Application of Monte Carlo Simulations to Calculate VaR

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Risk Management for Financial Institutions

- Financial Institutions:
    - Investment Banks, retail banks, pensions, hedge funds, etc

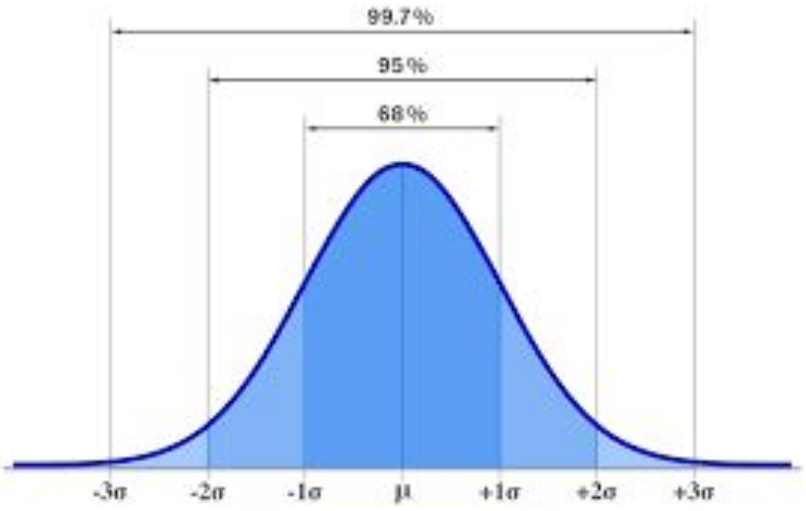
- Always have money invested in various avenues in their portfolios
    - E.g. stocks, fixed income (bonds, preferred stocks/dividends, etc), commodities

Accounting

- Assets, Equity, Leverage
  - Equity actual money value of company
  - Leverage borrowed money
  - Always have money invested in asset portfolios
  - Great Depression, what if market crashes
    - What if everyone pulls money out
    - Must prevent the firm from becoming bankrupt
    - It’s important for the financial institutions to have a way to decide when they should or should not pull out of all their positions

