Momentum Trading

Introduction

What is Momentum Trading?

Momentum is the speed or velocity of price changes in stock, security, or tradable instrument. Momentum shows the rate of change in price movement over a period of time to help investors determine the strength of a trend. Stocks that tend to move with the strength of momentum are called momentum stocks.

Momentum is used by investors to trade stocks in an uptrend by going long (or buying shares) and going short (or selling shares) in a downtrend. In other words, stock can be exhibit bullish momentum, meaning the price is rising, or bearish momentum where the price is steadily falling.

Precepts of Momentum Investing

Momentum investing seeks to take advantage of market volatility by taking short-term positions in stocks going up and selling them as soon as they show signs of going down. The investor then moves the capital to new positions. In this case, the market volatility is like waves in the ocean, and a momentum investor is sailing up the crest of one, only to jump to the next wave before the first wave crashes down again.

A momentum investor looks to take advantage of investor herding by leading the pack in and being the first one to take the money and run.

Elements of Momentum Investing

Trading momentum markets require sophisticated risk management rules to address volatility, overcrowding, and hidden traps that reduce profits. Market players routinely ignore these rules, blinded by an overwhelming fear they'll miss the rally or selloff while everyone else books windfall profits. The rules can be broken down into five elements:

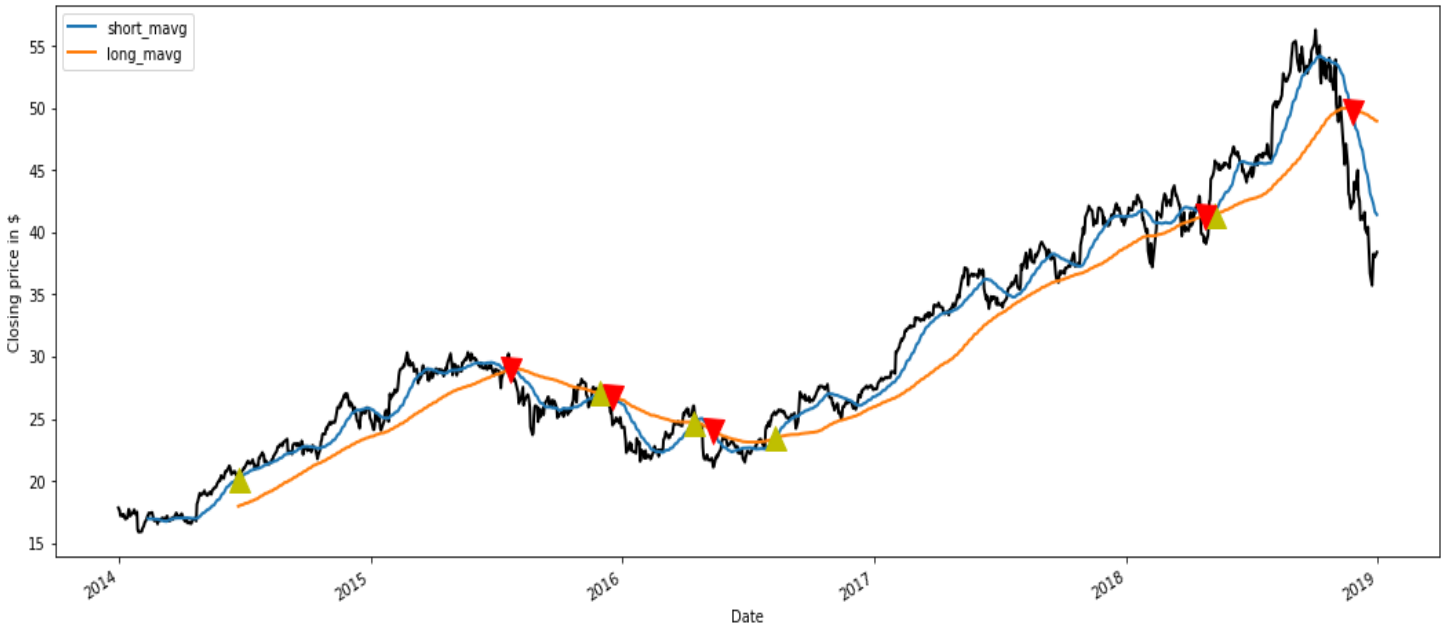
1. Selection, or what equities you choose
2. Risk revolve around timing in opening and closing the trades
3. Entry timing means getting into the trade early
4. Position management couples wide spreads and your holding period
5. Exit points require consistent charting

Momentum Indicators

Momentum indicators are technical analysis tools used to determine the strength or weakness of a stock's price. Momentum measures the rate of the rise or fall of stock prices.

