ECO 3323 Project 2: Principles of Money, Banking, and Credit

2025-11-24

Part I: Sovereign Risk & Macroeconomic Fundamentals

Load Data

```
load("data_risk.RData")
data_risk <- as_tibble(data_risk)
glimpse(data_risk)
```

```
## Rows: 1,370
## Columns: 32
## $ country_name      <chr> "Abu Dhabi", "Abu Dhabi", "Abu Dhabi", "Abu Dhabi"~
## $ country_code      <chr> "AEAD", "AEAD", "AEAD", "AEAD", "AEAD", "AEAD", "A~
## $ lt_fc_rating      <fct> AA, AA, AA, AA, AA, AA, AA, AA, AA, AA, BB-, BB-, ~
## $ year              <dbl> 2018, 2019, 2020, 2021, 2022, 2023, 2024, 2025, 20~
## $ banks_claim_gdp   <dbl> 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.~
## $ banks_claim_gr    <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, -3.65, 6.6~
## $ chg_net_gg_debt_gdp <dbl> -17.14, -17.02, -15.18, -26.09, -36.16, -19.23, -1~
## $ cpi_gr            <dbl> 3.30, -0.84, -2.41, 1.48, 5.55, 0.01, 1.50, 1.50, ~
## $ debt_rev          <dbl> 18.66, 33.21, 73.39, 53.71, 40.97, 46.90, 54.17, 5~
## $ exch_rate         <dbl> 3.67, 3.67, 3.67, 3.67, 3.67, 3.67, 3.67, 3.67, 3.~
## $ exp_gdp           <dbl> 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.~
## $ fc_claims         <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 50.77, 49.~
## $ fc_deposits       <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 53.87, 54.~
## $ gdp_def_gr        <dbl> 12.71, -4.16, -16.40, 23.84, 17.12, -4.08, 1.03, -~
## $ gdp_gr            <dbl> 1.68, -1.51, -7.74, 3.42, 9.24, 3.09, 4.51, 3.80, ~
## $ gdp_pc            <dbl> 84857.54, 78959.42, 60157.96, 76000.07, 94409.86, ~
## $ gdp_pc_gr         <dbl> 0.16, -2.91, -8.86, 2.01, 6.06, 0.08, 1.47, 0.77, ~
## $ gg_bal_gdp        <dbl> -0.12, 0.31, -5.33, 4.30, 10.90, 3.75, 3.63, 3.74,~
## $ gg_exp_gdp        <dbl> 34.94, 36.00, 37.49, 32.58, 26.00, 28.00, 28.00, 2~
## $ gg_int_exp_rev    <dbl> 0.63, 0.61, 1.65, 1.32, 1.12, 1.30, 1.19, 1.42, 1.~
## $ gg_rev_gdp        <dbl> 34.82, 36.31, 32.16, 36.88, 36.91, 31.75, 31.63, 3~
## $ gross_gg_debt_gdp <dbl> 6.50, 12.06, 23.60, 19.81, 15.12, 14.89, 17.13, 16~
## $ inv_gdp           <dbl> 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.~
## $ inv_gr            <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 2.35, -3.5~
## $ liq_assets_gdp    <dbl> 249.57, 286.57, 394.72, 335.64, 298.13, 320.32, 32~
## $ net_gg_debt_gdp   <dbl> -243.07, -274.51, -371.12, -315.84, -283.01, -305.~
## $ nom_gdp_lc        <dbl> 932.44, 880.20, 678.84, 869.49, 1112.51, 1100.10, ~
## $ nom_gdp_usd       <dbl> 253.90, 239.67, 184.84, 236.76, 302.93, 299.55, 31~
## $ prim_gg_bal_gdp   <dbl> 0.10, 0.53, -4.80, 4.78, 11.32, 4.16, 4.01, 4.17, ~
## $ reer_gr           <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 7.21, 3.43~
## $ sav_gdp           <dbl> 0.00, 0.00, 0.00, 0.00, 0.00, NA, NA, NA, NA, NA, ~
## $ unemp_rate        <dbl> 5.20, 6.90, 7.30, 6.90, 6.50, 6.00, 6.00, 6.00, 6.~
```

```
summary(data_risk)
```

```
##   country_name       country_code        lt_fc_rating       year
##   Length:1370        Length:1370        B-     :160    Min.   :2018
##   Class :character   Class :character   BBB-   :120    1st Qu.:2020
##   Mode  :character   Mode  :character   AAA    :110    Median :2022
##                                         BB-    :110    Mean   :2022
##                                         A+     :100    3rd Qu.:2025
##                                         B+     : 90    Max.   :2027
##                                         (Other):680
##   banks_claim_gdp   banks_claim_gr    chg_net_gg_debt_gdp     cpi_gr
##   Min.   :  0.00    Min.   :-27.750   Min.   :-66.440    Min.   : -5.820
##   1st Qu.: 29.59    1st Qu.:  3.000   1st Qu.:  0.690    1st Qu.:  1.960
##   Median : 51.94    Median :  5.615   Median :  3.280    Median :  2.900
##   Mean   : 65.03    Mean   :  7.632   Mean   :  3.712    Mean   :  5.801
##   3rd Qu.: 88.58    3rd Qu.: 10.000   3rd Qu.:  5.968    3rd Qu.:  5.485
##   Max.   :268.34    Max.   :299.160   Max.   :249.870    Max.   :250.010
##   NA's   :38        NA's   :74
##     debt_rev         exch_rate          exp_gdp           fc_claims
##   Min.   :  -3.8    Min.   :3.000e-01   Min.   :  0.00    Min.   :  0.000
##   1st Qu.: 119.2    1st Qu.:1.000e+00   1st Qu.: 25.47    1st Qu.:  0.000
##   Median : 200.1    Median :6.705e+00   Median : 38.14    Median :  7.365
##   Mean   : 234.3    Mean   :1.071e+03   Mean   : 45.85    Mean   : 16.760
##   3rd Qu.: 292.3    3rd Qu.:1.069e+02   3rd Qu.: 55.43    3rd Qu.: 26.600
##   Max.   :4781.5    Max.   :1.006e+05   Max.   :215.47    Max.   :103.790
##                                         NA's   :52        NA's   :554
##    fc_deposits       gdp_def_gr         gdp_gr            gdp_pc
##   Min.   :  0.00    Min.   :-32.740   Min.   :-33.820   Min.   :   455.4
##   1st Qu.:  3.35    1st Qu.:  1.840   1st Qu.:  1.465   1st Qu.:  4465.1
##   Median : 15.90    Median :  2.985   Median :  2.915   Median : 13706.2
##   Mean   : 21.50    Mean   :  5.540   Mean   :  2.765   Mean   : 26106.7
##   3rd Qu.: 33.00    3rd Qu.:  5.487   3rd Qu.:  4.857   3rd Qu.: 35012.1
##   Max.   :100.00    Max.   :247.510   Max.   : 91.140   Max.   :206135.2
##   NA's   :329
##    gdp_pc_gr          gg_bal_gdp         gg_exp_gdp        gg_int_exp_rev
##   Min.   :-36.180   Min.   :-31.6800   Min.   :  6.00    Min.   :-0.130
##   1st Qu.:  0.500   1st Qu.: -4.8400   1st Qu.: 23.54    1st Qu.: 2.962
##   Median :  1.915   Median : -2.8250   Median : 31.41    Median : 6.240
##   Mean   :  1.755   Mean   : -2.8281   Mean   : 33.36    Mean   : 8.984
##   3rd Qu.:  3.620   3rd Qu.: -0.7825   3rd Qu.: 41.64    3rd Qu.:11.360
##   Max.   : 83.830   Max.   : 25.5600   Max.   :129.82    Max.   :77.720
##
##    gg_rev_gdp       gross_gg_debt_gdp    inv_gdp           inv_gr
##   Min.   :  6.00    Min.   : -1.07     Min.   : 0.00     Min.   :-67.610
##   1st Qu.: 20.30    1st Qu.: 35.24     1st Qu.:18.97     1st Qu.:  1.000
##   Median : 28.36    Median : 53.10     Median :22.96     Median :  3.250
##   Mean   : 30.53    Mean   : 58.56     Mean   :23.03     Mean   :  3.409
##   3rd Qu.: 39.27    3rd Qu.: 73.71     3rd Qu.:26.94     3rd Qu.:  6.497
##   Max.   :126.75    Max.   :355.29     Max.   :55.02     Max.   :100.690
##                                        NA's   :66        NA's   :140
##   liq_assets_gdp    net_gg_debt_gdp     nom_gdp_lc         nom_gdp_usd
##   Min.   : -1.130   Min.   :-569.49    Min.   :0.000e+00   Min.   :     0.05
##   1st Qu.:  4.593   1st Qu.:  21.28    1st Qu.:8.770e+01   1st Qu.:    20.84
```

```
## Median :  8.050    Median :  43.70    Median :1.455e+03    Median :    87.22
## Mean   : 26.109    Mean   :  32.45    Mean   :2.986e+05    Mean   :   730.60
## 3rd Qu.: 16.390    3rd Qu.:  63.91    3rd Qu.:1.566e+04    3rd Qu.:   404.83
## Max.   :579.640    Max.   : 348.21    Max.   :2.845e+07    Max.   :32439.29
##
## prim_gg_bal_gdp        reer_gr           sav_gdp          unemp_rate
## Min.   :-31.2500    Min.   :-36.4300    Min.   :-34.27    Min.   : 0.000
## 1st Qu.: -2.3900    1st Qu.: -2.3700    1st Qu.: 17.11    1st Qu.: 3.800
## Median : -0.6900    Median :  0.5500    Median : 22.36    Median : 5.700
## Mean   : -0.7431    Mean   :  0.9209    Mean   : 22.86    Mean   : 7.727
## 3rd Qu.:  0.8700    3rd Qu.:  2.9550    3rd Qu.: 28.95    3rd Qu.: 9.107
## Max.   : 26.0800    Max.   :180.1300    Max.   : 57.72    Max.   :48.100
##                     NA's   :555         NA's   :97        NA's   :144
```

