Select Index Components & Import Data

Market Value-Weighted Index

- Composite performance of various stocks
- Components weighted by market capitalization
  - Share Price x Number of Shares => Market Value
- Larger components get higher percentage weightings
- Key market indexes are value-weighted:
  - S&P 500, NASDAQ, Wilshire 5000, Hang Seng

Build a Cap-Weighted Index

- Apply new skills to construct value-weighted index
  - Select components from exchange listing data
  - Get component number of shares and stock prices
  - Calculate component weights
  - Calculate index
  - Evaluate performance of components and index

Load Stock Listing Data

```
In [1]: nyse = pd.read_excel('listings.xlsx', sheetname='nyse',
                             na_values='n/a')
In [2]: nyse.info()

RangeIndex: 3147 entries, 0 to 3146
Data columns (total 7 columns):
Stock Symbol             3147 non-null object   # Stock Ticker
Company Name             3147 non-null object
Last Sale                3079 non-null float64  # Latest Stock Price
Market Capitalization    3147 non-null float64
IPO Year                 1361 non-null float64  # Year of listing
Sector                   2177 non-null object
Industry                 2177 non-null object
dtypes: float64(3), object(4)
```

Load & Prepare Listing Data

```
In [3]: nyse.set_index('Stock Symbol', inplace=True)

In [4]: nyse.dropna(subset=['Sector'], inplace=True)

In [5]: nyse['Market Capitalization'] /= 1e6  # in Million USD

Index: 2177 entries, DDD to ZTO
Data columns (total 6 columns):
Company Name             2177 non-null object
Last Sale                2175 non-null float64
Market Capitalization    2177 non-null float64
IPO Year                 967 non-null float64
Sector                   2177 non-null object
Industry                 2177 non-null object
dtypes: float64(3), object(3)
```

Select Index Components

```
In [5]: components = nyse.groupby(['Sector'])['Market Capitalization'].nlargest(1)

In [6]: components.sort_values(ascending=False)

Sector                 Stock Symbol
Health Care            JNJ             338834.390080
Energy                 XOM             338728.713874
Finance                JPM             300283.250479
Miscellaneous          BABA            275525.000000
Public Utilities       T               247339.517272
Basic Industries       PG              230159.644117
Consumer Services      WMT             221864.614129
Consumer Non-Durables  KO              183655.305119
Technology             ORCL            181046.096000
Capital Goods          TM              155660.252483
Transportation         UPS              90180.886756
Consumer Durables      ABB              48398.935676
Name: Market Capitalization, dtype: float64
```

Import & Prepare Listing Data

```
In [7]: tickers = components.index.get_level_values('Stock Symbol')

In [8]: tickers
Out[8]:
Index(['PG', 'TM', 'ABB', 'KO', 'WMT', 'XOM', 'JPM', 'JNJ', 'BABA', 'T',
       'ORCL', ‘UPS'], dtype='object', name='Stock Symbol’)

In [9]: tickers.tolist()
Out[9]:
['PG',
 'TM',
 'ABB',
 'KO',
 ‘WMT',
…
 'T',
 'ORCL',
 'UPS']
```

Stock Index Components

```
In [10]: columns = ['Company Name', 'Market Capitalization', 'Last Sale']

In [11]: component_info = nyse.loc[tickers, columns]

In [12]: pd.options.display.float_format = '{:,.2f}'.format

                            Company Name  Market Capitalization  Last Sale
Stock Symbol
PG              Procter & Gamble Company (The)             230,159.64      90.03
TM                   Toyota Motor Corp Ltd Ord             155,660.25     104.18
ABB                                    ABB Ltd              48,398.94      22.63
KO                     Coca-Cola Company (The)             183,655.31      42.79
WMT                       Wal-Mart Stores, Inc.             221,864.61      73.15
XOM                     Exxon Mobil Corporation             338,728.71      81.69
JPM                        J P Morgan Chase & Co             300,283.25      84.40
JNJ                          Johnson & Johnson             338,834.39     124.99
BABA             Alibaba Group Holding Limited             275,525.00     110.21
T                                   AT&T Inc.             247,339.52      40.28
ORCL                        Oracle Corporation             181,046.10      44.00
UPS                  United Parcel Service, Inc.              90,180.89     103.74
```

Import & Prepare Listing Data

```
In [13]: data = pd.read_csv('stocks.csv', parse_dates=['Date'],
                            index_col='Date').loc[:, tickers.tolist()]

In [14]: data.info()
DatetimeIndex: 252 entries, 2016-01-04 to 2016-12-30
Data columns (total 12 columns):
ABB     252 non-null float64
BABA    252 non-null float64
JNJ     252 non-null float64
JPM     252 non-null float64
KO      252 non-null float64
ORCL    252 non-null float64
PG      252 non-null float64
T       252 non-null float64
TM      252 non-null float64
UPS     252 non-null float64
WMT     252 non-null float64
XOM     252 non-null float64
dtypes: float64(12)
```

Let's practice!

