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Performance of the VIDYA Indicator using Bootstrap

Lucas Priskos

Abstract

This paper analyses the performance of the Volatility Index Dynamic Average Indicator (VIDYA) as a method for technical trading. The question was whether or not the buy and sell signals generated by VIDYA could allow a trader to outperform the benchmark rate of return. The strategy is implemented in a similar way to a standard moving average crossover where two lines are charted: a short period VIDYA and a long period VIDYA. The four combinations of VIDYA were used were as follows: 6 with 21 periods, 9 with 21 periods, 12 with 21 periods, and 21 with 50 periods. When the shorter period VIDYA is above the longer period this signals that the underlying asset should be bought. Conversely, when the long period VIDYA is above the short period VIDYA this generates a short signal for the underlying asset. A historical back test was conducted on daily data for SPY and FXE to generate a daily return for trading with the VIDYA. The returns were compared to a benchmark of a buy and hold strategy for SPY and FXE, respectively. A relative performance variable was calculated by taking the difference between the loss of the benchmark and the loss of the strategy. As pointed out in their paper, "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap" by Sullivan et al, data snooping is a serious problem when conducting a back test solely on historical data. I controlled for data snooping via bootstrapping by conducting an out of sample test using Hansen's SPA test. Rather than bootstrapping the underlying price data and running the back test on that, the bootstrap was conducted on the relative performance variable. These two methodologies should be equivalent but the latter is computationally less intense. None of the trading strategies were found to yield a significant return over the benchmark. At the end, this paper recommends further analysis that should be done.

I. Introduction

Whenever conducting a back test against historical data, one is subject to the problem of data-snooping. Data-snooping is comparable to the idea of p-hacking. However, p-hacking is often done intentionally by an author in order to produce a significant result that can be published. On the other hand, data-snooping can easily be done unintentionally, to the detriment of the analyst. If a researcher were to conduct a back test against historical data using thousands of different technical trading indicators, some of them are bound to outperform the benchmark simply by chance. This does not mean that those particular indicators will continue to outperform the benchmark return in the future. To illustrate the issue of data-snooping, consider the following example used by Jensen and Bennington (1970): “given enough computer time, we are sure that we can find a mechanical trading rule which ‘works’ on a table of random numbers – provided of course that we are allowed to test the rule on the same table of numbers which we used to discover the rule.”

This example illustrates the need to conduct out of sample testing when analyzing technical trading indicators. The goal of such analysis is to make the results forward looking rather than backward looking. This can be accomplished through economic forecasting. The idea behind economic forecasting is to use a loss function in order to build a predictive density.¹ This makes the trading strategy predictive of future returns rather than backward looking. In order to avoid the problem of testing a trading strategy on the same sample used to discover it, a bootstrap is conducted in order to perform an out of sample test. Three different types of

¹ See Elliot and Timmerman (2008) for a more complete discussion of economic forecasting.

bootstrapping that can be done include the moving block bootstrap (MBB), circular block bootstrap (CBB), and stationary bootstrap (SB). Both MBB and CBB use a constant block length. Having a constant block length would be best if the optimal block length were known. However, the optimal block length is rarely known so for this reason it is most common to see analysis done with a SB because it varies the length of the block. It is for this reason that the analysis in this paper will be using a SB. Once the bootstrap has been conducted, I then use Hansen's SPA test to see if any of the trading strategies were able to significantly outperform the benchmark.

The indicator of interest is the Volatility Index Dynamic Average Indicator (VIDYA). The equation for VIDYA is,

$$VIDYA_i = P_i * F * V_i + VIDYA_{i-1} * (1 - F * V_i)$$

where P_i is the current price of the asset, F is the smoothing factor and is calculated as $\frac{2}{Periods+1}$ (ie when a 6 period VIDYA is used that means the variable periods was assigned a value of 6 in the smoothing factor), $VIDYA_{i-1}$ is the value of VIDYA in the previous period, and V_i is the volatility factor. The volatility factor is calculated as,

$$\frac{SD - SD_{low}}{SD_{high} - SD_{low}}$$

where SD is the standard deviation of the price across the previous 20 periods, SD_{low} is the lowest value of the standard deviation in the last 20 periods, and SD_{high} is the highest value of the standard deviation in the last 20 periods. The standard deviation calculations are always taken across 20 periods, regardless of the number of periods used in the smoothing factor.

Note that this indicator looks similar to an exponential moving average. The only difference is that VIDYA contains a volatility factor. One major concern when using a technical

indicator to generate trade signals is that when markets become volatile the indicator will give faulty trade signals. VIDYA has the volatility factor in order to smooth it out during volatile periods in an attempt to avoid bad signals. V_i allows the indicator to adjust how much weight is given to new and old data based on how volatile the market currently is. In a more volatile market, V_i will be smaller so less weight will be given to the new price data. In a less volatile market, V_i will be larger so more weight will be given to the new price data.

The trading strategies that are tested in this paper are all crossover strategies that use different combinations of VIDYA to generate buy and sell signals. Each strategy uses two combinations of VIDYA: a short period and a long period. When the short period VIDYA is great than the long period VIDYA this means that the asset is on an upward trend and the trader should take a long position. When the short period VIDYA is less than the long period VIDYA this means that the asset is on a downward trend and the trader should take a short position on the asset. Figure I illustrates this strategy.



Figure I. Price candles for SPY from 2014-2016. The orange line is a 6 period VIDYA and the blue line is a 21 period VIDYA. The white circle is at a short signal and the purple circle is at a buy signal.

