "right",
  fill = NA
)

roll_corr_df2 <- data.frame(
  Date = index(returns),
  roll_corr_matrix
)

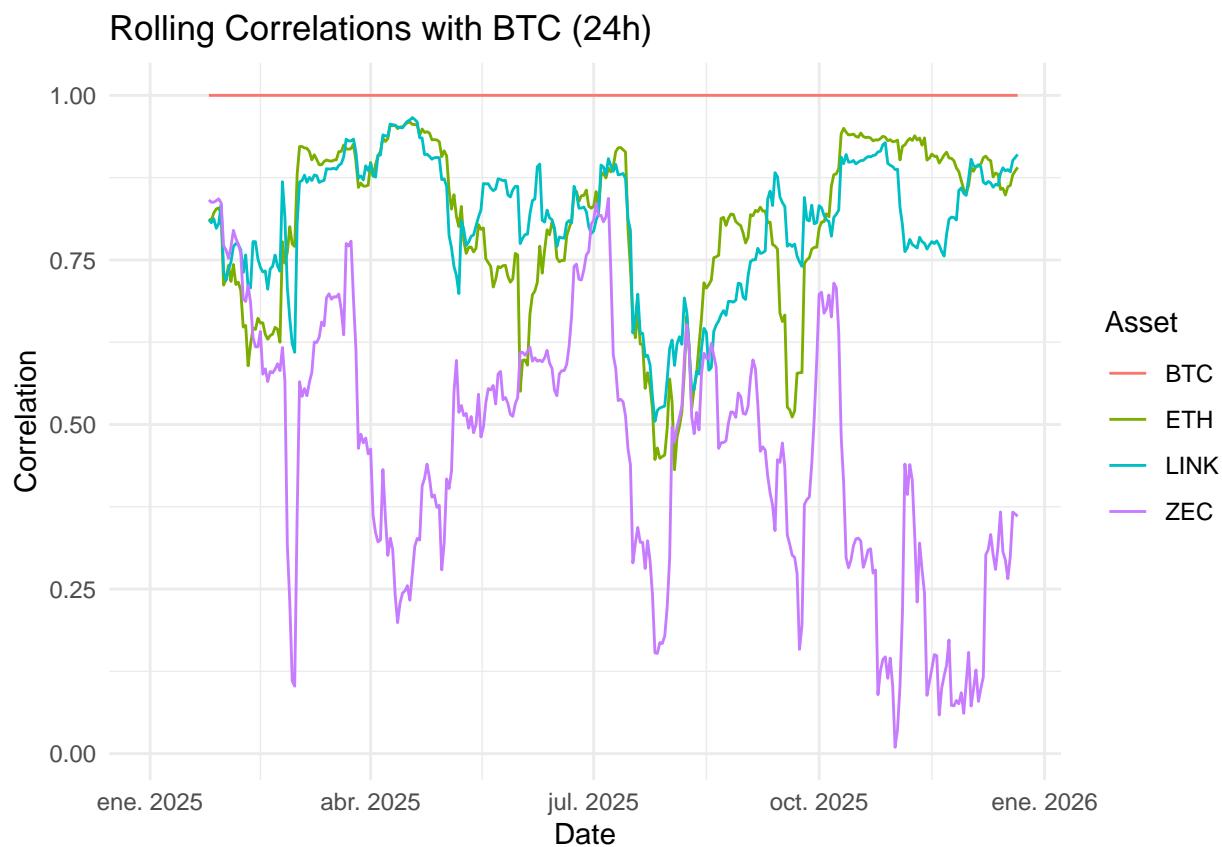
roll_corr_df2_long <- pivot_longer(
```

```

roll_corr_df2,
cols = -Date,
names_to = "Asset",
values_to = "Correlation"
)

ggplot(roll_corr_df2_long, aes(x = Date, y = Correlation, color = Asset)) +
  geom_line() +
  labs(
    title = "Rolling Correlations with BTC (24h)",
    y = "Correlation",
    x = "Date"
  ) +
  theme_minimal()

```



6. Portfolio Construction

An equally weighted portfolio is constructed to evaluate diversification and risk dynamics.

