\setcounter{secnumdepth}{0}

Tool Usage Rationale

- Excel was used for initial exploratory analysis, simple correlations, and time-series visualization.
- Python was used for data engineering, monthly alignment, regime-based analysis, volatility modeling, and SQL-style aggregation.

Project Introduction

Impact of US Fed Funds Rate on S&P 500 and NIFTY Returns

Objective:
This project uses Python for analytical modeling and Excel for initial data preparation.Analyze how changes in the US Federal Reserve interest rates affect the monthly returns of S&P 500 and NIFTY indices from 2000 to 2025.

Datasets Used:

1. US Fed Funds Rate (monthly)
2. S&P 500 monthly data
3. NIFTY monthly data

Steps Overview:

1. Load and prepare Dataset
2. Merge datasets by month
3. Calculate monthly returns
4. Visualize Fed Rate vs Market Returns
5. Analyze insights

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
```

Data Loading and Preparation

In [2]:
```
# Reading Excel File

fed = pd.read_excel("DATA/CLEANED/FEDFUNDS.xlsx")     # Fed Funds Rate dataset
spx = pd.read_excel("DATA/CLEANED/^spx_m.xlsx")       # S&P 500 dataset
nifty = pd.read_excel("DATA/CLEANED/Nifty 50 Historical Data.xlsx")  # NIFTY dat
```

In [3]:
```
# Renaming Columns

spx.rename(columns={'DATE-TIME': 'Date'}, inplace=True)
nifty.rename(columns={'DATE-TIME': 'Date'}, inplace=True)
nifty.rename(columns={'Monthly Return': 'NIFTY_Monthly_Return'}, inplace=True)
```

In [4]:
```
# Convert Date Columns To Datetime Format

spx['Date'] = pd.to_datetime(spx['Date'])
nifty['Date'] = pd.to_datetime(nifty['Date'])
```

In [5]:
```
# Sorting Data

fed = fed.sort_values('Date')
spx = spx.sort_values('Date')
nifty = nifty.sort_values('Date')
```

Monthly Alignment and Dataset Merging

Different datasets report dates differently (month start vs month end), so monthly periods are used to ensure correct alignment.

In [6]:
```
# Rename Date Column To YearMonth

fed['YearMonth'] = fed['Date'].dt.to_period('M')
spx['YearMonth'] = spx['Date'].dt.to_period('M')
nifty['YearMonth'] = nifty['Date'].dt.to_period('M')
```

In [7]:
```
# Merge datasets by YearMonth

master = pd.merge(
    fed[['YearMonth', 'Fed_Funds_Rate']],
    spx[['YearMonth', 'SP500_Monthly_Return']],
    on='YearMonth',
    how='inner'
)

master = pd.merge(
    master,
    nifty[['YearMonth', 'NIFTY_Monthly_Return']],
    on='YearMonth',
    how='inner'
)
```

Correlation Analysis

The following correlation analysis is included to validate Excel-based findings and motivate deeper regime and volatility analysis.

In [8]:
```
corr = master[['Fed_Funds_Rate',
               'SP500_Monthly_Return',
               'NIFTY_Monthly_Return']].corr()
```

```
corr
```

Out[8]:

	Fed_Funds_Rate	SP500_Monthly_Return	NIFTY_Monthly_Return
Fed_Funds_Rate	1.000000	-0.038445	-0.027594
SP500_Monthly_Return	-0.038445	1.000000	0.535298
NIFTY_Monthly_Return	-0.027594	0.535298	1.000000

In [9]:

```
# Convert Period to Timestamp for plotting

master['YearMonth_dt'] = master['YearMonth'].dt.to_timestamp()
```

Market Behavior by Fed Rate Regimes

In [10]:

```
def rate_regime(rate):
    if rate < 2:
        return 'Low Rate (<2%)'
    elif rate <= 4:
        return 'Medium Rate (2–4%)'
    else:
        return 'High Rate (>4%)'

master['Rate_Regime'] = master['Fed_Funds_Rate'].apply(rate_regime)
```

In [11]:

```
regime_summary = master.groupby('Rate_Regime').agg(
    SP500_Avg_Return=('SP500_Monthly_Return', 'mean'),
    SP500_Volatility=('SP500_Monthly_Return', 'std'),
    NIFTY_Avg_Return=('NIFTY_Monthly_Return', 'mean'),
    NIFTY_Volatility=('NIFTY_Monthly_Return', 'std')
)

regime_summary
```

Out[11]:

Rate_Regime	SP500_Avg_Return	SP500_Volatility	NIFTY_Avg_Return	NIFTY_Volatility
High Rate (>4%)	0.008282	0.037892	0.013158	0.056557
Low Rate (<2%)	0.007237	0.045146	0.011794	0.063225
Medium Rate (2–4%)	-0.002890	0.046531	0.004251	0.067710

Regime Summary

Key observations:

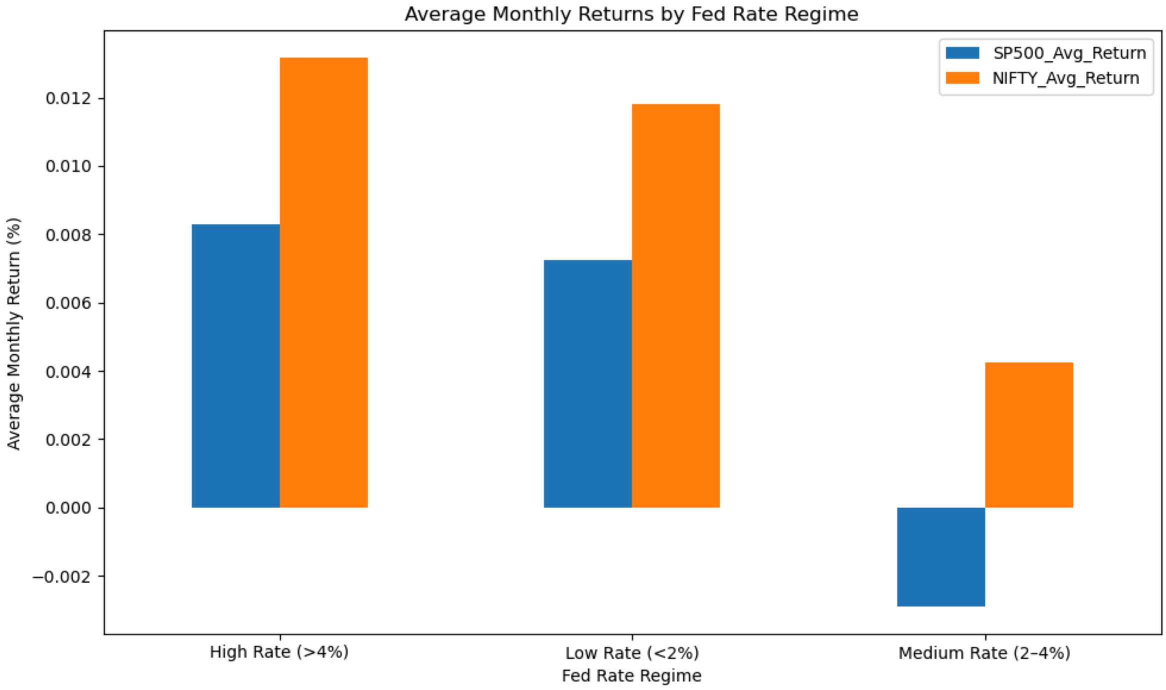
- Market returns differ significantly across Fed rate regimes.
- Low-rate environments generally support higher average returns.

- High-rate regimes show increased volatility, reflecting uncertainty.
- Weak overall correlation exists because markets react differently under different regimes.

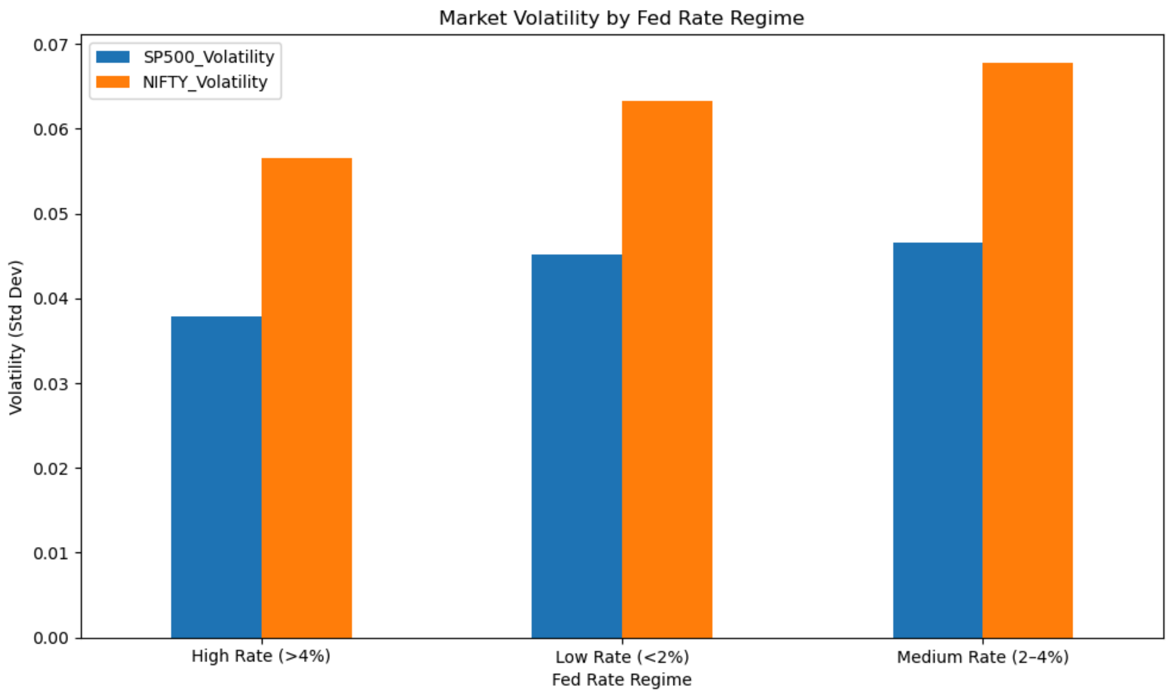
This explains why simple correlation analysis fails to capture the true Fed–market relationship.

Regime Visualization

In [12]:
```
regime_summary[['SP500_Avg_Return', 'NIFTY_Avg_Return']].plot(
    kind='bar',
    figsize=(10,6)
)