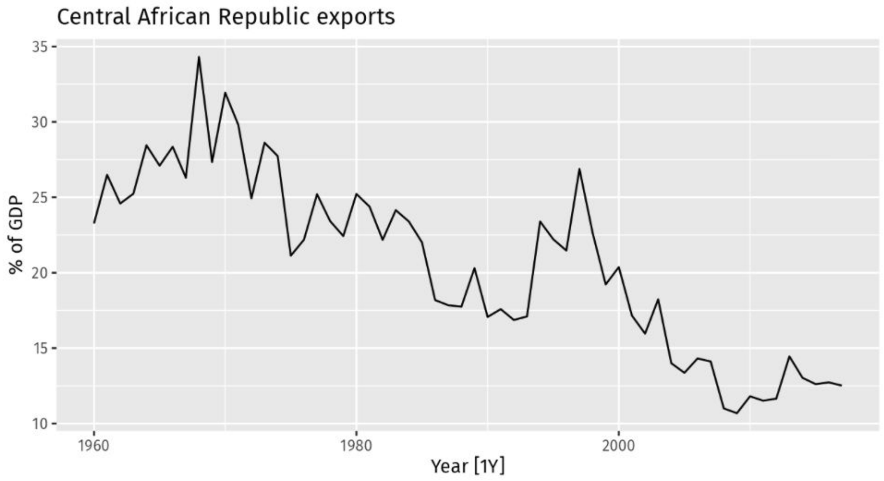
VaR Overview

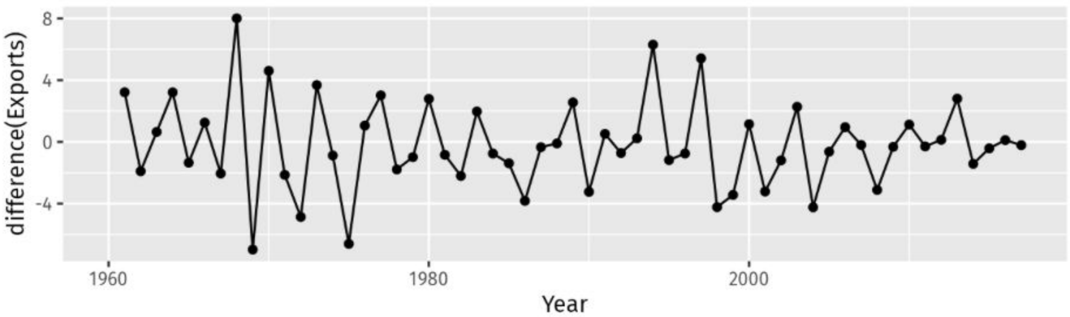
- Value at Risk
  - Model potential losses of the firm’s portfolio
- Analyze price movements
  - Examine exposure; e.g risk (variance)
- Pull 1% worst possible outcomes
  - E.g. Order Statistics
- Calculate standard deviation to look at price movement ranges



Time Series Data

- Stock data is generally time series data
  - Random Walk
- Stationarity
  - Time series methods:
    - ETS, ARMA, ARIMA
- Transformations
  - Percentage Changes
  - log()
  - Etc

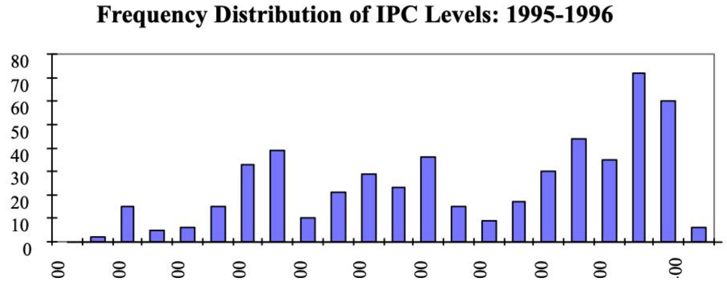


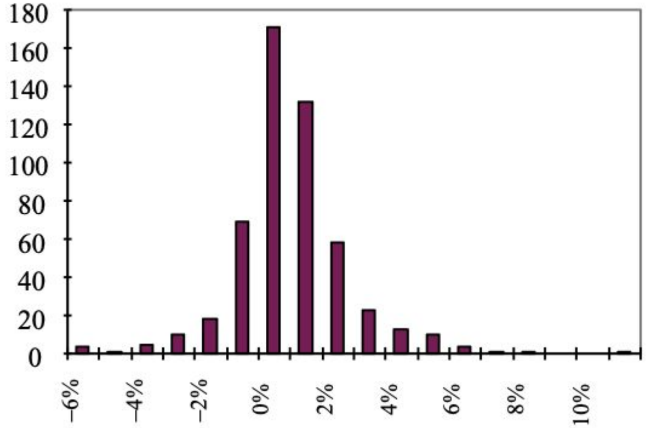


Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and Practice (3rd ed.). Otexts.

Why Monte Carlo

- Percent changes of IPC Mexico stock index
- Data from 1995-1996 would suggest VaR of 4.2%
    - In reality, 4.2% was lost 1.5% of the time
- Suggests we need more information on the tails
    - E.g. Use monte carlo simulations

