Part 2 — Workshop 5

TECH2: Introduction to Programming, Data, and Information Technology

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See GitHub repository for notebooks and data:
https://github.com/richardfoltyn/TECH2-H24

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1 Exercise: Daily returns of US stock market indices

In this exercise, we examine how the three major US stock market indices performed this year. Use the data in `indices.csv` from the folder `../data/stockmarket` to solve the following tasks:

1. Load the CSV data and restrict the sample to the calendar year 2024.

   Hint: You have to first figure out which character is used to separate individual columns.

   Hint: You should use `pd.read_csv(..., parse_dates=['Date'])` to automatically parse strings stored in the `Date` column as dates.

2. The data comes in a "long" format where each date-ticker combination is stored in a separate row. For the following analysis, the data needs to be reshaped such that each ticker symbol is in its own column ("wide" format).

   Use the `pivot()` method to reshape the `DataFrame` into the desired form. Consult the user guide to see a graphical illustration.

   Your pivoted `DataFrame` should look as follows:

```
    Ticker   DJIA    NASDAQ  SP500
Date
2024-01-02   37715.0 14765.9 4742.8
2024-01-03   37430.2 14592.2 4704.8
```

3. Create a line plot which shows the time series for each of the three ticker symbols in a single graph, for example using `DataFrame.plot()`.

4. The graph you just created is not very satisfactory as the three indices are recorded on vastly different scales. Express each index relative to its initial value in 2024 (so that all three start with the value 1.0) and recreate the previous graph with this normalized data.

5. Another way to check whether the three indices are co-moving is to compute and plot their daily returns. For each index, compute the daily returns, i.e., the relative change vs. the previous closing price in percent (e.g., using `pct_change()`), and plot the three time series of daily returns in a single graph.

6. The previous plots suggests that the three indices co-move a lot.

    1. In order to quantify the strength of this co-movement, compute the pairwise correlations of daily returns using `corr()`.

    2. Create a figure with 3-by-3 subplots where each off-diagonal plot shows the scatter plot for two of the indices.

        Hint: You can use the function `scatter_matrix()` to accomplish this task. Alternatively, you can create a figure with 3-by-3 subplots using Matplotlib's `subplots()`, iterate over all rows and columns and add a `scatter()` plot to each `axes` object.

    3. Add the correlation coefficient for each stockmarket index pair as text to the corresponding subplot in the figure you created (this can be done using `text()`).

Solution.

Part (1)

[1]:
```
# Uncomment this to use files in the local data/stockmarket directory
DATA_PATH = '../data/stockmarket'

# Uncomment this to load data directly from GitHub
# DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/TECH2-H24/main/data/
↪stockmarket'
```

[2]:
```
import pandas as pd

# path to CSV file
path = f'{DATA_PATH}/indices.csv'

# Parse data using tab character as separator
df = pd.read_csv(path, sep='\t', parse_dates=['Date'])

# Restrict dates to year 2024
df = df.loc[df['Date'] >= '2024']

# Reset to default index
df = df.reset_index(drop=True)

# Print first 6 observations
df.head(6)
```

[2]:

	Date	Ticker	Price
0	2024-01-02	DJIA	37715.0
1	2024-01-02	SP500	4742.8
2	2024-01-02	NASDAQ	14765.9
3	2024-01-03	DJIA	37430.2
4	2024-01-03	SP500	4704.8
5	2024-01-03	NASDAQ	14592.2

Part (2)

The values in column `Ticker` should provide the new column names, with values given by the column `Price`. The `Date` column is the (unique) index of the pivoted `DataFrame`.

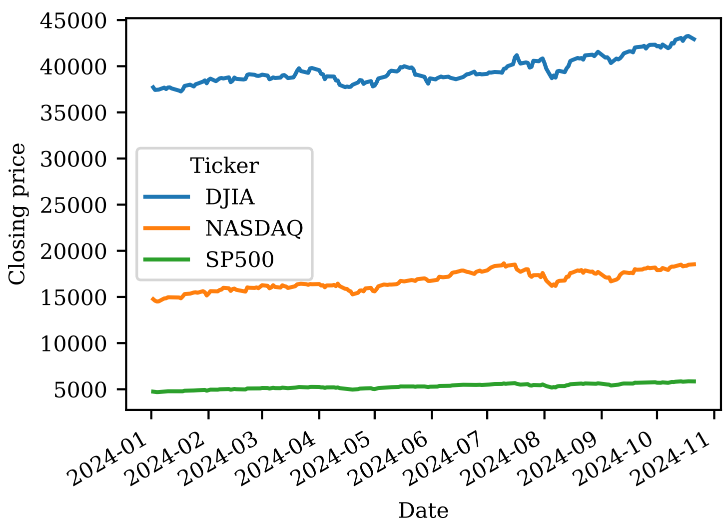
[3]:
```
# Reshape DataFrame, move ticker symbols to individual columns
df = df.pivot(index='Date', columns='Ticker', values='Price')

df.head(5)
```

