

# market\_overview

January 12, 2026

## 1 Market Overview & Risk Analysis — S&P 500

### Objective:

To analyze historical equity index data using return-based statistics and standard risk metrics commonly used in quantitative finance.

### Key Focus Areas:

- Returns & volatility
- Drawdowns
- Risk-adjusted performance

This notebook demonstrates applied Python, statistics, and financial reasoning.

```
[32]: import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings

warnings.filterwarnings("ignore")
plt.style.use("default")
```

```
[33]: symbol = "^GSPC"
data = yf.download(symbol, start="2015-01-01", auto_adjust=True)

# Basic data checks
data = data.dropna()
data.head()
```

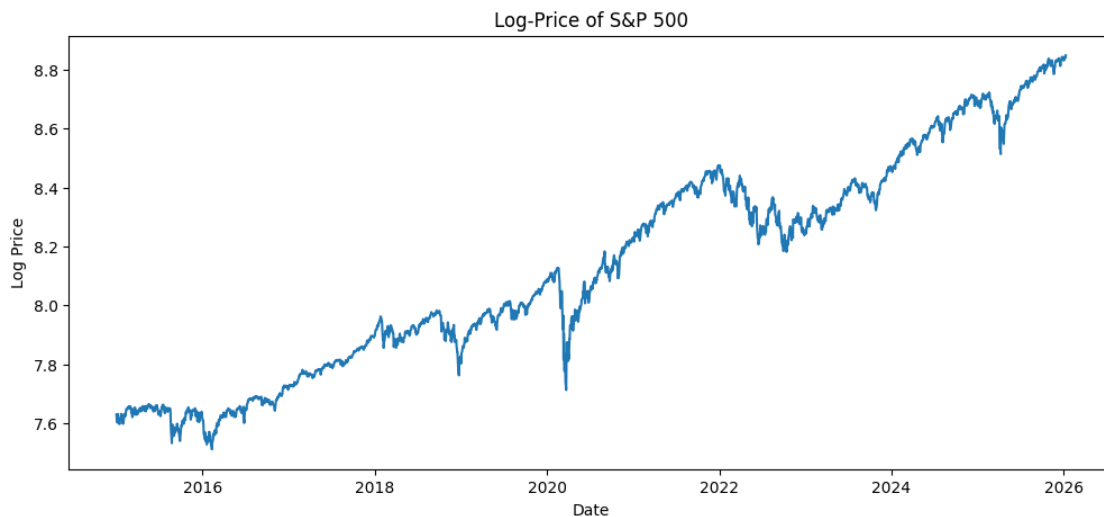
[\*\*\*\*\*100%\*\*\*\*\*] 1 of 1 completed

```
[33]: Price          Close          High          Low          Open          Volume
Ticker          ^GSPC          ^GSPC          ^GSPC          ^GSPC          ^GSPC
Date
2015-01-02    2058.199951    2072.360107    2046.040039    2058.899902    2708700000
2015-01-05    2020.579956    2054.439941    2017.339966    2054.439941    3799120000
2015-01-06    2002.609985    2030.250000    1992.439941    2022.150024    4460110000
2015-01-07    2025.900024    2029.609985    2005.550049    2005.550049    3805480000
2015-01-08    2062.139893    2064.080078    2030.609985    2030.609985    3934010000
```

### 1.0.1 Dataset Summary

We use adjusted daily price data to ensure returns correctly reflect total market movement. The analysis period starts in 2015 to capture multiple market regimes: - Bull markets - COVID crash - High-inflation period

```
[34]: plt.figure(figsize=(12,5))
plt.plot(np.log(data['Close']))
plt.title("Log-Price of S&P 500")
plt.xlabel("Date")
plt.ylabel("Log Price")
plt.show()
```