Exercise 1: Cross-Section by Rating (2024)

```r
data_2024 <- data_risk %>% filter(year == 2024)
# GDP per Capita
ggplot(data_2024, aes(x = lt_fc_rating, y = gdp_pc)) +
  geom_boxplot() +
  labs(title = "GDP per Capita vs LT FC Rating (2024)",
       x = "Long-Term FC Rating", y = "GDP per Capita (USD)") +
  theme_minimal()
```


GDP per Capita vs LT FC Rating (2024)
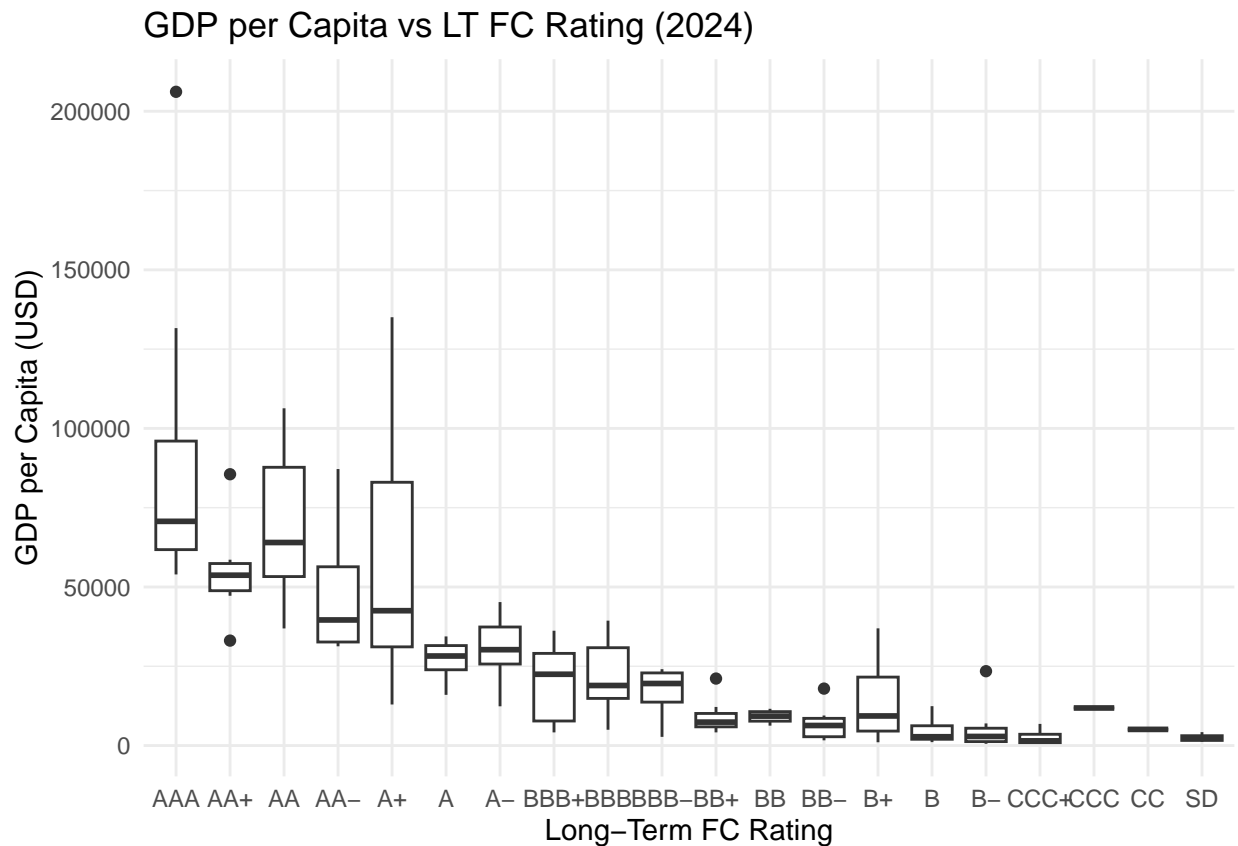
Interpretation: Higher-rated countries tend to have higher GDP per capita. Some overlap exists between mid-tier ratings. Outliers in lower ratings show very low GDP.

```
# CPI Growth
ggplot(data_2024, aes(x = lt_fc_rating, y = cpi_gr)) +
  geom_boxplot() +
  labs(title = "CPI Growth vs LT FC Rating (2024)",
       x = "Long-Term FC Rating", y = "CPI Growth (%)") +
  theme_minimal()
```


CPI Growth vs LT FC Rating (2024)
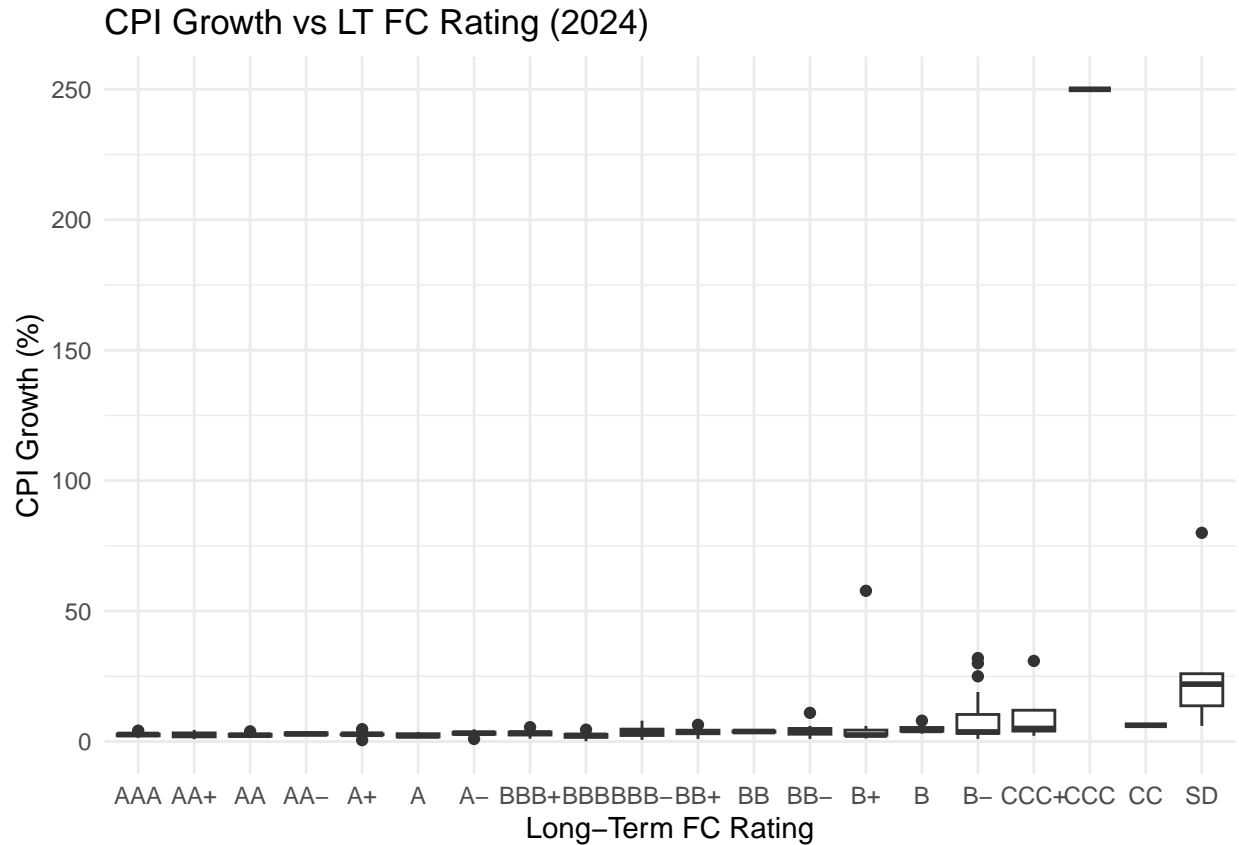
Interpretation: Countries with better ratings generally show moderate and stable CPI growth; low-rated countries show more volatility and higher inflation outliers.

```
# Unemployment Rate
ggplot(data_2024, aes(x = lt_fc_rating, y = unemp_rate)) +
  geom_boxplot() +
  labs(title = "Unemployment Rate vs LT FC Rating (2024)",
       x = "Long-Term FC Rating", y = "Unemployment Rate (%)") +
  theme_minimal()
```