Moving Average Crossover

A very common way to obtain a momentum signal is to look for moving average crossovers. This means computing two moving averages of different lengths, and waiting for one to cross the other. The direction of the cross will indicate the direction of the momentum.



Con: Overfitting

The choice of lengths will strongly affect the signal that you receive from your moving average crossover strategy. There may be better windows and attempts to find them can be made with robust optimization techniques. However, it is incredibly easy to overfit your moving window lengths. For an example of this see the Dangers of Overfitting.

Log Returns

The benefit of using returns, versus prices, is normalization: measuring all variables in a comparable metric, thus enabling evaluation of analytic relationships amongst two or more variables despite originating from price series of unequal values.

This is a requirement for many multidimensional statistical analyses and machine learning techniques. For example, interpreting an equity covariance matrix is made sane when the variables are both measured in percentage.

Several benefits of using log returns, both theoretic and algorithmic.

First, **log-normality**: if we assume that prices are distributed log-normally (which, in practice, may or may not be true for any given price series), then $log(1 + r_i)$ is conveniently normally distributed, because:

$$1 + r_i = \frac{p_i}{p_j} = \exp^{\log(\frac{p_i}{p_j})}$$

This is handy given much of classic statistics presumes normality.

Second, **approximate raw-log equality**: when returns are very small (common for trades with short holding durations), the following approximation ensures they are close in value to raw returns:

$$\log(1 + r) \approx r \text{ , } r \ll 1$$

Third, **time-additivity**: consider an ordered sequence of n trades. A statistic frequently calculated from this sequence is the compounding return, which is the running return of this sequence of trades over time:

$$(1 + r_1)(1 + r_2) \cdots (1 + r_n) = \prod_i (1 + r_i)$$

We will be proceeding with Log return as our Momentum Indicator

Dataset Description

S&P 500

The S&P 500 Index, or the Standard & Poor's 500 Index, is a market-capitalization-weighted index of the 500 largest publicly traded companies in the U.S. It is not an exact list of the top 500 U.S. companies by market capitalization because there are other criteria to be included in the index. The index is widely regarded as the best gauge of large-cap U.S. equities.

Weighting Formula and Calculation for the S&P 500

The S&P 500 uses a market capitalization weighting method, giving a higher percentage allocation to companies with the largest market capitalizations.

Company Weighting in S & P= Total of all market caps / Company market cap

Name Date	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	ABT	ACN	ADBE	...	XEL	XLNX	XOM
2013-12-31	38.247646	23.804220	108.574318	17.819059	38.783775	62.277599	26.740000	33.028294	71.508987	59.880001	...	22.132151	39.482224	72.806999
2014-01-02	37.592243	23.907927	107.652184	17.568451	38.174229	61.905617	26.850000	32.942123	70.560982	59.290001	...	21.791540	39.525215	71.763840
2014-01-03	38.067078	25.020357	110.732445	17.182550	38.409229	61.949898	27.059999	33.295418	70.795822	59.160000	...	21.783617	39.224277	71.591171
2014-01-06	37.879810	25.482304	109.672997	17.276245	37.006523	61.728436	27.299999	33.734875	70.047867	58.119999	...	21.664799	39.052319	71.699089
2014-01-07	38.421539	25.369177	111.026726	17.152693	37.079971	62.401627	27.620001	33.476364	70.900169	58.970001	...	22.037098	39.138302	72.713493

5 rows × 496 columns

The **Training Data** ranges From 2014 - 2019 and **Testing Data** ranges From 2019-2012 June.

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 618387 entries, 2013-12-31 to 2018-12-31
Data columns (total 7 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   Open       618387 non-null  float64
 1   High       618387 non-null  float64
 2   Low        618387 non-null  float64
 3   Close      618387 non-null  float64
 4   Adj Close  618387 non-null  float64
 5   Volume     618387 non-null  int64
 6   Name       618387 non-null  object
dtypes: float64(5), int64(1), object(1)
memory usage: 37.7+ MB
```

