06_performance_eval_alphalens

September 29, 2021

1 Separating signal and noise – how to use alphalens

Quantopian has open sourced the Python library, alphalens, for the performance analysis of predictive stock factors that integrates well with the backtesting library zipline and the portfolio performance and risk analysis library pyfolio that we will explore in the next chapter. alphalens facilitates the analysis of the predictive power of alpha factors concerning the: - Correlation of the signals with subsequent returns - Profitability of an equal or factor-weighted portfolio based on a (subset of) the signals - Turnover of factors to indicate the potential trading costs - Factor-performance during specific events - Breakdowns of the preceding by sector

The analysis can be conducted using tearsheets or individual computations and plots.

> This notebook requires the `conda` environment `backtest`. Please see the installation instructions for running the latest Docker image or alternative ways to set up your environment.

1.1 Imports & Settings

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
%matplotlib inline
import re
from alphalens.utils import get_clean_factor_and_forward_returns
from alphalens.performance import *
from alphalens.plotting import *
from alphalens.tears import *

import seaborn as sns
import matplotlib.pyplot as plt
```

[3]:
```
sns.set_style('whitegrid')
```

1.2 Creating forward returns and factor quantiles

To utilize `alpahalens`, we need to provide signals for a universe of assets like those returned by the ranks of the MeanReversion factor, and the forward returns earned by investing in an asset for a given holding period. .

> This notebook uses the file `single_factor.pickle` with the results generated in the notebook `single_factor_zipline.ipynb` in this directory.

We will recover the prices from the `single_factor.pickle` file as follows (`factor_data` accordingly):

[4]:
```
performance = pd.read_pickle('single_factor.pickle')
```

[5]:
```
performance.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 755 entries, 2015-01-02 21:00:00+00:00 to 2017-12-29
21:00:00+00:00
Data columns (total 39 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   period_open              755 non-null    datetime64[ns, UTC]
 1   period_close             755 non-null    datetime64[ns, UTC]
 2   shorts_count             755 non-null    int64
 3   long_value               755 non-null    float64
 4   short_value              755 non-null    float64
 5   long_exposure            755 non-null    float64
 6   pnl                      755 non-null    float64
 7   capital_used             755 non-null    float64
 8   short_exposure           755 non-null    float64
 9   orders                   755 non-null    object
 10  transactions             755 non-null    object
 11  positions                755 non-null    object
 12  gross_leverage           755 non-null    float64
 13  starting_exposure        755 non-null    float64
 14  net_leverage             755 non-null    float64
 15  ending_exposure          755 non-null    float64
 16  starting_value           755 non-null    float64
 17  ending_value             755 non-null    float64
 18  starting_cash            755 non-null    float64
 19  ending_cash              755 non-null    float64
 20  portfolio_value          755 non-null    float64
 21  returns                  755 non-null    float64
 22  longs_count              755 non-null    int64
 23  algo_volatility          754 non-null    float64
 24  benchmark_period_return  755 non-null    float64
 25  benchmark_volatility     754 non-null    float64
 26  alpha                    0 non-null      object
 27  beta                     0 non-null      object
 28  sharpe                   753 non-null    float64
 29  sortino                  753 non-null    float64
 30  max_drawdown             755 non-null    float64
 31  max_leverage             755 non-null    float64
```

