*The following is written on trading the Direxion YINN US ETF*

After reading a paper on [**Leverage for the Long Run – A Systematic Approach to Managing Risk and Magnifying Returns in Stocks**](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2741701), by, Michael A. Gayed, CFA (2016 Charles H. Dow Award Winner), I arrived at the idea to build a systematic strategy to trade the YINN US ETF which aims to return 3x the FTSE China A50 Index.

**Introduction**

For retail investors to access leverage without exposure to leveraged Exchange-Traded Funds (ETF) are plagued with various regulatory and capital limitations, such cost of margin calls, and possibility of bankruptcy. From my findings and readings of various academic papers, I’ve come to understand that using leverage to enhance returns in a portfolio have primarily been centred on low beta stocks (Frazzini and Pedersen (2012) and using moving average indicators is a way to trade leverage ETFs to provide superior returns (Michael A. Gayed 2020)

In his paper, he showed an example of his strategy employed with the 2x and 3x leveraged SPX ETFs. However, I have since adapted it to trade the 3x leveraged YINN ETF.

**Leverage – risks and returns**

Leverage – introduction to leveraged etfs, relationship between volatility and leverage, how using MA helps in identifying entries (Michael A. Gayed)

**Methodology**

1. Data preprocessing – gather price data from various sources (investing.com) and ensure formatting is constant for all columns in the dataset, especially the date and integrity of the prices. (recommend to do it in excel, unless proficient in python) (Remember to check the price integrity, if pulling data from investing.com, check volume and if its blank, remove it.)
2. Moving Average and Volatility calculations – do it in python

Testing phase:  
According to Michael, when the S&P 500 trades above its Moving Average, volatility going forward is considerably higher than when it trades above its Moving Average (Maybe start to test this first, on the A50 futures, see if its volatility is indeed lower after the price moves above their Moving average. Use days = {10,20,50,100,200}

Revised criteria:

1. The ETF and index tracked are offered by the same broker
2. Must have higher correlation… maybe above 70%?
3. The Annualized volatility must be lower when price is above moving average than when price is below moving average
4. NEW DISCOVERY: The signal generated is the Index price moving ABOVE the ETF’s moving average instead. So if SPX goes above ETF’s ma, we buy and sell if vice versa..? Meaning, it is extremely important that the index and ETF’s prices are synchronized
5. Currently there are two versions, one that uses underlying index MA while the other uses ETF’s MA. Problem: im using that day’s close to generate a signal for the same day which doesn’t make sense > Solved, using index open price instead to generate the signal and using the same day’s ETF open price

* Costs: Transaction costs on entry and exit, slippage costs (bid-ask) (found by using the average bid-ask spread) , brokerage commission costs, meanwhile expense ratio already embedded in historical price.
* Beat the benchmark on total return but lost on risk-adjusted return, signalling a bad risk-reward measure. Can improve on it by using dynamic trailing stops and clearer volatility-based entry/based signals or perhaps not since I’m using leverage
* Solution 1: Using dynamic trailing stops so far ok.
* Solution 2: Using fixed position size based on risk doesn’t work, gains get eroded by costs
* Using Dynamic trailing stops and scaling out of positions, + marking-to-market have greatly improved the risk-adjusted returns but however, it is still not beating the benchmark. But perhaps that’s ok.
* Next step would probably be to split up the data and test the strategy on different periods in time. E.g. how it compares to the underlying during market downturns and during bull markets. And test it on other similar etfs
* May need to implement adaptive parameters that change based on different volatilities, market cycles, or a statistic.
* 🚨 **If walk-forward significantly underperforms, it usually means the original backtest was overfit**—not necessarily that walk-forward is bad.
* You can now explore whether:
* The strategy itself is **not robust across regimes** (fundamental issue).
* The **parameter choices** are suboptimal in different windows (parameter tuning issue).
* The **walk-forward design** (window size, step size) can be improved.
* Would you like me to modify your walk-forward framework to include **adaptive parameter selection** or **rolling window overlaps**? 🚀
* FURTHER Improvements:
  + Adaptive parameter selection
    - Compare segment’s average ATR to the global median ATR (whole dataset) and if higher, use 20% higher ATR multiplier and 10% wider scaling threshold.

Also, list of ETFs to test on:

1. SPXL which tracks the S&P 500 Index
2. ProShares UltraPro QQQ which tracks the Nasdaq-100 Index
3. Direxion Daily Financial Bull 3x, which tracks the Russell 1000 Financial Services Index
4. Direxion Daily Mid Cap Bull 3x, which tracks the S&P Midcap 400 index
5. Direxion Daily MSCI Emerging Markets Bull 3x, which tracks the MSCI EM index
6. Direxion Daily FTSE Europe Bull 3x, which tracks the FTSE Developed Europe All Cap Index
7. SPXL Strategy
   1. Signal currently is generated when SPX’s close price is above the moving averages of the leveraged ETF.
   2. Costs considered are the transaction costs (per share) as well as slippage costs as a % of trade price (open or close), expense ratio assumed embedded into price
   3. Here, using the SPX close price to generate the signal is using it as a relative indicator, i.e. if SPX Price is above the ETF’s MA, there is a strong market trend and thus a calmer market, conducive to enter.

Even without machine learning, you can ensure your strategy’s robustness by:

* Splitting your data into distinct in-sample and out-of-sample periods.
* Performing walk-forward analysis.
* Testing in various market conditions.
* Supplementing your analysis with Monte Carlo simulations.
* Monitoring key performance metrics to ensure consistency.

By following these steps, you’ll be better positioned to evaluate whether your strategy’s edge is genuine or simply a product of overfitting to past data.

# LIVE TRADING

Hi, well done on the back-testing so far, now its time to take it to paper-trading and then finally to live trading. Here are some thoughts:

* + - 1. Daily bar assumptions:

By using the daily bars, it means I’m approximating the intraday movements and my trailing stops are based on day’s high and low may not capture intraday gaps. Beware of potential execution difference in live markets