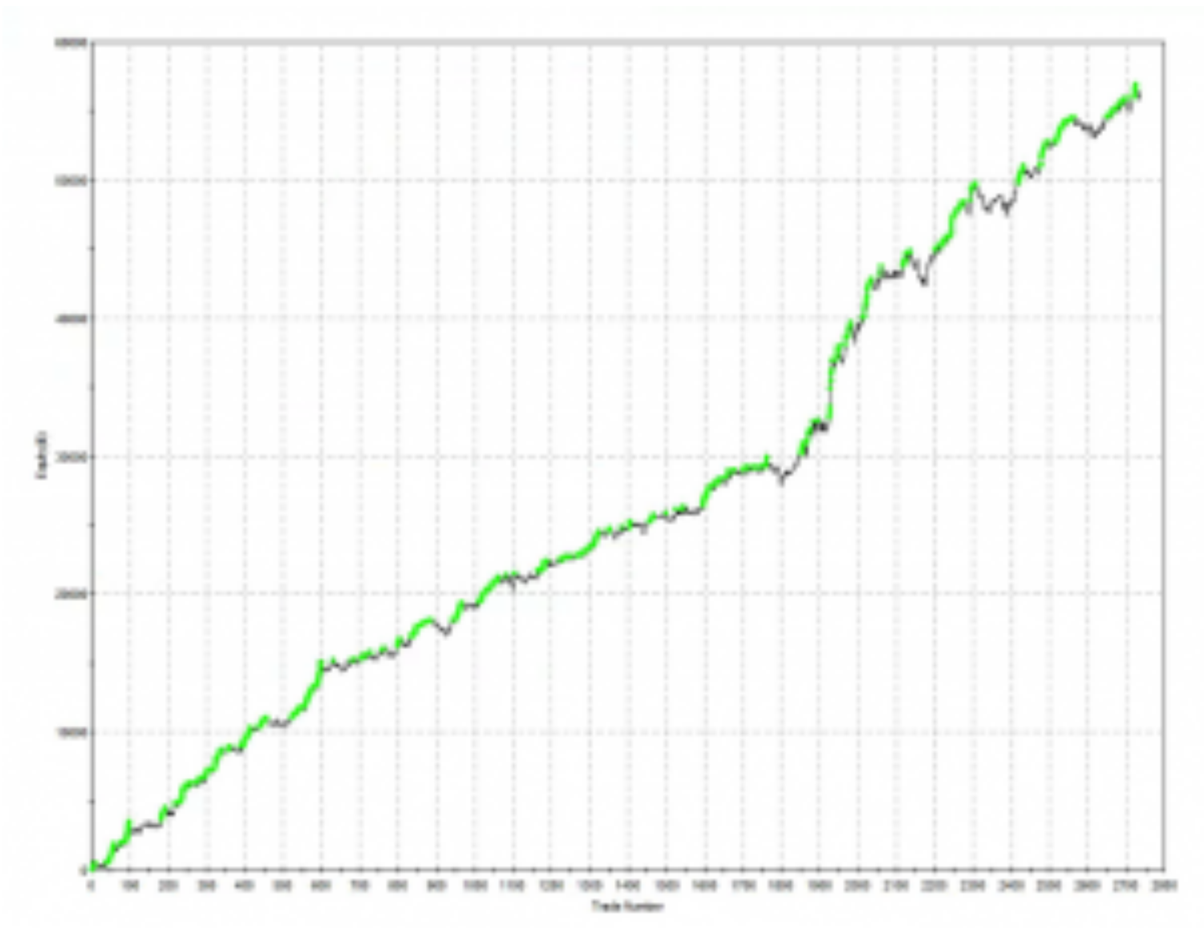
# META-STRATEGIES AND THEIR APPLICATIONS

## 1. Identifying Drivers of Trading Strategy Performance

Building a winning strategy, like the one in the e-Mini S&P500 futures described here is only half the challenge:  it remains for the strategy architect to gain an understanding of the sources of strategy alpha, and risk.  This means identifying the factors that drive strategy performance and, ideally, building a model so that their relative importance can be evaluated.  A more advanced step is the construction of a meta-model that will predict strategy performance and provided recommendations as to whether the strategy should be traded over the upcoming period.

### Strategy Performance – Case Study

Let's take a look at how this works in practice.  Our case study makes use of the following daytrading strategy in e-Mini futures.