```
 32   excess_return             755 non-null    float64
 33   treasury_period_return    755 non-null    float64
 34   trading_days              755 non-null    int64
 35   period_label              755 non-null    object
 36   algorithm_period_return   755 non-null    float64
 37   factor_data               754 non-null    object
 38   prices                    754 non-null    object
dtypes: datetime64[ns, UTC](2), float64(26), int64(3), object(8)
memory usage: 235.9+ KB
```

[6]:
```
prices = pd.concat([df.to_frame(d) for d, df in performance.prices.dropna().
 ↪items()],axis=1).T
prices.columns = [re.findall(r"\[(.+)\]", str(col))[0] for col in prices.
 ↪columns]
prices.index = prices.index.normalize()
prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 754 entries, 2015-01-05 00:00:00+00:00 to 2017-12-29
00:00:00+00:00
Columns: 1649 entries, A to NETE
dtypes: float64(1649)
memory usage: 9.5 MB
```

[7]:
```
factor_data = pd.concat([df.to_frame(d) for d, df in performance.factor_data.
 ↪dropna().items()],axis=1).T
factor_data.columns = [re.findall(r"\[(.+)\]", str(col))[0] for col in␣
 ↪factor_data.columns]
factor_data.index = factor_data.index.normalize()
factor_data = factor_data.stack()
factor_data.index.names = ['date', 'asset']
factor_data.head()
```

[7]:
```
date                       asset
2015-01-05 00:00:00+00:00  A        2707.0
                           AAL       870.0
                           AAP      1253.0
                           AAPL     2977.0
                           ABBV     2806.0
dtype: float64
```

[8]:
```
with pd.HDFStore('../data/assets.h5') as store:
    sp500 = store['sp500/stooq'].close
sp500 = sp500.resample('D').ffill().tz_localize('utc').filter(prices.index.
 ↪get_level_values(0))
sp500.head()
```

[8]:
```
Date
2015-01-05 00:00:00+00:00    2020.58
2015-01-06 00:00:00+00:00    2002.61
2015-01-07 00:00:00+00:00    2025.90
2015-01-08 00:00:00+00:00    2062.14
2015-01-09 00:00:00+00:00    2044.81
Name: close, dtype: float64
```

We can create the alphalens input data in the required format using the `get_clean_factor_and_forward_returns` utility function that also returns the signal quartiles and the forward returns for the given holding periods:

[9]:
```
HOLDING_PERIODS = (5, 10, 21, 42)
QUANTILES = 5
alphalens_data = get_clean_factor_and_forward_returns(factor=factor_data,
                                                      prices=prices,
                                                      periods=HOLDING_PERIODS,
                                                      quantiles=QUANTILES)
```

```
Dropped 5.6% entries from factor data: 5.6% in forward returns computation and
0.0% in binning phase (set max_loss=0 to see potentially suppressed Exceptions).
max_loss is 35.0%, not exceeded: OK!
```

The `alphalens_data` `DataFrame` contains the returns on an investment in the given asset on a given date for the indicated holding period, as well as the factor value, that is, the asset's `MeanReversion` ranking on that date, and the corresponding quantile value:

[10]:
```
alphalens_data.head()
```

[10]:
```
                                       5D       10D       21D       42D  \
date                      asset
2015-01-05 00:00:00+00:00 A      0.007789 -0.046985 -0.027889  0.072864
                          AAL   -0.079722 -0.020882 -0.095684 -0.103295
                          AAP    0.015722 -0.024350 -0.003196 -0.010865
                          AAPL   0.028235  0.023247  0.116518  0.214965
                          ABBV   0.017169 -0.018561 -0.061098 -0.064811

                                 factor  factor_quantile
date                      asset
2015-01-05 00:00:00+00:00 A      2707.0                5
                          AAL     870.0                1
                          AAP    1253.0                2
                          AAPL   2977.0                5
                          ABBV   2806.0                5
```

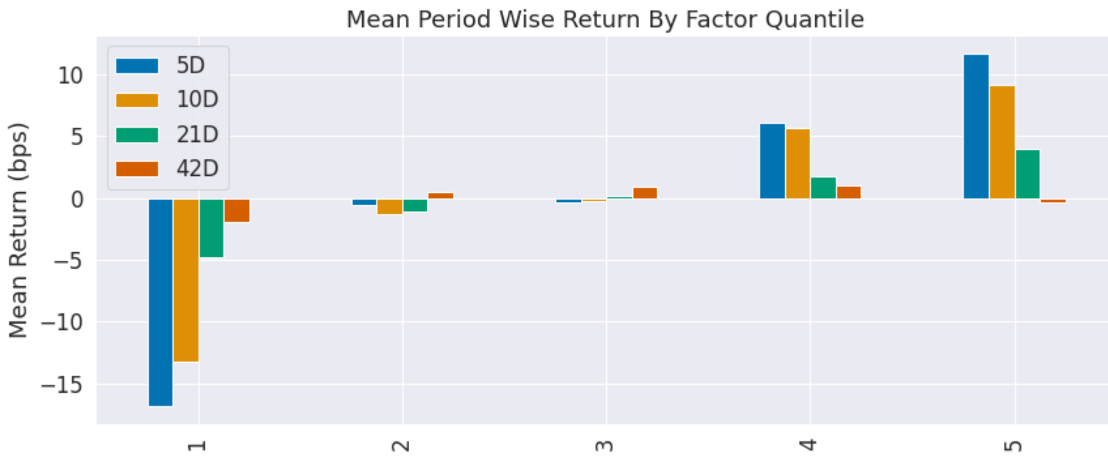
[11]:
```
alphalens_data.reset_index().head().to_csv('factor_data.csv', index=False)
```

The forward returns and the signal quantiles are the basis for evaluating the predictive power of the signal. Typically, a factor should deliver markedly different returns for distinct quantiles, such as negative returns for the bottom quintile of the factor values and positive returns for the top quantile.

1.3 Summary Tear Sheet

[12]:
```
create_summary_tear_sheet(alphalens_data)
```