[3]:
```
Ticker          DJIA    NASDAQ   SP500
Date
2024-01-02  37715.0  14765.9  4742.8
2024-01-03  37430.2  14592.2  4704.8
2024-01-04  37440.3  14510.3  4688.7
2024-01-05  37466.1  14524.1  4697.2
2024-01-08  37683.0  14843.8  4763.5
```

Part (3)

[4]:
```
# Plot all three indices, setting a label for the y-axis.
df.plot(ylabel='Closing price')
```

[4]:
```
<Axes: xlabel='Date', ylabel='Closing price'>
```



Part (4)

One way to normalize each column by its first value is to select the first row and divide the data by this row:

[5]:
```
# Use .iloc[0] to select the first row, divide data by values in first row.
df_norm = df / df.iloc[0]
```

You can use `head()` to verify that the first normalized element of each column is now 1.

[6]:
```
df_norm.head(3)
```

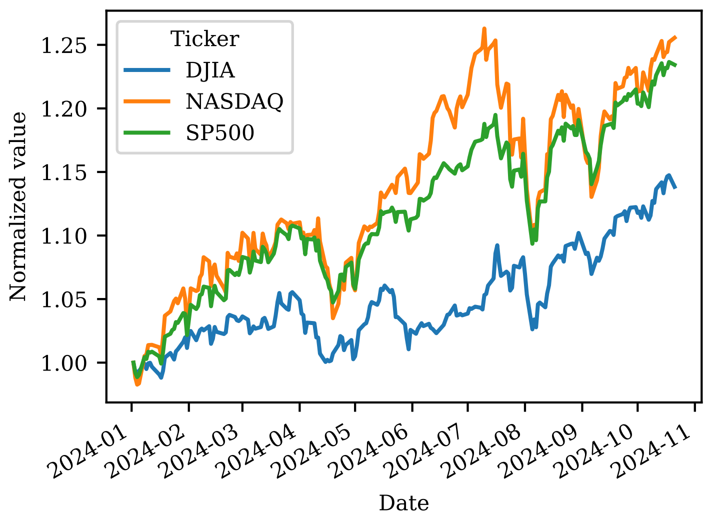
[6]:
```
Ticker          DJIA     NASDAQ      SP500
Date
2024-01-02  1.000000  1.000000  1.000000
```

```
2024-01-03  0.992449  0.988236  0.991988
2024-01-04  0.992716  0.982690  0.988593
```

Finally, we plot the normalized indices just like in the previous sub-question. It is now much easier to see that these indices moved very similarly over this year.

[7]:
```python
df_norm.plot(ylabel='Normalized value')
```

[7]:
```
<Axes: xlabel='Date', ylabel='Normalized value'>
```



Part (5)

We use the `pct_change()` method to compute the relative difference between two consecutive closing prices.

[8]:
```python
# Relative difference from previous closing price in percent
df_returns = df.pct_change() * 100.0
```

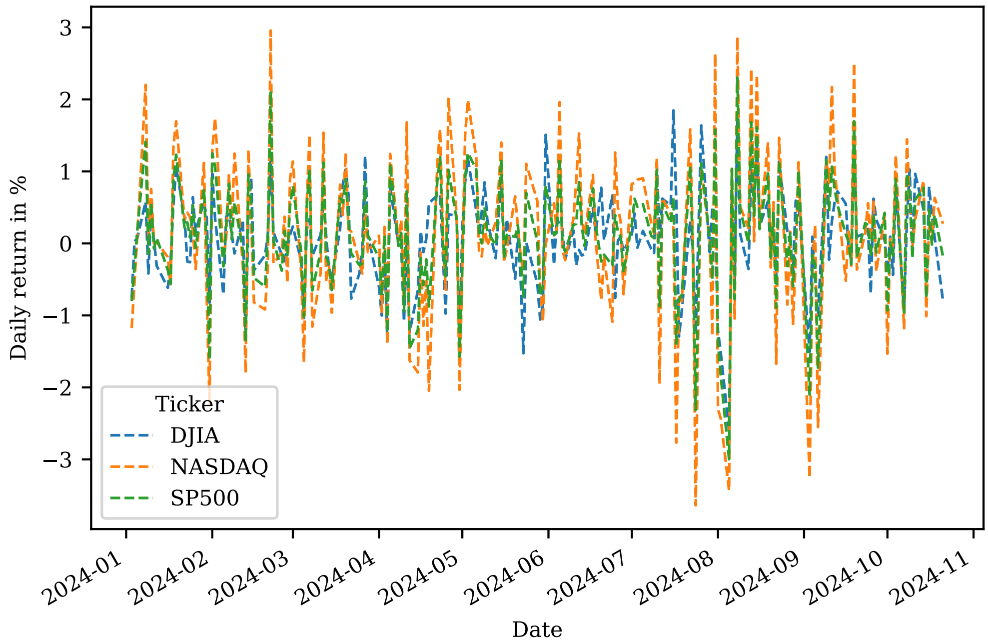
Because we cannot compute a difference for the very first observation, this value is set to `NaN`.