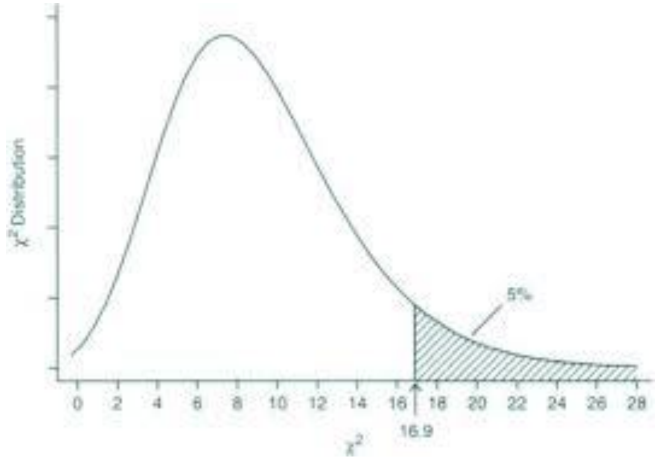




Ken Abbott (2013). Value at Risk (VAR) Models. MIT Open Courseware.

Order Statistics/Distribution

- Use simulations to estimate 1% order statistic
- Enhance data by using assumed p.d.f.
    - E.g. normal distribution
        - variance used with F or Chi-Squared distribution
- Generate simulation of data
    - 2.33 standard deviations represents the largest 99% price movement area



Variance/Covariance or Bootstrap

- Quantify overall portfolio risk (variance)
  - To calculate, we need individual variance of each asset
    - Then calculate covariance of the assets
- Use portfolio variance (standard deviation) to estimate order statistic
- Alternatively, use Bootstrapping
  - Directly simulate percent changes
- Can also compare our risk to other potential portfolios or the risk free rate (e.g. treasury bonds)

Sample Covariance

$$Cov(x,y) = \frac{\Sigma(x_i-\bar{x})(y_i-y)}{N-1}$$

$$var(a+b+c)=var(a)+var(b)+var(c) +2cov(ab)+2cov(ac)+2cov(bc)$$

$$var(xa+yb+zc)= x^2var(a)+y^2var(b)+z^2var(c) +2xy\, cov(ab)+2xz\, cov(ac)+2yz\, cov(bc)$$

$$var(a+b+c+d)=var(a)+var(b)+var(c)+var(d) +2cov(ab)+2cov(ac)+2cov(ad)+2cov(bc)+2cov(bd) +2cov(cd)$$

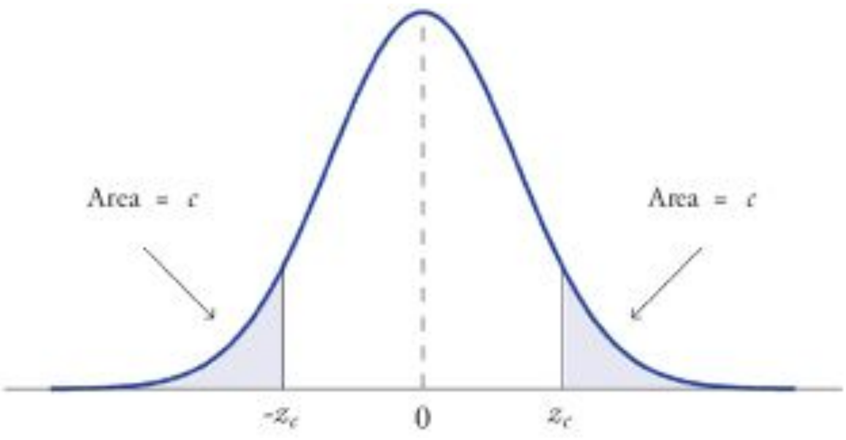
Ken Abbott (2013). Value at Risk (VAR) Models. MIT Open Courseware.

Advantages for VaR Modeling

- Flexibility in Modelling
  - Enables realistic representation of complex portfolios
    - Can fill missing data and expand low frequency data
  - Provides a comprehensive view of portfolio risk
- Can use in conjunction with stress testing and scenario analysis
  - Assesses portfolio performance under diverse conditions

Advantages for VaR Modeling

- Quantification of Tail Risks
  - Enhance areas with low amounts of data
- Ease of Interpretability
- Dynamic Modelling
  - Models time-dependent behavior of financial instruments
  - Captures the evolution of portfolio value over time.