```
Quantiles Statistics

                    min     max         mean         std   count    count %
factor_quantile
1                   1.0  1011.0   303.057978  188.562449  142313  20.020145
2                 352.0  1636.0   856.678631  234.705707  142117  19.992572
3                 794.0  2153.0  1417.174265  259.942787  142019  19.978786
4                1273.0  2621.0  1979.178578  253.504821  142117  19.992572
5                1827.0  3050.0  2519.578804  227.348609  142283  20.015925

Returns Analysis

                                                 5D     10D    21D    42D
Ann. alpha                                    0.046   0.036  0.009  0.001
beta                                          0.083   0.098  0.077  0.019
Mean Period Wise Return Top Quantile (bps)   11.724   9.110  3.948 -0.376
Mean Period Wise Return Bottom Quantile (bps) -16.862 -13.259 -4.742 -1.979
Mean Period Wise Spread (bps)                28.587  22.343  8.711  1.582

Information Analysis

                      5D    10D    21D    42D
IC Mean            0.022  0.026  0.017  0.003
IC Std.            0.140  0.127  0.116  0.115
Risk-Adjusted IC   0.160  0.207  0.148  0.027
t-stat(IC)         4.261  5.529  3.953  0.729
p-value(IC)        0.000  0.000  0.000  0.466
IC Skew            0.372  0.266  0.115  0.113
IC Kurtosis        0.054 -0.515 -0.333 -0.557

Turnover Analysis

                                5D    10D    21D    42D
Quantile 1 Mean Turnover     0.411  0.590  0.830  0.831
Quantile 2 Mean Turnover     0.645  0.740  0.804  0.812
Quantile 3 Mean Turnover     0.679  0.765  0.808  0.812
Quantile 4 Mean Turnover     0.642  0.741  0.810  0.814
Quantile 5 Mean Turnover     0.394  0.569  0.811  0.819

                                       5D    10D    21D    42D
Mean Factor Rank Autocorrelation    0.713  0.454 -0.013 -0.017