[9]:
```python
df_returns.head(3)
```

[9]:
```
Ticker          DJIA    NASDAQ     SP500
Date
2024-01-02       NaN       NaN       NaN
2024-01-03 -0.755137 -1.176359 -0.801214
2024-01-04  0.026984 -0.561259 -0.342204
```

[10]:
```python
# use dashed lines since daily returns are overlapping
df_returns.plot(ylabel='Daily return in %', lw=1.0, ls='--', figsize=(6, 4))
```

[10]:
```
<Axes: xlabel='Date', ylabel='Daily return in %'>
```



Part (6)

To compute the pairwise correlation between all columns, we call `corr()`. The results show that all three daily returns are highly correlated, which is what we would have expected from looking at the time series of daily returns we plotted earlier.

Note that in all these operations, the `NaN` in the first row are automatically excluded.

[11]:
```
df_corr = df_returns.corr()
df_corr
```

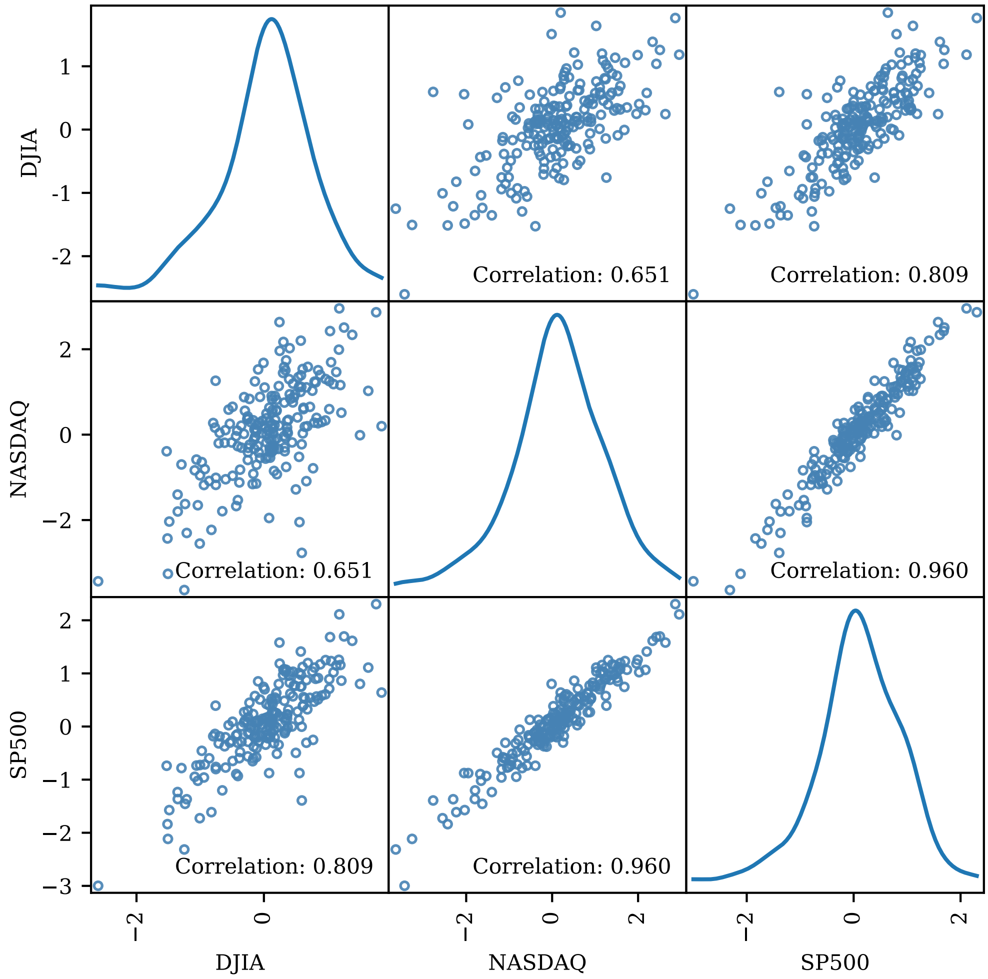
[11]:
```
Ticker       DJIA    NASDAQ     SP500
Ticker
DJIA     1.000000  0.651024  0.808597
NASDAQ   0.651024  1.000000  0.959787
SP500    0.808597  0.959787  1.000000
```

Recall that the correlation coefficient is normalized onto the interval $[-1, 1]$. A positive value means that two variables co-move in the same direction, whereas the opposite is true for a negative value. An absolute value close to 1 means that this co-movement is particularly strong, whereas values around zero mean that there is almost no co-movement.

