statistical_analysis

June 9, 2025

1 Brazilian Stock Risk and Return Analysis

This notebook calculates and visualizes descriptive statistics of daily returns for stocks traded on B3, using the Yahoo Finance API.

[2]:
```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import skew, kurtosis, norm

sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (12,6)
```

1.1 Data Download and Return Calculation

[3]:
```
def fetch_and_prepare_data(ticker: str, start="2010-01-01", end=None):
    df = yf.download(ticker, start=start, end=end)
    df = df[["Close"]].rename(columns={"Close": "adjusted_close"})
    df["daily_return"] = df["adjusted_close"].pct_change()
    return df.dropna()

ticker = "BBDC3.SA"
df = fetch_and_prepare_data(ticker)
```

```
YF.download() has changed argument auto_adjust default to True

[*********************100%***********************]  1 of 1 completed
```

1.2 Descriptive Statistics of Daily Returns

[4]:
```
stats = df["daily_return"].describe()
print(f" Daily Return Descriptive Statistics for {ticker}:")
display(stats)

mean = df["daily_return"].mean()
std = df["daily_return"].std()
skewness = skew(df["daily_return"])
```

```
kurt = kurtosis(df["daily_return"])

print(f"\n Mean: {mean:.4%}")
print(f" Standard Deviation: {std:.4%}")
print(f" Skewness: {skewness:.4f}")
print(f" Kurtosis: {kurt:.4f}")
```

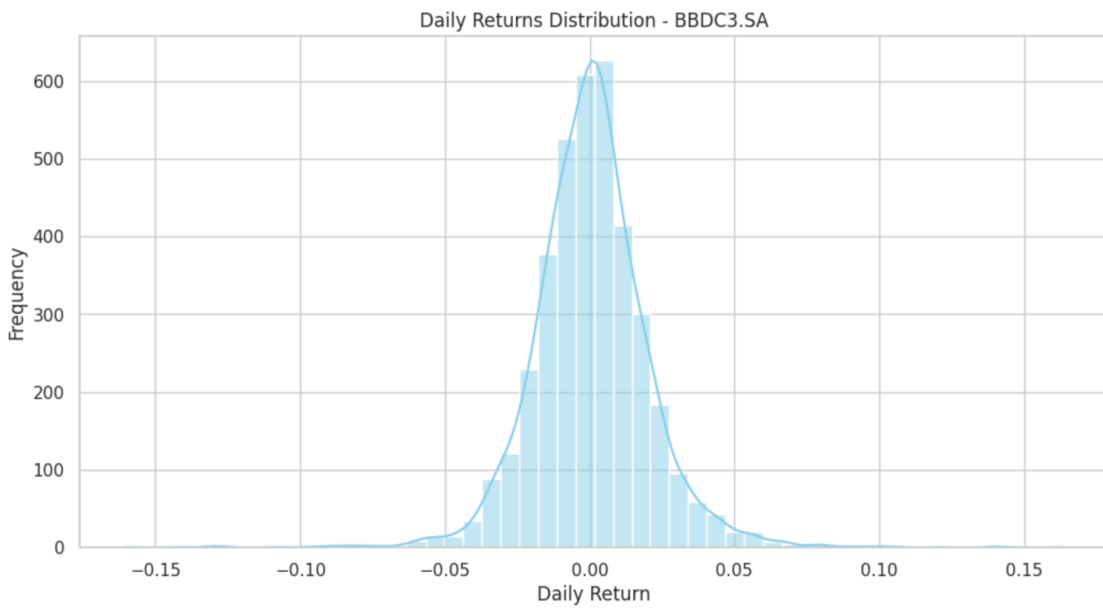
```
 Daily Return Descriptive Statistics for BBDC3.SA:

count    3831.000000
mean        0.000494
std         0.020455
min        -0.160126
25%        -0.010611
50%         0.000000
75%         0.011054
max         0.163276
Name: daily_return, dtype: float64


 Mean: 0.0494%
 Standard Deviation: 2.0455%
 Skewness: 0.0683
 Kurtosis: 6.9158
```

1.3 Daily Returns Distribution

[5]:
```
sns.histplot(df["daily_return"], bins=50, kde=True, color="skyblue")
plt.title(f"Daily Returns Distribution - {ticker}")
plt.xlabel("Daily Return")
plt.ylabel("Frequency")
plt.show()
```



The histogram visualizes the distribution of returns, showing a central peak and denser, more extended tails (especially to the left). This confirms the negative skewness and positive kurtosis, indicating a higher risk of extreme losses and that rare events are more frequent than predicted by common models.

