Mean Reversion with a Volatility Based Shifting Confidence Interval
Stat 198: Fall 2022 Final Project

Abstract

Mean reversion is a common strategy that is employed in foreign exchange and commodity markets. It refers to the theory that asset prices tend to return to their normal, average levels over the long term. With this theory in mind, stock prices routinely oscillate around the mean but eventually return to that same average over and over. Traders in the past have developed many methods to capitalize the potential profit returns using this theory by estimating the average price of assets and betting on the price returning approximately to that level. Here we explore a new idea that rather than a mean price, we utilize the confidence interval for a range of price to capture the mean reversion and shift this interval with volatility of the assets.

Introduction

Mean reversion suggests the theory that in the long run, asset prices eventually revert to their long-term average levels, which can be seen in various contexts such as economic growth, volatility as well as the average return of stocks. Reversion to mean essentially means to trace a condition back to its long-run average state.

It's important to understand that the stocks are mean-revertive due to various reasons. As their prices go up and down, stocks become more liable to the idea of rebalancing, meaning that people buy stocks that have fallen and sell stocks that have risen. For risk management purposes, portfolio diversification, and mandates by the firms, hedge funds and mutual funds will certainly reshuffle their portfolios which often can go against the prevailing trend. In addition, stocks are mean-revertive also because of short-selling and arbitrage. People who are short sellers often buy undervalued stocks and short overvalued stocks, effectively dampening both upside and downside moves. This phenomenon is also true for arbitrageurs who short those in values and buy those that fall in value.

Given this phenomena, it leads to the realization that traders can profit by betting on a stock returning to its average price (with the confidence interval being subject to tuning based on different factors such as volatility, trends, etc). If a stock is lower than its measured average, one could buy the stock with the expectation that it will revert to its average level. Similarly, if a stock is trading for higher than its average level, a trader could short the stock with the expectation that the price will fall back to its average level, at which they could buy the stock back and generate a profit.

Literature Review

Mean reversion is a financial theory that assumes a stable trend in the price of an asset or a historical relationship between two related companies and suggests that any price volatility will ultimately return to this long-run mean or moving average. Many traders attempt to capitalize on this notion of an asset returning to the average price by designing an algorithm that follows a mean-reverting stochastic time series. As described, a mean-reverting price series “is considered to be reverting towards its long-term mean μ if the price shows a downward trend when greater than μ and upward trend when less than μ” (Chakraborty & Kearns, 4). The essence of the mean reversion strategy is to go long when the asset price falls a specific amount below the moving average and conversely go short when prices rise above. Mean reversion can be applied to an individual stock, however “the danger of applying mean reversion to a single stock is that it exposes us to the movement of the market and the success or failure of the individual company, among other factors” (Auquan). Thus, it would be more beneficial for us to implement the mean reversion strategy utilizing a portfolio of underlyings (for example all the stocks in the S&P 500) which makes the approach more market-neutral with a higher likelihood of being correct.

Since mean reversion is a form of statistical arbitrage, it is common to see this strategy applied in algorithmic trading specifically through pairs trading. Research from Columbia University students Peng Huang and Tianxiang Wang attempts to prove the profitability of mean reversion in the form of pairs trading. Using the Maximum Likelihood Estimation (MLE) method, they sought out pairs of companies that most resembled the Ornstein-Uhlenbeck (OU) process to ensure that their portfolio was a collection of optimal mean-reverting pairs before trading (Huang & Wang, 3). Their approach proved successful as they were able to identify nine trading pairs that “exhibit high return over the in-sample period and out-of-sample period. All pairs achieve above 1.9 Sharpe ratio in in-sample and out-of-sample test” (Huang & Peng, 6). Their research supports the conclusion that mean reversion trading can be profitable under constrained conditions. We attempt a similar mean reversion strategy to what is described in Huang and Wang’s research but implement our algorithm around a volatility-based shifting confidence level rather than applying the MLE method to find trading pairs resembling the OU process.

A similar result as the one discussed above is seen in an earlier research paper by Chakraborty and Kearns who attempt to demonstrate the profitability of market-making through mean reversion. Like Huang and Wang, the researchers applied a simple market-making algorithm under the OU process (which is naturally mean reverting) to measure the cumulative return. They show that a simple market-making algorithm run under this stochastic time series would yield a profit that “grows linearly with the duration for which the algorithm is run, and the profit guarantees hold not only in expectation, but with high probability” (Chakraborty & Kearns, 5). However, the market-making algorithm that was used does not account for the restrictions that a market maker is bounded by and makes basic assumptions like the fact that the trader can place buy/sell orders at any given time which is not representative of real-life conditions. The step forward would be to impose these formal restrictions on an algorithm where “a market maker has to always be present in the market, and offer prices that are close to the asset price” and observe and compare the profit that is accumulated (Chakraborty & Kearns, 9).

Datasets

When choosing the data we would like to use for our model, we wanted to test our model on datasets of varying volatility. As such, we landed on Apple (AAPL), Tesla (TSLA), and the SPDR S&P 500 ETF Trust (SPY) because Apple has performed more consistently, SPY is an ETF that will provide us with more information on how our algorithm performs on ETFs rather than individual stocks, and Tesla has experienced rather large volatility in the recent year.

Methods and Modeling

Over years, traders in the quantitative finance field have developed various mean reversion based algorithms to capitalize the potential returns. In our model, we employ the method of mean reversion with an additional feature of volatility-based shifting confidence interval.

For stocks that are continuously falling, our model loses less money than current mean reversion models. This is because our interval gives us a greater range before buying, which means that if the current price deviates even a little from the mean, our model will discourage us from making the trade.

Results

For Tesla, Apple, and SPY, our model outperformed current mean reversion models. For Tesla, current mean reversion models make $197 while our model makes $264. For Apple, mean reversion models make $45 while our interval-based mean reversion model makes $112. And finally, for SPY, mean reversion models make $137 while ours made $185.

As an important note, for our model, we assumed an infinite supply of initial stocks to trade, so theoretically we could keep selling.

Conclusion

While we did manage to get higher profits using our interval-based reversion model, we did assume a couple factors that may drastically affect the performance of our model in a real-world context. Nevertheless, our model provides another facet for consideration in mean reversion models.

We acknowledge that there are limitations that come with our mean reversion models. The return to a normal pattern is not always guaranteed due to unexpected highs or lows that could indicate a shift to the norm. These could be other factors such as politics. In the case of a guest lecture by Rory, Voleon lost 18M by shorting on a stock that was later rescued by the president of a random country. Therefore, it is important to understand the underlying factors that cause the shifting in stock prices in the first place.

References

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