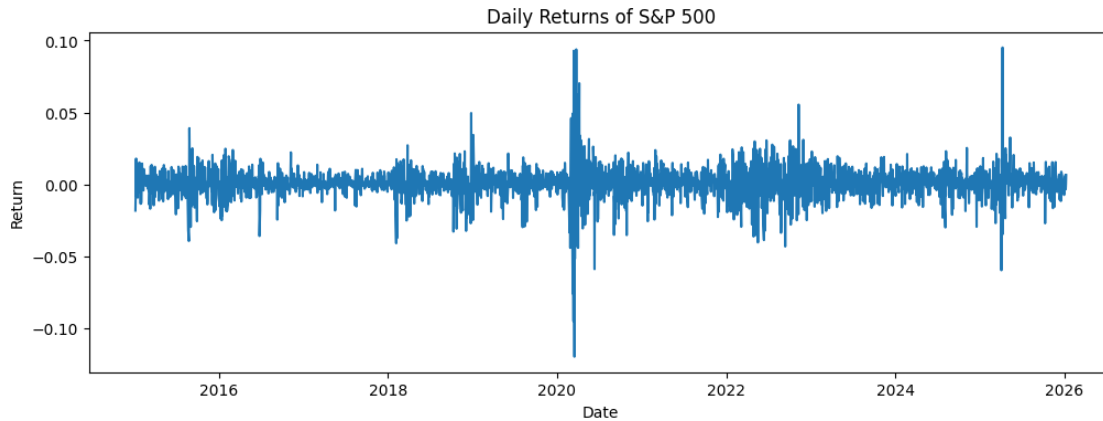


### 1.0.2 Daily Returns

Returns are analyzed instead of prices because: - Returns are stationary (prices are not) - Risk is defined in return space - Most quantitative strategies operate on returns - Adjusted prices account for dividends and splits and are required for accurate return calculations.

```
[35]: data['Returns'] = data['Close'].pct_change()
data = data.dropna()

plt.figure(figsize=(12,4))
plt.plot(data['Returns'])
plt.title("Daily Returns of S&P 500")
plt.xlabel("Date")
plt.ylabel("Return")
plt.show()
```



### 1.0.3 Return Statistics

We compute key descriptive statistics to understand return distribution.

```
[36]: stats = {
    "Mean Daily Return": data['Returns'].mean(),
    "Volatility (Std)": data['Returns'].std(),
    "Skewness": data['Returns'].skew(),
    "Kurtosis": data['Returns'].kurtosis()
}

pd.Series(stats)
```

```
[36]: Mean Daily Return      0.000504
Volatility (Std)           0.011272
Skewness                  -0.364731
Kurtosis                   15.126114
dtype: float64
```

### 1.0.4 Annualized Risk Metrics

Annualized metrics assume 252 trading days.

Sharpe Ratio is computed assuming a zero risk-free rate for simplicity.

```
[37]: annualized_return = data['Returns'].mean() * 252
annualized_vol = data['Returns'].std() * np.sqrt(252)
risk_free_rate = 0.0
sharpe_ratio = (annualized_return - risk_free_rate) / annualized_vol

pd.Series({
    "Annualized Return": annualized_return,
```

```

    "Annualized Volatility": annualized_vol,
    "Sharpe Ratio": sharpe_ratio
})

```

```

[37]: Annualized Return      0.126963
      Annualized Volatility  0.178936
      Sharpe Ratio          0.709540
      dtype: float64

```

### 1.0.5 Drawdown Analysis

Drawdowns capture downside risk ignored by volatility.

```

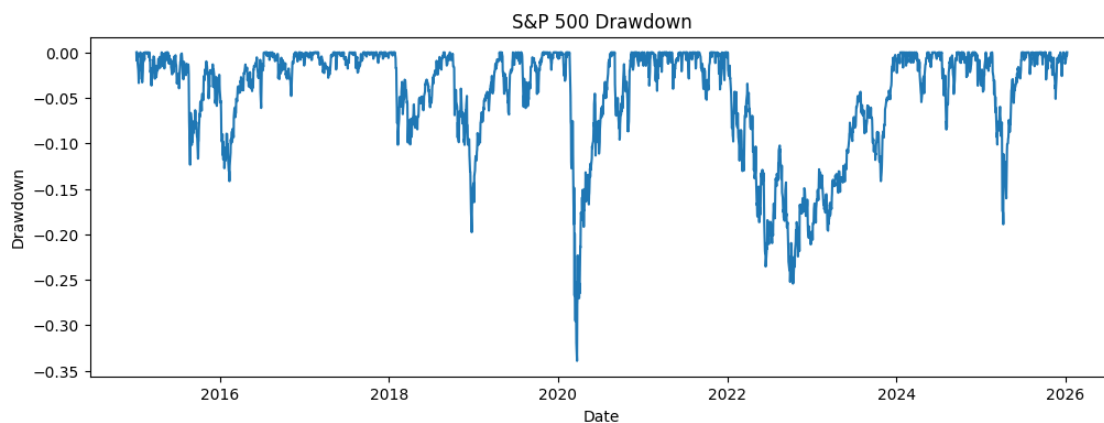
[38]: cum_returns = (1 + data['Returns']).cumprod()
      rolling_max = cum_returns.cummax()
      drawdown = (cum_returns - rolling_max) / rolling_max
      max_dd = drawdown.min()
      print(f"Maximum Drawdown: {max_dd:.2%}")

      plt.figure(figsize=(12,4))
      plt.plot(drawdown)
      plt.title("S&P 500 Drawdown")
      plt.xlabel("Date")
      plt.ylabel("Drawdown")
      plt.show()

      drawdown.min()