```
df_test.info()
```

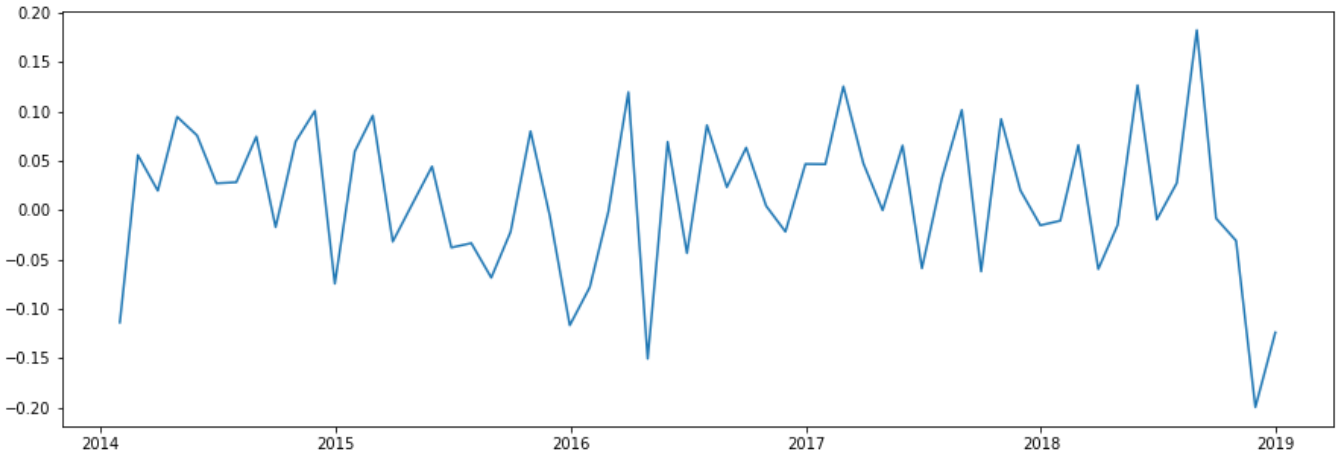
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 304061 entries, 2018-12-31 to 2021-05-28
Data columns (total 7 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   Open       304057 non-null  float64
 1   High       304057 non-null  float64
 2   Low        304057 non-null  float64
 3   Close      304057 non-null  float64
 4   Adj Close  304057 non-null  float64
 5   Volume     304057 non-null  float64
 6   Name       304061 non-null  object
dtypes: float64(6), object(1)
memory usage: 18.6+ MB
```

Methodology

Calculating Log Returns

Log returns (R_t) from prices (P_t) as my primary momentum indicator:

$$R_t = \log_e(P_t) - \log_e(P_{t-1})$$

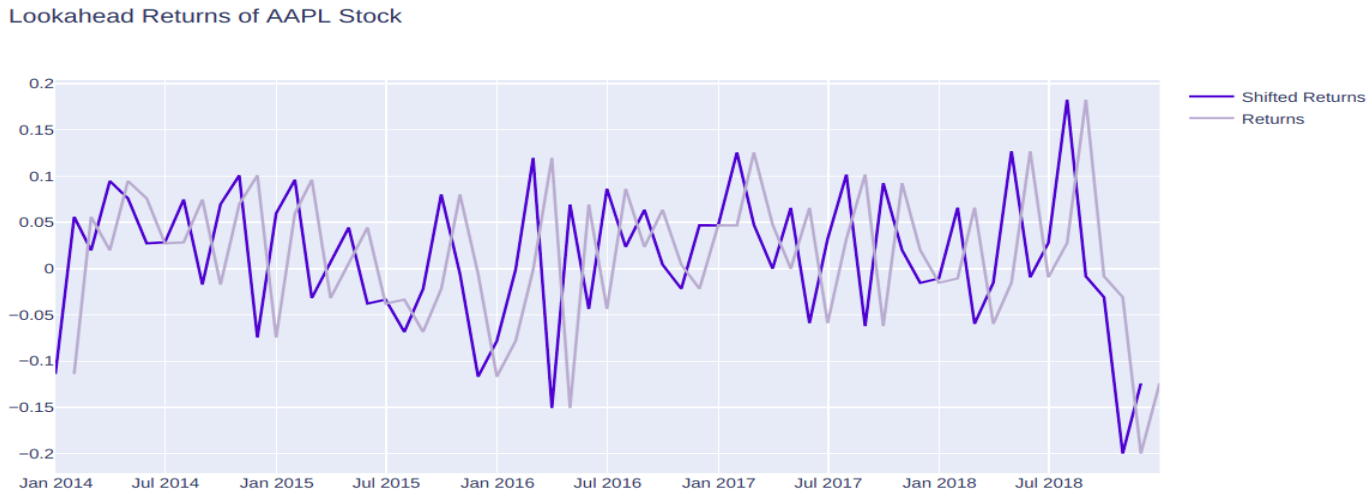


Shift Returns

Shift the log returns to calculate:

1. Previous Return: Shift to -1 time period

2. Lookahead Return: Shit to +1 time period



Generate Trading Signal

A trading signal is a sequence of trading actions or results that can be used to take trading actions. A common form is to produce a "long" and "short" portfolio of stocks on each date (e.g. end of each month, or whatever frequency you desire to trade at). This signal can be interpreted as rebalancing your portfolio on each of those dates, entering long ("buy") and short ("sell") positions as indicated.