Unemployment Rate vs LT FC Rating (2024)
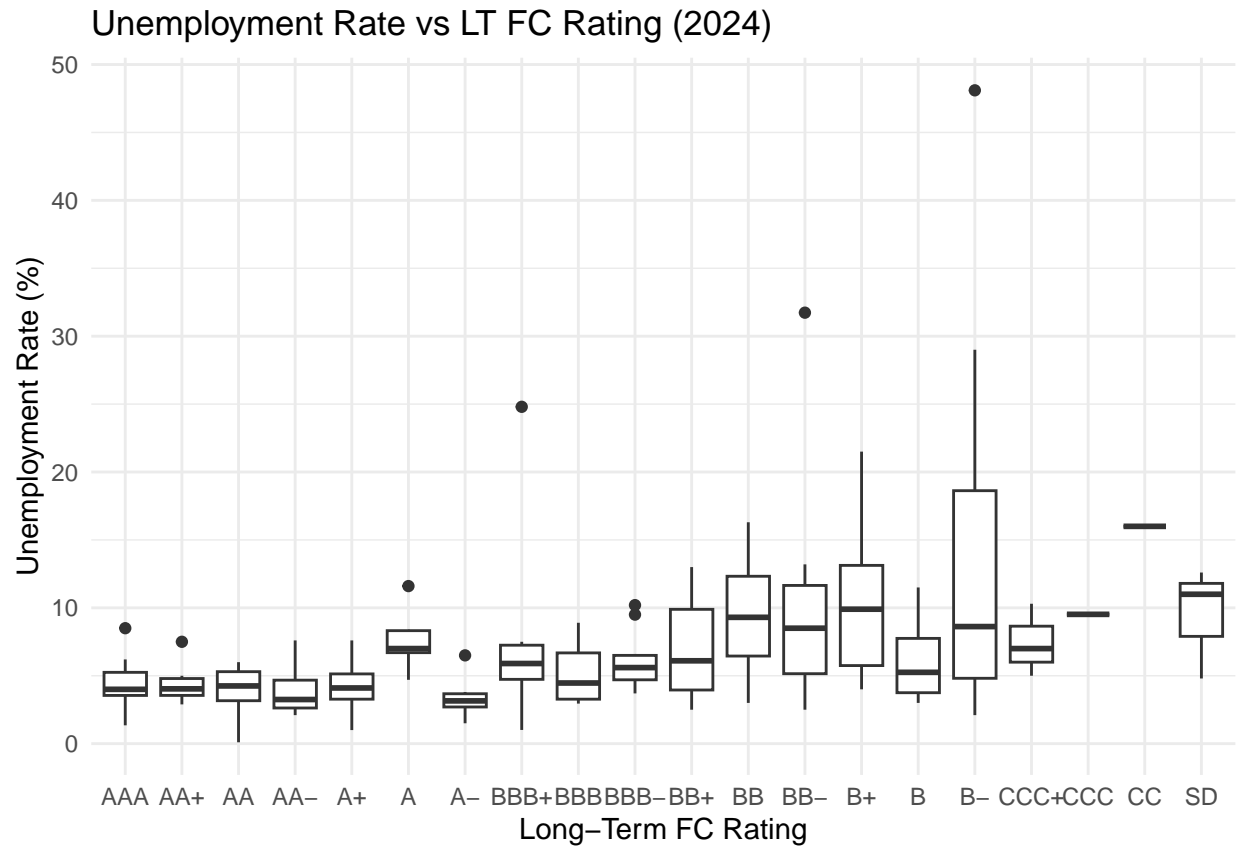
Interpretation: Lower unemployment aligns with better ratings, though some outliers in mid-ratings indicate overlap.

```
# Government Balance
ggplot(data_2024, aes(x = lt_fc_rating, y = gg_bal_gdp)) +
  geom_boxplot() +
  labs(title = "Government Balance (% of GDP) vs LT FC Rating (2024)",
       x = "Long-Term FC Rating", y = "Government Balance (% of GDP)") +
  theme_minimal()
```

Government Balance (% of GDP) vs LT FC Rating (2024)
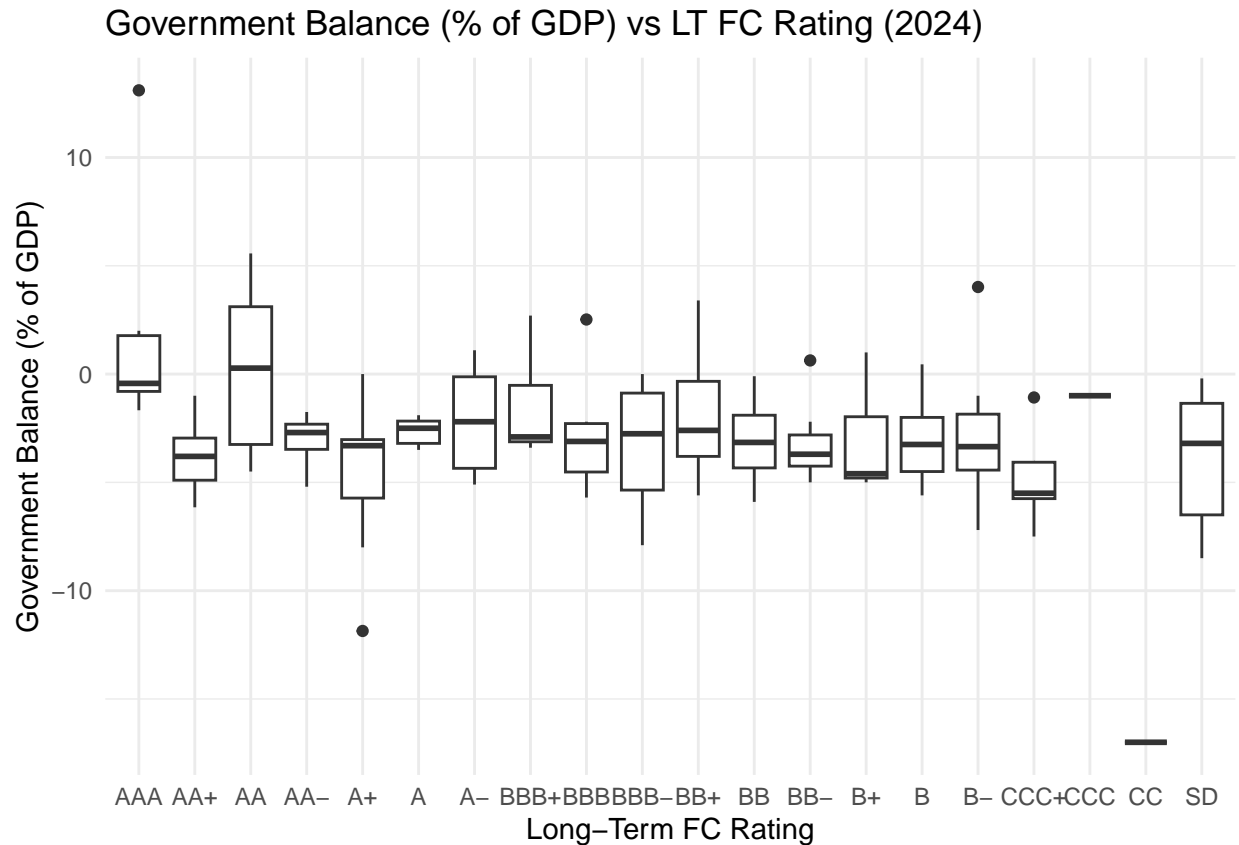
Interpretation: Positive fiscal balances are more common in higher-rated countries, with lower ratings showing deficits and outliers.

Exercise 2: Simple Relationships

```
# Debt/Revenues vs GDP per Capita
ggplot(data_2024, aes(x = debt_rev, y = gdp_pc, color = lt_fc_rating)) +
  geom_point() +
  labs(title = "Debt/Revenues vs GDP per Capita (2024)",
       x = "Debt / Revenues (%)", y = "GDP per Capita (USD)", color = "Rating") +
  theme_minimal()
```

