pyfolio_demo

September 29, 2021

1 From zipline to pyfolio

Pyfolio facilitates the analysis of portfolio performance and risk in-sample and out-of-sample using many standard metrics. It produces tear sheets covering the analysis of returns, positions, and transactions, as well as event risk during periods of market stress using several built-in scenarios, and also includes Bayesian out-of-sample performance analysis.

- Open-source backtester by Quantopian Inc.
- Powers Quantopian.com
- State-of-the-art portfolio and risk analytics
- Various models for transaction costs and slippage.
- Open source and free: Apache v2 license
- Can be used:
  - stand alone
  - with Zipline
  - on Quantopian

Run this note the following from the command line to create a `conda` environment with `zipline` and `pyfolio`:

`conda env create -f environment.yml`

This assumes you have miniconda3 installed.

1.1 Imports & Settings

[1]:
```
from pathlib import Path
import warnings
import re
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
from pyfolio.utils import extract_rets_pos_txn_from_zipline
from pyfolio.plotting import (plot_perf_stats,
                              show_perf_stats,
                              plot_rolling_beta,
                              plot_rolling_fama_french,
                              plot_rolling_returns,
```

```
                              plot_rolling_sharpe,
                              plot_rolling_volatility,
                              plot_drawdown_periods,
                              plot_drawdown_underwater)

from pyfolio.timeseries import perf_stats, extract_interesting_date_ranges
# from pyfolio.tears import create_returns_tear_sheet
```

[3]:
```
%matplotlib inline
plt.style.use('fivethirtyeight')
warnings.filterwarnings('ignore')
```

1.2 Converting data from zipline to pyfolio

[4]:
```
with pd.HDFStore('../01_trading_zipline/backtests.h5') as store:
    backtest = store['backtest']
backtest.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2013 entries, 2010-01-04 to 2017-12-29
Data columns (total 39 columns):
algo_volatility            2012 non-null float64
algorithm_period_return    2013 non-null float64
alpha                      2012 non-null float64
benchmark_period_return    2013 non-null float64
benchmark_volatility       2012 non-null float64
beta                       2012 non-null float64
capital_used               2013 non-null float64
ending_cash                2013 non-null float64
ending_exposure            2013 non-null float64
ending_value               2013 non-null float64
excess_return              2013 non-null float64
factor_data                2013 non-null object
gross_leverage             2013 non-null float64
long_exposure              2013 non-null float64
long_value                 2013 non-null float64
longs_count                2013 non-null int64
max_drawdown               2013 non-null float64
max_leverage               2013 non-null float64
net_leverage               2013 non-null float64
orders                     2013 non-null object
period_close               2013 non-null datetime64[ns, UTC]
period_label               2013 non-null object
period_open                2013 non-null datetime64[ns, UTC]
pnl                        2013 non-null float64
portfolio_value            2013 non-null float64
positions                  2013 non-null object
```

```
prices                         2013 non-null object
returns                        2013 non-null float64
sharpe                         2012 non-null float64
short_exposure                 2013 non-null float64
short_value                    2013 non-null float64
shorts_count                   2013 non-null int64
sortino                        2012 non-null float64
starting_cash                  2013 non-null float64
starting_exposure              2013 non-null float64
starting_value                 2013 non-null float64
trading_days                   2013 non-null int64
transactions                   2013 non-null object
treasury_period_return         2013 non-null float64
dtypes: datetime64[ns, UTC](2), float64(28), int64(3), object(6)
memory usage: 629.1+ KB
```

pyfolio relies on portfolio returns and position data, and can also take into account the transaction costs and slippage losses of trading activity. The metrics are computed using the empyrical library that can also be used on a standalone basis. The performance DataFrame produced by the zipline backtesting engine can be translated into the requisite pyfolio input.