Build a Market-Cap Weighted Index

Build your Value-Weighted Index

- Key inputs:
  - Number of Shares
  - Stock Price Series

Aggregate Market Value per Period

- Normalize Index to start at 100

Stock Index Components

```
In [1]: components

                             Company Name  Market Capitalization  Last Sale
Stock Symbol
PG           Procter & Gamble Company (The)             230,159.64      90.03
TM                Toyota Motor Corp Ltd Ord             155,660.25     104.18
ABB                                 ABB Ltd              48,398.94      22.63
KO              Coca-Cola Company (The)                 183,655.31      42.79
WMT                   Wal-Mart Stores, Inc.             221,864.61      73.15
XOM                 Exxon Mobil Corporation             338,728.71      81.69
JPM                   J P Morgan Chase & Co             300,283.25      84.40
JNJ                       Johnson & Johnson             338,834.39     124.99
BABA          Alibaba Group Holding Limited             275,525.00     110.21
T                                AT&T Inc.              247,339.52      40.28
ORCL                     Oracle Corporation             181,046.10      44.00
UPS                United Parcel Service, Inc.           90,180.89     103.74
```

Number of Shares Outstanding

```
In [2]: shares = components['Market Capitalization'].div(components['Last Sale'])

Stock Symbol
PG       2,556.48 # Outstanding shares in million
TM       1,494.15
ABB      2,138.71
KO       4,292.01
WMT      3,033.01
XOM      4,146.51
JPM      3,557.86
JNJ      2,710.89
BABA     2,500.00
T        6,140.50
ORCL     4,114.68
UPS        869.30
dtype: float64
```

Market Capitalization = Number of Shares x Share Price

Historical Stock Prices

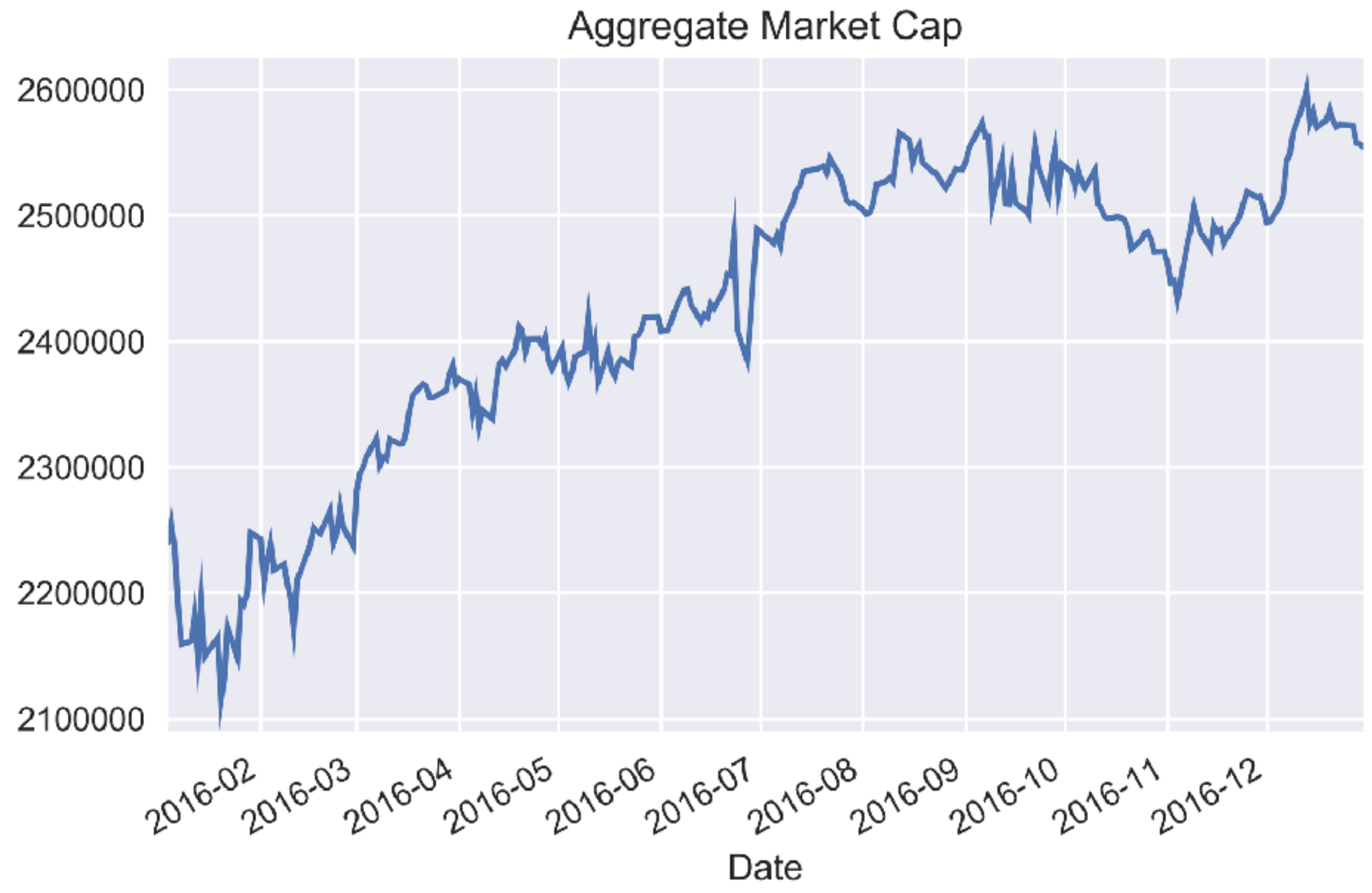
```
In [3]: data = pd.read_csv('stocks.csv', parse_dates=['Date'],
                           index_col='Date').loc[:, tickers.tolist()]

In [4]: market_cap_series = data.mul(no_shares)

In [5]: market_series.info()

DatetimeIndex: 252 entries, 2016-01-04 to 2016-12-30
Data columns (total 12 columns):
ABB     252 non-null float64
BABA    252 non-null float64
JNJ     252 non-null float64
JPM     252 non-null float64
…
TM      252 non-null float64
UPS     252 non-null float64
WMT     252 non-null float64
XOM     252 non-null float64
dtypes: float64(12)
```