```

weights <- rep(1 / ncol(returns), ncol(returns))
portfolio_returns <- xts(as.matrix(returns) %*% weights, order.by = index(returns))

colnames(portfolio_returns) <- "Portfolio"

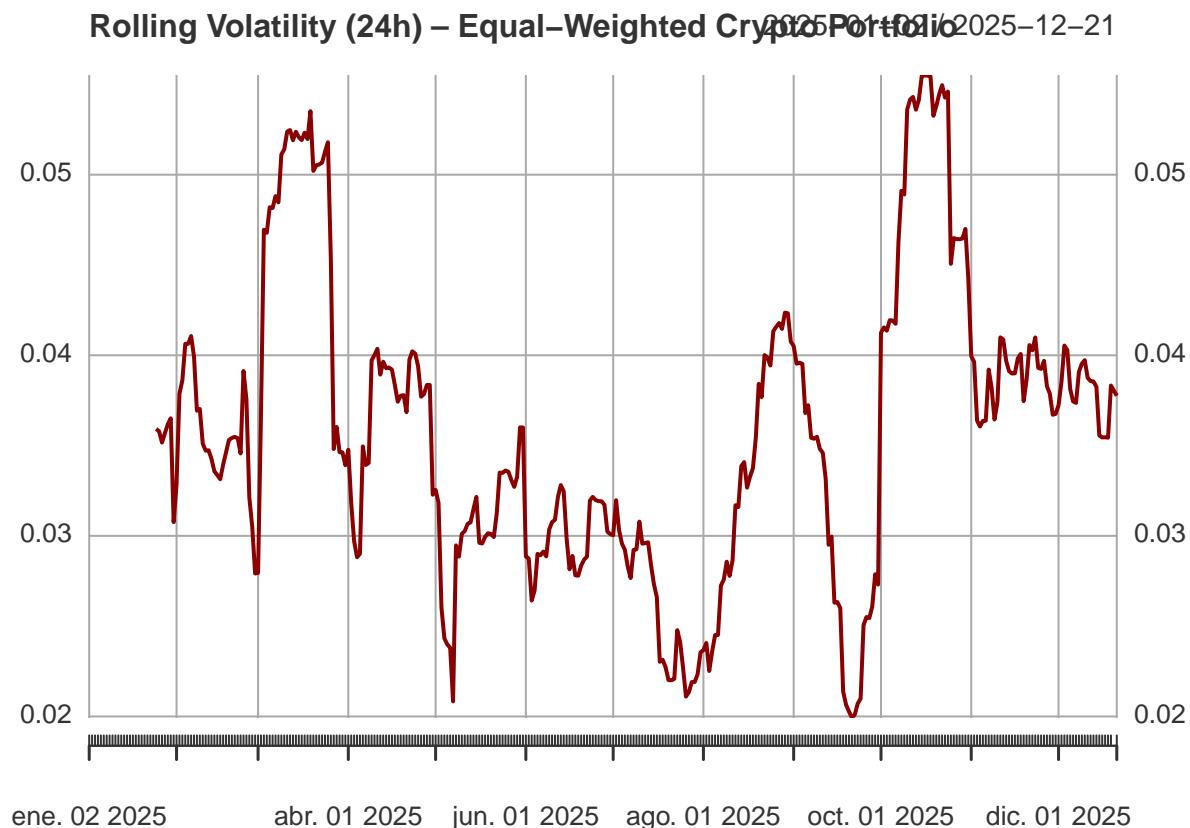
```

7. Portfolio Risk Measures

7.1 Rolling Volatility

```
portfolio_vol <- rollapply(
  portfolio_returns,
  width = 24,
  FUN = sd,
  align = "right",
  fill = NA
)

plot(portfolio_vol,
  main = "Rolling Volatility (24h) - Equal-Weighted Crypto Portfolio",
  col = "darkred")
```



7.2 Value-at-Risk (VaR)

A historical 5% VaR is computed.