Debt/Revenues vs GDP per Capita (2024)
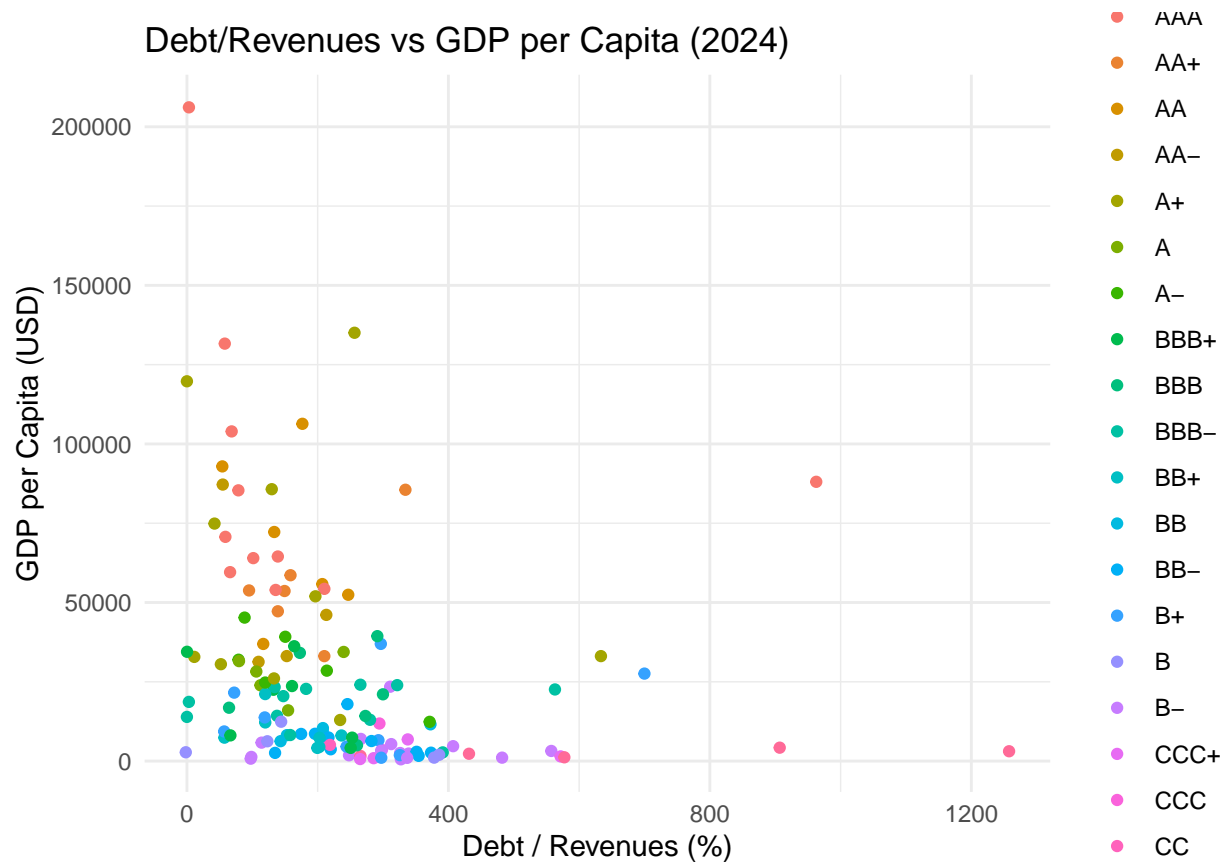
Interpretation: There is a negative relationship: higher debt/revenues correlate with lower GDP per capita. Higher ratings cluster in low debt/high GDP areas.

```r
# Unemployment vs CPI Growth
ggplot(data_2024, aes(x = unemp_rate, y = cpi_gr, color = lt_fc_rating)) +
  geom_point() +
  labs(title = "Unemployment vs CPI Growth (2024)",
       x = "Unemployment Rate (%)", y = "CPI Growth (%)", color = "Rating") +
  theme_minimal()
```

Unemployment vs CPI Growth (2024)
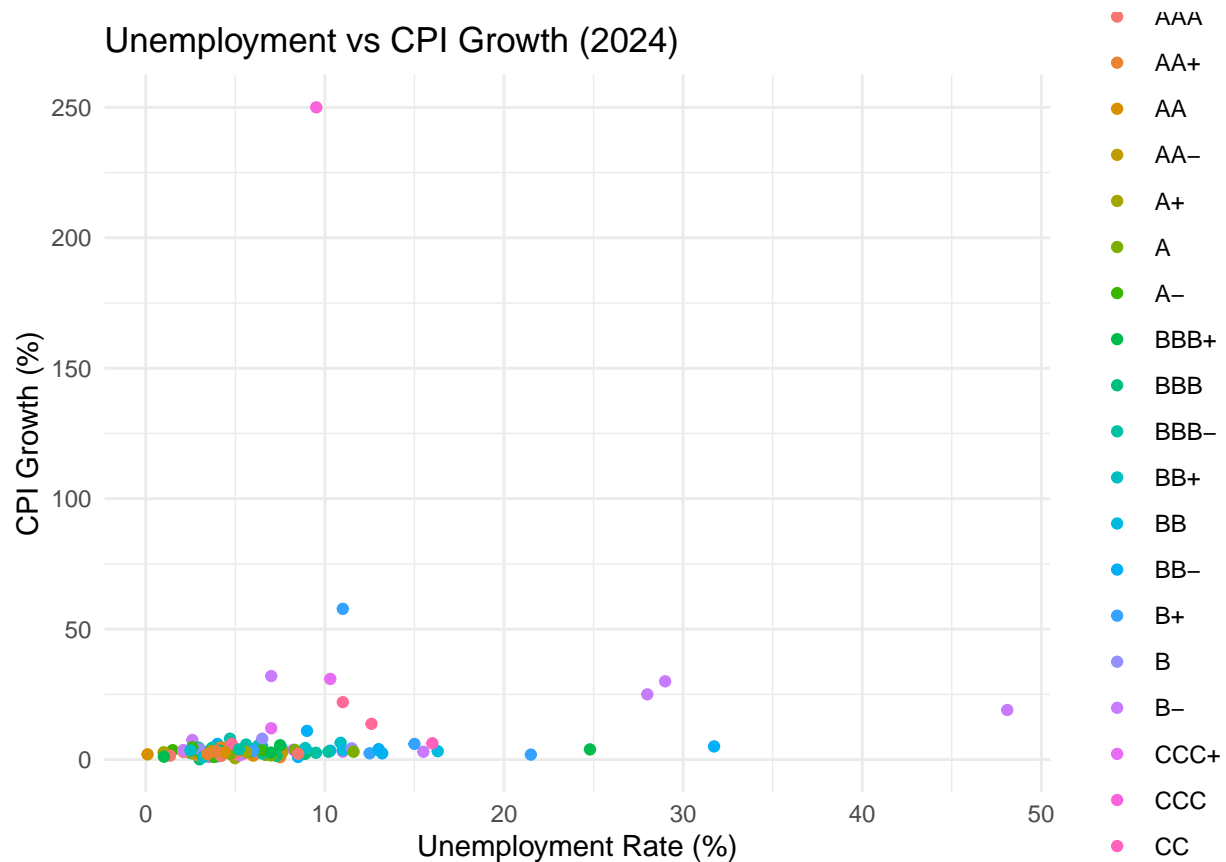
Interpretation: Weak positive correlation between unemployment and CPI growth; lower-rated countries cluster in high unemployment and high/instable inflation.

Exercise 3: Median Trends by Rating

```r
median_trends <- data_risk %>%
  group_by(year, lt_fc_rating) %>%
  summarize(
    median_gdp_pc = median(gdp_pc, na.rm = TRUE),
    median_cpi_gr = median(cpi_gr, na.rm = TRUE)
  )
# Median GDP per capita
ggplot(median_trends, aes(x = year, y = median_gdp_pc, color = lt_fc_rating)) +
  geom_line() +
  labs(title = "Median GDP per Capita Over Time by Rating",
       x = "Year", y = "Median GDP per Capita (USD)", color = "Rating") +
  theme_minimal()
```

Median GDP per Capita Over Time by Rating
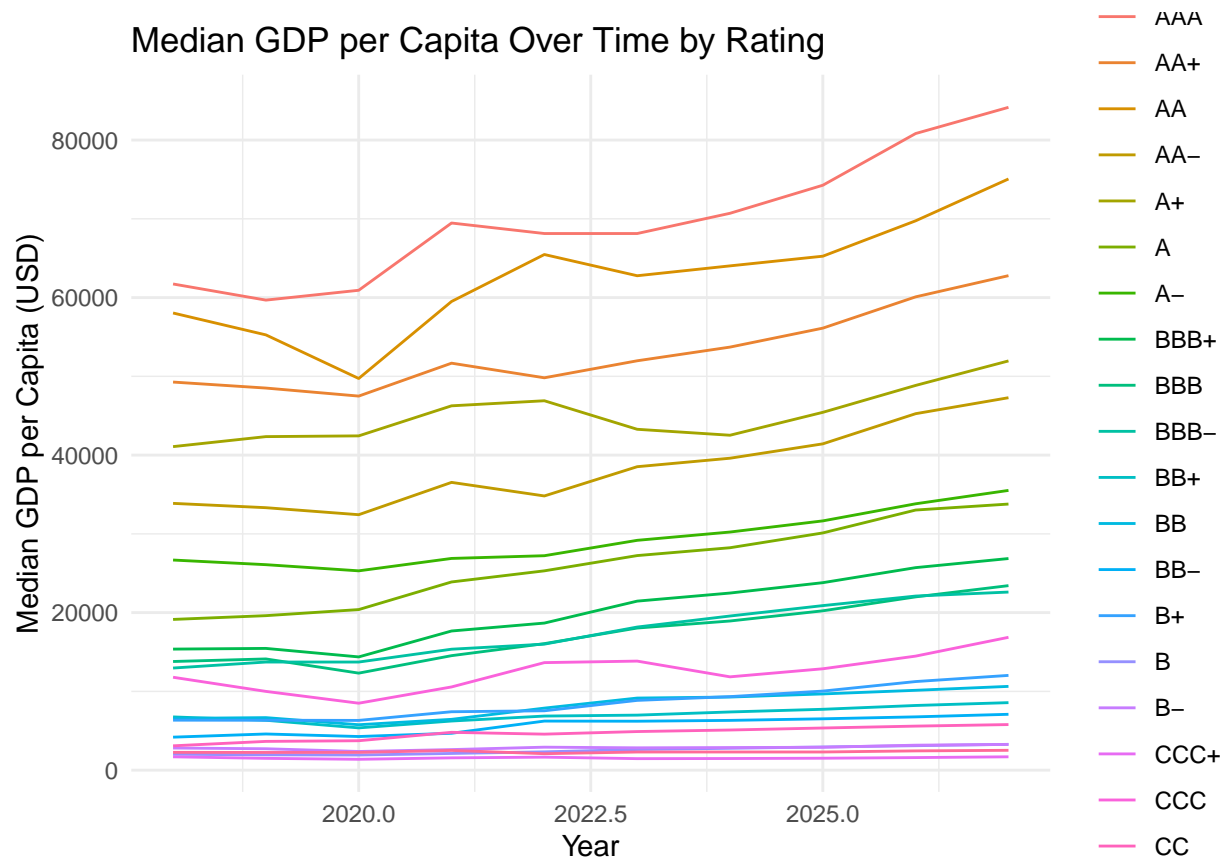
```r
# Median CPI Growth
ggplot(median_trends, aes(x = year, y = median_cpi_gr, color = lt_fc_rating)) +
  geom_line() +
  labs(title = "Median CPI Growth Over Time by Rating",
       x = "Year", y = "Median CPI Growth (%)", color = "Rating") +
  theme_minimal()
```