From Stock Prices to Market Value

```
In [6]: market_cap_series.first('D').append(market_cap_series.last('D'))
Out[6]:
                 ABB       BABA        JNJ        JPM         KO       ORCL  \
Date
2016-01-04 37,470.14 191,725.00 272,390.43 226,350.95 181,981.42 147,099.95
2016-12-30 45,062.55 219,525.00 312,321.87 307,007.60 177,946.93 158,209.60

                   PG          T         TM       UPS        WMT        XOM
Date
2016-01-04 200,351.12 210,926.33 181,479.12 82,444.14 186,408.74 321,188.96
2016-12-30 214,948.60 261,155.65 175,114.05 99,656.23 209,641.59 374,264.34
```

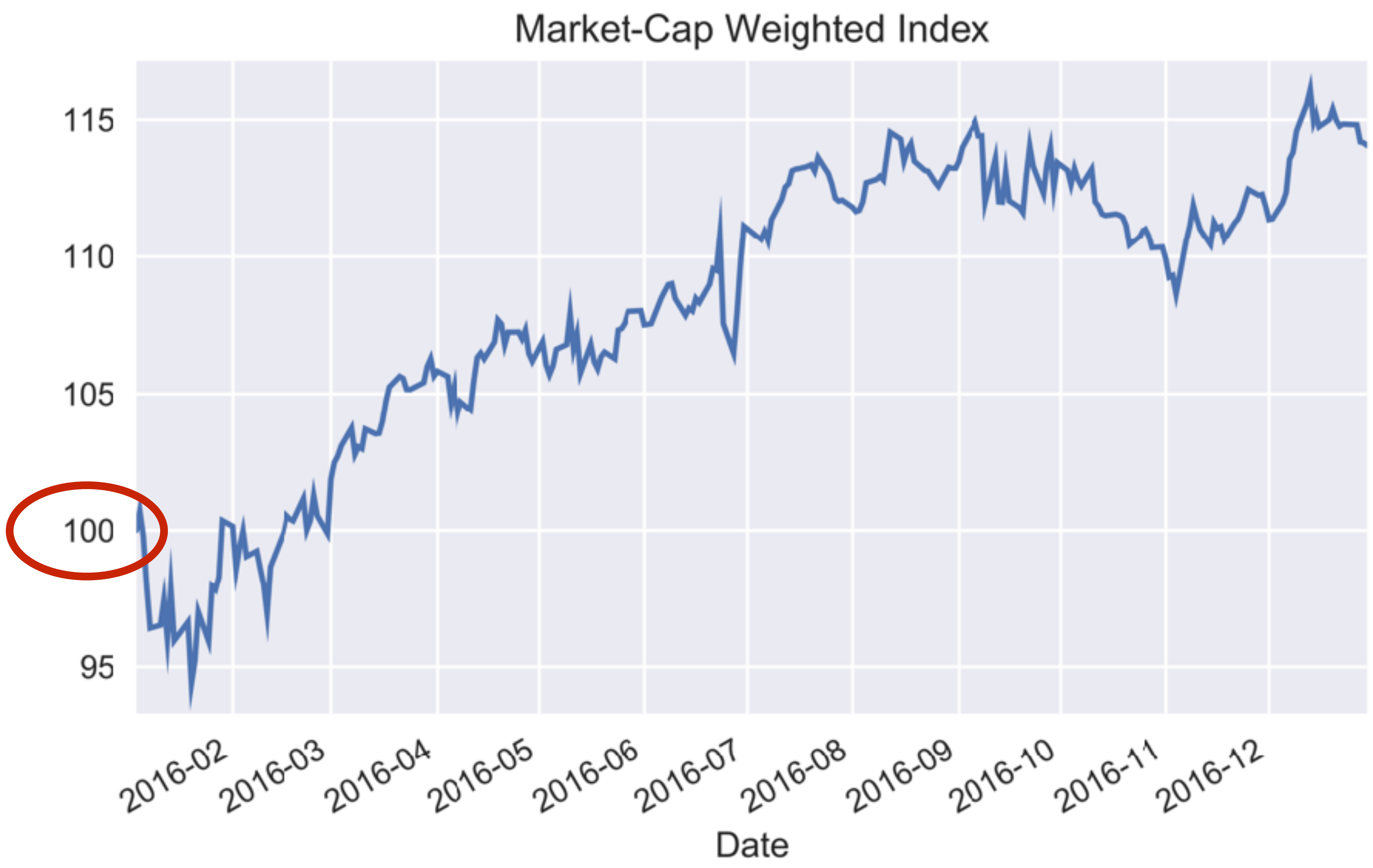
Aggregate Market Value per Period

```
In [7]: agg_mcap = market_cap_series.sum(axis=1) # Total market cap

In [8]: agg_mcap(title='Aggregate Market Cap')
```



Value-Based Index

```
In [9]: index = agg_mcap.div(agg_mcap.iloc[0]).mul(100) # Divide by 1st value

In [10]: index.plot(title='Market-Cap Weighted Index')
```



Let's practice!

