STARR Ratio Time Series Momentum Trading
A.R.16' a.k.a Trend Chasers

Abstract

Our strategy is to take advantage of momentum based price signals in order to capitalize on "past winners" (consistently high absolute returns) and "past losers" (consistently low absolute returns). Momentum strategies tend to be susceptible to higher than normal volatility, so we sort our stock picks by not only average return but also CVaR (conditional value at risk) or expected shortfall. We've done this by creating a STARR ratio variable in our pipeline. As such, we go long on the highest STARR and short on the lowest STARR ratio percentages, which allows for a natural portfolio hedge. Moreover, we implemented a rolling net beta variable to hedge against market risk. According to Eugene Fama, the father of "EMH", momentum trading is one of the few forecasting strategies in the stock market that can relatively accurately predict future returns. Albeit, while implementing this strategy we wanted to minimize any inherent bias by ensuring a random selection of stocks and not overfitting our strategy.

Requirements

- Code works from 01/01/15-03/31/15 ✅
    - Yes - see figure 1 in the appendix
- One trade signal per day ✅
    - Yes - see figure 1 in the appendix - we averaged about seventy trades per month.
- Involves trade of five different assets ✅
    - Yes - see figure 1 in the appendix – we had seventy simultaneous positions
- Uses pipeline ✅
    - Yes - we used pipeline to select stocks via Starr Ratio rankings
- Optimization ✅
    - Yes - see table 4 in the appendix
- Time weighted cash position ✅
    - This seemed to be true most of the time. Our time weighted cash position fluctuated based off our portfolio's net beta imbalance and beta-hedging transactions, but using small amounts of leverage seemed to help with this. Our algorithm is officially in the Quantopian competition, so this shouldn't be an issue.

From some of the academic papers that we read, assumed that past returns would be a strong indicator of future returns. As seen in Figure 2, this was a reasonable assumption, but we could not make a profitable strategy from momentum alone. From there, we assumed Sharpe Ratio would serve as a strong indicator of future performance and help us to achieve a portfolio with a high Sharpe Ratio, but this assumption failed badly. From figure 3, we see that our Sharpe Momentum strategy failed to provide any decent results. From there, we assumed that Starr Ratio would be a strong indicator of momentum, but it is still unclear whether this assumption is true.

Judging from our performance in 2016 so far, we have made decent improvements over our previous code. Although we still can't find consistent returns, we have managed to gain a fair amount of consistency in our betas by implementing a manual beta-hedge into our portfolio. This means that our portfolio performances are mostly determined by our alpha when back testing over longer periods of time. Additionally, to ranks based off of Starr Ratios helped us to consistently limit our drawdowns. While using returns and Sharpe Ratio to generate ranks, we could profit in one period and still see large downturns, whereas our drawdowns mostly stay in the ~10% ballpark while using Starr Ratio.

The main feature of our strategy that defied our expectations was the failure of Sharpe Ratio to produce profitable rankings. We hypothesized that this has to do with the failure of standard deviation to capture risk and because the Sharpe ratio penalizes both upside and downside volatility. Over long enough time periods, a large downturn in a stock's price can be washed away by stationarity elsewhere when using standard deviation as a metric for risk. We believe that this caused Sharpe Ratio to favor stocks with little movement over stocks that had favorable return-to-risk ratios. Using Starr Ratio for our rankings seemed to help because it uses CVaR (expected shortfall) to calculate risk. With Starr Ratio, longer lookback periods didn't seem to generate any noisy rankings because CVaR only accounts for tail-end shortfalls when calculating risks instead of using all of a stock's variation.

For our strategy, we believe that regime changes could have played a role in explaining the variation of our code over different time periods. Because our strategy did relatively well in 2015 but did poorly for the first three quarters of 2016, we believe that our strategy could have performed differently because of shifting market conditions. This could be because in 2016, markets became less correlated in general which led to dispersion. This means that a momentum based strategy such as ours may not be ideal during this time. Furthermore, the market performed better in 2016 than in 2015, which could explain some of the drop off in our performance. In theory, CVaR should be a stronger indicator of risk when most stocks have experienced some significant shortfall so that you can compare their relative volatilities. This would help our selection process because there would be a greater variation in our stock rankings, which would help make our selections less arbitrary. In the future, we could potentially alter our selection by market performance over the last year. We could also potentially attempt to improve our code by implementing an Augmented Dickey Fuller test to determine whether our stock selections are stationary. Then, we could either discard these stocks from our selection or implement a simultaneous mean-reversion strategy.