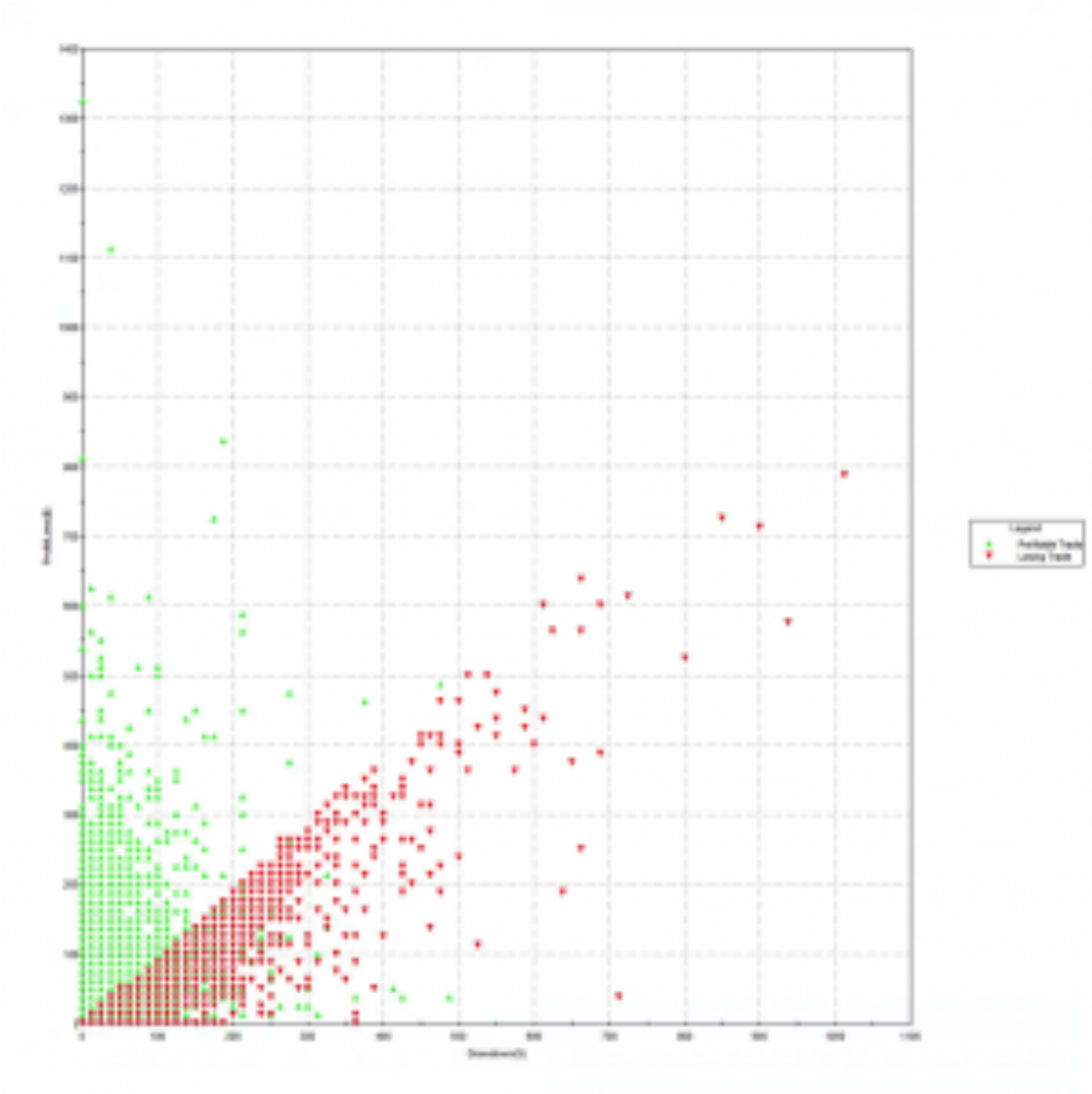


The overall performance of the strategy is quite good. Average monthly PNL over the period from April to Oct 2015 is almost $8,000 per contract, after fees, with a standard deviation of only $5,500. That equates to an annual Sharpe Ratio in the region of 5.0. On a decent execution platform the strategy should scale to around 10-15 contracts, with an annual PNL of around $1.0 to $1.5 million.

Looking into the performance more closely we find that the win rate (56%) and profit factor (1.43) are typical for a profitable strategy of medium frequency, trading around 20 times per session (in this case from 9:30AM to 4PM EST).

| | All Trades | Long Trades | Short Trades |
|---|---|---|---|
| Total Net Profit | $55,840.50 | $25,121.00 | $30,719.50 |
| Gross Profit | $185,613.50 | $88,689.00 | $96,924.50 |
| Gross Loss | ($129,773.00) | ($63,568.00) | ($66,205.00) |
| Profit Factor | 1.43 | 1.40 | 1.46 |
| | | | |
| Roll Over Credit | $0.00 | $0.00 | $0.00 |
| Open Position P/L | $0.00 | $0.00 | $0.00 |
| | | | |
| Select Total Net Profit | $52,066.50 | $19,085.00 | $32,981.50 |
| Select Gross Profit | $170,238.50 | $79,635.50 | $90,603.00 |
| Select Gross Loss | ($118,172.00) | ($60,550.50) | ($57,621.50) |
| Select Profit Factor | 1.44 | 1.32 | 1.57 |
| | | | |
| Adjusted Total Net Profit | $47,358.94 | $19,306.72 | $24,539.40 |
| Adjusted Gross Profit | $180,904.98 | $85,463.41 | $93,493.41 |
| Adjusted Gross Loss | ($133,546.04) | ($66,156.69) | ($68,954.01) |
| Adjusted Profit Factor | 1.35 | 1.29 | 1.36 |
| | | | |
| Total Number of Trades | 2737 | 1359 | 1378 |
| Percent Profitable | 56.78% | 55.63% | 57.91% |
| Winning Trades | 1554 | 756 | 798 |
| Losing Trades | 1183 | 603 | 580 |
| Even Trades | 0 | 0 | 0 |
| | | | |
| Avg. Trade Net Profit | $20.40 | $18.48 | $22.29 |
| Avg. Winning Trade | $119.44 | $117.31 | $121.46 |
| Avg. Losing Trade | ($109.70) | ($105.42) | ($114.15) |
| Ratio Avg. Win:Avg. Loss | 1.09 | 1.11 | 1.06 |
| Largest Winning Trade | $1,319.00 | $1,319.00 | $806.50 |
| Largest Losing Trade | ($793.50) | ($731.00) | ($793.50) |
| Largest Winner as % of Gross Profit | 0.71% | 1.49% | 0.83% |
| Largest Loser as % of Gross Loss | 0.61% | 1.15% | 1.20% |
| | | | |
| Net Profit as % of Largest Loss | 7037.24% | 3436.53% | 3871.39% |
| Select Net Profit as % of Largest Loss | 6561.63% | 2610.81% | 4156.46% |
| Adjusted Net Profit as % of Largest Loss | 5968.36% | 2641.14% | 3092.55% |
| | | | |
| Max. Consecutive Winning Trades | 14 | 10 | 10 |
| Max. Consecutive Losing Trades | 9 | 9 | 7 |
| Avg. Bars in Total Trades | 2.71 | 2.55 | 2.86 |
| Avg. Bars in Winning Trades | 2.59 | 2.47 | 2.72 |
| Avg. Bars in Losing Trades | 2.85 | 2.65 | 3.07 |
| Avg. Bars in Even Trades | 0.00 | 0.00 | 0.00 |
| | | | |
| Max. Shares/Contracts Held | 1 | 1 | 1 |
| Total Shares/Contracts Held | 2737 | 1359 | 1378 |
| Account Size Required | $2,565.50 | $2,061.00 | $2,733.50 |
| Total Slippage | $0.00 | $0.00 | $0.00 |
| Total Commission | $16,422.00 | $8,154.00 | $8,268.00 |
| | | | |
| Return on Initial Capital | 55.84% | | |
| Annual Rate of Return | 92.48% | | |
| Buy & Hold Return | (5.92%) | | |
| Return on Account | 2176.59% | | |
| Avg. Monthly Return | $7,977.21 | | |
| Std. Deviation of Monthly Return | $5,542.86 | | |
| | | | |
| Return Retracement Ratio | 3.48 | | |
| RINA Index | 2149.88 | | |
| Sharpe Ratio | n/a | | |
| K-Ratio | n/a | | |
| | | | |
| Trading Period | 5 Mths, 22 Dys, 5 Hrs, 14 Mins | | |
| Percent of Time in the Market | 18.34% | | |
| Time in the Market | 1 Mth, 1 Dy, 3 Hrs, 22 Mins | | |
| Longest Flat Period | 3 Dys, 17 Hrs, 37 Mins | | |
| | | | |
| Max. Equity Run-up | $57,043.00 | | |
| Date of Max. Equity Run-up | 10/02/15 11:52:22 | | |
| Max. Equity Run-up as % of Initial Capital | 57.04% | | |
| | | | |
| **Max. Drawdown (Intra-day Peak to Valley)** | | | |
| Value | ($2,847.00) | ($2,255.00) | ($3,102.50) |
| Date | 09/02/15 12:47:20 | | |
| as % of Initial Capital | 2.85% | 2.25% | 3.10% |
| Net Profit as % of Drawdown | 1961.38% | 1114.01% | 990.15% |
| Select Net Profit as % of Drawdown | 1828.82% | 846.34% | 1063.06% |
| Adjusted Net Profit as % of Drawdown | 1663.47% | 856.17% | 790.96% |