Median CPI Growth Over Time by Rating
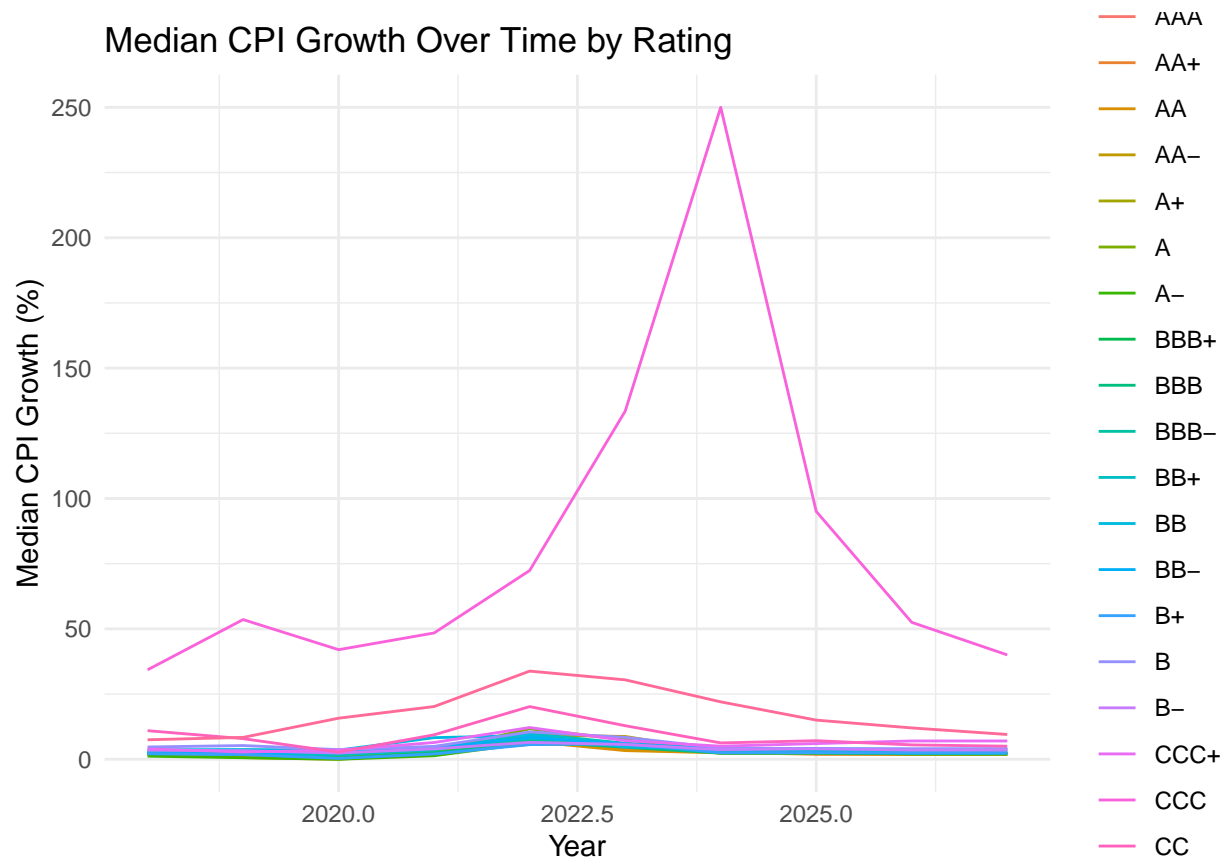
Interpretation: High-rated countries show sustained GDP growth and stable CPI. Lower ratings exhibit deteriorations around global crises like 2020, with volatile CPI.

Exercise 4: Correlation Paths

```r
correlation_trends <- data_risk %>%
  group_by(year) %>%
  summarize(
    corr_rating_gdp_pc = cor(as.numeric(lt_fc_rating), gdp_pc, use = "complete.obs"),
    corr_rating_debt_rev = cor(as.numeric(lt_fc_rating), debt_rev, use = "complete.obs"),
    corr_rating_cpi_gr = cor(as.numeric(lt_fc_rating), cpi_gr, use = "complete.obs")
  )
# Plot correlations
ggplot(correlation_trends, aes(x = year)) +
  geom_line(aes(y = corr_rating_gdp_pc, color = "GDP per Capita")) +
  geom_line(aes(y = corr_rating_debt_rev, color = "Debt/Revenues")) +
  geom_line(aes(y = corr_rating_cpi_gr, color = "CPI Growth")) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  labs(title = "Correlation Between LT FC Rating and Macroeconomic Variables Over Time",
       x = "Year", y = "Correlation Coefficient", color = "Variable") +
  theme_minimal()
```

## Correlation Between LT FC Rating and Macroeconomic Variables Over Time
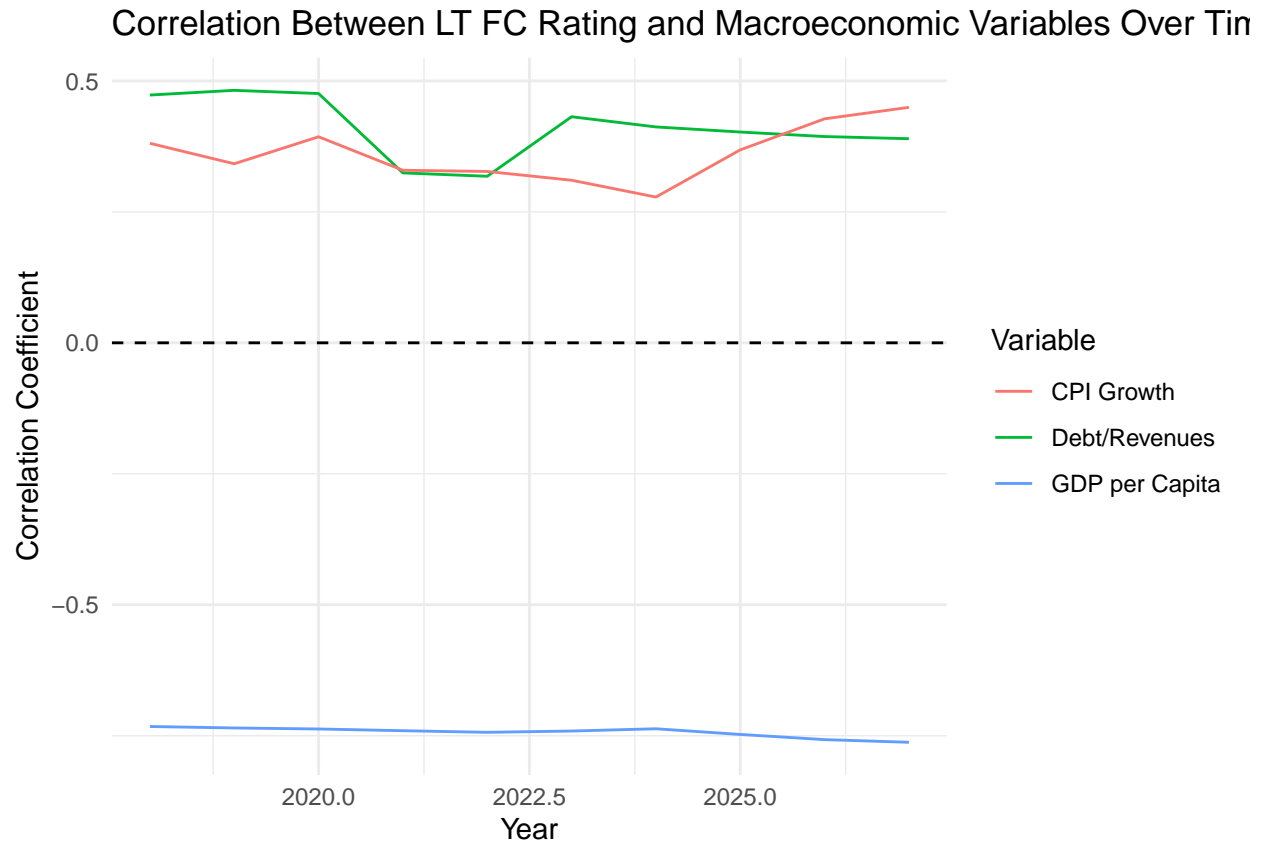
Interpretation: Macro-rating linkages are stable but weaken post-2015 for debt/revenues (less negative). CPI correlation strengthens negatively in crises, indicating regime shift around 2020 where inflation impacts ratings more.