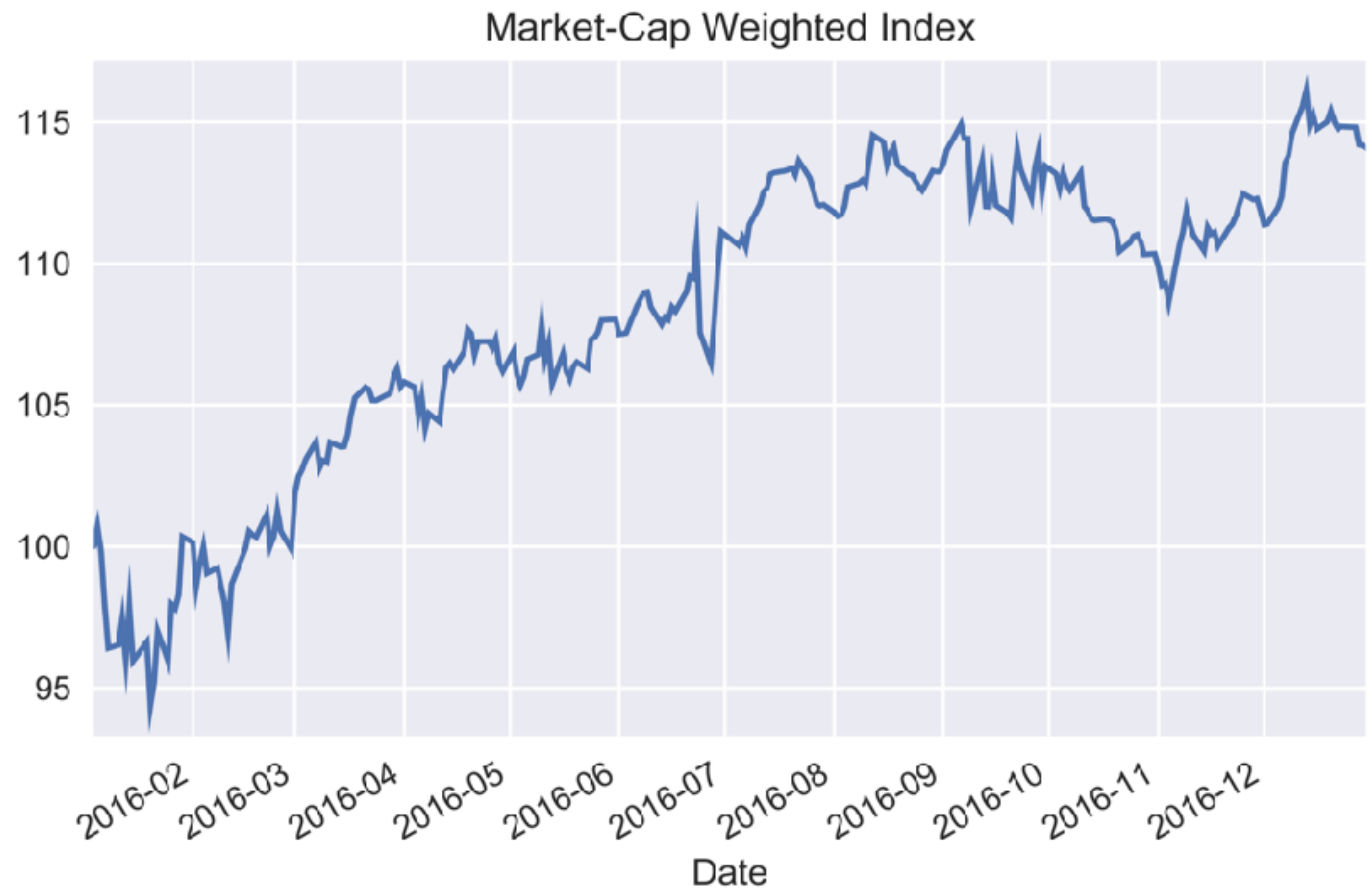
Evaluate Index Performance

Evaluate your Value-Weighted Index

- Index return:
    - Total index return
    - Contribution by component
- Performance vs Benchmark
    - Total period return
    - Rolling returns for sub periods

Value-Based Index - Recap

```
In [1]: agg_market_cap = market_cap_series.sum(axis=1)

In [2]: index = agg_market_cap.div(agg_market_cap.iloc[0]).mul(100)

In [3]: index.plot(title='Market-Cap Weighted Index')
```



Value Contribution by Stock

```
In [3]: agg_market_cap.iloc[-1] - agg_market_cap.iloc[0]
315,037.71

In [4]: change = market_cap_series.first('D').append(market_cap_series.last('D'))

In [5]: change.diff().iloc[-1].sort_values() # or: .loc['2016-12-30']
TM      -6,365.07
KO      -4,034.49
ABB      7,592.41
ORCL    11,109.65
PG      14,597.48
UPS     17,212.08
WMT     23,232.85
BABA    27,800.00
JNJ     39,931.44
T       50,229.33
XOM     53,075.38
JPM     80,656.65
Name: 2016-12-30 00:00:00, dtype: float64
```