Another attractive feature of the strategy risk profile is the Max Adverse Execution, the drawdown experienced in individual trades (rather than the realized drawdown). In the chart below we see that the MAE increases steadily, without major outliers, to a maximum of only around $1,000 per contract.



One concern is that the average trade PL is rather small – $20, just over 1.5 ticks. Strategies that enter and exit with limit orders and have small average trade are generally highly dependent on the fill rate – i.e. the proportion of limit orders that are filled.  If the fill rate is too low, the strategy will be left with too many missed trades on entry or exit, or both.  This is likely to damage strategy performance, perhaps to a significant degree – see, for example my post on High Frequency Trading Strategies.

The fill rate is dependent on the number of limit orders posted at the extreme high or low of the bar, known as the extreme hit rate.  In this case the strategy has been designed specifically to operate at an extreme hit rate of only around 10%, which means that, on average, only around one trade in ten occurs at the high or low of the bar.  Consequently, the strategy is not highly fill-rate dependent and should execute satisfactorily even on a retail platform like Tradestation or Interactive Brokers.

## Drivers of Strategy Performance

So far so good.  But before we put the strategy into production, let's try to understand some of the key factors that determine its performance.  Hopefully that way we will be better placed to judge how profitable the strategy is likely to be as market conditions evolve.

In fact, we have already identified one potential key performance driver: the extreme hit rate (required fill rate) and determined that it is not a major concern in this case. However, in cases where the extreme hit rate rises to perhaps 20%, or more, the fill ratio is likely to become a major factor in determining the success of the strategy.  It would be highly inadvisable to attempt implementation of such a strategy on a retail platform.

What other factors might affect strategy performance?  The correct approach here is to apply the scientific method:  develop some theories about the drivers of performance and see if we can find evidence to support them.

For this case study we might conjecture that, since the strategy enters and exits using limit orders, it should exhibit characteristics of a mean reversion strategy, which will tend to do better when the market moves sideways and rather worse in a strongly trending market.

Another hypothesis is that, in common with most day-trading and high frequency strategies, this strategy will produce better results during periods of higher market volatility.  Empirically, HFT firms have always produced higher profits during volatile market conditions  – 2008 was a banner year for many of them, for example.  In broad terms, times when the market is whipsawing around create additional opportunities for strategies that seek to exploit temporary mis-pricings.  We shall attempt to qualify this general understanding shortly. For now let's try to gather some evidence that might support the hypotheses we have formulated.

I am going to take a very simple approach to this, using linear regression analysis. It's possible to do much more sophisticated analysis using nonlinear methods, including machine learning techniques. In our regression model the dependent variable will be the daily strategy returns. In the first iteration, let's use measures of market returns, trading volume and market volatility as the independent variables.

| SUMMARY OUTPUT | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| *Regression Statistics* | | | | | |
| Multiple R | 0.546506 | | | | |
| R Square | 0.298669 | | | | |
| Adjusted R Square | 0.282102 | | | | |
| Standard Error | 0.005568 | | | | |
| Observations | 131 | | | | |
| | | | | | |
| ANOVA | | | | | |
| | *df* | *SS* | *MS* | *F* | *ignificance F* |
| Regression | 3 | 0.001677 | 0.000559 | 18.02808 | 8.28E-10 |
| Residual | 127 | 0.003938 | 3.1E-05 | | |
| Total | 130 | 0.005615 | | | |
| | | | | | |
| | *Coefficients* | *andard Errc* | *t Stat* | *P-value* | |
| Intercept | -0.01098 | 0.002935 | -3.74034 | 0.000277 | |
| SP500 Return | 0.011215 | 0.048843 | 0.229614 | 0.818761 | |
| Volume | 3.4E-12 | 9.75E-13 | 3.490099 | 0.000664 | |
| SP500 Voltility | -0.20969 | 0.087719 | -2.39049 | 0.018294 | |

The first surprise is the size of the (adjusted) R Square – at 28%, this far exceeds the typical 5% to 10% level achieved in most such regression models, when applied to trading systems. In other words, this model does a very good job of account for a large proportion of the variation in strategy returns.