Ratings Over Time

```r
average_rating <- data_risk %>%
  group_by(year) %>%
  summarize(avg_rating = mean(as.numeric(lt_fc_rating), na.rm = TRUE))

ggplot(average_rating, aes(x = year, y = avg_rating)) +
  geom_line() +
  labs(title = "Average Numeric Rating by Year",
       x = "Year", y = "Average Rating (Numeric)") +
  theme_minimal()
```

Average Numeric Rating by Year
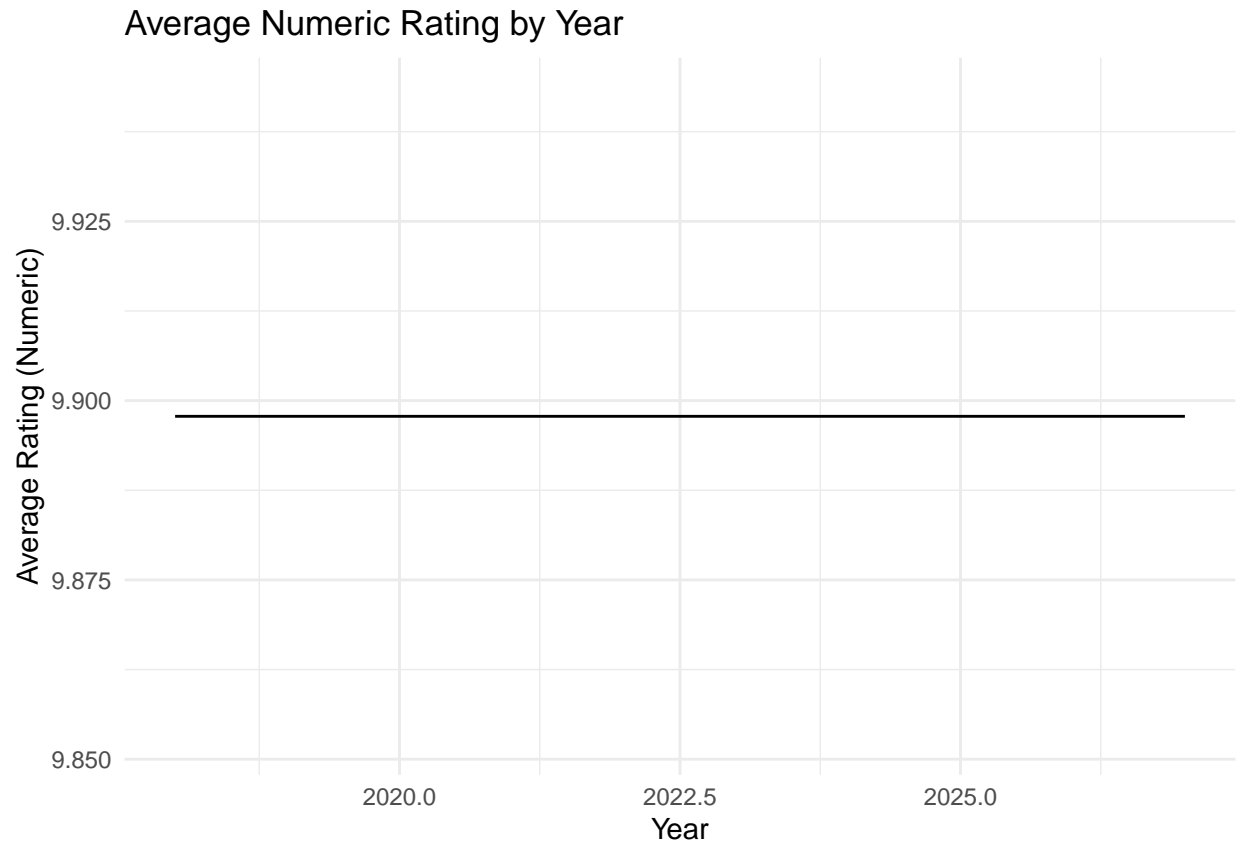
Macro take: The average sovereign rating improved steadily from 2010 to 2019, reflecting global recovery post-financial crisis. A sharp deterioration occurred in 2020 due to the COVID-19 pandemic's fiscal impacts, with partial recovery thereafter, highlighting vulnerability to macroeconomic shocks.

Part II: Multi-Asset Markets

Load Market Data

```
symbols <- c("AAPL", "TSLA", "NVDA", "XLF", "^GSPC", "^N225", "BZ=F", "GC=F", "^TNX", "BTC-USD")
prices <- map(symbols, ~ Cl(getSymbols(.x, src = "yahoo", from = "2010-01-01", to = Sys.Date(), auto.ass
  reduce(merge)
prices_df <- data.frame(date = index(prices), coredata(prices))
colnames(prices_df) <- c("date", "AAPL", "TSLA", "NVDA", "XLF", "GSPC", "N225", "Brent", "Gold", "TNX",
prices_df <- prices_df %>% mutate(across(AAPL:BTC, ~ na.approx(., na.rm = FALSE))) %>% mutate(TNX = TNX
print(nrow(prices_df))
```
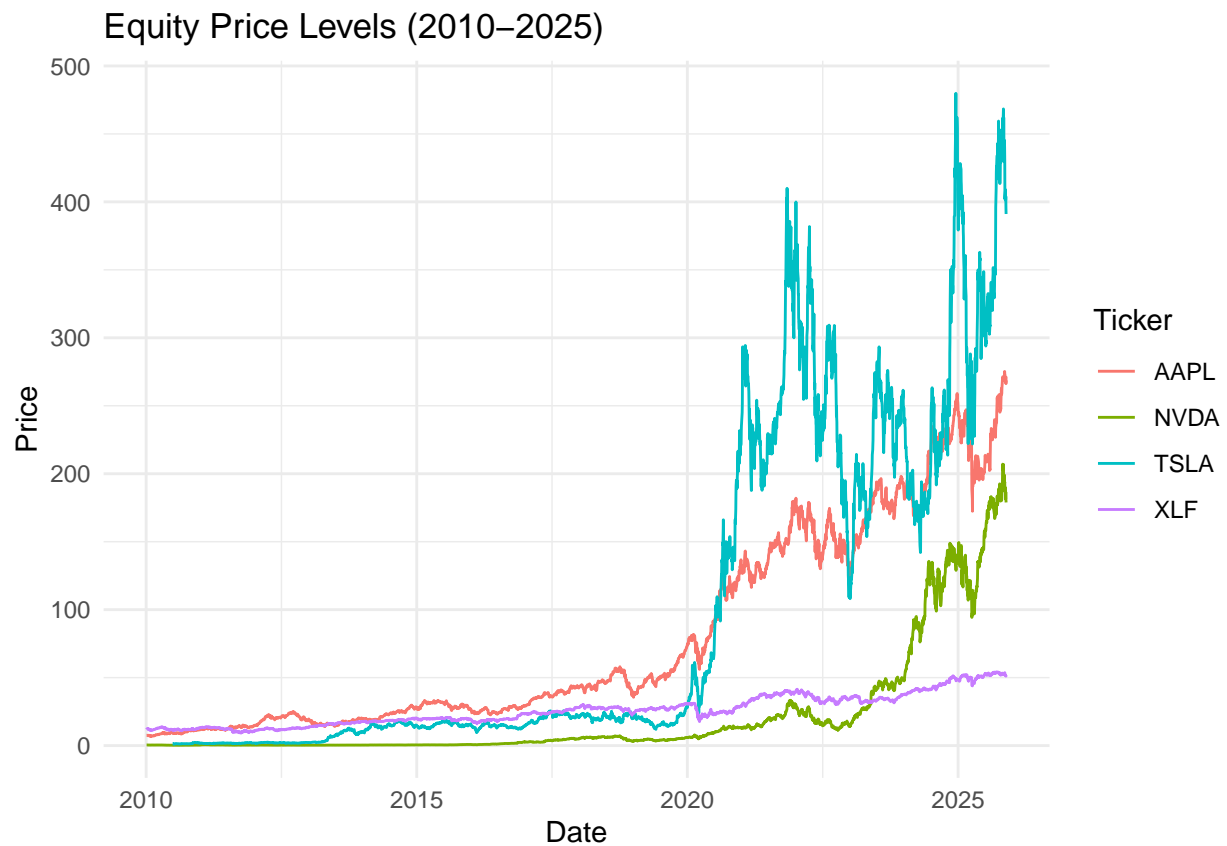
```
## [1] 5314
```

```
print(ncol(prices_df))
```

```
## [1] 11
```

