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.

[53]:
```python
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")
```

[54]:
```python
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
```

[54]:

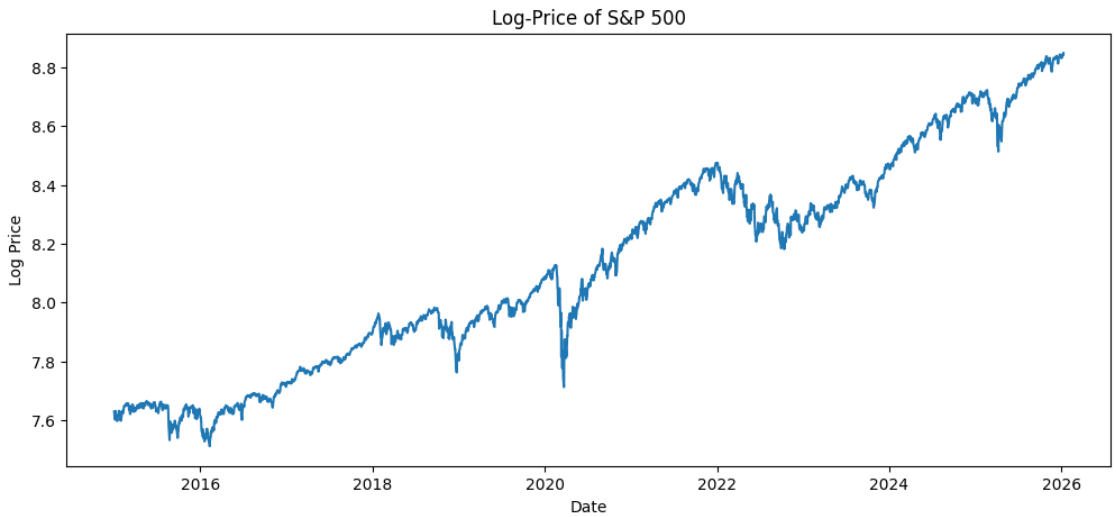
Price	Close	High	Low	Open	Volume
Ticker	^GSPC	^GSPC	^GSPC	^GSPC	^GSPC
Date					
2015-01-02	2058.199951	2072.360107	2046.040039	2058.899902	2708700000
2015-01-05	2020.579956	2054.439941	2017.339966	2054.439941	3799120000
2015-01-06	2002.609985	2030.250000	1992.439941	2022.150024	4460110000
2015-01-07	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

[55]:

```
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()
```



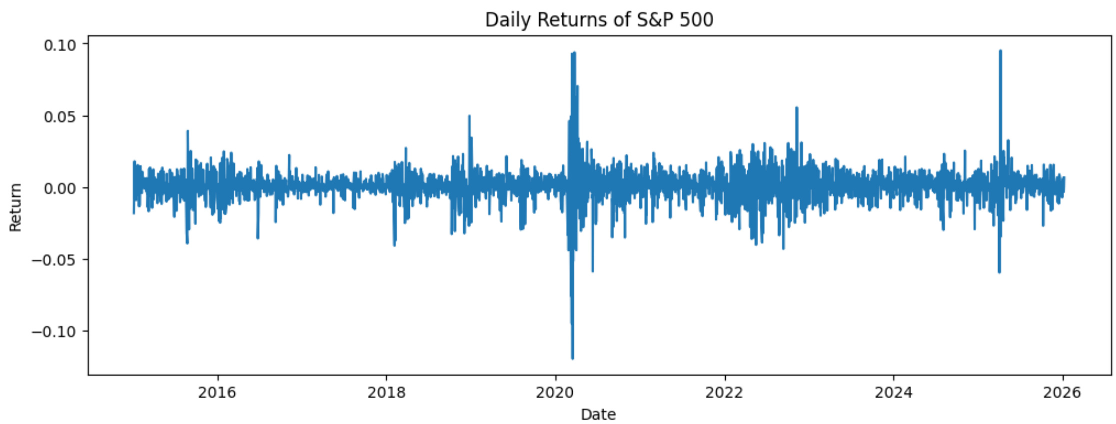
1.0.2 Daily Returns

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.