Note that the returns in the underlying S&P500 index play no part (the coefficient is not statistically significant). We might expect this: ours is a trading strategy that is not specifically designed to be directional and has approximately equivalent performance characteristics on both the long and short side, as you can see from the performance report.

Now for the next surprise: the sign of the volatility coefficient. Our ex-ante hypothesis is that the strategy would benefit from higher levels of market volatility. In fact, the reverse appears to be true (due to the negative coefficient). How can this be? On further reflection, the reason why most HFT strategies tend to benefit from higher market volatility is that they are momentum strategies. A momentum strategy typically enters and exits using market orders and hence requires a major market move to overcome the drag of the bid-offer spread (assuming it calls the market direction correctly!). This strategy, by contrast, is a mean-reversion strategy, since entry/exits are implemented using limit orders. The strategy wants the S&P500 index to revert to the mean – a large move that continues in the same direction is going to hurt, not help, this strategy.

Note, by contrast, that the coefficient for the volume factor is positive and statistically significant. Again, this makes sense: as anyone who has traded the e-mini futures overnight can tell you, the market tends to make major moves when volume is light – simply because it is easier to push around. Conversely, during a heavy trading day there is likely to be significant opposition to a move in any direction. In other words, the market is more likely to trade sideways on days when trading volume is high, and this is beneficial for our strategy.

The final surprise and perhaps the greatest of all, is that the strategy alpha appears to be negative (and statistically significant)! How can this be? What the regression analysis appears to be telling us is that the strategy's performance is largely determined by two underlying factors, volume and volatility.

Let's dig into this a little more deeply with another regression, this time relating the current day's strategy return to the prior day's volume, volatility and market return.

| SUMMARY OUTPUT | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| *Regression Statistics* | | | | | |
| Multiple R | 0.470336 | | | | |
| R Square | 0.221216 | | | | |
| Adjusted R Square | 0.202674 | | | | |
| Standard Error | 0.005891 | | | | |
| Observations | 130 | | | | |
| | | | | | |
| ANOVA | | | | | |
| | *df* | *SS* | *MS* | *F* | *ignificance F* |
| Regression | 3 | 0.001242 | 0.000414 | 11.93025 | 6.28E-07 |
| Residual | 126 | 0.004373 | 3.47E-05 | | |
| Total | 129 | 0.005615 | | | |
| | | | | | |
| | *Coefficients* | *andard Errc* | *t Stat* | *P-value* | |
| Intercept | -7E-05 | 0.003105 | -0.02251 | 0.982078 | |
| SP500 Return Lag 1 | -0.14659 | 0.052626 | -2.78554 | 0.00617 | |
| Volume Lag 1 | 8.98E-15 | 1.03E-12 | 0.0087 | 0.993072 | |
| SP500 Volatility Lag 1 | -0.30458 | 0.095183 | -3.19992 | 0.001739 | |

In this regression model the strategy alpha is effectively zero and statistically insignificant, as is the case for lagged volume. The strategy returns relate inversely to the prior day's market return, which again appears to make sense for a mean reversion strategy: our model anticipates that, in the mean, the market will reverse the prior day's gain or loss. The coefficient for the lagged volatility factor is once again negative and statistically significant. This, too, makes sense: volatility tends to be highly autocorrelated, so if the strategy performance is dependent on market volatility during the current session, it is likely to show dependency on volatility in the prior day's session also.

So, in summary, we can provisionally conclude that:

This strategy has no market directional predictive power: rather it is a pure, mean-reversal strategy that looks to make money by betting on a reversal in the prior session's market direction. It will do better during periods when trading volume is high, and when market volatility is low.

# Conclusion

Now that we have some understanding of where the strategy performance comes from, where do we go from here? The next steps might include some, or all, of the following:

(i) A more sophisticated econometric model bringing in additional lags of the explanatory variables and allowing for interaction effects between them.

(ii) Introducing additional exogenous variables that may have predictive power. Depending on the nature of the strategy, likely candidates might include related equity indices and futures contracts.

(iii) Constructing a predictive model and meta-strategy that would enable us assess the likely future performance of the strategy, and which could then be used to determine position size.  Machine learning techniques can often be helpful in this content.

I will give an example of the latter approach in the next section of the article.

# 2. Improving Trading System Performance Using a Meta-Strategy

## What is a Meta-Strategy?

.A meta-strategy is a trading system that trades trading systems. The idea is to develop a strategy that will make sensible decisions about when to trade a specific system, in a way that yields superior performance compared to simply following the underlying trading system. Put another way, the simplest kind of meta-strategy is a long-only strategy that takes positions in some underlying trading system. At times, it will follow the underlying system exactly; at other times it is out of the market and ignore the trading system's recommendations.