[5]:
```
returns, positions, transactions = extract_rets_pos_txn_from_zipline(backtest)
```

[6]:
```
returns.head().append(returns.tail())
```

[6]:
```
2010-01-04 00:00:00+00:00    0.000000
2010-01-05 00:00:00+00:00   -0.000013
2010-01-06 00:00:00+00:00    0.003291
2010-01-07 00:00:00+00:00   -0.001066
2010-01-08 00:00:00+00:00    0.002430
2017-12-22 00:00:00+00:00   -0.006448
2017-12-26 00:00:00+00:00   -0.001845
2017-12-27 00:00:00+00:00    0.001239
2017-12-28 00:00:00+00:00    0.004486
2017-12-29 00:00:00+00:00   -0.005241
Name: returns, dtype: float64
```

[9]:
```
positions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2012 entries, 2010-01-05 to 2017-12-29
Columns: 1717 entries, A to cash
dtypes: float64(1717)
memory usage: 26.4 MB
```

[10]:
```
positions.columns = [c for c in positions.columns[:-1]] + ['cash']
positions.index = positions.index.normalize()
positions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2012 entries, 2010-01-05 to 2017-12-29
Columns: 1717 entries, A to cash
dtypes: float64(1717)
memory usage: 26.4 MB
```

[11]:
```python
transactions.symbol = transactions.symbol.apply(lambda x: x.symbol)
```

[12]:
```python
transactions.head().append(transactions.tail())
```

[12]:
```
                           amount commission                        dt  \
2010-01-05 21:00:00+00:00    1342       None 2010-01-05 21:00:00+00:00
2010-01-05 21:00:00+00:00    1575       None 2010-01-05 21:00:00+00:00
2010-01-05 21:00:00+00:00    2668       None 2010-01-05 21:00:00+00:00
2010-01-05 21:00:00+00:00    8169       None 2010-01-05 21:00:00+00:00
2010-01-05 21:00:00+00:00    2145       None 2010-01-05 21:00:00+00:00
2017-12-29 21:00:00+00:00    -161       None 2017-12-29 21:00:00+00:00
2017-12-29 21:00:00+00:00     500       None 2017-12-29 21:00:00+00:00
2017-12-29 21:00:00+00:00    4170       None 2017-12-29 21:00:00+00:00
2017-12-29 21:00:00+00:00     305       None 2017-12-29 21:00:00+00:00
2017-12-29 21:00:00+00:00    -562       None 2017-12-29 21:00:00+00:00

                                                   order_id       price  \
2010-01-05 21:00:00+00:00  aaa877f655fb4b2580d6f546f8ec40ae   37.630001
2010-01-05 21:00:00+00:00  d54eab8b952e4237922dbc4c64cf3bfb   30.710002
2010-01-05 21:00:00+00:00  1292be565bf947ed88c39e32ba6f5a2c   19.050000
2010-01-05 21:00:00+00:00  a07de7b20289474faa611fc719d18020    6.060000
2010-01-05 21:00:00+00:00  869232ede9154e9e8d13f281ae651003   23.300000
2017-12-29 21:00:00+00:00  727f68eef9394f9284f6076a9309b563  103.799999
2017-12-29 21:00:00+00:00  3d33b14e815046f8a6c85f607111d5fc   54.160003
2017-12-29 21:00:00+00:00  271ab329a4024b299def4eae93885e72   16.260001
2017-12-29 21:00:00+00:00  e07be39bda5c4f0499eebf1f6473fb35   64.510001
2017-12-29 21:00:00+00:00  cfaf6aa723114b45a102dd7824824691   23.090000

                                         sid symbol   txn_dollars
2010-01-05 21:00:00+00:00    Equity(262 [ATW])    ATW -50499.461342
2010-01-05 21:00:00+00:00   Equity(263 [AUXL])   AUXL -48368.253022
2010-01-05 21:00:00+00:00    Equity(521 [CDE])    CDE -50825.400612
2010-01-05 21:00:00+00:00   Equity(523 [CDNS])   CDNS -49504.142084
2010-01-05 21:00:00+00:00   Equity(528 [CECO])   CECO -49978.500972
2017-12-29 21:00:00+00:00  Equity(3181 [ZBRA])   ZBRA  16711.799828
2017-12-29 21:00:00+00:00   Equity(2351 [QTS])    QTS -27080.001689
2017-12-29 21:00:00+00:00   Equity(2889 [TWO])    TWO -67804.204236
2017-12-29 21:00:00+00:00  Equity(2890 [TWOU])   TWOU -19675.550307
2017-12-29 21:00:00+00:00  Equity(2918 [UCTT])   UCTT  12976.579998
```