```
portfolio_var <- rollapply(
  portfolio_returns,
  width = 24,
```

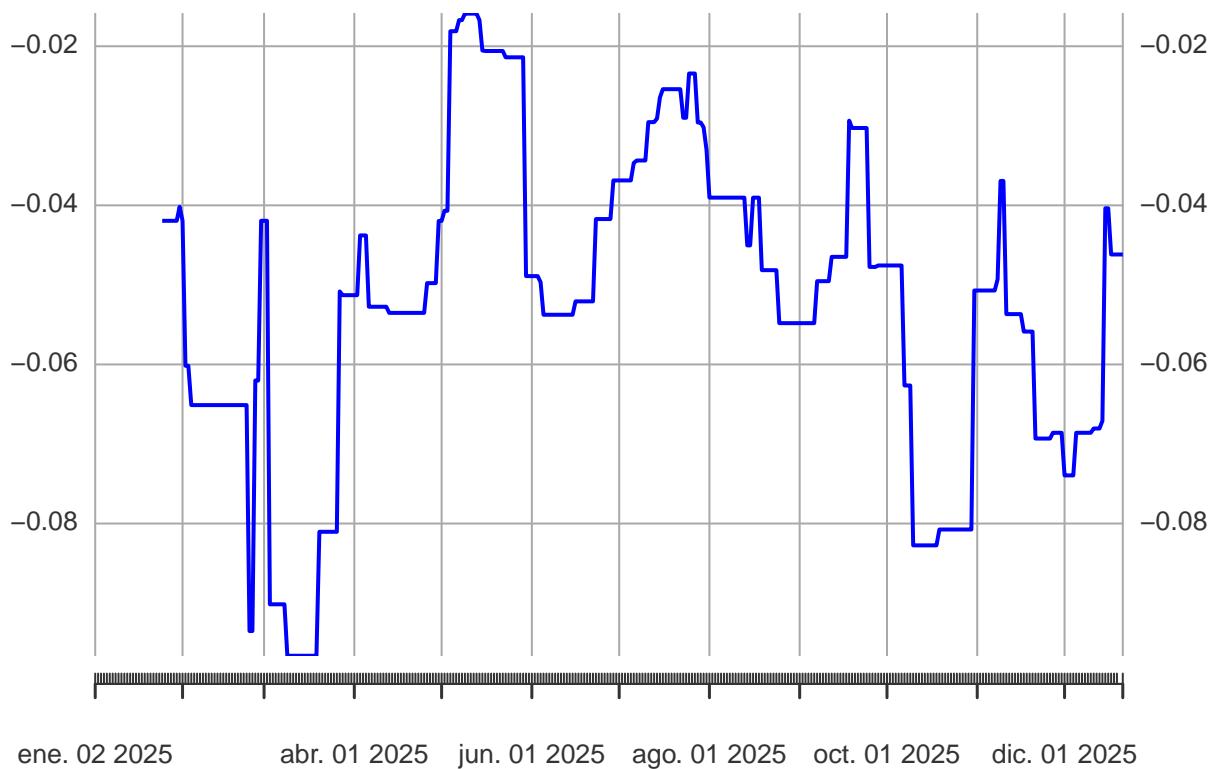
```

FUN = function(x) {
  quantile(x, 0.05)
},
align = "right",
fill = NA
)

plot(portfolio_var,
main = "Rolling 5% VaR - Equal-Weighted Crypto Portfolio",
col = "blue")

```

Rolling 5% VaR – Equal-Weighted Crypto Portfolio 2025-01-02 / 2025-12-21



8. Interpretation

Rolling correlations reveal strong time variation in dependence between BTC and altcoins.

Periods of market stress tend to exhibit higher correlations, reducing diversification benefits.

Portfolio volatility and VaR increase during high-correlation regimes.

Static correlation measures would underestimate risk during turbulent periods.

9. Limitations

Rolling window choice is arbitrary and may affect results.

Correlations are unconditional and do not account for volatility clustering.

VaR is computed using a historical quantile approach and assumes equal portfolio weights.

These limitations motivate the use of DCC-GARCH models in Project 3.

10. Conclusion

This project demonstrates how:

Dependence between crypto-assets is dynamic rather than constant.

Portfolio risk is strongly affected by changing correlation structures.

Rolling correlation analysis provides intuition but lacks a full probabilistic framework.

Project 2 provides the conceptual and empirical bridge between univariate volatility modeling (Project 1) and multivariate conditional dependence modeling (Project 3).