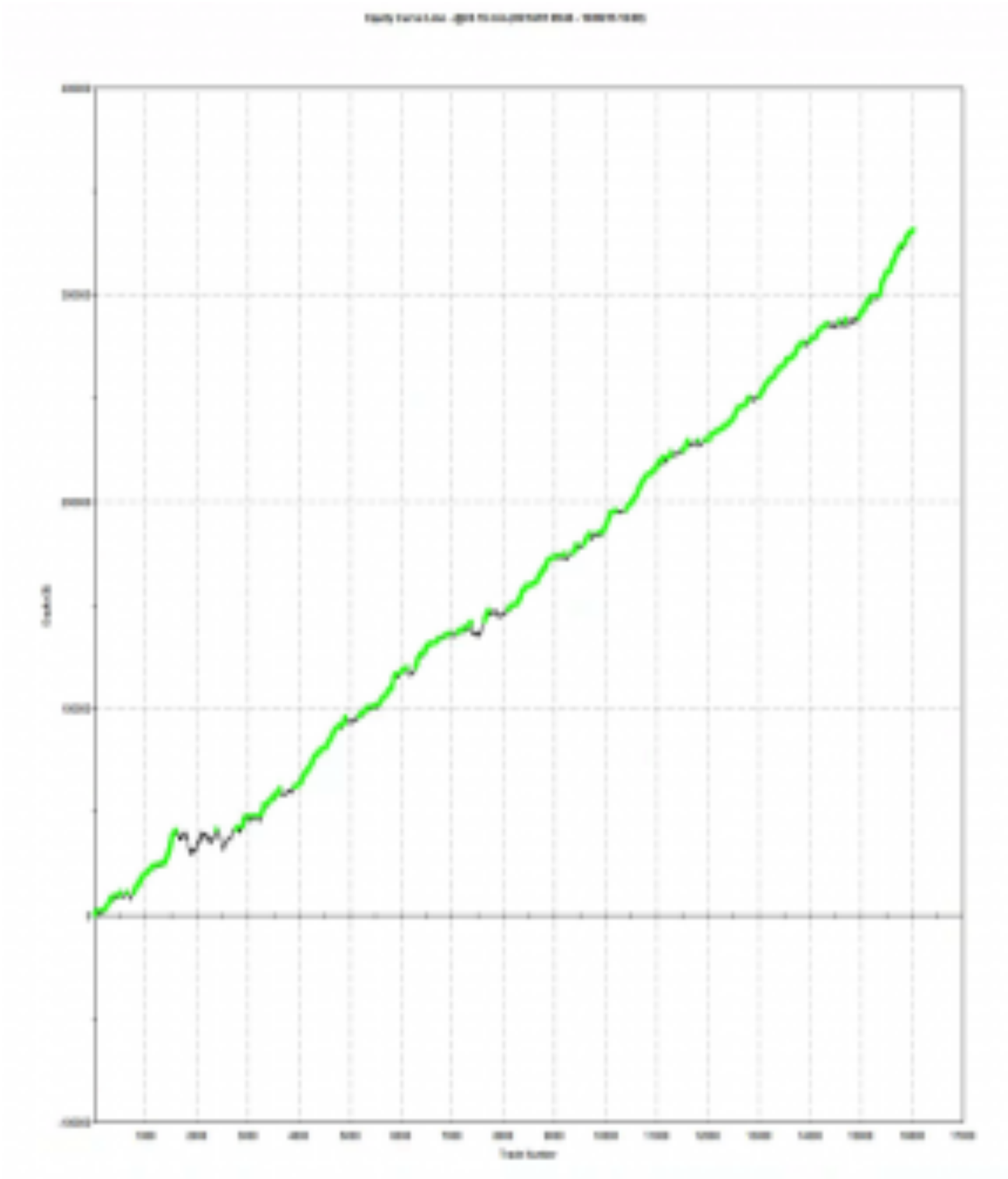
More generally, a meta-strategy can determine the size in which one, or several, systems should be traded at any point in time, including periods where the size can be zero (i.e. the system is not currently traded). Typically, a meta-strategy is long-only: in theory there is nothing to stop you developing a meta-strategy that shorts your underlying strategy from time to time, but that is a little counter-intuitive to say the least!

A meta-strategy is something that could be very useful for a fund-of-funds, as a way of deciding how to allocate capital amongst managers.

Caissa Capital operated a meta-strategy in its option arbitrage hedge fund back in the early 2000's. The meta-strategy (we called it a "model management system") selected from a half dozen different volatility models to be used for option pricing, depending their performance, as measured by around 30 different criteria. The criteria included both statistical metrics, such as the mean absolute percentage error in the forward volatility forecasts, as well as trading performance criteria such as the moving average of the trade PNL. The model management system probably added 100 – 200 basis points per annum to the performance the underlying strategy, so it was a valuable add-on.

## Illustration of a Meta-Strategy in US Bond Futures

To illustrate the concept, we will use an underlying system that trades US Bond futures at 15-minute bar intervals. The performance of the system is summarized in the chart and table below.



**Mark-To-Market Period Analysis:**

| Period | Net Profit | % Gain | Profit Factor | # Trades | % Profitable |
|---|---|---|---|---|---|
| Last 12 month | $54,625.50 | 14.51% | 1.36 | 2177 | 61.97% |
| 1/1/2015 | $45,436.75 | 11.79% | 1.36 | 1672 | 62.08% |
| 1/1/2014 | $48,179.00 | 14.28% | 1.63 | 1991 | 63.39% |
| 1/1/2013 | $42,600.50 | 14.45% | 1.45 | 2077 | 62.69% |
| 1/1/2012 | $44,627.00 | 17.84% | 1.42 | 2083 | 61.31% |
| 1/1/2011 | $34,247.00 | 15.86% | 1.23 | 2063 | 61.85% |
| 1/1/2010 | $48,128.00 | 28.69% | 1.42 | 2062 | 62.85% |
| 1/1/2009 | $34,031.00 | 25.45% | 1.20 | 2099 | 61.17% |
| 1/1/2008 | $33,720.00 | 33.72% | 1.21 | 2005 | 61.20% |

Strategy performance has been very consistent over the last seven years, in terms of the annual returns, number of trades and % win rate. Can it be improved further?