[13]:
```python
HDF_PATH = Path('..', '..', 'data', 'assets.h5')
```

1.2.1 Sector Map

[14]:
```
assets = positions.columns[:-1]
with pd.HDFStore(HDF_PATH) as store:
    df = store.get('us_equities/stocks')['sector'].dropna()
    df = df[~df.index.duplicated()]
sector_map = df.reindex(assets).fillna('Unknown').to_dict()
```

1.2.2 Benchmark

[15]:
```
with pd.HDFStore(HDF_PATH) as store:
    benchmark_rets = store['sp500/prices'].close.pct_change()
benchmark_rets.name = 'S&P500'
benchmark_rets = benchmark_rets.tz_localize('UTC').filter(returns.index)
benchmark_rets.tail()
```

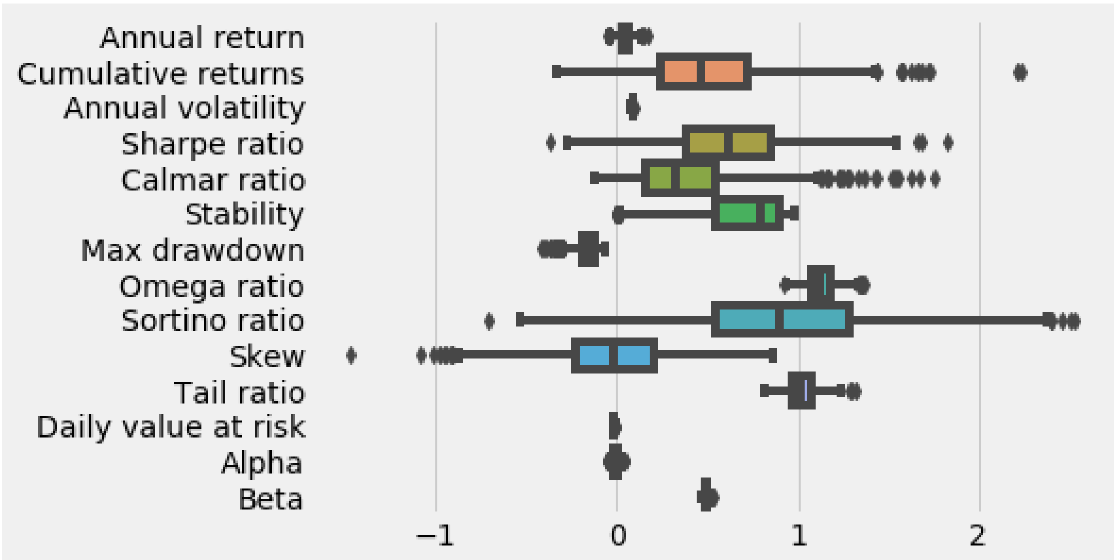
[15]:
```
date
2017-12-22 00:00:00+00:00   -0.000458
2017-12-26 00:00:00+00:00   -0.001058
2017-12-27 00:00:00+00:00    0.000791
2017-12-28 00:00:00+00:00    0.001834
2017-12-29 00:00:00+00:00   -0.005183
Name: S&P500, dtype: float64
```

[16]:
```
perf_stats(returns=returns, factor_returns=benchmark_rets, positions=positions,␣
 ↪transactions=transactions)
```