1.4 Risk Metrics: Annualized Volatility and VaR

[6]:
```
annual_volatility = df["daily_return"].std() * np.sqrt(252)
confidence_level = 0.95
VaR_95 = np.percentile(df["daily_return"], (1 -  confidence_level) * 100)
VaR_parametric = norm.ppf(1 - confidence_level, df["daily_return"].mean(),␣
 ↪df["daily_return"].std())

print(f"  Annualized Volatility: {annual_volatility:.2%}")
print(f"  Historical VaR (95%): {VaR_95:.2%}")
print(f"  Parametric Normal VaR (95%): {VaR_parametric:.2%}")
```

```
Annualized Volatility: 32.47%
Historical VaR (95%): -2.99%
Parametric Normal VaR (95%): -3.32%
```

Parametric VaR (95% ~-3.31%): This value assumes 'normal' returns and underestimates potential losses in real scenarios (difference of ~0.32%), making Historical VaR more reliable for financial assets with 'fat tails'.

1.5 Comparison Across Multiple Assets

This code block prepares and displays the returns of multiple assets for comparison, along with their basic statistics.

[7]:
```
tickers = ["BBDC3.SA", "ITUB4.SA", "BBAS3.SA"]
returns = {}
all_data = {}

for t in tickers:
    df_temp = fetch_and_prepare_data(t)
    all_data[t] = df_temp
    returns[t] = df_temp["daily_return"]

returns_df = pd.DataFrame(returns).dropna()
display(returns_df.head())
display(returns_df.describe().T[["mean", "std"]].rename(columns={"mean":␣
↪"Mean", "std": "Standard Deviation"}))
```

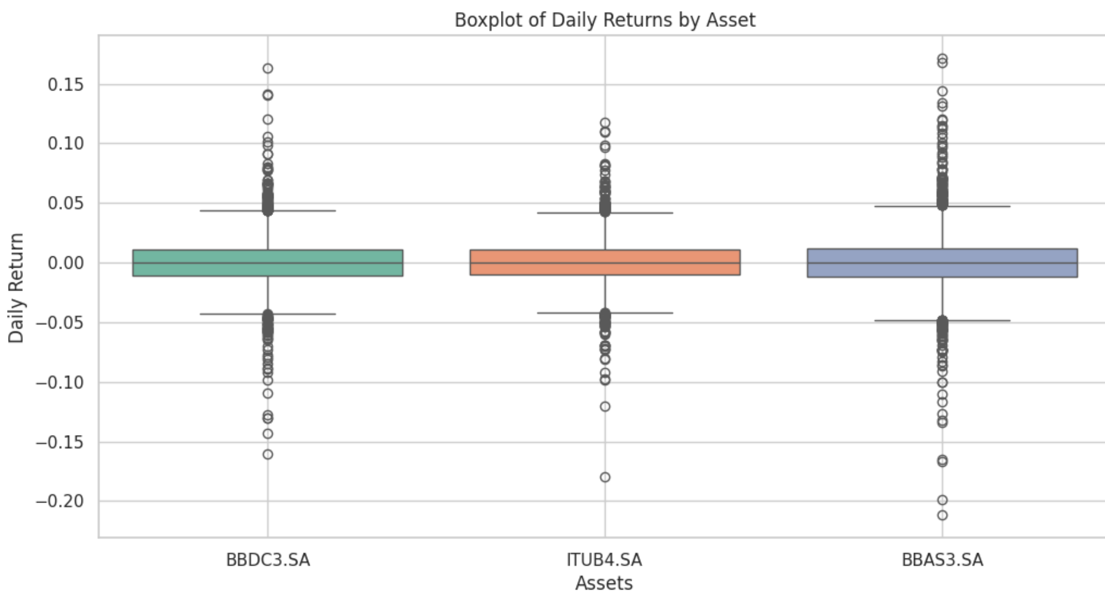
```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
```

```
            BBDC3.SA  ITUB4.SA  BBAS3.SA
Date
2010-01-05 -0.013772  0.006480 -0.010034
2010-01-06 -0.005891 -0.008667  0.001351
2010-01-07 -0.002304 -0.010243  0.000338
2010-01-08  0.001320 -0.015144  0.005733
2010-01-11 -0.003295 -0.008713  0.007713
```

```
              Mean  Standard Deviation
BBDC3.SA  0.000494            0.020455
ITUB4.SA  0.000463            0.019132
BBAS3.SA  0.000651            0.024186
```