plt.title('Average Monthly Returns by Fed Rate Regime')
plt.ylabel('Average Monthly Return (%)')
plt.xlabel('Fed Rate Regime')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



In [13]:
```
regime_summary[['SP500_Volatility', 'NIFTY_Volatility']].plot(
    kind='bar',
    figsize=(10,6)
)

plt.title('Market Volatility by Fed Rate Regime')
plt.ylabel('Volatility (Std Dev)')
plt.xlabel('Fed Rate Regime')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



MONTHLY RETURNS VS ROLLING VOLATILITY

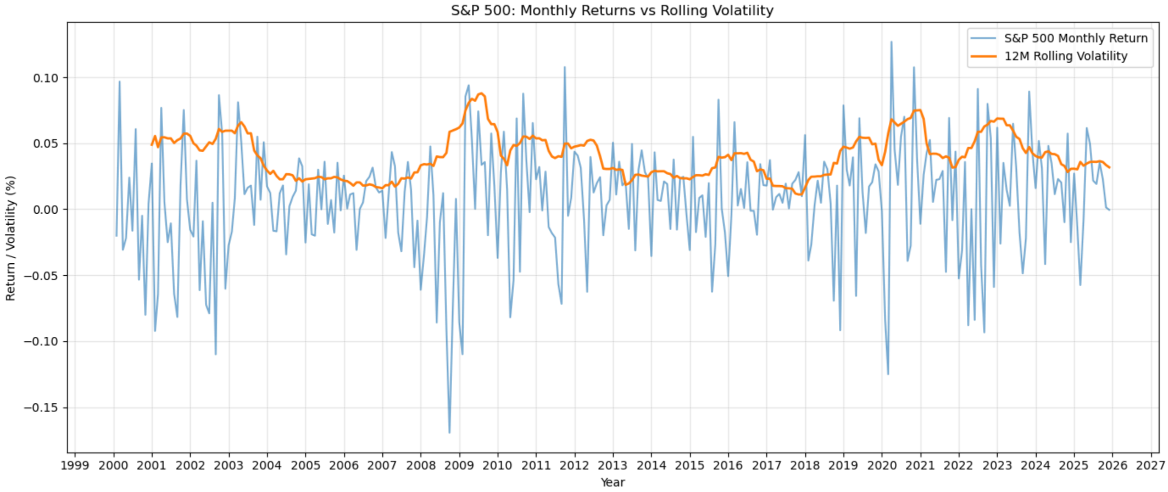
In [14]:

```
# Calculate 12-month rolling volatility

master['SP500_Rolling_Volatility_12M'] = (
    master['SP500_Monthly_Return']
    .rolling(window=12)
    .std()
)

master['NIFTY_Rolling_Volatility_12M'] = (
    master['NIFTY_Monthly_Return']
    .rolling(window=12)
    .std()
)
```

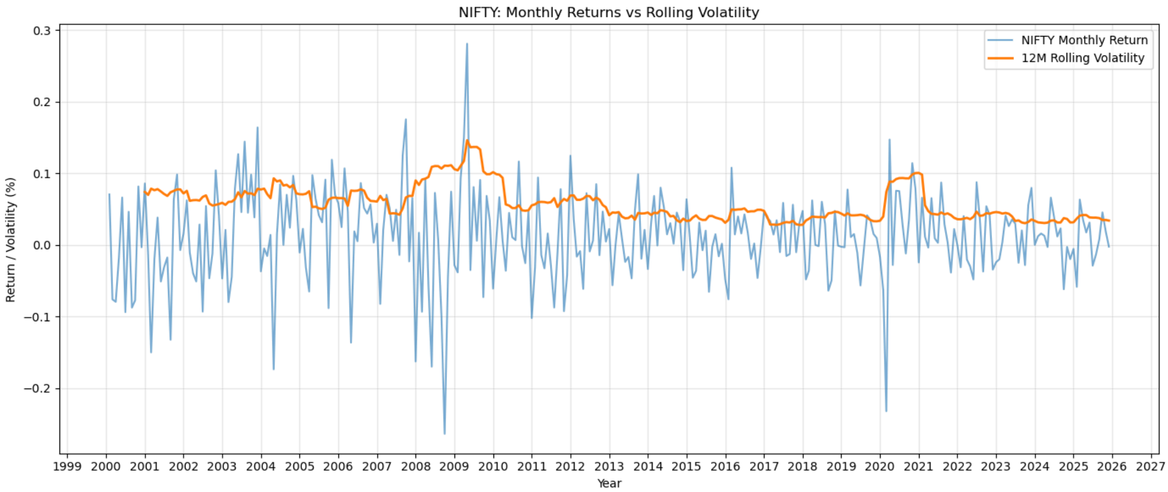
In [15]:

```
plt.figure(figsize=(14,6))

# Returns
plt.plot(master['YearMonth_dt'],
         master['SP500_Monthly_Return'],
         label='S&P 500 Monthly Return',
         alpha=0.6)