Here's a strategy that we will try:

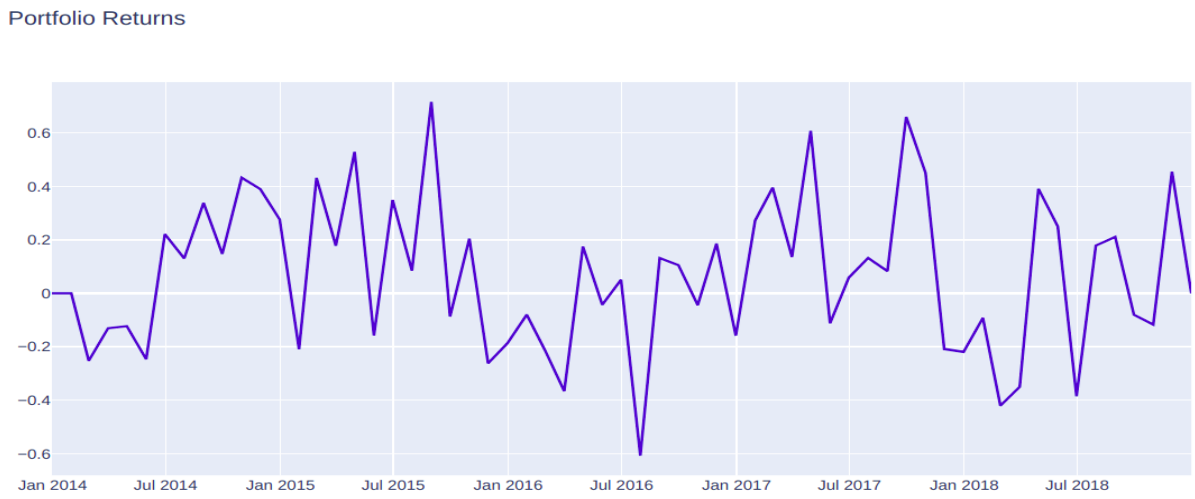
> *For each month-end observation period, rank the stocks by _previous_ returns, from the highest to the lowest. Select the top-performing stocks for the long portfolio, and the bottom-performing stocks for the short portfolio.*

```
In [419]: print_top(df_long, 'Longed Stocks')
          print_top(df_short, 'Shorted Stocks')
```

```
15 Most Longed Stocks:
AMD, ABMD, ENPH, DXCM, NVDA, CZR, SWKS, MU, TSLA, PAYC, ILMN, INCY, ANET, NFLX, TWTR
15 Most Shorted Stocks:
ENPH, MRO, FCX, TWTR, APA, DVN, HAL, WYNN, LB, AAL, DISCK, HES, UAA, CF, MOS
```

Returns

Check if our trading signal has the potential to become profitable!



Results

Training Data Result

Mean:	0.0690
Standard Error:	0.0365
Standard Deviation:	0.2855
Annualized Rate of Return:	128.85%
Initilal Invested Amount:	1000000
Total Numer of Trading Done:	61
Total Trading Charge:	1220.0
Current Portfolio Amount:	2287310.7479
Total profit Amount:	1287310.7479

Testing Data Result

Mean:	0.0268
Standard Error:	0.0833
Standard Deviation:	0.4560
Annualized Rate of Return:	37.88%
Initilal Invested Amount:	1000000
Total Numer of Trading Done:	30
Total Trading Charge:	600.0
Current Portfolio Amount:	1378192.6986
Total profit Amount:	378192.6986

Conclusion

T-Test

Our null hypothesis (H_0) is that the actual mean return from the signal is zero. We'll perform a one-sample, one-sided t-test on the observed mean return, to see if we can reject H_0.

We'll need to first compute the t-statistic and then find its corresponding p-value. The p-value will indicate the probability of observing a mean return equally or more extreme than the one we observed if the null hypothesis were true. A small p-value means that the chance of observing the mean we observed under the null hypothesis is small, and thus casts doubt on the null hypothesis. It's good practice to set the desired level of significance or alpha(α) before computing the p-value, and then reject the null hypothesis if $p < \alpha$.

We'll use $\alpha = 0.05$ since it's a common value to use.

Alpha analysis:

t-value: 1.888

p-value: 0.031957

References

Dataset: ***Yahoo Finance***

S&P 500

Introduction to Momentum Trading

Crossover Trading Strategy

Log Returns