**Introduction:**

Mean reversion is the theory suggesting that prices and returns eventually move back toward the mean or average. This mean or average can be the historical average of the price or return, or another relevant average such as the growth in the economy or the average return of an industry. Specifically, in the algorithm I played with, the short term mean reversion strategy is based on the hypothesis that the worst performed stocks in the past 5 days will rise and the best performed stocks in the past 5 days will drop down in the near future. So this could help us construct a simple long strategy with stocks poorly performed in the past 5 days short term and short strategy with stocks well performed in the past 5 days.

There are at least two competing theories about why short-term mean-reversion strategies work:

* Because of behavioral biases (for example, investors overweight recent information), the market overreacts to both good news and bad news
* Liquidity shocks (for example, a large portfolio rebalancing trade by an uniformed trader) lead to temporary moves that get reversed

**Stock picking:**

We developed a two steps procedure in the stock picking stage: 1. we applied several filters to create a initial equities pool; 2. From the initial equities pool, we applied numerical filters based on the mean-reversion hypothesis to create final long equities’ candidate list and final short equities’ candidate list.

For the initial equities pool generating, we used three filters:

a. Q500US () filter: A default universe containing approximately 500 US equities each day. Constituents are chosen at the start of each calendar month by selecting the top 500 “tradeable” stocks by 200-day average dollar volume, capped at 30% of equities allocated to any single sector.

A stock is considered “tradeable” if it meets the following criteria:

1. The stock must be the primary share class for its company.
2. The company issuing the stock must have known market capitalization.
3. The stock must not be a depository receipt.
4. The stock must not be traded over the counter (OTC).
5. The stock must not be for a limited partnership.
6. The stock must have a known previous-day close price.
7. The stock must have had nonzero volume on the previous trading day.

b. Volatility filter: This filter is based on the idea that presented at a UBS Quant Conference in 2013. The rationale is that when there is less uncertainty about a stock’s “fair value”, stock prices are more likely to reverse after large price moves that deviate from “fair value”.

The improvement was modest but robust: it worked for different trading frequencies as well as a different universe (UBS looked at a monthly reversal strategy and a universe of 1000 stocks in North America). And although the results were not always strictly monotonic, the higher volatility quantiles consistently performed worse than any other quantile, both in terms of Sharpe Ratio and in terms of returns as well.

Applying this concept to a low analyst dispersion universe performed even better, according to UBS. Their measure of dispersion was the standard deviation of analyst earnings estimates. The rationale is the same, and in fact, the two measures are correlated. Quantopian is in the process of incorporating a dataset of analyst earnings forecasts, and as soon as this data is available, I’ll post the results and the algorithm.

These strategies also highlight the idea of using data, like analysts’ earnings estimates, not as a signal per se, but in a totally different way – as a means to condition your alpha or modify the universe of stocks.

Volatility measure: log (return of the past 6 month exclude the most recent 5 days)

c. Liquidity filter: An academic paper by [Avramov, Chordia, and Goyal](http://www.hec.unil.ch/agoyal/docs/LiquidityAutocorrelation_JoF.pdf) suggests that stocks that are less liquid have stronger reversals. The argument is that the compensation demanded by liquidity providers is greater for less liquid stocks. I tested this out using a simple measure of liquidity, volume/ (shares outstanding), and it worked reasonably well. Avramov et al. suggest a more sophisticated measure of liquidity, which I did not try but might be interesting to look at.

The final long, short stock list generating stage consisted by the following steps:

1. We calculate the log of daily returns in the past 5 days, which being calculated as today’s close price divided by the previous day’s close price.

2. Calculate the standard deviation of the returns in the past 5 days.

3. Generate the long list with stocks have lowest log daily returns and lower standard deviation of the returns.

4. Generate the short list with stocks have highest log daily returns and lower standard deviation of the returns.

Note：Quantiles in both step 3 and 4 are manually defined.

**Rebalance strategy:**

1. For securities we have position but moved out from Q500US, we close the positions.

2. For securities we have already taken long positions, if the short term performance are not below first quantile, we close the positions.

3. For securities we have taken short positions, if the short term performance are below user defined quantile, we close the positions.

4. For securities in our long list, we use half of our cash to take long positions with weight of 0.5 / (length of the long positions we will have).

5. For securities in our short list, we use half of our cash to take short positions with weight of 0.5 / (length of the short positions we will have).

**Entering time:**

We do analysis, calculations 5 minutes before market close and we rebalance positions right before market close.

**Miscellaneous:**

Why use log returns in the algorithm: <https://quantivity.wordpress.com/2011/02/21/why-log-returns/>

**Possible Improvement:**

Stock picking:

a. Discover new relationships between some numerical measure and stock more likely to reverse.

b. Change current filter’s threshold.

c. Industry or sector neutralizing the portfolio

Rebalance strategy:

a. Develop a more complex way to calculate the weight, which considers each stock’s performance and level of reverse could be predicted.

b. Add a stop loss logic here to reduce the risk

Entering time:

a. Try different trading frequencies, daily vs. weekly vs. monthly

b. Try different entering timing like market open vs. market close