Market-Cap based Weights

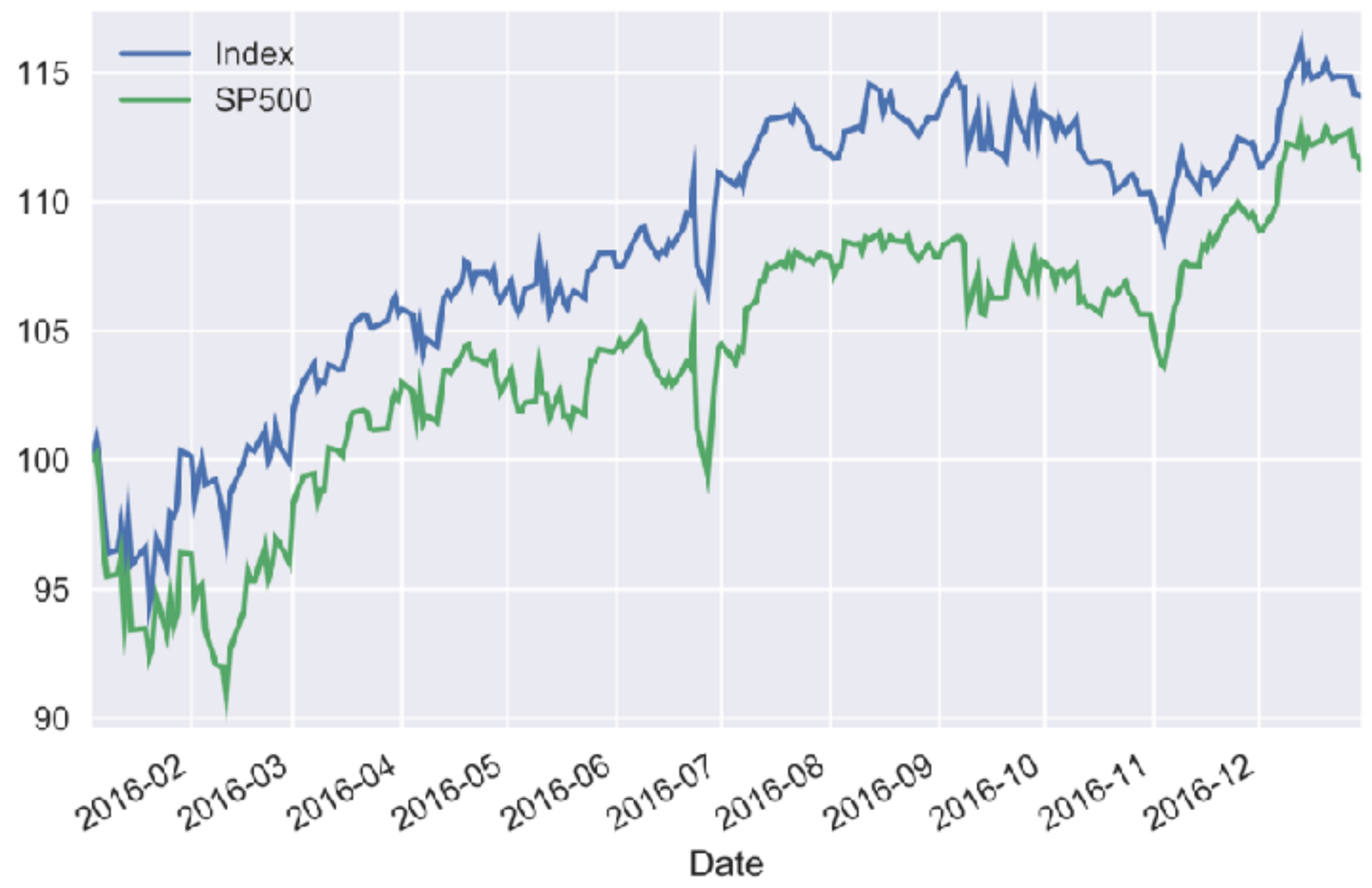
```
In [6]: market_cap = components['Market Capitalization']

In [7]: weights = market_cap.div(market_cap.sum())

In [8]: weights.sort_values().mul(100)
Stock Symbol
ABB      1.85
UPS      3.45
TM       5.96
ORCL     6.93
KO       7.03
WMT      8.50
PG       8.81
T        9.47
BABA    10.55
JPM     11.50
XOM     12.97
JNJ     12.97
Name: Market Capitalization, dtype: float64
```

Value-Weighted Component Returns

```
In [9]: index_return = (index.iloc[-1] / index.iloc[0] - 1) * 100
14.06

In [10]: weighted_returns = weights.mul(index_return)

In [11]: weighted_returns.sort_values().plot(kind='barh')
```