Disadvantages for VaR Modeling

- Computational Intensity
  - Potentially limiting real-time applications; e.g. dynamic modelling
- Modelling Complexity
  - Complex models may increase the likelihood of errors and uncertainties in simulation outcomes
- Dependency on the Historical Data
  - Relies on historical data
- Difficulty in capturing regime changes
  - Modeling sudden market shifts or discontinuities

Implementation

```
#import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import yfinance as yf

#Create a function to return a dataframe for daily adjusted closing prices
def pull_prices(company_tickers):
    price_data= pd.DataFrame()
    ticker_list= list()

    for i in company_tickers:
        price_data= pd.concat([price_data,
                               pd.DataFrame(
                                   yf.download(i, start=datetime(2023, 1, 19),
                                               end=datetime(2024, 1, 19)
                                          ).iloc[:,4]
                                      )
                              ], axis = 1
                             )
        ticker_list.append(i)

    price_data.columns= ticker_list
    price_data['Date']= price_data.index
    return price_data


tickers= ["SPY"]
df= pull_prices(tickers)
```

Implementation

```
# Transformation to compute daily percent change for each stock
df_percent_change = pd.DataFrame()
for column in df.columns[:-1]:  # Exclude the 'Date' column
    df_percent_change[column + '_daily_percent_change'] = (df[column].shift(-1) - df[column]) / df[column]

# Drop the last row which will contain NaN values
df_percent_change = df_percent_change.iloc[:-1]

print(df_percent_change)



# Covariance Matrix
cv_matrix = df_percent_change.cov()
```

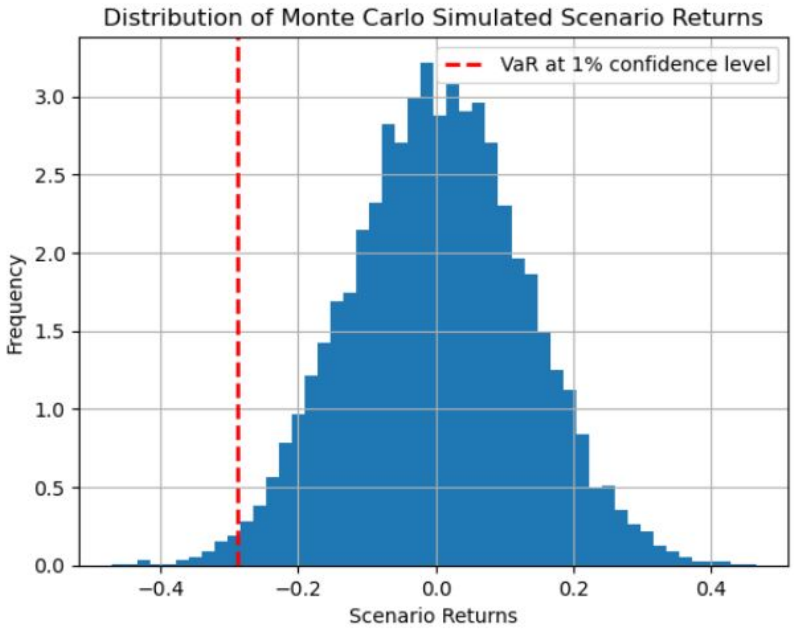
Implementation

```
# Number of simulations
simulations = 10000

# Monte Carlo Simulation
scenarioReturns = []
for _ in range(simulations):
    z_scores = np.random.normal(0, 1, len(df_percent_change.columns))
    scenario_return = np.sum(z_scores * np.sqrt(np.diag(cv_matrix))) * np.sqrt(250)
    scenarioReturns.append(scenario_return)

# VaR Calculation
confidence_level = 0.99
VaR = np.percentile(scenarioReturns, 100 * (1 - confidence_level))
```

Implementation




```
Value at Risk (VaR) at 99% confidence level: -29.3687 percent
```

Works Cited

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