[16]:
```
Annual return          0.049890
Cumulative returns     0.475359
Annual volatility      0.085951
Sharpe ratio           0.609440
Calmar ratio           0.455694
Stability              0.932530
Max drawdown          -0.109481
Omega ratio            1.122683
Sortino ratio          0.879044
Skew                  -0.032073
Kurtosis               7.164640
Tail ratio             1.014405
Daily value at risk   -0.010621
Gross leverage         0.401869
Daily turnover         0.040424
Alpha                 -0.007162
Beta                   0.494708
dtype: float64
```

[17]:
```
plot_perf_stats(returns=returns, factor_returns=benchmark_rets)
```

[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbc1fc6d668>



1.3 Returns Analysis

Testing a trading strategy involves backtesting against historical data to fine-tune alpha factor parameters, as well as forward-testing against new market data to validate that the strategy performs well out of sample or if the parameters are too closely tailored to specific historical circumstances.

Pyfolio allows for the designation of an out-of-sample period to simulate walk-forward testing. There are numerous aspects to take into account when testing a strategy to obtain statistically reliable results, which we will address here.

[18]:
```
oos_date = '2017-01-01'
```

[19]:
```
show_perf_stats(returns=returns,
                factor_returns=benchmark_rets,
                positions=positions,
                transactions=transactions,
                live_start_date=oos_date)
```

```
In-sample months: 83
Out-of-sample months: 11
```

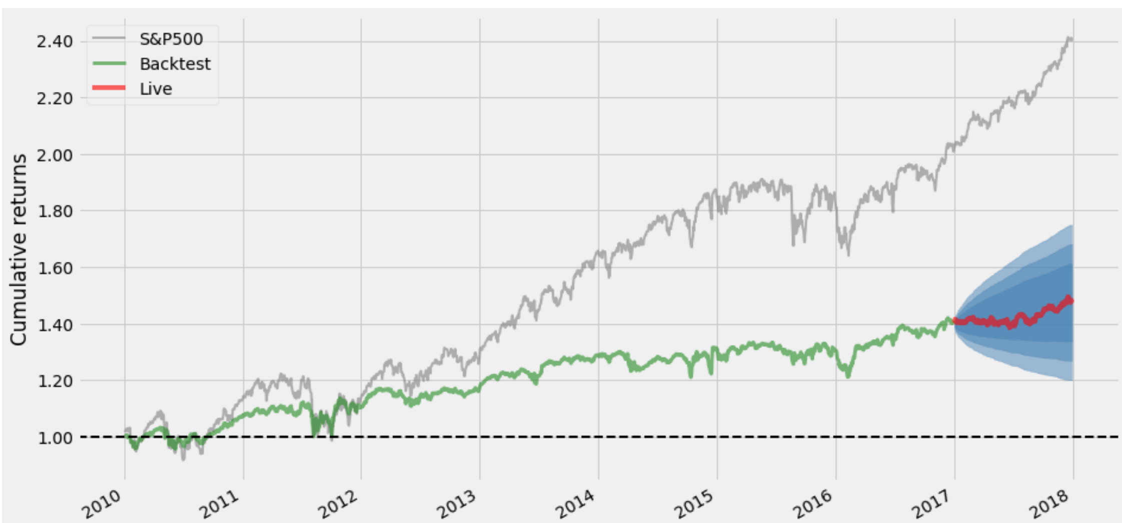
	All	In-sample	Out-of-sample
Annual return	5.0%	4.9%	5.6%
Cumulative returns	47.5%	39.8%	5.5%
Annual volatility	8.6%	9.0%	4.9%
Sharpe ratio	0.61	0.58	1.13
Calmar ratio	0.46	0.45	2.09
Stability	0.93	0.91	0.60

```
Max drawdown          -10.9%    -10.9%        -2.7%
Omega ratio             1.12      1.12         1.20
Sortino ratio           0.88      0.83         1.70
Skew                   -0.03     -0.03         0.07
Kurtosis                7.16      6.62         0.20
Tail ratio              1.01      1.00         1.11
Daily value at risk    -1.1%     -1.1%        -0.6%
Gross leverage          0.40      0.40         0.45
Daily turnover          4.0%      4.0%         4.2%
Alpha                  -0.01     -0.00        -0.04
Beta                    0.49      0.49         0.54
```