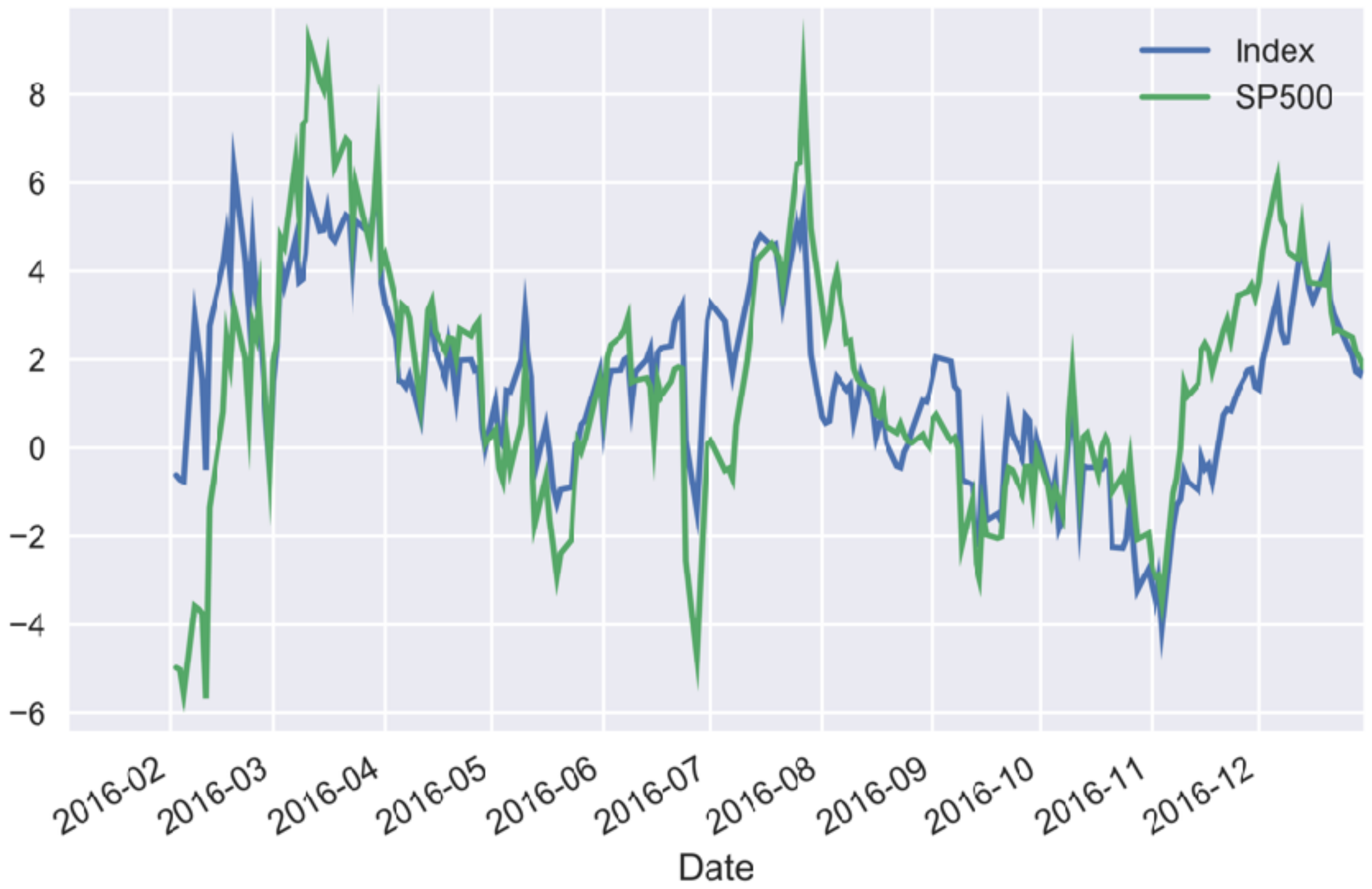
Performance vs Benchmark

```
In [10]: data = index.to_frame('Index') # Convert pd.Series to pd.DataFrame

In [11]: data['SP500'] = pd.read_csv('sp500.csv', parse_dates=['Date'],
                                     index_col='Date')

In [12] data.SP500 = data.SP500.div(data.SP500.iloc[0], axis=0).mul(100)
```



Performance vs Benchmark: 30D Rolling Return

```
In [13]: def multi_period_return(r):
             return (np.prod(r + 1) - 1) * 100

In [14]: data.pct_change().rolling('30D').apply(multi_period_return).plot()
```



Let’s practice!

Index Correlation & Exporting to Excel

Some additional analysis of your Index

- Daily return correlations:
  - Calculate among all components
  - Visualize the result as heatmap
- Write results to excel using '.xls' and '.xlsx' formats:
  - Single worksheet
  - Multiple worksheets