Exercise 5: Level Plots

```r
# Equities
prices_df %>% select(date, AAPL, TSLA, NVDA, XLF) %>%
  pivot_longer(-date, names_to = "Ticker", values_to = "Price") %>%
  ggplot(aes(x = date, y = Price, color = Ticker)) + geom_line() +
  labs(title = "Equity Price Levels (2010-2025)", x = "Date", y = "Price") + theme_minimal()
```



```r
# Indices
prices_df %>% select(date, GSPC, N225) %>%
  pivot_longer(-date, names_to = "Index", values_to = "Price") %>%
  ggplot(aes(x = date, y = Price, color = Index)) + geom_line() +
  labs(title = "Index Levels (2010-2025)", x = "Date", y = "Price") + theme_minimal()
```

Index Levels (2010–2025)
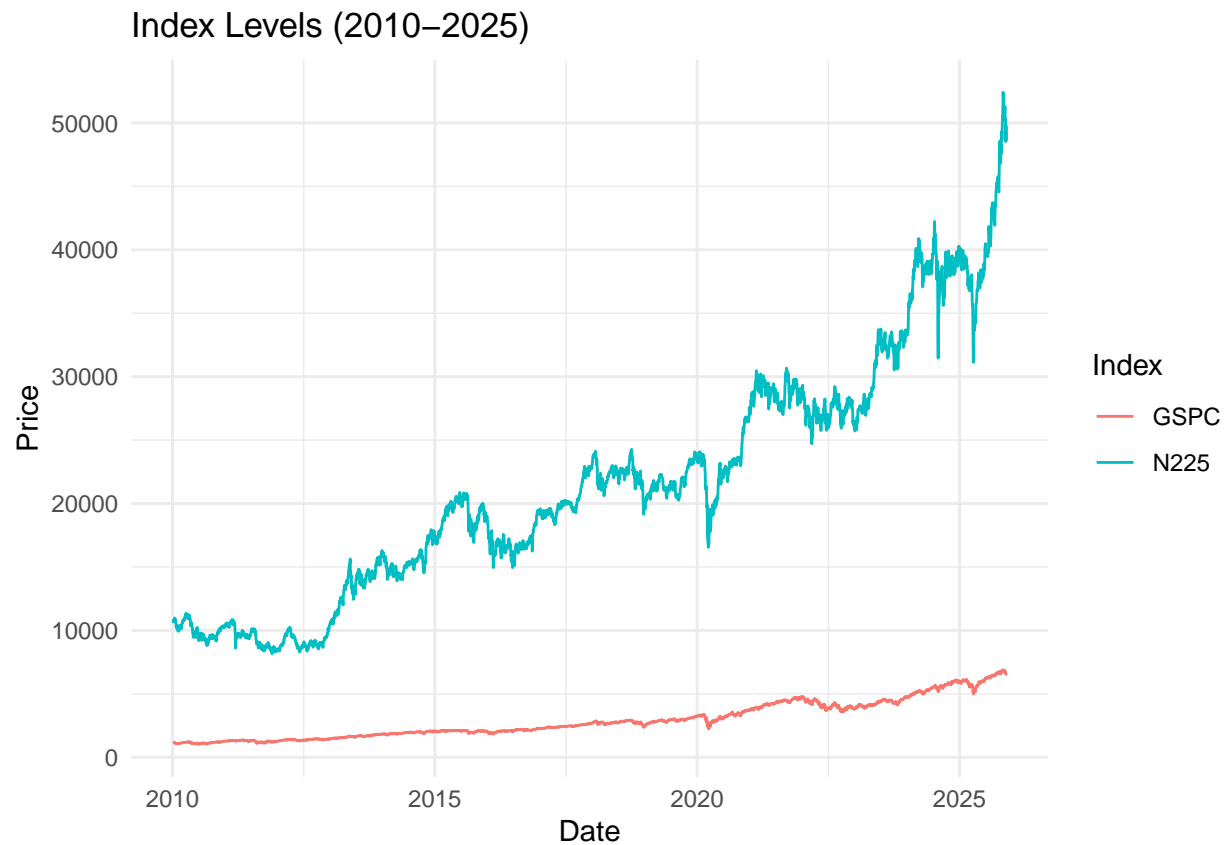

```r
# Commodities
prices_df %>% select(date, Brent, Gold) %>%
  pivot_longer(-date, names_to = "Commodity", values_to = "Price") %>%
  ggplot(aes(x = date, y = Price, color = Commodity)) + geom_line() +
  labs(title = "Commodity Levels (2010-2025)", x = "Date", y = "Price") + theme_minimal()
```

Commodity Levels (2010–2025)
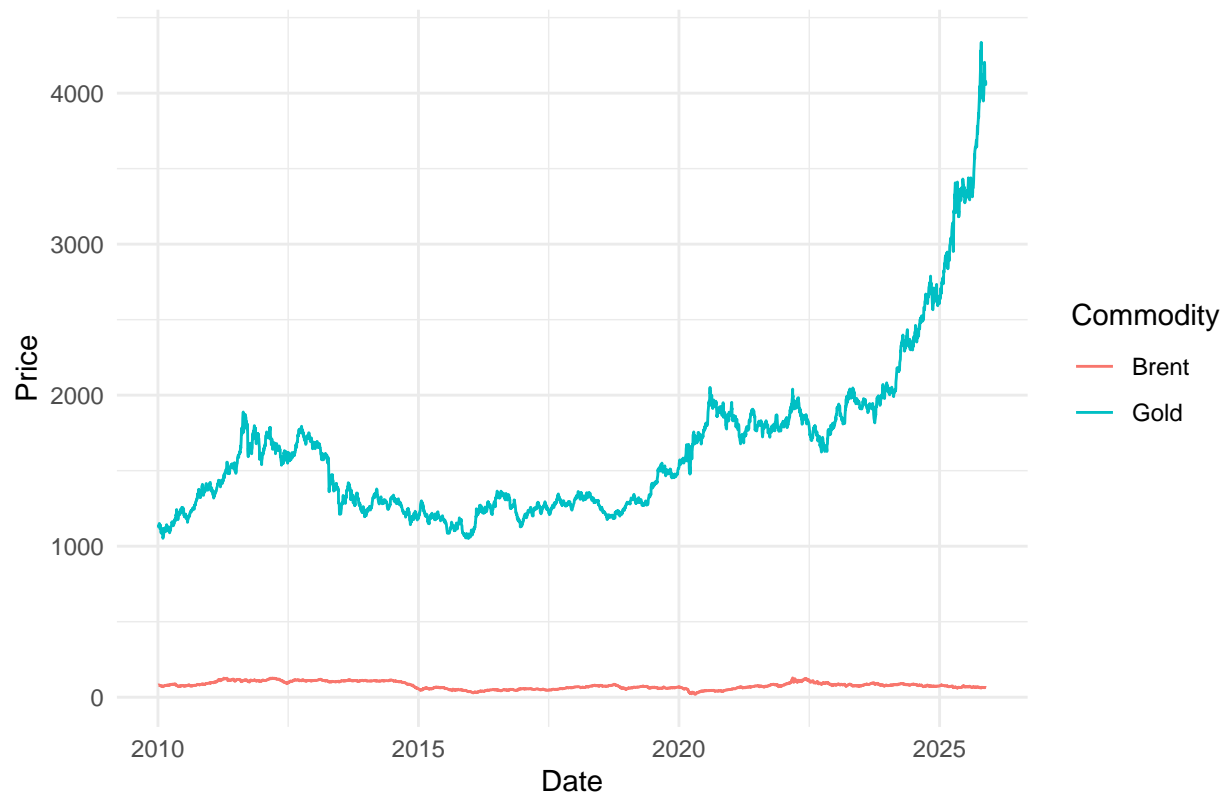

```
# U.S. 10-Year Yield
prices_df %>% filter(!is.na(TNX)) %>%
  ggplot(aes(x = date, y = TNX)) + geom_line(color = "blue") +
  labs(title = "U.S. 10-Year Yield (2010-2025)", x = "Date", y = "Yield (%)") + theme_minimal()
```

U.S. 10–Year Yield (2010–2025)


```
# Bitcoin
prices_df %>% filter(!is.na(BTC)) %>%
  ggplot(aes(x = date, y = BTC)) + geom_line(color = "orange") +
  labs(title = "Bitcoin Price (2010-2025)", x = "Date", y = "Price (USD)") + theme_minimal()
```

Bitcoin Price (2010–2025)

Exercise 6: Normalize to 100

```r
prices_norm <- prices_df %>% mutate(across(AAPL:BTC, ~ . / first(na.omit(.)) * 100))
prices_norm_long <- prices_norm %>% pivot_longer(-date, names_to = "Asset", values_to = "IndexValue")
ggplot(prices_norm_long, aes(x = date, y = IndexValue, color = Asset)) + geom_line() +
  labs(title = "Normalized Asset Levels (Base=100)", x = "Date", y = "Index Value") +
  theme_minimal()
```