<Figure size 432x288 with 0 Axes>
```



1.4 Predictive performance by factor quantiles - Returns Analysis

As a first step, we would like to visualize the average period return by factor quantile. We can use the built-in function mean_return_by_quantile from the performance and plot_quantile_returns_bar from the plotting modules

[13]:
```
mean_return_by_q, std_err = mean_return_by_quantile(alphalens_data)
mean_return_by_q_norm = mean_return_by_q.apply(lambda x: x.add(1).pow(1/int(x.
 ↪name[:-1])).sub(1))
```

1.4.1 Mean Return by Holding Period and Quintile

The result is a bar chart that breaks down the mean of the forward returns for the four different holding periods based on the quintile of the factor signal. As you can see, the bottom quintiles yielded markedly more negative results than the top quintiles, except for the longest holding period:

[14]:
```
plot_quantile_returns_bar(mean_return_by_q)
plt.tight_layout()
sns.despine();
```

The 10D holding period provides slightly better results for the first and fourth quartiles. We would also like to see the performance over time of investments driven by each of the signal quintiles.

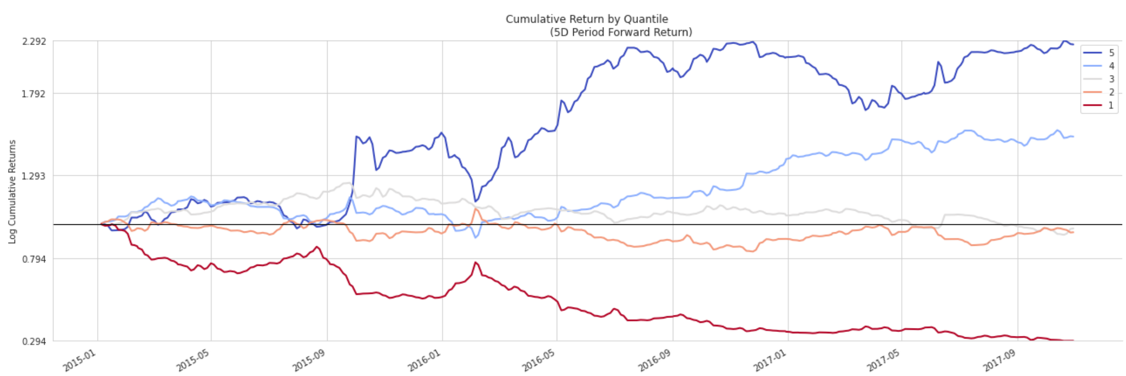
We will calculate daily, as opposed to average returns for the 5D holding period, and alphalens will adjust the period returns to account for the mismatch between daily signals and a longer holding period (for details, see docs):

[15]:
```
mean_return_by_q_daily, std_err = mean_return_by_quantile(alphalens_data, by_date=True)
```

1.4.2 Cumulative 5D Return

The resulting line plot shows that, for most of this three-year period, the top two quintiles significantly outperformed the bottom two quintiles. However, as suggested by the previous plot, signals by the fourth quintile produced a better performance than those by the top quintile

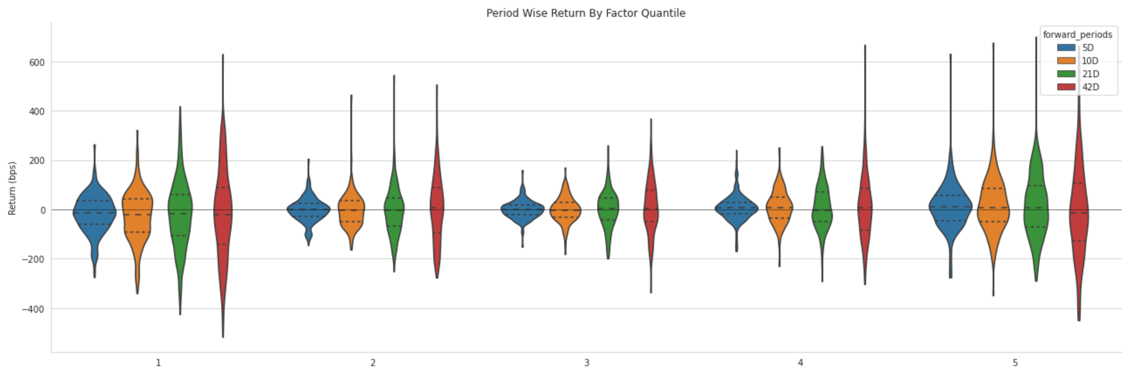
[16]:
```
plot_cumulative_returns_by_quantile(mean_return_by_q_daily['5D'], period='5D', freq=None)
plt.tight_layout()
sns.despine();
```



1.4.3 Return Distribution by Holding Period and Quintile

This distributional plot highlights that the range of daily returns is fairly wide and, despite different means, the separation of the distributions is very limited so that, on any given day, the differences in performance between the different quintiles may be rather limited:

[17]:
```
plot_quantile_returns_violin(mean_return_by_q_daily)
plt.tight_layout()
sns.despine();
```



1.5 Information Coefficient