[56]:

```
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.

[57]:
```
stats = {
    "Mean Daily Return": data['Returns'].mean(),
    "Volatility (Std)": data['Returns'].std(),
    "Skewness": data['Returns'].skew(),
    "Kurtosis": data['Returns'].kurtosis()
}

pd.Series(stats)
```

[57]:
```
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.

[58]:
```
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
})
```

[58]:
```
Annualized Return        0.126963
Annualized Volatility    0.178936
Sharpe Ratio             0.709540
dtype: float64
```

1.0.5 Drawdown Analysis

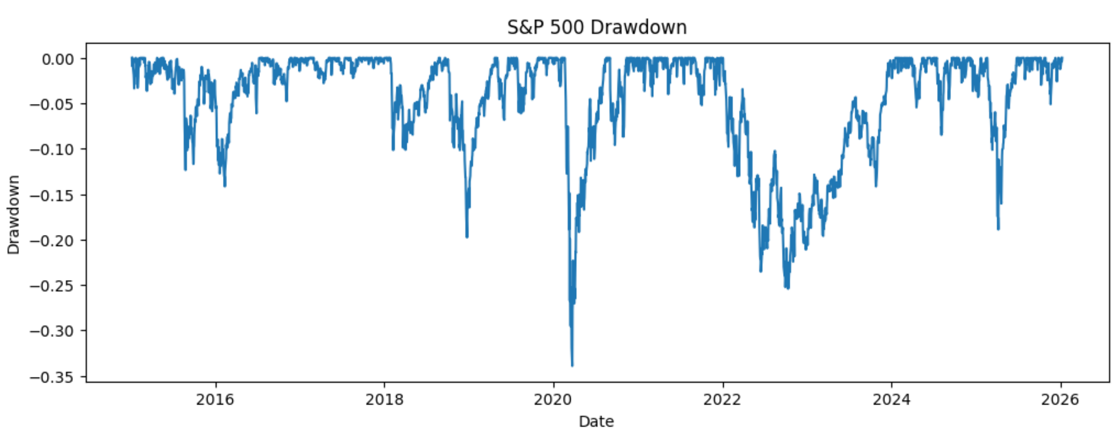
Drawdowns capture downside risk ignored by volatility.

[59]:
```python
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%
```



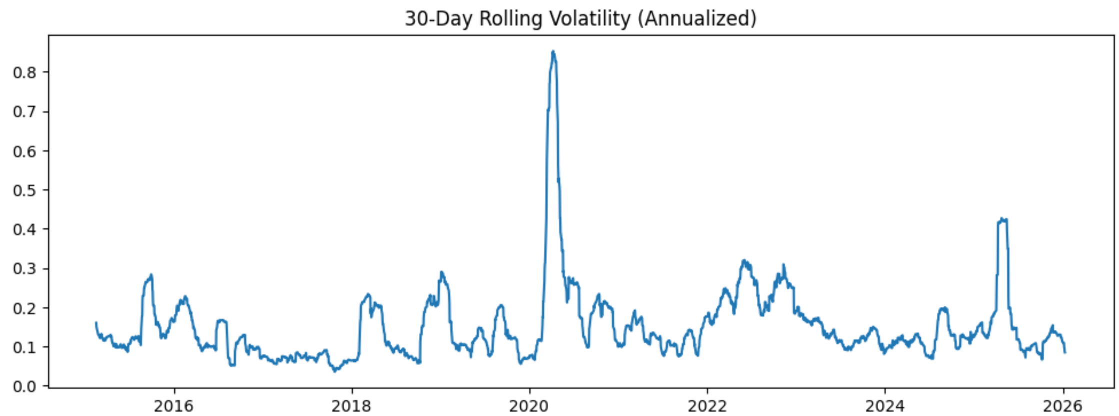
[59]:
```
np.float64(-0.3392496000265331)
```

1.0.6 Rolling volatility

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

[60]:
```
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()
```



We classify volatility regimes using the median rolling volatility as a simple, distribution-robust threshold.