We can plot the pairwise correlations using the `scatter_matrix()` from the module `pandas.plotting` which takes a `DataFrame` as its argument and creates pairwise scatter plots for all columns. The function either plots a histogram or a kernel density plot along the main diagonal, since creating a scatter plot of one and the same variable against itself just yields a diagonal line!

[12]:
```
from pandas.plotting import scatter_matrix

# Create figure with 3x3 scatter plots. Main diagonal shows kernel density
# for each index.
axes = scatter_matrix(df_returns,
        figsize=(6, 6),
        alpha=0.9,
        color='none',
        edgecolors='steelblue',
        diagonal='kde'
    )
```

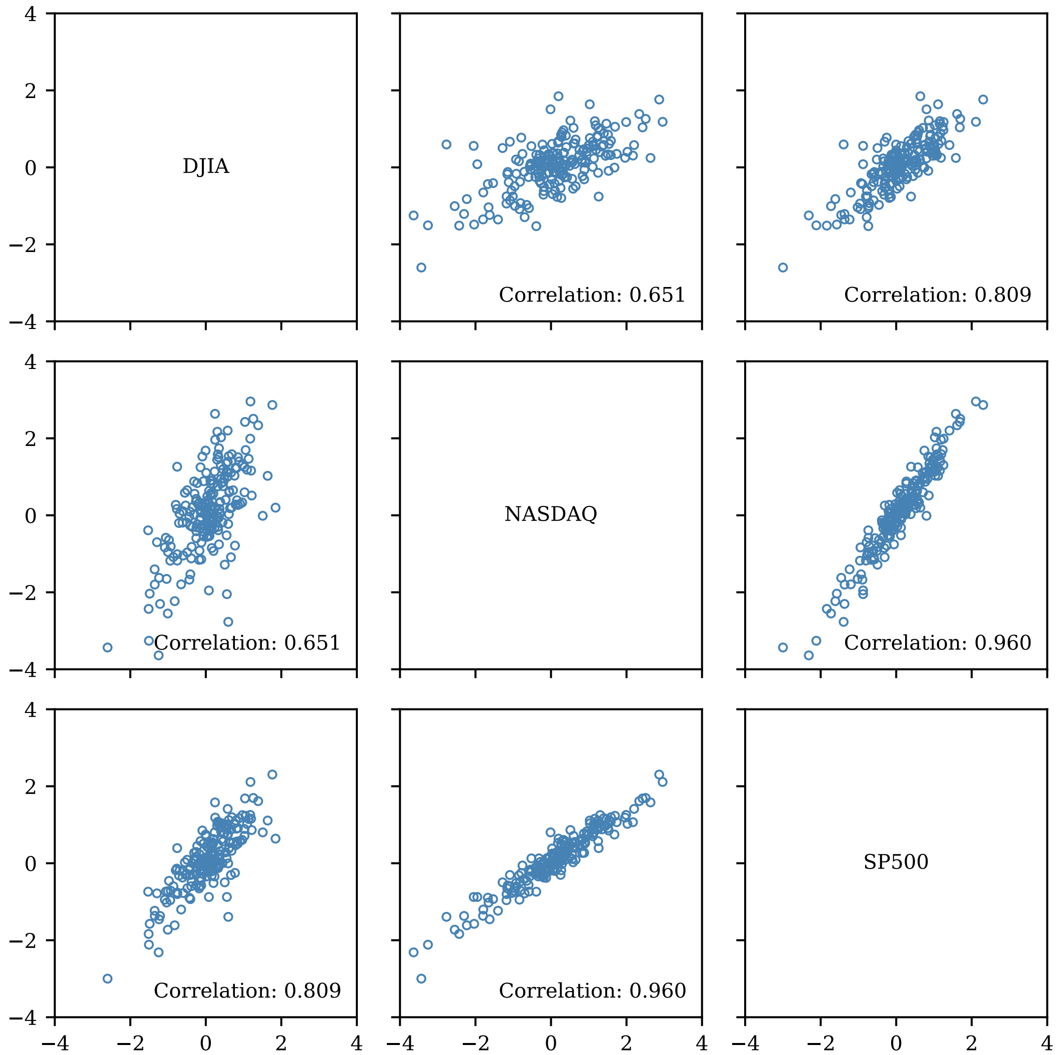
```
# Iterate over subplots, add correlation text to each off-diagonal panel
for i in range(axes.shape[0]):
    for j in range(axes.shape[1]):
        # Skip diagonal panels, correlation is 1.0 by construction
        if i == j:
            continue
        ax = axes[i, j]
        c = df_corr.iloc[i, j]
        ax.text(0.95, 0.05, f'Correlation: {c:.3f}',
            transform=ax.transAxes, va='bottom', ha='right'
        )
```



Alternatively, we can create the 3-by-3 scatter plots manually. We first ask Matplotlib to create a figure with 3-by-3 panels and then iterate over rows and columns, using `ax.scatter()` to add the bivariate scatter plot to each panel.