Index Components - Price Data

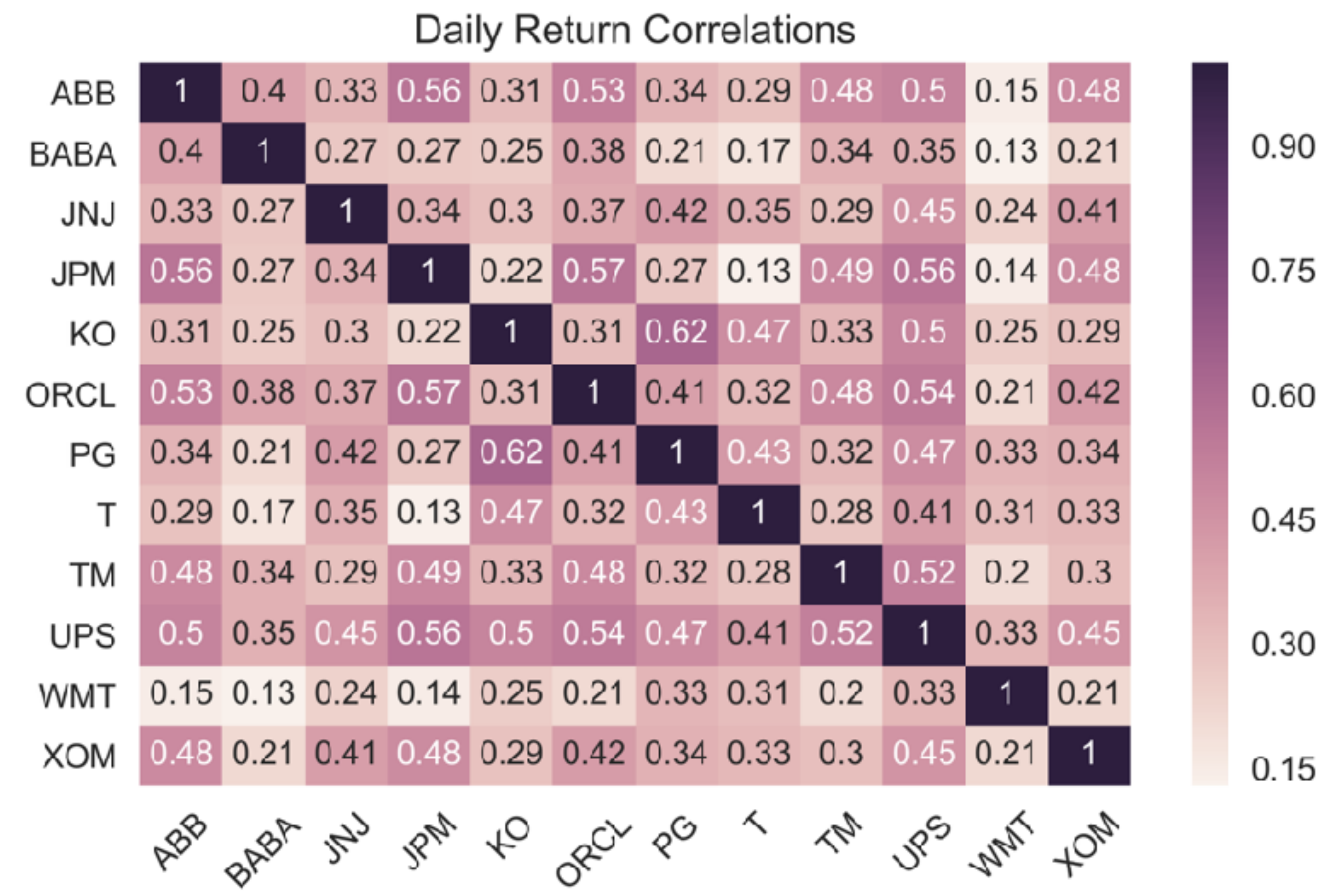
```
In [1]: data = DataReader(tickers, 'google', start='2016', end='2017')['Close']

In [2]: data.info()

DatetimeIndex: 252 entries, 2016-01-04 to 2016-12-30
Data columns (total 12 columns):
ABB     252 non-null float64
BABA    252 non-null float64
JNJ     252 non-null float64
JPM     252 non-null float64
KO      252 non-null float64
ORCL    252 non-null float64
PG      252 non-null float64
T       252 non-null float64
TM      252 non-null float64
UPS     252 non-null float64
WMT     252 non-null float64
XOM     252 non-null float64
```

Index Components: Return Correlations

```
In [3]: daily_returns = data.pct_change()

In [4]: correlations = daily_returns.corr()

       ABB   BABA  JNJ  JPM   KO   ORCL   PG    T    TM  UPS   WMT  XOM
ABB   1.00  0.40 0.33 0.56 0.31  0.53 0.34 0.29 0.48 0.50 0.15 0.48
BABA  0.40  1.00 0.27 0.27 0.25  0.38 0.21 0.17 0.34 0.35 0.13 0.21
JNJ   0.33  0.27 1.00 0.34 0.30  0.37 0.42 0.35 0.29 0.45 0.24 0.41
JPM   0.56  0.27 0.34 1.00 0.22  0.57 0.27 0.13 0.49 0.56 0.14 0.48
KO    0.31  0.25 0.30 0.22 1.00  0.31 0.62 0.47 0.33 0.50 0.25 0.29
ORCL  0.53  0.38 0.37 0.57 0.31  1.00 0.41 0.32 0.48 0.54 0.21 0.42
PG    0.34  0.21 0.42 0.27 0.62  0.41 1.00 0.43 0.32 0.47 0.33 0.34
T     0.29  0.17 0.35 0.13 0.47  0.32 0.43 1.00 0.28 0.41 0.31 0.33
TM    0.48  0.34 0.29 0.49 0.33  0.48 0.32 0.28 1.00 0.52 0.20 0.30
UPS   0.50  0.35 0.45 0.56 0.50  0.54 0.47 0.41 0.52 1.00 0.33 0.45
WMT   0.15  0.13 0.24 0.14 0.25  0.21 0.33 0.31 0.20 0.33 1.00 0.21
XOM   0.48  0.21 0.41 0.48 0.29  0.42 0.34 0.33 0.30 0.45 0.21 1.00
```