[61]:
```
vol_threshold = data['RollingVol_30'].median()
vol_threshold
```

[61]: np.float64(0.12479549056019992)

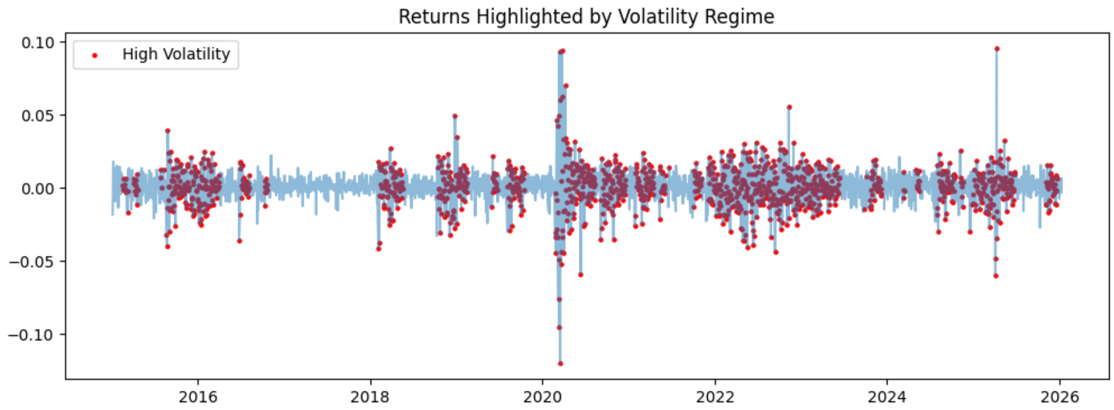
[62]:
```
data['Vol_Regime'] = np.where(
    data['RollingVol_30'] > vol_threshold,
    'High Volatility',
    'Low Volatility'
)
```

[63]:
```
plt.figure(figsize=(12,4))
plt.plot(data['Returns'], alpha=0.5)

high_vol = data['Vol_Regime'] == 'High Volatility'
plt.scatter(
    data.index[high_vol],
    data.loc[high_vol, 'Returns'],
    color='red',
```

```
    s=5,
    label='High Volatility'
)

plt.legend()
plt.title("Returns Highlighted by Volatility Regime")
plt.show()
```



High-volatility periods are associated with larger return dispersion and increased downside risk.

[68]:
```
regime_stats = data.groupby('Vol_Regime')['Returns'].agg(
    Mean_Return='mean',
    Volatility='std',
    Skewness='skew',
    Kurtosis=lambda x: x.kurt()
)

regime_stats
```

[68]:

	Mean_Return	Volatility	Skewness	Kurtosis
Vol_Regime				
High Volatility	0.000525	0.014698	-0.288926	9.525955
Low Volatility	0.000483	0.006325	-0.583247	2.000549

- Kurtosis is computed explicitly using a lambda function to ensure compatibility across pandas versions and to measure excess kurtosis (fat tails) in return distributions.
- Return distributions differ significantly across volatility regimes, particularly in variance and tail behavior.

[69]:
```
regime_annual = data.groupby('Vol_Regime')['Returns'].agg(
    Annualized_Return=lambda x: x.mean() * 252,
    Annualized_Volatility=lambda x: x.std() * np.sqrt(252)
)
```

```
regime_annual
```

[69]:

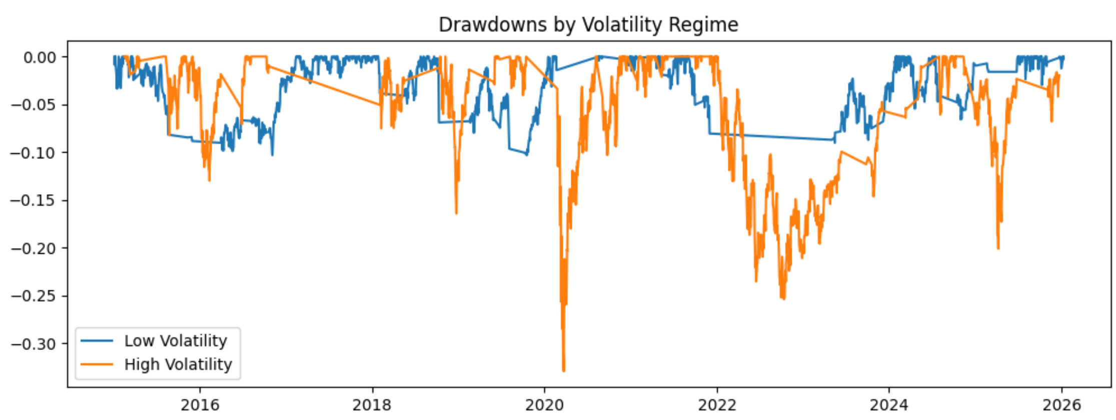
Vol_Regime	Annualized_Return	Annualized_Volatility
High Volatility	0.132323	0.233328
Low Volatility	0.121713	0.100408

[70]:

```
plt.figure(figsize=(12,4))

for regime in ['Low Volatility', 'High Volatility']:
    subset = data[data['Vol_Regime'] == regime]
    cum = (1 + subset['Returns']).cumprod()
    dd = cum / cum.cummax() - 1
    plt.plot(dd, label=regime)

plt.legend()
plt.title("Drawdowns by Volatility Regime")
plt.show()
```



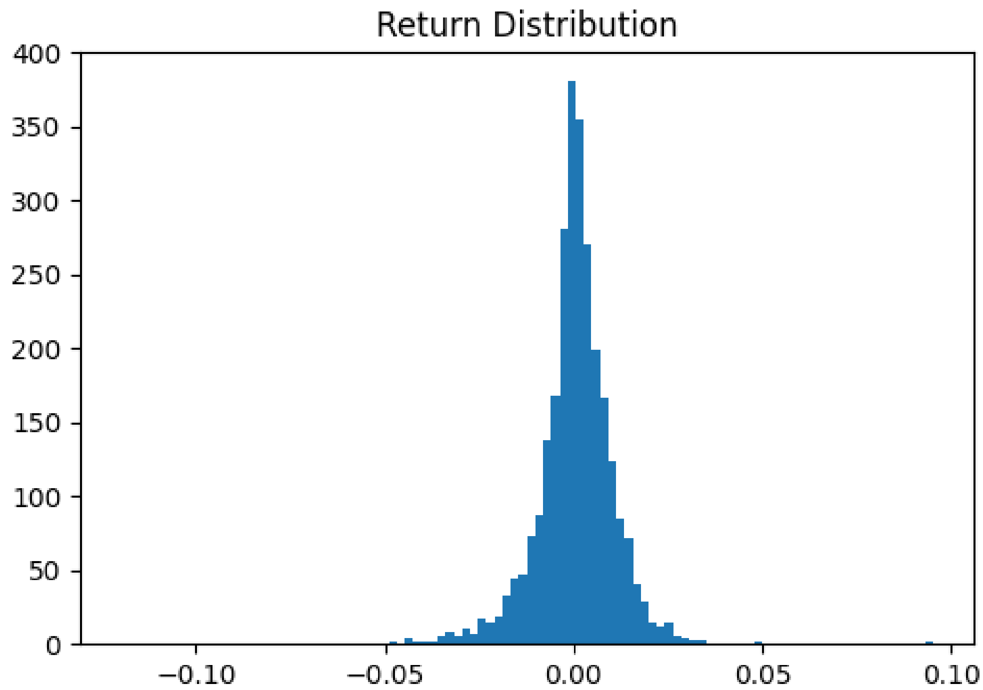
Drawdowns during high-volatility regimes are deeper and recover more slowly.

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.

[71]:

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



1.1 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

1.2 Volatility Regime Insights

- High-volatility regimes exhibit higher variance, fatter tails, and deeper drawdowns
- Risk-adjusted performance deteriorates during high-volatility periods
- Low-volatility regimes are associated with more stable compounding
- Volatility regimes cluster over time, indicating regime persistence
- Simple regime classification already provides actionable risk context