1.3.1 Rolling Returns OOS

The `plot_rolling_returns` function displays cumulative in and out-of-sample returns against a user-defined benchmark (we are using the S&P 500):

[20]:
```python
plot_rolling_returns(returns=returns, factor_returns=benchmark_rets,␣
 ↪live_start_date=oos_date, cone_std=(1.0, 1.5, 2.0))
plt.gcf().set_size_inches(14, 8)
```



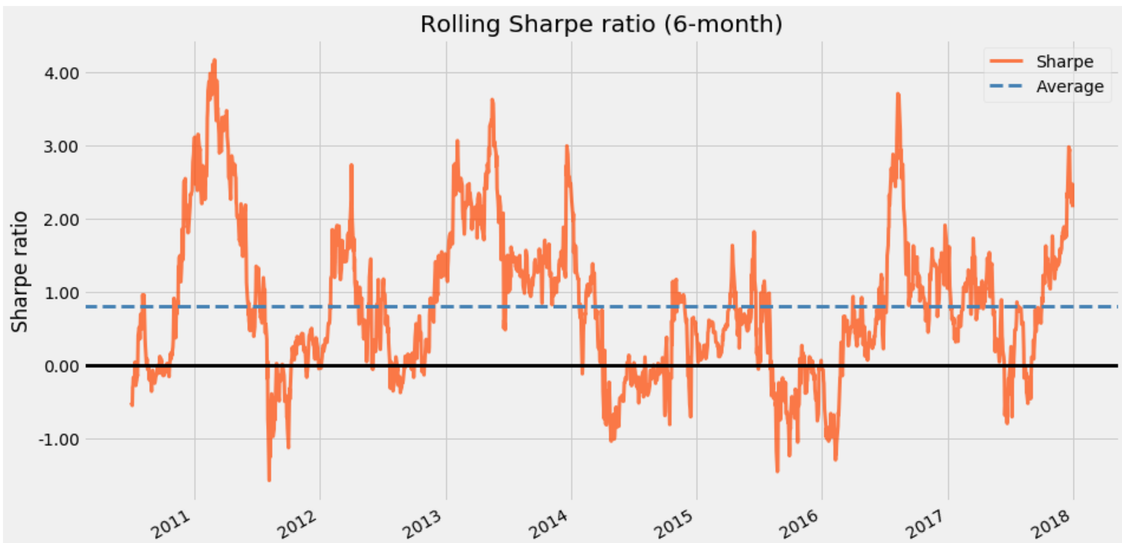
The plot includes a cone that shows expanding confidence intervals to indicate when out-of-sample returns appear unlikely given random-walk assumptions. Here, our strategy did not perform well against the benchmark during the simulated 2017 out-of-sample period

1.4 Summary Performance Statistics

pyfolio offers several analytic functions and plots. The perf_stats summary displays the annual and cumulative returns, volatility, skew, and kurtosis of returns and the SR. The following additional metrics (which can also be calculated individually) are most important: - Max drawdown: Highest percentage loss from the previous peak - Calmar ratio: Annual portfolio return relative to maximal drawdown - Omega ratio: The probability-weighted ratio of gains versus losses for a return target, zero per default - Sortino ratio: Excess return relative to downside standard deviation - Tail ratio: Size of the right tail (gains, the absolute value of the 95th percentile) relative to the size of the left tail (losses, abs. value of the 5th percentile) - Daily value at risk (VaR): Loss corresponding to a return two standard deviations below the daily mean - Alpha: Portfolio return unexplained by the benchmark return - Beta: Exposure to the benchmark