Most of this book is about the design of alpha factors using ML models. ML is about optimizing some predictive objective, and in this section, we will introduce the key metrics used to measure the performance of an alpha factor. We will define alpha as the average return in excess of a benchmark. This leads to the information ratio (IR) that measures the average excess return per unit of risk taken by dividing alpha by the tracking risk. When the benchmark is the risk-free rate, the IR corresponds to the well-known Sharpe ratio, and we will highlight crucial statistical measurement issues that arise in the typical case when returns are not normally distributed. We will also explain the fundamental law of active management that breaks the IR down into a combination of forecasting skill and a strategy's ability to effectively leverage the forecasting skills.

1.5.1 5D Information Coefficient (Rolling Average)

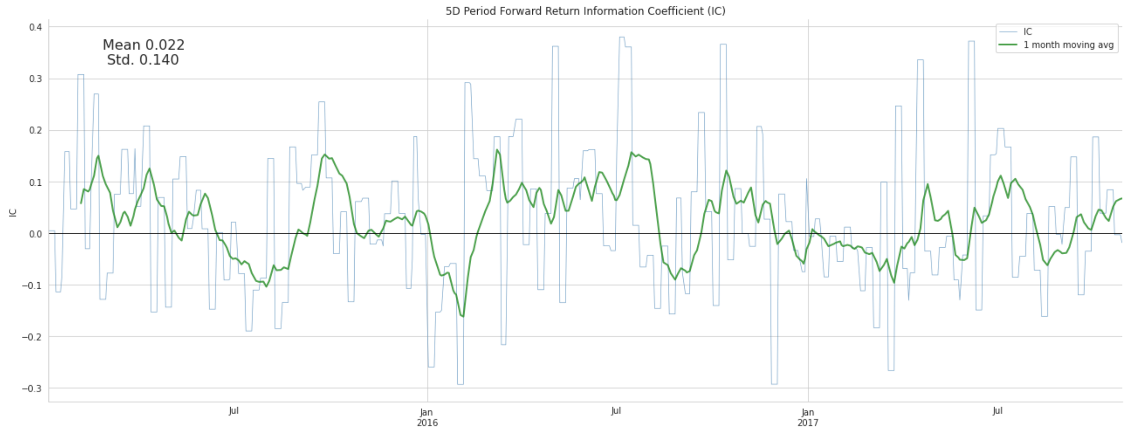
The goal of alpha factors is the accurate directional prediction of future returns. Hence, a natural performance measure is the correlation between an alpha factor's predictions and the forward returns of the target assets.

It is better to use the non-parametric Spearman rank correlation coefficient that measures how well the relationship between two variables can be described using a monotonic function, as opposed to the Pearson correlation that measures the strength of a linear relationship.

We can obtain the information coefficient using alphalens, which relies on `scipy.stats.spearmanr` under the hood.

The `factor_information_coefficient` function computes the period-wise correlation and plot_ic_ts creates a time-series plot with one-month moving average:

[18]:
```
ic = factor_information_coefficient(alphalens_data)
plot_ic_ts(ic[['5D']])
plt.tight_layout()
sns.despine();
```

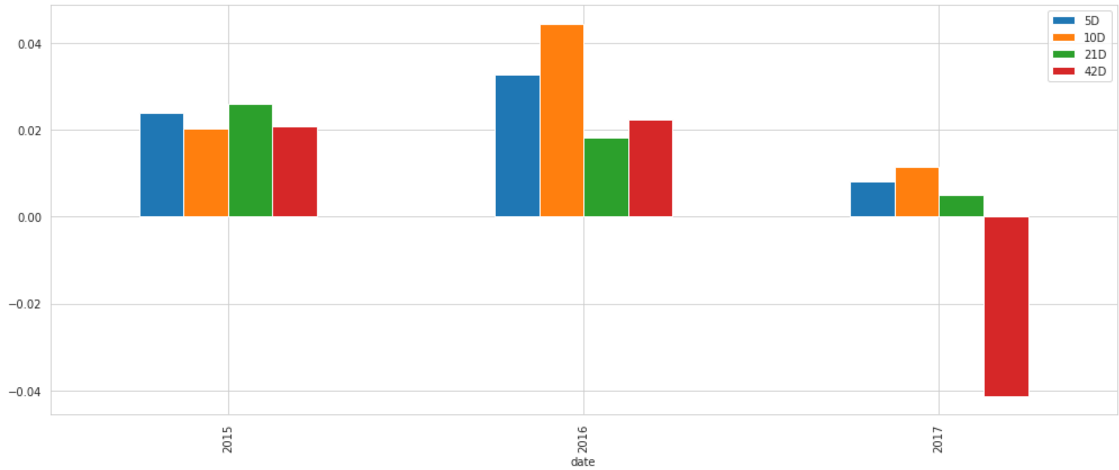


1.5.2 Information Coefficient by Holding Period

This time series plot shows extended periods with significantly positive moving-average IC. An IC of 0.05 or even 0.1 allows for significant outperformance if there are sufficient opportunities to apply this forecasting skill, as the fundamental law of active management will illustrate:

A plot of the annual mean IC highlights how the factor's performance was historically uneven:

[19]:
```
ic = factor_information_coefficient(alphalens_data)
ic_by_year = ic.resample('A').mean()
ic_by_year.index = ic_by_year.index.year
ic_by_year.plot.bar(figsize=(14, 6))
plt.tight_layout();
```

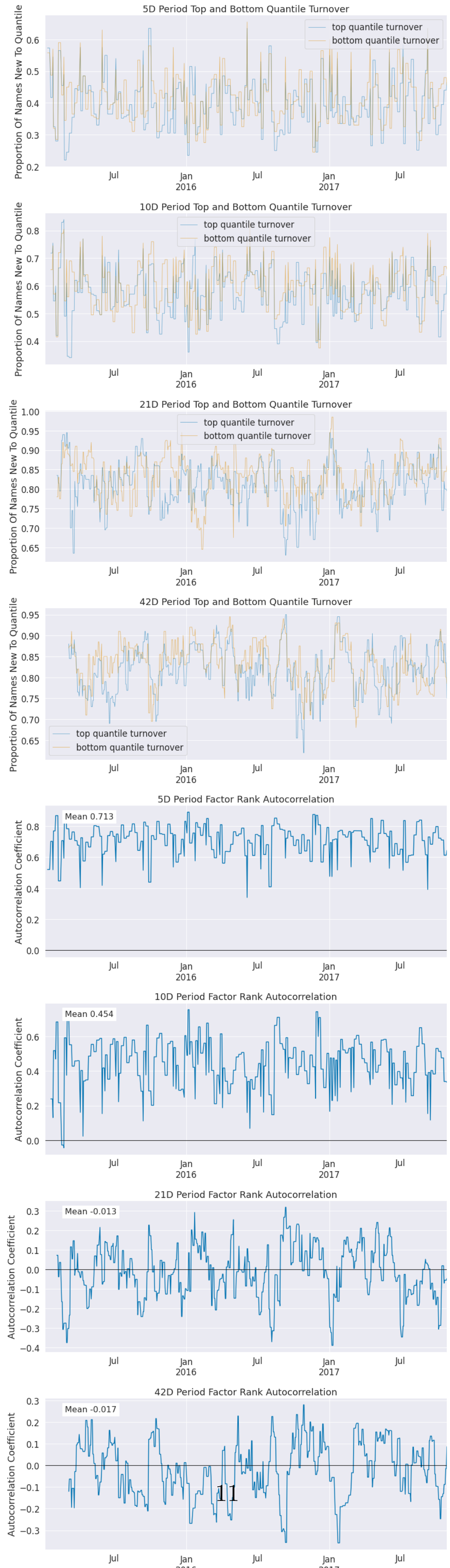


1.6 Turnover Tear Sheet

Factor turnover measures how frequently the assets associated with a given quantile change, that is, how many trades are required to adjust a portfolio to the sequence of signals. More specifically, it measures the share of assets currently in a factor quantile that was not in that quantile in the last period.

[20]:
```
create_turnover_tear_sheet(alphalens_data);
```