[13]:
```
import matplotlib.pyplot as plt
import numpy as np

fig, axes = plt.subplots(3, 3, figsize=(6, 6), sharex=True, sharey=True)

# Index names used as labels along the diagonal
labels = df_returns.columns.to_list()

# Iterate over rows and columns
for i in range(axes.shape[0]):
```

```
    for j in range(axes.shape[1]):

        ax = axes[i, j]

        # For diagonal panels, print the index name instead of
        # (exactly diagonal) scatter plot.
        if i == j:
            ax.text(0.5, 0.5, labels[i], transform=ax.transAxes,
                va='center', ha='center')
            continue

        # Get x- and y-values for this panel
        xvalues = df_returns.iloc[:, j]
        yvalues = df_returns.iloc[:, i]

        ax.scatter(xvalues, yvalues, s=10, alpha=1.0, lw=0.75,
            color='none', edgecolors='steelblue')

        # Set uniform x- and y-ticks for all axes
        ticks = np.linspace(-4, 4, 5)
        ax.set_xticks(ticks)
        ax.set_yticks(ticks)

        # Add correlation to any off-diagonal graphs
        if i != j:
            c = df_corr.iloc[i, j]
            ax.text(0.95, 0.05, f'Correlation: {c:.3f}',
                transform=ax.transAxes, va='bottom', ha='right'
            )

fig.tight_layout()
```



2 Exercise: Long-run returns of the S&P 500

For this question, we restrict our attention to the S&P 500 stock market index and examine its long-run annual returns. Use the data from `SP500.csv` from the folder `../data/stockmarket` to solve the following tasks:

1. Load the CSV data and set the `Date` column as the index.

   Hint: You should use `pd.read_csv(..., parse_dates=['Date'])` to automatically parse strings stored in the `Date` column as dates.

2. You are interested in computing annual returns, but the data you just loaded contains daily observations. For each calendar year, select the first observation to get an annualized time series.

   Hint: Use the `resample()` method to aggregate by year.

3. Compute the annual returns of the S&P 500, defined as the relative change from the previous-year's price on the first trading day (e.g., using `pct_change()`). Plot the resulting annual return time series.

4. What are the mean and standard deviation of annual returns? Indicate the average annual returns over this period using a horizontal line in the plot you previously created.

Solution.

Part (1)

[14]:
```
# Uncomment this to use files in the local data/stockmarket directory
DATA_PATH = '../data/stockmarket'

# Uncomment this to load data directly from GitHub
# DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/TECH2-H24/main/data/
 ↪stockmarket'
```

[15]:
```
import pandas as pd

# Path to CSV file
fn = f'{DATA_PATH}/SP500.csv'

# Load S&P 500 data, set Date column as index
df = pd.read_csv(fn, parse_dates=['Date'], index_col='Date')

# Print first 5 rows
df.head(5)
```

[15]:
```
            SP500
Date
1950-01-03   16.7
1950-01-04   16.9
1950-01-05   16.9
1950-01-06   17.0
1950-01-09   17.1
```

Part (2)

To aggregate to annual frequency, we use `resample('YS')` and use `first()` to select the first observation of each calendar year. The string 'YS' tells pandas that you want to use the *year start* as the index of the resulting aggregated time series, i.e., January 1 of each calendar year.

[16]:
```
# Select first row for each calendar year, use year start (YS) aggregation method
yearly = df.resample('YS').first()

yearly.head(5)
```

[16]:
```
            SP500
Date
1950-01-01   16.7
1951-01-01   20.8
1952-01-01   23.8
1953-01-01   26.5
1954-01-01   25.0
```

Part (3)