1.6 Comparative Returns Boxplot

[10]:
```
return_melted = returns_df.reset_index().melt(id_vars="Date", var_name="Asset",␣
↪value_name="Return")
sns.boxplot(data=return_melted, x="Asset", y="Return",hue="Asset",␣
↪palette="Set2", legend=False)
plt.title("Boxplot of Daily Returns by Asset")
plt.xlabel("Assets")
plt.ylabel("Daily Return")
plt.grid(True)
plt.show()
```



The three banking assets show very similar risk and volatility profiles, with comparable fluctuations and occurrences of extreme values.

1.7 Asset Correlation

[1]:
```
correlation_matrix = returns_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f",␣
↪linewidths=0.5)
plt.title("Asset Correlation Matrix")
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[1], line 1
----> 1 correlation_matrix = returns_df.corr()
      2 sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f",␣
↪linewidths=0.5)
      3 plt.title("Asset Correlation Matrix")

NameError: name 'returns_df' is not defined
```

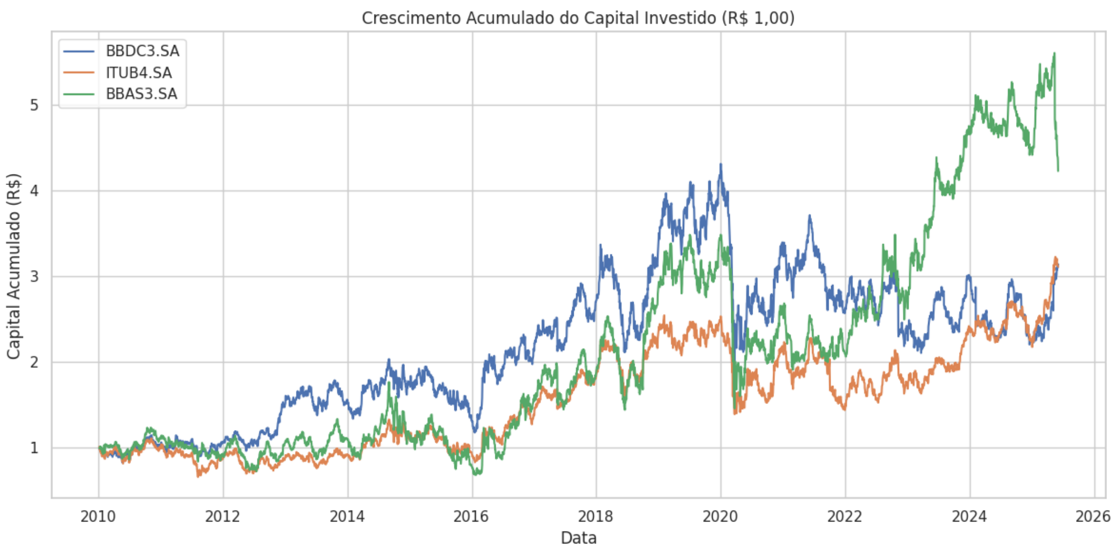
The correlations between these assets are extremely high and positive (close to 1.00). This means they move in the same direction, offering little diversification for a portfolio. To reduce risk, assets from other sectors would be needed.

1.8 Cumulative Capital Growth

[ ]:
```
plt.figure(figsize=(12,6))

for ticker, df in all_data.items():
    cumulative_growth = (1 + df["daily_return"]).cumprod()
    plt.plot(cumulative_growth, label=ticker)

plt.title("Cumulative Growth of Invested Capital (R$ 1.00)")
plt.xlabel("Data")
plt.ylabel("Cumulative Capital (R$)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



The growth trajectories of the three banks are remarkably similar, moving in unison. This visually reinforces the low diversification of a portfolio with only these assets, highlighting vulnerability to sectoral shocks.