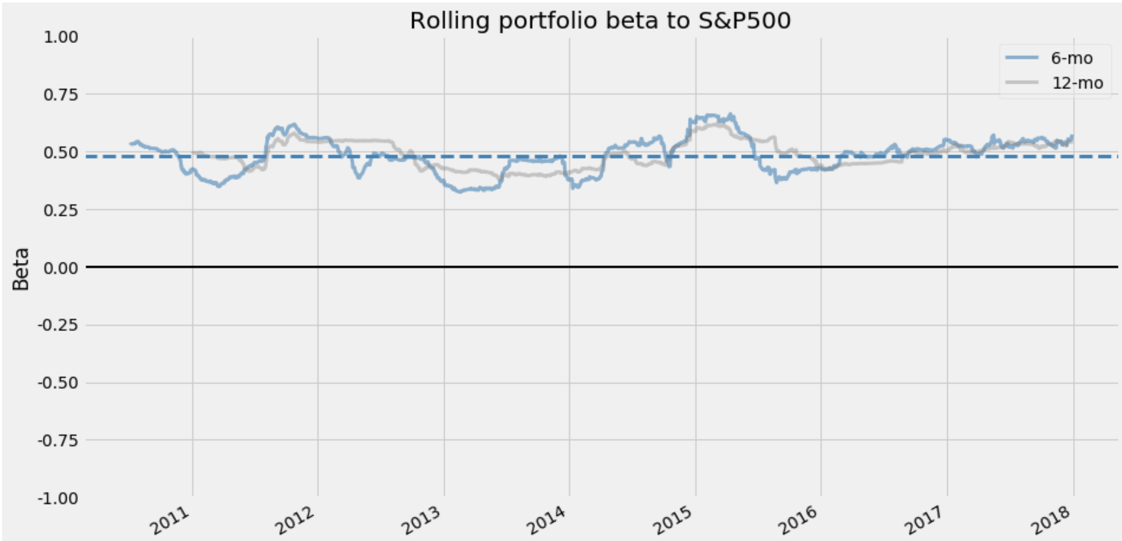
1.4.1 Rolling Sharpe

[21]:
```
plot_rolling_sharpe(returns=returns)
plt.gcf().set_size_inches(14, 8);
```



1.4.2 Rolling Beta

[22]:
```
plot_rolling_beta(returns=returns, factor_returns=benchmark_rets)
plt.gcf().set_size_inches(14, 8);
```