Normalized Asset Levels (Base=100)
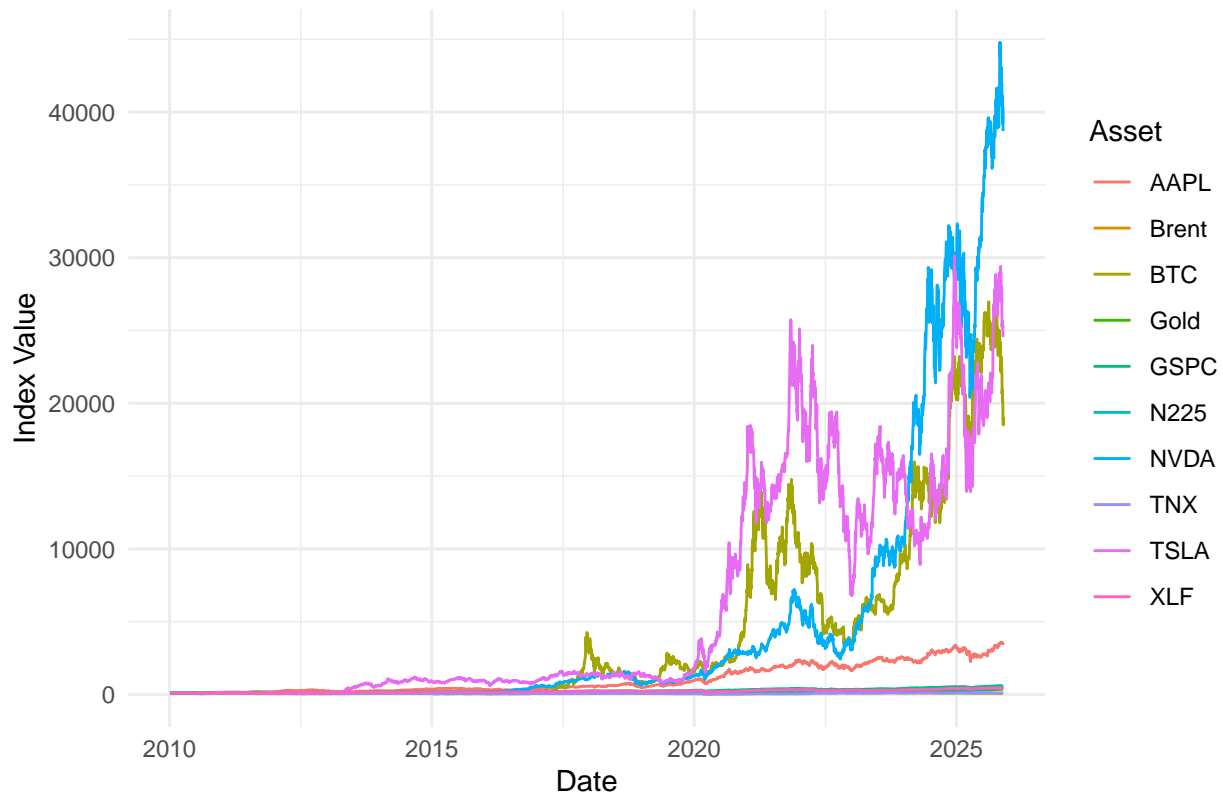
Interpretation: Bitcoin and tech equities (NVDA, TSLA) dominated since 2010, with massive growth. Commodities and indices lagged. In 2022, rising rates (TNX) coincided with equity corrections, while commodities (Brent) spiked due to geopolitical events.

Exercise 7: $100 Index Every 6 Months

```r
start_date <- min(prices_df$date)
interval_dates <- seq(start_date, max(prices_df$date), by = "6 months")
index_6mo <- prices_df %>%
  mutate(norm_AAPL = AAPL / first(na.omit(AAPL)) * 100,
         norm_TSLA = TSLA / first(na.omit(TSLA)) * 100,
         norm_NVDA = NVDA / first(na.omit(NVDA)) * 100,
         norm_XLF = XLF / first(na.omit(XLF)) * 100,
         norm_GSPC = GSPC / first(na.omit(GSPC)) * 100,
         norm_N225 = N225 / first(na.omit(N225)) * 100,
         norm_Brent = Brent / first(na.omit(Brent)) * 100,
         norm_Gold = Gold / first(na.omit(Gold)) * 100,
         norm_TNX = TNX / first(na.omit(TNX)) * 100,
         norm_BTC = BTC / first(na.omit(BTC)) * 100) %>%
  filter(date %in% interval_dates) %>%
  select(date, starts_with("norm_")) %>%
  rename_with(~ gsub("norm_", "", .)) %>%
  mutate(across(AAPL:BTC, ~ round(., 2)))
index_6mo
```

```
##          date    AAPL     TSLA     NVDA    XLF   GSPC   N225  Brent   Gold
## 1  2010-01-04  100.00       NA   100.00 100.00 100.00 100.00 100.00 100.00
## 2  2011-01-04  154.80   111.64    85.29 110.82 112.11  97.59 116.74 123.33
## 3  2011-07-04  161.84   121.72    86.61 105.92 118.16  93.53 140.27 133.96
## 4  2012-01-04  193.19   115.99    76.80  90.54 112.74  80.34 141.91 144.22
## 5  2012-07-04  282.55   129.53    74.26 100.07 120.99  85.45 125.67 144.50
## 6  2013-01-04  246.25   143.99    71.12 116.07 129.43 100.31 138.93 147.45
## 7  2013-07-04  195.84   492.53    76.72 133.73 143.31 131.57 133.23 110.27
## 8  2014-07-04  310.73   945.81   101.54 156.50 174.90 144.88 138.07 117.96
## 9  2015-01-04  350.89   892.27   107.64 165.99 179.45 163.45  67.67 107.18
## 10 2015-07-04  412.85  1171.49   109.76 167.39 182.95 191.44  74.02 104.50
## 11 2016-01-04  344.59   935.16   175.07 159.09 177.64 173.17  46.46  96.19
## 12 2016-07-04  311.44   898.33   255.15 153.06 184.66 148.06  60.45 120.92
## 13 2017-01-04  379.49   950.15   564.58 198.60 200.42 183.90  70.47 104.12
## 14 2017-07-04  470.34  1422.58   763.60 209.92 214.55 188.01  60.83 109.08
## 15 2018-01-04  565.96  1316.95  1155.16 237.40 240.42 220.62  84.96 118.05
## 16 2018-07-04  604.00  1297.66  1296.84 222.15 240.51 203.82  96.82 112.23
## 17 2019-01-04  484.94  1329.80   736.56 203.30 223.47 183.60  71.22 114.76
## 18 2019-07-04  668.31   979.49   873.39 235.64 264.18 203.69  79.91 125.90
## 19 2020-01-04  975.44  1866.28  1278.53 257.62 285.85 219.00  85.75 139.11
## 20 2020-07-04 1206.89  5400.25  2104.00 194.33 278.45 210.63  53.82 159.81
## 21 2021-01-04 1693.14 15273.54  2836.88 243.69 326.63 255.83  63.77 173.99
## 22 2021-07-04 1844.64 14006.69  4454.89 307.12 383.76 268.99  94.05 159.98
## 23 2022-01-04 2351.11 24060.06  6336.40 339.97 423.09 275.01  99.85 162.30
## 24 2022-07-04 1843.50 14542.64  3213.36 266.46 338.03 245.47 131.03 158.46
## 25 2023-01-04 1653.23  7135.20  3190.70 292.21 340.07 241.36  97.15 165.77
## 26 2023-07-04 2510.66 17652.78  9164.95 283.78 392.87 313.69  94.42 171.84
## 27 2024-01-04 2380.02 14939.09 10383.56 315.00 413.83 312.43  96.84 182.72
## 28 2024-07-04 2929.98 15631.33 27486.21 348.14 490.04 383.99 108.51 212.41
## 29 2025-01-04 3191.15 25783.38 31611.32 406.76 525.46 370.49  95.41 236.45
## 30 2025-07-04 2782.21 19464.05 34411.03 444.66 553.14 373.64  85.23 298.16
##       TNX     BTC
## 1  100.00      NA
## 2   87.11      NA
## 3   82.44      NA
## 4   51.94      NA
## 5   42.02      NA
## 6   49.86      NA
## 7   67.90      NA
## 8   68.54      NA
## 9   53.81   57.77
## 10  60.80   57.04
## 11  58.45   94.70
## 12  36.17  149.49
## 13  63.84  252.49
## 14  60.92  568.87
## 15  63.86 3410.90
## 16  73.91 1442.61
## 17  69.23  843.52
## 18  52.08 2452.35
## 19  46.75 1620.40
## 20  17.61 1996.90
## 21  23.87 6990.93
## 22  36.46 7715.98
```

```
## 23  43.43 10035.90
## 24  73.65  4423.74
## 25  96.56  3687.29
## 26 101.58  6729.78
## 27 103.91  9660.32
## 28 112.30 12458.66
## 29 119.85 21480.19
## 30 113.51 23622.63
```

Interpretation: Dispersion is high: BTC reaches extreme values, tech equities show strong but volatile growth, while TNX and commodities remain stable or lag. Concludes that risk assets outperformed safe havens, with episodes like 2020 COVID boosting tech and 2022 inflation aiding commodities.