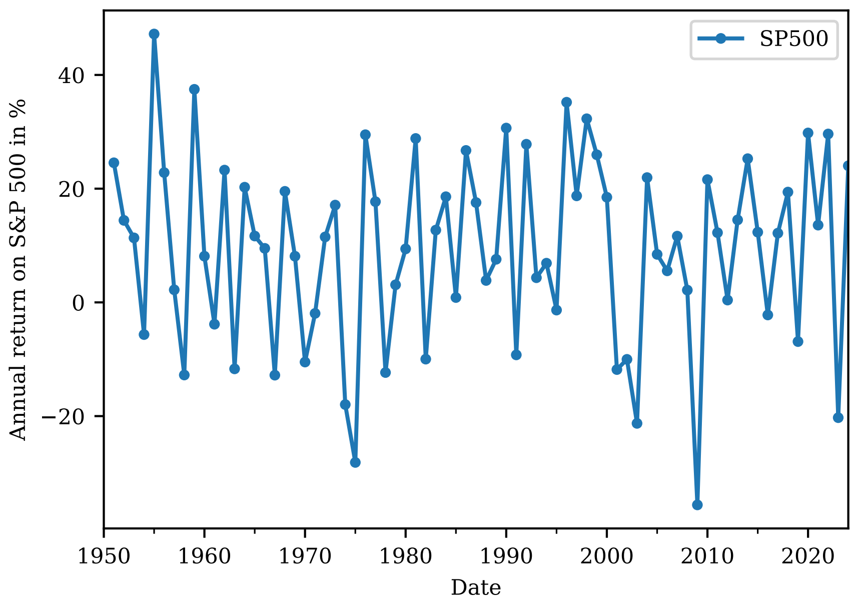
[17]:
```
# Compute annual returns in percent
returns = yearly.pct_change() * 100.0

# Print first 5 rows
returns.head(5)
```

[17]:
```
                 SP500
Date
1950-01-01         NaN
1951-01-01   24.550898
1952-01-01   14.423077
1953-01-01   11.344538
1954-01-01   -5.660377
```

To plot the return series, we use the `plot()` method.

[18]:
```
import matplotlib.pyplot as plt

returns.plot(ylabel='Annual return on S&P 500 in %',
    marker='o',
    markersize=3,
    figsize=(5, 3.5),
    label='Annual return'
)
```

[18]:
```
<Axes: xlabel='Date', ylabel='Annual return on S&P 500 in %'>
```



Part (4)

We first compute the mean and standard deviation of the return series:

[19]:
```
# Compute mean and std. dev. of return time series, extract first (and only) element
mean = returns.mean().iat[0]
std = returns.std().iat[0]

print(f'Mean: {mean:.2f}%, Standard deviation: {std:.2f}%')
```

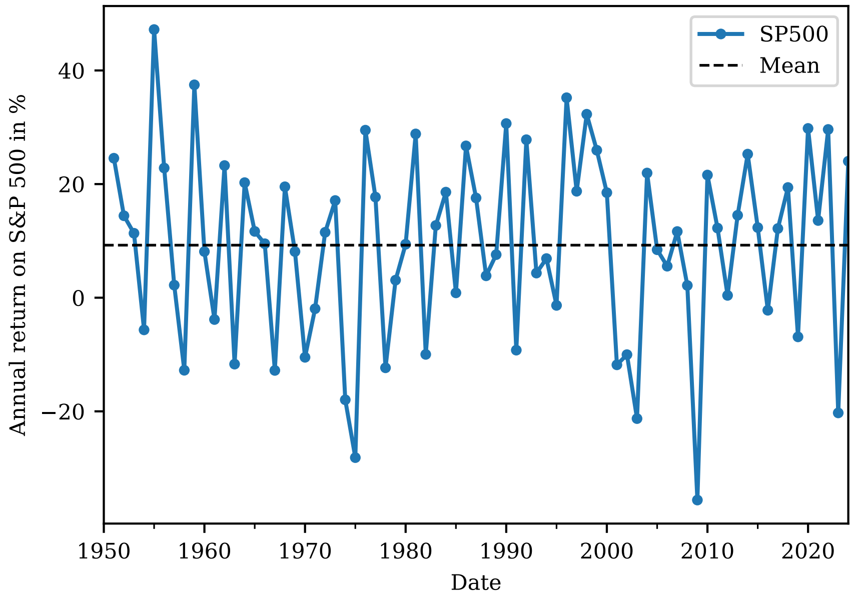
```
Mean: 9.25%, Standard deviation: 16.52%
```

Once we have computed the mean, we can recreate the plot and add a horizontal line indicating the average return.

[20]:
```
import matplotlib.pyplot as plt

# Plot return time series, store Axes object returned by plot()
```

```python
ax = returns.plot(ylabel='Annual return on S&P 500 in %',
    marker='o',
    markersize=3,
    figsize=(5, 3.5),
    label='Annual return'
)

# Add horizontal line at sample mean
ax.axhline(mean, lw=1.0, ls='--', color='black', label='Mean')

# Add legend
plt.legend()
```

[20]: <matplotlib.legend.Legend at 0x7f6fa8b61010>



3 Exercise: Daily returns of Apple, Nvidia and Tesla

In this exercise, you are asked to compute various statistics of daily returns for selected stocks and plot these as bar charts. You'll be using data from files located in the folder `../data/stockmarket`.