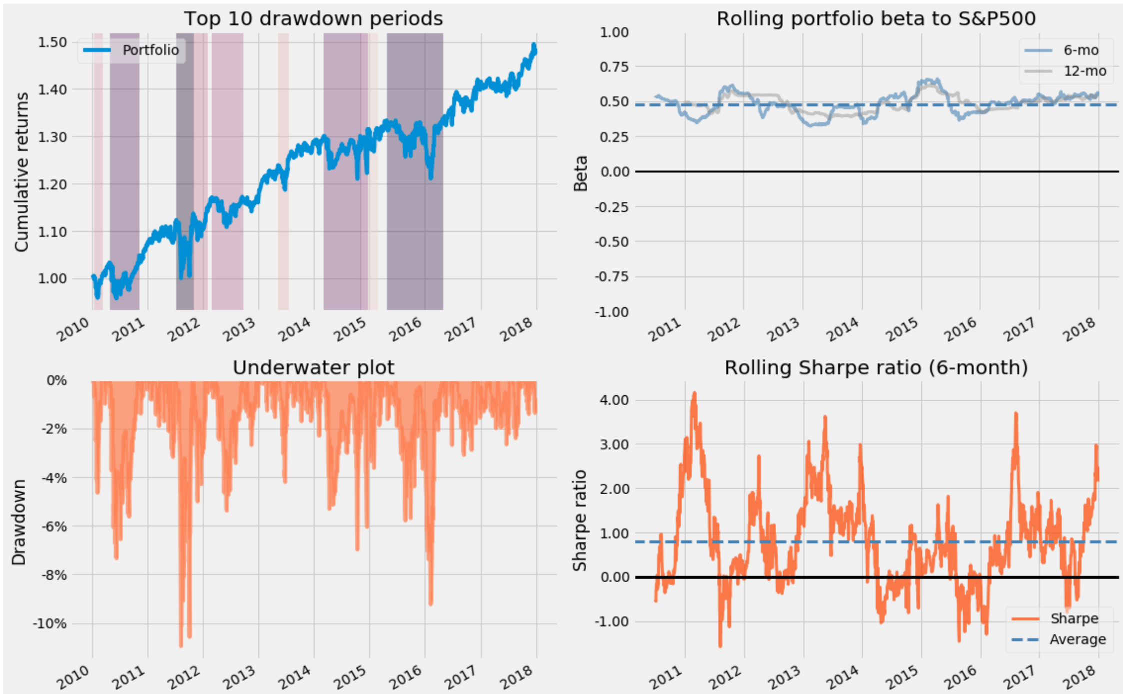


1.5 Drawdown Periods

The plot_drawdown_periods(returns) function plots the principal drawdown periods for the portfolio, and several other plotting functions show the rolling SR and rolling factor exposures to the market beta or the Fama French size, growth, and momentum factors:

[23]:
```
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(16, 10))
axes = ax.flatten()

plot_drawdown_periods(returns=returns, ax=axes[0])
plot_rolling_beta(returns=returns, factor_returns=benchmark_rets, ax=axes[1])
plot_drawdown_underwater(returns=returns, ax=axes[2])
plot_rolling_sharpe(returns=returns)
plt.tight_layout();
```

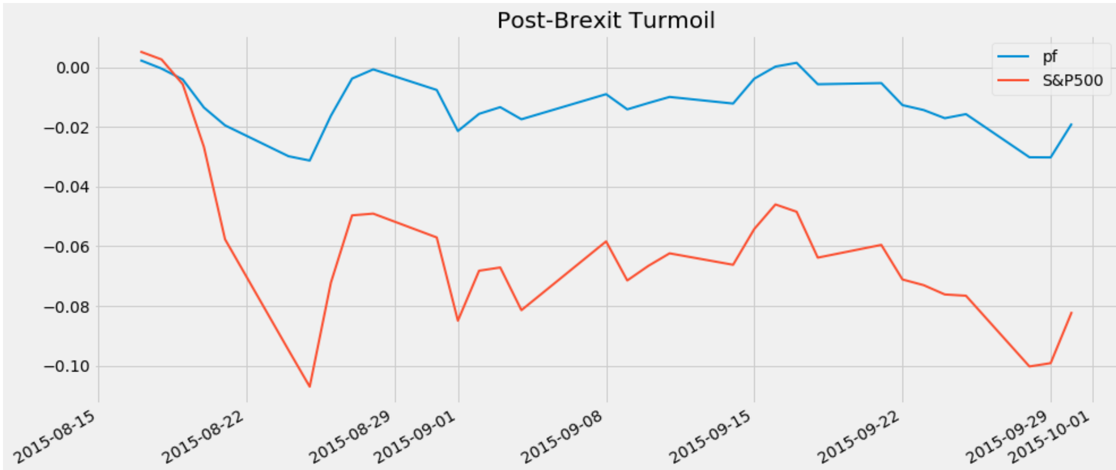


This plot, which highlights a subset of the visualization contained in the various tear sheets, illustrates how pyfolio allows us to drill down into the performance characteristics and exposure to fundamental drivers of risk and returns.

1.6 Modeling Event Risk

Pyfolio also includes timelines for various events that you can use to compare the performance of a portfolio to a benchmark during this period, for example, during the fall 2015 selloff following the Brexit vote.

[24]:
```
interesting_times = extract_interesting_date_ranges(returns=returns)
(interesting_times['Fall2015']
 .to_frame('pf').join(benchmark_rets)
 .add(1).cumprod().sub(1)
 .plot(lw=2, figsize=(14, 6), title='Post-Brexit Turmoil'))
plt.tight_layout()
```


Post-Brexit Turmoil
pf
S&P500
0.00
−0.02
−0.04
−0.06
−0.08
−0.10
2015-08-15
2015-08-22
2015-08-29
2015-09-01
2015-09-08
2015-09-15
2015-09-22
2015-09-29
2015-10-01