I analyze trading signals for the following VIDYA combination: 6 periods with 21 periods, 9 periods with 21 periods, 12 periods with 21 periods, and 21 periods with 51 periods. Each of these combinations were tested against SPY and FXE for a total of 8 trading strategies.

II. Data

I used daily close price data for SPY and FXE to test the trading strategies. The data was downloaded from Yahoo Finance. The time period used for the historical data was December 12, 2005-present. The time frame was chosen because this is as far back as the historical data goes for FXE. A historical back test for both of these assets was conducted for each of the 4 different combinations of VIDYA. The results of these back tests are contained in tables I and II.

SPY	
Strategy	Return
Buy and Hold	75.25%
6/21 periods	55.78%
9/21 periods	72.24%
12/21 periods	70.04%
21/50 periods	36.26%

Table I. Returns for the benchmark (buy and hold) of SPY as well as the returns for each of the trading strategies.

FXE	
Strategy	Return
Buy and Hold	-2.88%
6/21 periods	-10.27%
9/21 periods	-9.06%
12/21 periods	-6.83%
21/50 periods	33.60%

Table I. Returns for the benchmark (buy and hold) of SPY as well as the returns for each of the trading strategies.

As can be seen in Table II, the only strategy that outperformed the benchmark in the historical back test was the 21 and 50 period VIDYA combination on the FXE. However, these are not the results that I am interested in. As mentioned before, a historical back test is backward looking. The next step is to make the results forward looking by bootstrapping the data.

III. Process

The process followed in this paper is similar to the process that is followed by Sullivan et al. (1999). In their paper, they apply White's Reality Check after conducting the bootstrap. I have chosen to use Hansen's SPA test instead of White's Reality Check. The problem with White's process is that the results of a technical trading strategy can be manipulated into being significant by including some strategies that are known to perform poorly. Hansen's SPA test controls for this to prevent the results from being unfairly manipulated.

The first step was to calculate a daily return for both SPY and FXE. Since the benchmark for each of the trading strategies was a buy and hold of the underlying asset that VIDYA was being applied to, these daily returns were used as the benchmark. Then a daily return was calculated for each of the four strategies on both of these assets. Once the daily returns have been

calculated for the benchmark and the trading strategies the next step is to calculate a daily relative performance variable. This is computed as,

$$X_{k,t} = L_{0,t} - L_{k,t}$$

where $X_{k,t}$ is the relative performance of the trading strategy with respect to the benchmark, $L_{0,t}$ is the loss of the benchmark, and $L_{k,t}$ is the loss of the trading strategy. The subscript k denotes the k^{th} trading strategy. The relative performance values are the numbers are bootstrapped using the SB in order to conduct an out of sample test. The null hypothesis is then $H_0: \lambda = E(X_{k,t}) \leq 0$ for all values of k . In other words, the null hypothesis is that the expected returns of the trading strategy do not exceed the expected returns of the benchmark.

Hansen's SPA test was used to test this null hypothesis.² This test will yield three p-values for each of the assets the strategies are being tested on. So three p-values will be generated for the testing on SPY and three for the testing on FXE. These three p-values correspond to the best performing trading strategy used in the test. The p-values that are generated are denoted as: p_l , p_c , and p_u , where l stands for lower, c stands for consistent, and u stands for upper. It can be shown that p_c is consistent with the true p-value under the null hypothesis.³ The values for p_l and p_u provide an upper and lower bound for the true p-value. Hansen's SPA test with also return the t-statistic that is associated with these p-values.

IV. Results

The results from the Hansen SPA test for SPY is are summarized in Table II and the results for the test on FXE are summarized in Table III.

² For a complete description of Hansen's SPA test see Hansen (2005)

³ See Hansen and Lunde (2005)

SPY Results			
t_spa	p_l	p_c	p_u
0.000	0.537	0.597	0.597

Table II. Results of Hansen SPA test on SPY.

FXE Results			
t_spa	p_l	p_c	p_u
0.533	0.360	0.393	0.393

Table III. Results of Hansen SPA test on FXE.

The focus in analyzing these results should be on the p_c values since these are the ones that should be consistent with the true p-value. The p-values for both SPY and FXE are insignificant which means that none of the trading strategies outperformed the benchmark to a significant degree. For SPY, the t-statistic is 0, which means that all four strategies tested on SPY underperformed the benchmark of a buy and hold for SPY. For FXE, the t-statistic is 0.533, which means that at least one of the four strategies outperformed a buy and hold strategy for FXE but it did not outperform the benchmark at a significant level.

V. Conclusion

None of the strategies tested were able to outperform the benchmark return of a buy and hold of the underlying. However, finding a strategy that could outperform the benchmark was not the purpose of this analysis. This paper is to demonstrate the process of using a SB to conduct an out of sample test and then using Hansen's SPA test to check for significant returns in excess of the benchmark using VIDYA as the technical indicator. These results do not provide sufficient evidence to conclude that VIDYA is not valuable as a trading indicator.

Only 8 strategies were tested which is an insufficient amount to draw any real conclusions about the performance of VIDYA. Further analysis would need to be done that tests thousands of different period combinations of VIDYA on several different assets in order to draw more robust conclusions about the value of this indicator.

Additionally, having a good indicator is only one aspect to having a good technical trading strategy. Another element to a good strategy is proper money management when placing trades. In this paper, whenever a buy or sell signal was generated, the entire value of the trading portfolio was used to conduct the trade. In the real world, a trader would never trade in this manner. In addition to testing thousands of combinations of VIDYA, further analysis should include some type of money management used in executing the trades.

VI. References

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