1. Load the price data for Apple Inc (`AAPL.csv`), Nvidia Inc (`NVDA.csv`) and Tesla Inc (`TSLA.csv`). Set the `Date` column as the index and merge these data sets into a single DataFrame, keeping only those dates for which you have observations on all three stocks. Restrict your data to the calendar years 2015-2023.

   Hint: All three time series have a `Price` column which you should rename to the respective ticker symbol (e.g., `AAPL`) before merging the data to avoid overlapping column names.

   Hint: You should use `pd.read_csv(..., parse_dates=['Date'])` to automatically parse strings stored in the `Date` column as dates.

2. Compute the average daily returns for each of the three stocks, e.g., using `pct_change()`. For simplicity, we assume that daily returns are defined as the percentage change vs. the previous observation even though these may be multiple days apart.

Compute the average daily returns, the standard deviation of daily returns, and the Sharpe ratio of daily returns by calendar year (using `resample()`). For this exercise, we define Sharpe ratio as the ratio of average returns divided by their standard deviation.

3. Create three figures visualizing these statistics. Each figure should contain a bar chart that shows one of the statistics (mean, std. deviation, Sharpe ratio) for all three companies by calendar year. Properly label your figures (using labels for x-axis, y-axis and titles), and add a horizontal line at zero for the figures depicting average returns and the Sharpe ratio.

Solution.

Part (1)

[21]:
```
# Uncomment this to use files in the local data/stockmarket directory
DATA_PATH = '../data/stockmarket'

# Uncomment this to load data directly from GitHub
# DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/TECH2-H24/main/data/
↪stockmarket'
```

[22]:
```
import pandas as pd

symbols = ['AAPL', 'NVDA', 'TSLA']

data = []

for symbol in symbols:
    # path to file containing data for current ticker symbol
    path = f'{DATA_PATH}/{symbol}.csv'
    print(f'Loading data from {path}')

    # Load data & set index
    df = pd.read_csv(path, parse_dates=['Date'], index_col='Date')

    # Rename Price column to current ticker
    df = df.rename(columns={'Price': symbol})

    data.append(df)

# concatenate data along column axis, keep only intersection of rows present
# in all data sets
df = pd.concat(data, axis=1, join='inner')

# Restrict to desired calendar years
df = df.loc['2015':'2023']

# Print first 5 observations
df.head(5)
```

```
Loading data from ../data/stockmarket/AAPL.csv
Loading data from ../data/stockmarket/NVDA.csv
Loading data from ../data/stockmarket/TSLA.csv
```

[22]:

Date	AAPL	NVDA	TSLA
2015-01-02	24.3740	0.4832	14.6207
2015-01-05	23.6873	0.4750	14.0060
2015-01-06	23.6895	0.4606	14.0853
2015-01-07	24.0217	0.4594	14.0633
2015-01-08	24.9447	0.4767	14.0413

Part (2)

[23]:
```
# Daily returns
df_returns = df.pct_change() * 100.0
```

With these daily returns, we can compute the statistics of interest.

[24]:
```
# Compute average daily returns by year
means = df_returns.resample('YE').mean()

# Compute std. deviation of daily returns by year
std = df_returns.resample('YE').std()

# Compute sharpe ratio (by year)
sharpe = means/std

# Tabulate sharpe ratio
sharpe
```

[24]:
```
                AAPL      NVDA      TSLA
Date
2015-12-31  0.003432  0.103916  0.026839
2016-12-31  0.039089  0.172739 -0.006592
2017-12-31  0.147563  0.106357  0.078500
2018-12-31 -0.003162 -0.031413  0.025262
2019-12-31  0.161827  0.101453  0.044762
2020-12-31  0.095517  0.105093  0.178591
2021-12-31  0.082575  0.128031  0.063443
2022-12-31 -0.043119 -0.049994 -0.078403
2023-12-31  0.131216  0.174980  0.099487
```

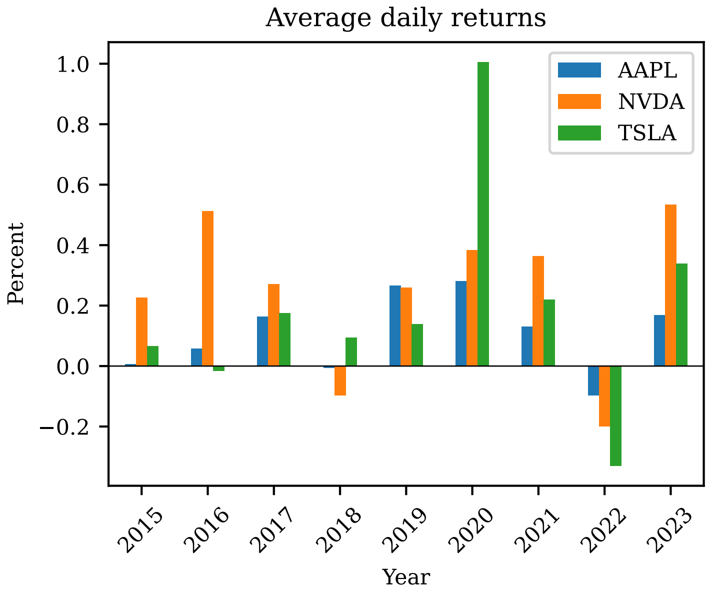
Part (3)

Before creating the bar charts, it is advisable to replace the index with simple calendar years since these look better on the resulting graphs.