In future iterations of our code, we could also possibly explore holding stocks for different lengths of time. For this iteration, we mainly focused on tweaking other aspects of our code, but altering the amount of time for which we hold our stocks could possibly have a large impact on our performance. Furthermore, we could also attempt to cycle our portfolio. We would do this by still holding stocks for a month, but making it so that we pick new stocks every week and dedicate a quarter of our resources to them. This would help to diversify our portfolio because we could hold as many as four times the original amount of stocks that we would have otherwise. Furthermore, this method would also help us to exploit the changes in ranks that occur between weeks, which could potentially strengthen our positions.

Appendix

Figure 1 (Backtest of final algorithm from 01/01/15-03/31/15)

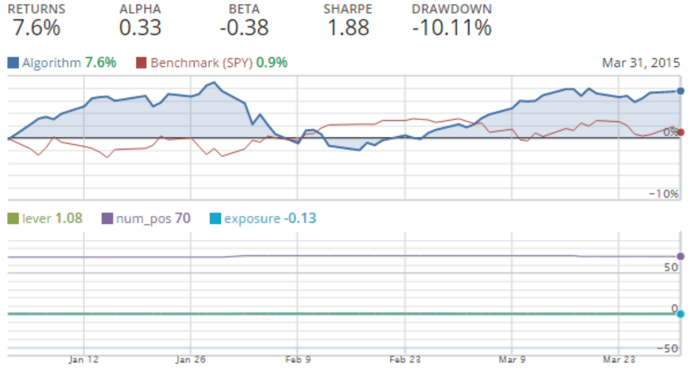

Figure 2 (Momentum backtest from 2012 to 2016)

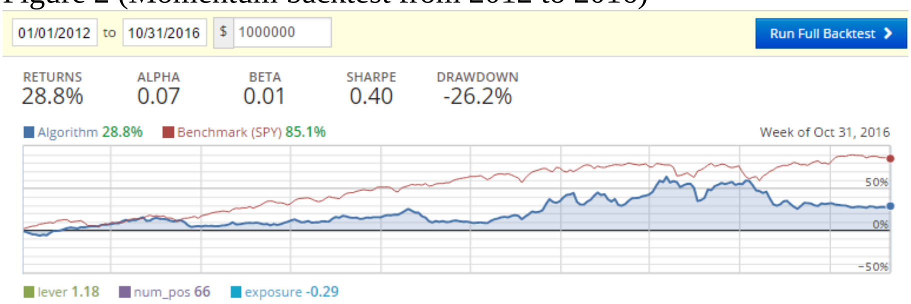

Figure 3 (Sharpe Momentum Backtest)

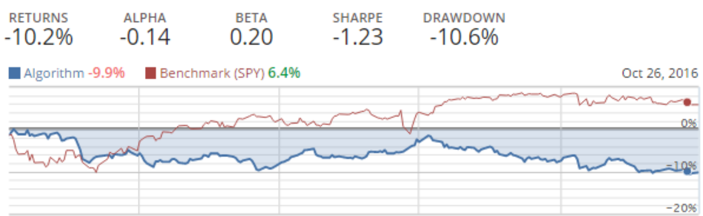

Table 4 (Sharpe Ratios for fixed CVaR percentile over given dates)

CVaR Cutoff	09/01/16-09/31/16	10/01/16-10/31/16	12/01/2015-12/31/2015	12/01/2014-12/31/2014
0.66	0.58	2.3	1.55	2.31
1	1	4.12	2.28	2.95
1.33	0.43	2.55	2.16	3.23
1.66	0.01	3.35	1.25	3.1
2	-0.08	2.68	1.23	2.66
2.33	0.15	1.84	0.47	2.09
2.66	-0.13	1.83	0.73	2.47
3	0.46	1.41	0.55	2.51