```
Turnover Analysis

                             5D    10D    21D    42D
Quantile 1 Mean Turnover   0.411  0.590  0.830  0.831
Quantile 2 Mean Turnover   0.645  0.740  0.804  0.812
Quantile 3 Mean Turnover   0.679  0.765  0.808  0.812
Quantile 4 Mean Turnover   0.642  0.741  0.810  0.814
Quantile 5 Mean Turnover   0.394  0.569  0.811  0.819

                                    5D    10D    21D    42D
Mean Factor Rank Autocorrelation  0.713  0.454 -0.013 -0.017

<Figure size 432x288 with 0 Axes>
```


5D Period Top and Bottom Quantile Turnover
top quantile turnover
bottom quantile turnover
Proportion Of Names New To Quantile
10D Period Top and Bottom Quantile Turnover
top quantile turnover
bottom quantile turnover
Proportion Of Names New To Quantile
21D Period Top and Bottom Quantile Turnover
top quantile turnover
bottom quantile turnover
Proportion Of Names New To Quantile
42D Period Top and Bottom Quantile Turnover
top quantile turnover
bottom quantile turnover
Proportion Of Names New To Quantile
5D Period Factor Rank Autocorrelation
Mean 0.713
Autocorrelation Coefficient
10D Period Factor Rank Autocorrelation
Mean 0.454
Autocorrelation Coefficient
21D Period Factor Rank Autocorrelation
Mean -0.013
Autocorrelation Coefficient
42D Period Factor Rank Autocorrelation
Mean -0.017
Autocorrelation Coefficient
Jul
Jan 2016
Jul
Jan 2017
Jul