```

Maximum Drawdown: -33.92%



```

[38]: np.float64(-0.3392496000265331)

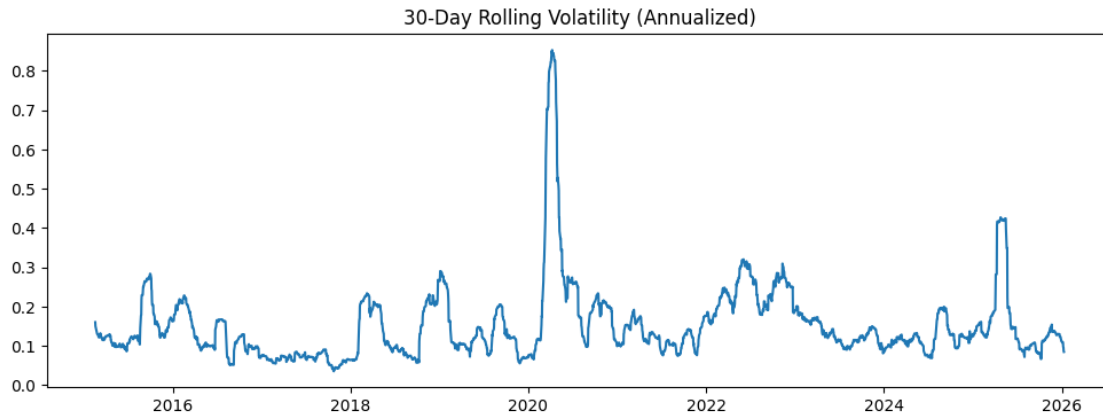
```

### 1.0.6 Rolling volatility

Rolling volatility is annualized using  $\sqrt{252}$  and expressed in percentage terms.

```
[39]: data['RollingVol_30'] = data['Returns'].rolling(30).std() * np.sqrt(252)

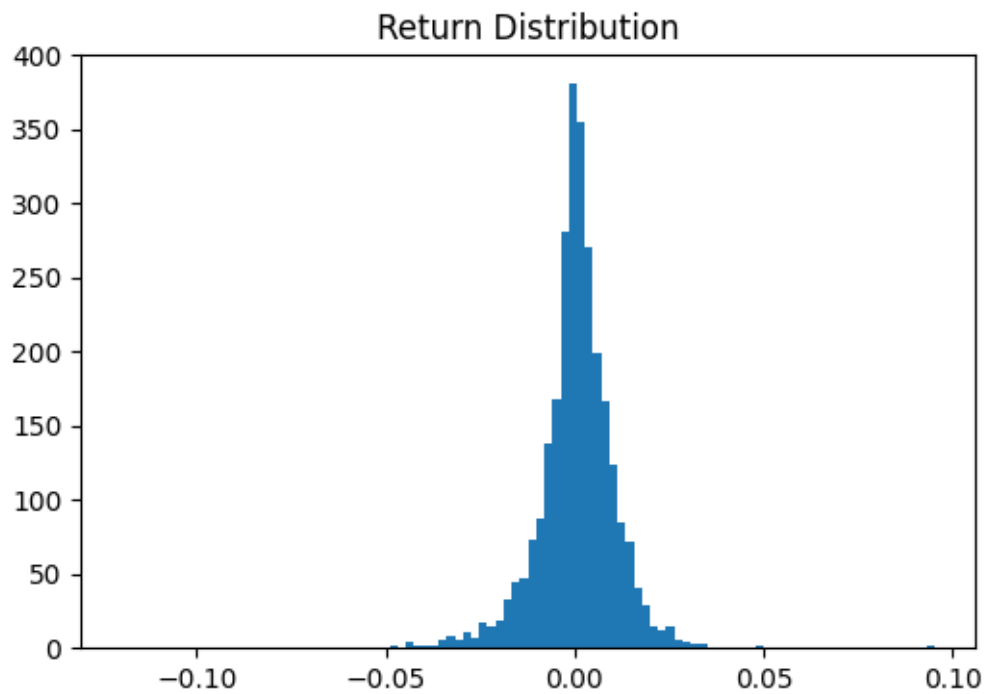
plt.figure(figsize=(12,4))
plt.plot(data['RollingVol_30'])
plt.title("30-Day Rolling Volatility (Annualized)")
plt.show()
```



### 1.0.7 Histogram of returns

The distribution exhibits fat tails and negative skewness, highlighting the presence of extreme downside events not captured by normal assumptions.

```
[40]: plt.figure(figsize=(6,4))
plt.hist(data['Returns'], bins=100)
plt.title("Return Distribution")
plt.show()
```



### 1.0.8 Interpretation

- Volatility clustering confirms non-constant variance in equity returns
- Drawdowns highlight asymmetric downside risk
- Risk-adjusted performance varies significantly across regimes
- Simple descriptive statistics already reveal meaningful market structure