Index Components: Return Correlations

```
In [5]: sns.heatmap(correlations, annot=True)

In [6]: plt.xticks(rotation=45)

In [7]: plt.title('Daily Return Correlations')
```



Saving to a single Excel worksheet

```
In [6]: correlations.to_excel(excel_writer= 'correlations.xls',
                              sheet_name='correlations',
                              startrow=1,
                              startcol=1)
```

	ABB	BABA	JNJ	JPM	KO	ORCL	PG	T	TM	UPS	WMT	XOM
ABB	1	0.39555585	0.32891596	0.5643354	0.3107695	0.52567231	0.33805453	0.29154698	0.4811663	0.50364638	0.14570181	0.48047938
BABA	0.39555585	1	0.27351295	0.26757096	0.25469353	0.38152916	0.20984304	0.17185549	0.3441176	0.34586608	0.12875563	0.21343378
JNJ	0.32891596	0.27351295	1	0.34411679	0.29692033	0.3660821	0.4156087	0.35491563	0.29325945	0.44752929	0.23701022	0.41131953
JPM	0.5643354	0.26757096	0.34411679	1	0.21580444	0.56726056	0.26851762	0.13227963	0.48929681	0.56167644	0.14470551	0.4786446
KO	0.3107695	0.25469353	0.29692033	0.21580444	1	0.30504268	0.62309121	0.47343678	0.32628641	0.49974088	0.25212848	0.29083239
ORCL	0.52567231	0.38152916	0.3660821	0.56726056	0.30504268	1	0.40756056	0.3172322	0.48291105	0.53730831	0.20877637	0.41788884
PG	0.33805453	0.20984304	0.4156087	0.26851762	0.62309121	0.40756056	1	0.43109914	0.3202123	0.46917055	0.33296357	0.34344745
T	0.29154698	0.17185549	0.35491563	0.13227963	0.47343678	0.3172322	0.43109914	1	0.2768923	0.41361628	0.30828404	0.32548258
TM	0.4811663	0.3441176	0.29325945	0.48929681	0.32628641	0.48291105	0.3202123	0.2768923	1	0.51720123	0.20347816	0.29674931
UPS	0.50364638	0.34586608	0.44752929	0.56167644	0.49974088	0.53730831	0.46917055	0.41361628	0.51720123	1	0.32516481	0.4466948
WMT	0.14570181	0.12875563	0.23701022	0.14470551	0.25212848	0.20877637	0.33296357	0.30828404	0.20347816	0.32516481	1	0.21102101
XOM	0.48047938	0.21343378	0.41131953	0.4786446	0.29083239	0.41788884	0.34344745	0.32548258	0.29674931	0.4466948	0.21102101	1

correlations

Saving to multiple Excel worksheets

```
In [7]: data.index = data.index.date # Keep only date component

In [8]: with pd.ExcelWriter('stock_data.xlsx') as writer:
            corr.to_excel(excel_writer=writer, sheet_name='correlations')
            data.to_excel(excel_writer=writer, sheet_name='prices')
            data.pct_change().to_excel(writer, sheet_name='returns')
```

	A	B	C	D	E	F	G	H	I	J	K	L	M
1		ABB	BABA	JNJ	JPM	KO	ORCL	PG	T	TM	UPS	WMT	XOM
2	2016-01-04	17.52	76.69	100.48	63.62	42.4	35.75	78.37	34.35	121.46	94.84	61.46	77.46
3	2016-01-05	17.21	78.63	100.9	63.73	42.55	35.64	78.62	34.59	121.14	95.78	62.92	78.12
4	2016-01-06	16.92	77.33	100.39	62.81	42.32	35.82	77.86	34.06	118.38	94.42	63.55	77.47
5	2016-01-07	16.6	72.72	99.22	60.27	41.62	35.04	77.18	33.51	115.57	92.6	65.03	76.23
6	2016-01-08	16.31	70.8	98.16	58.92	41.51	34.65	75.97	33.54	113.06	91.39	63.54	74.69
7	2016-01-11	16.31	69.92	97.57	58.83	41.58	34.94	76.67	33.95	114.81	91.66	64.22	73.69
8	2016-01-12	16.66	72.68	98.24	58.96	42.12	35.37	76.51	33.9	115.83	93	63.62	75.2
9	2016-01-13	16.3	70.29	97.02	57.34	41.85	34.08	75.85	33.74	114.99	90.61	61.92	75.65
10	2016-01-14	16.73	72.25	98.89	58.2	41.88	34.79	76.15	34.3	116.29	91.15	63.06	79.12
11	2016-01-15	16.06	69.59	97	57.04	41.5	34.12	74.98	33.99	112.6	90.04	61.93	77.58
12	2016-01-19	16.26	70.13	97.5	57.01	41.92	34.55	76.73	34.51	115.02	90.35	62.56	76.4

correlations | prices | returns | +

Let's practice!

Congratulations!