# Volatility
plt.plot(master['YearMonth_dt'],
         master['SP500_Rolling_Volatility_12M'],
         label='12M Rolling Volatility',
         linewidth=2)

plt.title('S&P 500: Monthly Returns vs Rolling Volatility')
plt.xlabel('Year')
plt.ylabel('Return / Volatility (%)')
plt.legend()
plt.grid(alpha=0.3)
```

```python
ax = plt.gca()
ax.xaxis.set_major_locator(mdates.YearLocator())
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y'))

plt.tight_layout()
plt.show()
```



In [16]:
```python
plt.figure(figsize=(14,6))

plt.plot(master['YearMonth_dt'],
         master['NIFTY_Monthly_Return'],
         label='NIFTY Monthly Return',
         alpha=0.6)

plt.plot(master['YearMonth_dt'],
         master['NIFTY_Rolling_Volatility_12M'],
         label='12M Rolling Volatility',
         linewidth=2)

plt.title('NIFTY: Monthly Returns vs Rolling Volatility')
plt.xlabel('Year')
plt.ylabel('Return / Volatility (%)')
plt.legend()
plt.grid(alpha=0.3)

ax = plt.gca()
ax.xaxis.set_major_locator(mdates.YearLocator())
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y'))

plt.tight_layout()
plt.show()
```



SQL-style Analysis (SQLite Demonstration)

This section demonstrates SQL-based aggregation logic using SQLite to summarize market behavior across Fed rate regimes.

In [17]:
```
import sqlite3

master_sql = master.copy()
master_sql['YearMonth'] = master_sql['YearMonth'].astype(str)

conn = sqlite3.connect(':memory:')
master_sql.to_sql('market_data', conn, index=False, if_exists='replace')
```

Out[17]: 312

The SQL results below validate the regime-based analysis performed using pandas.

In [18]:
```
query = """
SELECT
    Rate_Regime,
    AVG(SP500_Monthly_Return) AS avg_sp500_return,
    AVG(NIFTY_Monthly_Return) AS avg_nifty_return,
    AVG(SP500_Rolling_Volatility_12M) AS avg_sp500_volatility
FROM market_data
GROUP BY Rate_Regime
ORDER BY Rate_Regime;
"""

from IPython.display import display

sql_regime_summary = pd.read_sql(query, conn)

display(sql_regime_summary)
```

	Rate_Regime	avg_sp500_return	avg_nifty_return	avg_sp500_volatility
0	High Rate (>4%)	0.008282	0.013158	0.035587
1	Low Rate (<2%)	0.007237	0.011794	0.041781
2	Medium Rate (2–4%)	-0.002890	0.004251	0.040494

In [19]:
```
conn.close()
```

Volatility as a Driver of Market Behavior

- Market volatility spikes during crisis periods such as 2008 and COVID-19.
- During high volatility phases, returns become unstable and unpredictable.
- This explains why markets show weak correlation with Fed rate levels alone.
- Investors respond more strongly to uncertainty and risk than to interest rate levels.
- Thus, volatility plays a more dominant role than rate levels in driving short-term market behavior.

The following section summarizes the overall findings of the analysis.

Dashboard Dataset Preparation

This section prepares a business-ready dataset for dashboard visualization. All calculations are performed in Python; the exported file is used only for visualization.

In [20]:
```
# Select final columns required for dashboard
dashboard_df = master[[
    'YearMonth_dt',
    'Rate_Regime',
    'Fed_Funds_Rate',
    'SP500_Monthly_Return',
    'NIFTY_Monthly_Return',
    'SP500_Rolling_Volatility_12M',
    'NIFTY_Rolling_Volatility_12M'
]]

# Export dashboard dataset
dashboard_df.to_excel('dashboard_data.xlsx', index=False)
```

Key Takeaways

• Market returns show weak linear correlation with Fed rate levels
• Return behavior differs significantly across rate regimes
• Volatility spikes align more with macroeconomic uncertainty than rate changes
• Regime-based analysis explains why simple correlation fails