To assess this possibility, we create a new data series comprising the points of the equity curve illustrated above. More specifically, we form a series comprising the open, high, low and close values of the strategy equity, for each trade. We will proceed to treat this as a new data series and apply a range of different modeling techniques to see if we can develop a trading strategy, in exactly the same way as we would if the underlying was a price series for a stock.

It is important to note here that, for the meta-strategy at least, we are working in *trade-time*, not calendar time. The x-axis will measure the trade number of the underlying strategy, rather than the date of entry (or exit) of the underlying trade. Thus, equally spaced points on the x-axis represent different lengths of calendar time, depending on the duration of each trade.

It is necessary to work in trade time rather than calendar time because, unlike a stock, it isn't possible to trade the underlying strategy whenever we want to – we can only enter or exit the strategy at points in time when it is about to take a trade, by accepting that trade or passing on it (we ignore the other possibility which is sizing the underlying trade, for now).

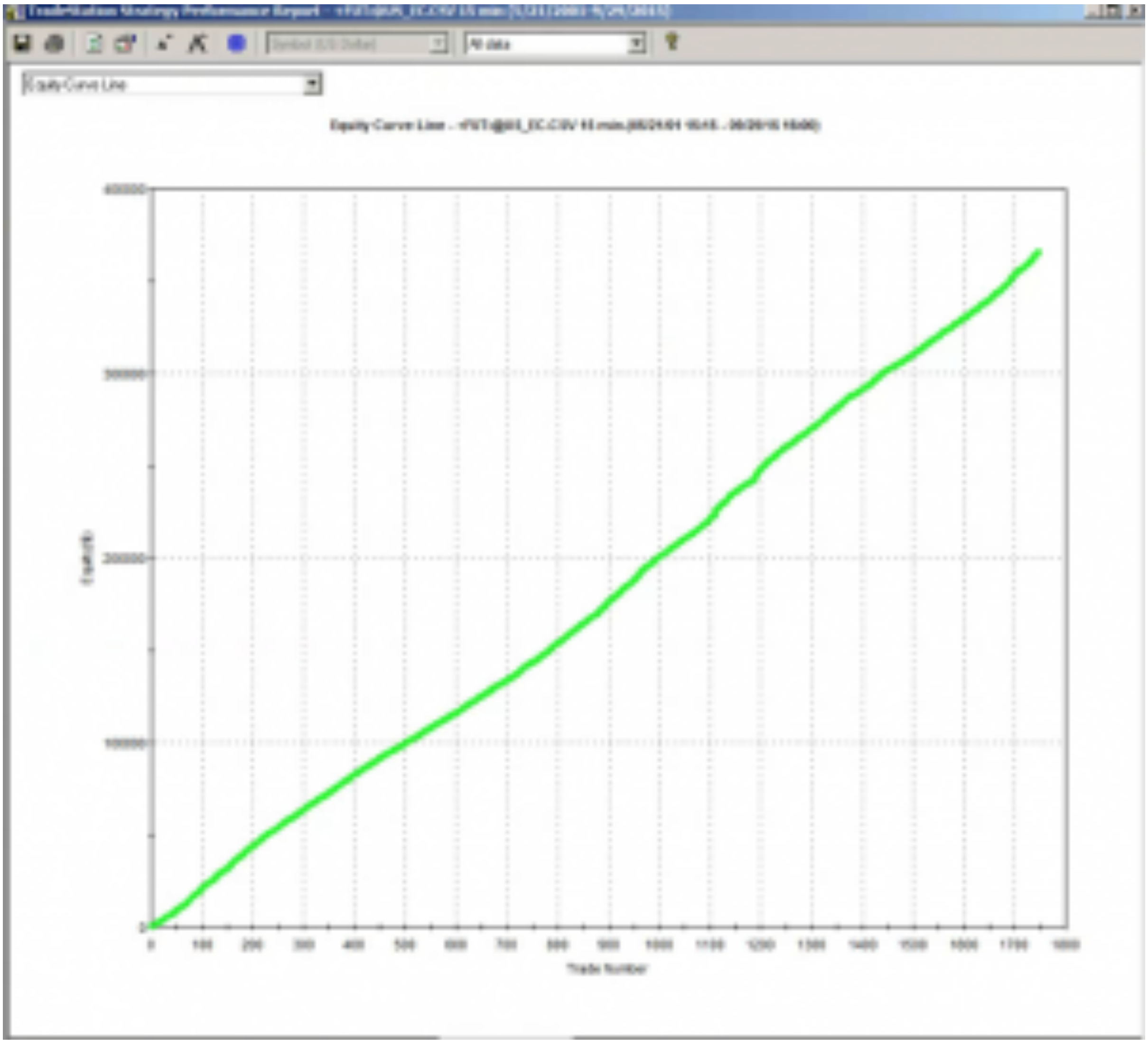
Another question is what kinds of trading ideas do we want to consider for the meta-strategy? In principle one could incorporate almost any trading concept, including the usual range of technical indicators such as RSI, or

Bollinger bands. One can go further and use machine learning techniques, including Neural Networks, Random Forest, or SVM.

In practice, one tends to gravitate towards the simpler kinds of trading algorithm, such as moving averages (or MA crossover techniques), although there is nothing to say that more complex trading rules should not be considered. The development process follows a familiar path: you create a hypothesis, for example, that the equity curve of the underlying bond futures strategy tends to be mean-reverting, and then proceed to test it using various signals – perhaps a moving average, in this case. If the signal results in a potential improvement in the performance of the default meta-strategy (which is to take every trade in the underlying system system), one includes it in the library of signals that may ultimately be combined to create the finished meta-strategy.

As with any strategy development you should follows the usual procedure of separating the trade data to create a set used for in-sample modeling and out-of-sample performance testing.

Following this general procedure, I arrived at the following meta-strategy for the bond futures trading system.