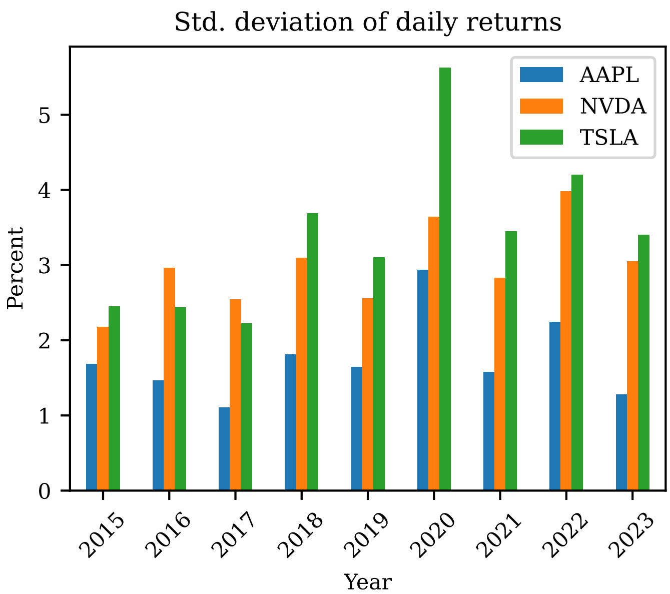
[25]:
```
# Convert index to calendar year for nicer graphs
for df in (means, std, sharpe):
    # Extract calendar year from index, store in Year column
    df['Year'] = df.index.year

    # Update index in place
    df.set_index('Year', inplace=True)
```

[26]:
```
# Plot average daily return by year and ticker
ax = means.plot.bar(
    y=['AAPL', 'NVDA', 'TSLA'],
    rot=45,
    title='Average daily returns',
    ylabel='Percent'
)
ax.axhline(0.0, lw=0.5, color='black')
```

[26]:
```
<matplotlib.lines.Line2D at 0x7f6fa9f95520>
```

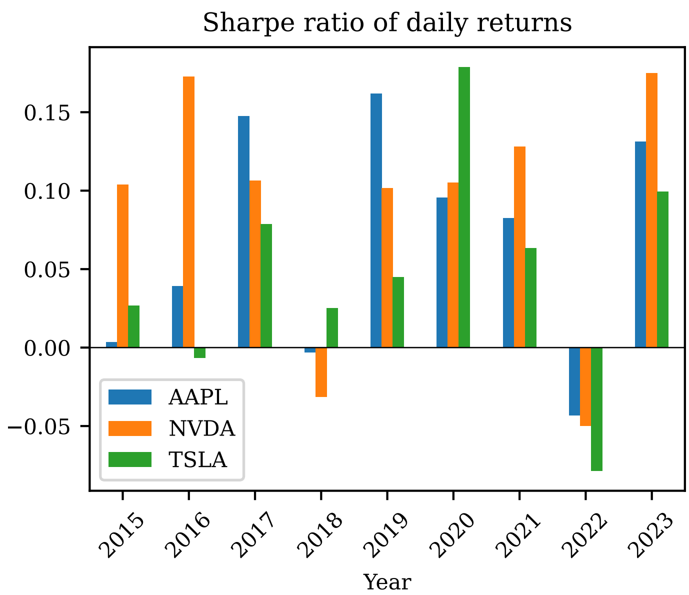


[27]:
```
# Plot std. deviation of daily returns by year and ticker
ax = std.plot.bar(
    y=['AAPL', 'NVDA', 'TSLA'],
    rot=45,
    title='Std. deviation of daily returns',
    ylabel='Percent'
)
```



[28]:
```
# Plot sharpe ratio daily returns by year and ticker
ax = sharpe.plot.bar(
    y=['AAPL', 'NVDA', 'TSLA'],
    rot=45,
    title='Sharpe ratio of daily returns'
)
ax.axhline(0.0, lw=0.5, color='black')
```

[28]: <matplotlib.lines.Line2D at 0x7f6fa950a420>


Sharpe ratio of daily returns
0.15
0.10
0.05
0.00
−0.05
AAPL
NVDA
TSLA
2015
2016
2017
2018
2019
2020
2021
2022
2023
Year