Equity Curve Line
All data
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
Trade Number

TradeStation Strategy Performance Report - +FUT:@US_EC.CSV 15 min (5/21/2001-9/29/2015)

Display: Column View

**TradeStation Performance Summary**

| | All Trades | Long Trades | Short Trades |
|---|---|---|---|
| Total Net Profit | $365,541.85 | $365,541.85 | $0.00 |
| Gross Profit | $365,541.85 | $365,541.85 | $0.00 |
| Gross Loss | $0.00 | $0.00 | $0.00 |
| Profit Factor | n/a | n/a | n/a |
| Roll Over Credit | $0.00 | $0.00 | $0.00 |
| Open Position P/L | $0.00 | $0.00 | $0.00 |
| Select Total Net Profit | $338,564.85 | $338,564.85 | $0.00 |
| Select Gross Profit | $338,564.85 | $338,564.85 | $0.00 |
| Select Gross Loss | $0.00 | $0.00 | $0.00 |
| Select Profit Factor | n/a | n/a | n/a |
| Adjusted Total Net Profit | $356,796.23 | $356,796.23 | $0.00 |
| Adjusted Gross Profit | $356,796.23 | $356,796.23 | $0.00 |
| Adjusted Gross Loss | $0.00 | $0.00 | $0.00 |
| Adjusted Profit Factor | n/a | n/a | n/a |
| Total Number of Trades | 1747 | 1747 | 0 |
| Percent Profitable | 100.00% | 100.00% | 0.00% |
| Winning Trades | 1747 | 1747 | 0 |
| Losing Trades | 0 | 0 | 0 |
| Even Trades | 0 | 0 | 0 |
| Avg. Trade Net Profit | $209.24 | $209.24 | $0.00 |
| Avg. Winning Trade | $209.24 | $209.24 | $0.00 |
| Avg. Losing Trade | $0.00 | $0.00 | $0.00 |
| Ratio Avg. Win:Avg. Loss | n/a | n/a | n/a |
| Largest Winning Trade | $2,325.75 | $2,325.75 | $0.00 |
| Largest Losing Trade | $0.00 | $0.00 | $0.00 |
| Largest Winner as % of Gross Profit | 0.64% | 0.64% | n/a |
| Largest Loser as % of Gross Loss | n/a | n/a | n/a |
| Net Profit as % of Largest Loss | n/a | n/a | n/a |
| Select Net Profit as % of Largest Loss | n/a | n/a | n/a |
| Adjusted Net Profit as % of Largest Loss | n/a | n/a | n/a |
| Max. Consecutive Winning Trades | 1747 | 1747 | 0 |
| Max. Consecutive Losing Trades | 0 | 0 | 0 |
| Avg. Bars in Total Trades | 11.80 | 11.80 | 0.00 |
| Avg. Bars in Winning Trades | 11.80 | 11.80 | 0.00 |
| Avg. Bars in Losing Trades | 0.00 | 0.00 | 0.00 |
| Avg. Bars in Even Trades | 0.00 | 0.00 | 0.00 |
| Max. Shares/Contracts Held | 1 | 1 | 0 |
| Total Shares/Contracts Held | 1748 | 1748 | 0 |

The meta-strategy has succeeded in eliminating all of the losing trades in the underlying bond futures system, during both in-sample and out-of-sample periods (comprising the most recent 20% of trades).

In general, it is unlikely that one can hope to improve the performance of the underlying strategy quite as much as this, of course. But it may well be possible to eliminate a sufficient proportion of losing trades to reduce the equity curve drawdown and/or increase the overall Sharpe ratio by a significant amount.

# 3. Improving A Hedge Fund Investment – Cantab Capital's Quantitative Aristarchus Fund


I am going to take a look at what an investor can do to improve a hedge fund investment through the use of dynamic capital allocation. For the purposes of illustration I am going to use Cantab Capital's Aristarchus program – a quantitative fund which has grown to over $3.5Bn in assets under management since its opening with $30M in 2007 by co-founders Dr. Ewan Kirk and Erich Schlaikjer.

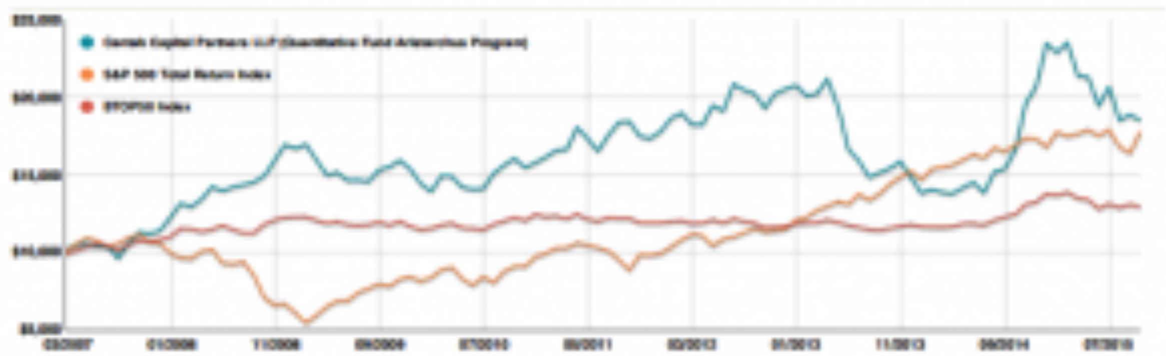
I chose this product because, firstly, it is one of the most successful quantitative funds in existence and, secondly, because as a CTA its performance record is publicly available.

## Cantab's Aristarchus Fund

Cantab's stated investment philosophy is that algorithmic trading can help to overcome cognitive biases inherent in human-based trading decisions, by exploiting persistent statistical relationships between markets. Taking a multi-asset, multi-model approach, the majority of Cantab's traded instruments are liquid futures and forwards, across currencies, fixed income, equity indices and commodities.

Let's take a look at how that has worked out in practice:

**Performance comparison: Growth of $10,000 invested since inception** — Mar 2007 to Oct 2015



## Performance statistics — Mar 2007 to Oct 2015

| | |
|---|---|
| Cumulative total return | 85.23% |
| Annualized compound return | 7.37% |
| Annualized standard deviation | 17.98% |
| Monthly correlation to S&P 500 TRI | 0.02 |
| Annualized sharpe ratio (0%) | 0.49 |
| Monthly maximum loss (Jun 2013) | -14.22% |
| Maximum drawdown (Apr 2013 - Apr 2014) | -34.87% |

Whatever the fund's attractions may be, we can at least agree that alpha is not amongst them. A Sharpe ratio of < 0.5 (I calculate to be nearer 0.41) is hardly in Renaissance territory, so one imagines that the chief benefit of the product must lie in its liquidity and low market correlation. Uncorrelated it may be, but an investor in the fund must have extremely deep pockets – and a very strong stomach – to handle the 34% drawdown that the fund suffered in 2013.

## Improving the Aristarchus Fund Performance

If we make the assumption that an investment in this product is warranted in the first place, what can be done to improve its performance characteristics? We'll look at that question from two different perspectives – the investor's and the manager's.

Firstly, from the investor's perspective, there are relatively few options available to enhance the fund's contribution, other than through diversification. One other possibility available to the investor, however, is to develop a program for dynamic capital allocation. This requires the manager to be open to allowing significant changes in the amount of capital to be allocated from month to month, or quarter to quarter, but in a liquid product like Aristarchus some measure of flexibility ought to be feasible.

An analysis of the fund's performance indicates the presence of a strong dependency in the returns process. This is not at all unusual. Often investment strategies have a tendency to mean-revert: a negative dependency in which periods of poor performance tend to be followed by positive performance, and vice versa. CTA strategies such as Aristarchus tend to be trend-following, and this can induce positive dependency in the strategy returns process, in which positive months tend to follow earlier positive months, while losing months tend to be followed by further losses. This is the pattern we find here.

Consequently, rather than maintaining a constant capital allocation, an investor would do better to allocate capital dynamically, increasing the amount of capital after a positive period, while decreasing the allocation after a period of losses. Let's consider a variation of this allocation plan, in which the amount of allocated capital is increased by 70% when the last monthly equity value exceeds the quarterly moving average, while the allocation is reduced to zero when the last month's equity falls below the average. A dynamic capital allocation plan as simple as this appears to produce a significant improvement in the overall performance of the investment:

| | Static | Dynamic |
|---|---|---|
| Return on Equity | 85.23% | 155.80% |
| CAGR | 7.45% | 11.57% |
| Ann. St. Dev. | 17.98% | 19.13% |
| Sharpe Ratio | 0.41 | 0.60 |
| Return/Drawdown Ratio | 2.44 | 6.52 |
| Average Drawdown (%) | 8.52% | 7.93% |
| Worst Case Drawdown (%) | 34.87% | 23.92% |

The slight increase in annual volatility in the returns produced by the dynamic capital allocation model is more than offset by the 412bp improvement in the CAGR. Consequently, the Sharpe Ratio improves from 0.41 to 0.60.

Nor is this by any means the entire story: the dynamic model produces lower average drawdowns (7.93% vs. 8.52%) and, more importantly, reduces the maximum drawdown over the life of the fund from a painful 34.87% to more palatable 23.92%.

The much-improved risk profile of the dynamic allocation scheme is reflected in the Return/Drawdown Ratio, which rises from 2.44 to 6.52.

Note, too, that the average level of capital allocated in the dynamic scheme is very slightly *less* than the original static allocation. In other words, the dynamic allocation technique results in a more efficient use of capital, while at the same time producing a higher rate of risk-adjusted return and enhancing the overall risk characteristics of the strategy.

## Improving Fund Performance Using a Meta-Strategy

So much for the investor. What could the manager to do improve the strategy performance? Of course, there is nothing in principle to prevent the manager from also adopting a dynamic approach to capital allocation, although his investment mandate may require him to be fully invested at all times.

Assuming for the moment that this approach is not available to the manager, he can instead look into the possibilities for developing a meta-strategy. As I explained in my earlier post on the topic:

*A meta-strategy is a trading system that trades trading systems. The idea is to develop a strategy that will make sensible decisions about when to trade a specific system, in a way that yields superior performance compared to simply following the underlying trading system.*

It turns out to be quite straightforward to develop such a meta-strategy, using a combination of stop-loss limits and profit targets to decide when to turn the strategy on or off. In so doing, the manager is able to avoid some periods of negative performance, producing a significant uplift in the overall risk-adjusted return:

| | Aristarchus | Meta-Strategy |
|---|---|---|
| Total Return | 85.23% | 106.28% |
| CAGR | 7.35% | 8.69% |
| Ann Stdev | 17.98% | 17.52% |
| Sharpe | 0.41 | 0.50 |

## Conclusion

Meta-strategies and dynamic capital allocation schemes can enable the investor and the investment manager to improve the performance characteristics of their investment and investment strategy, by increasing returns, reducing volatility and the propensity of the strategy to produce substantial drawdowns.

We have demonstrated how these approaches can be applied successfully to Cantab's Aristarchus quantitative fund, producing substantial gains in risk adjusted performance and reductions in the average and maximum drawdowns produced over the life of the fund.

# 4. A Meta-Strategy in S&P 500 E-Mini Futures

I have previously described the idea of a meta-strategy as a strategy that trades strategies. It is an algorithm, or set of rules, that is used to decide when to trade an underlying strategy. In some cases, a meta-strategy may influence the size in which the underlying strategy is traded, or may even amend the base code. In other word, a meta-strategy actively "trades" an underlying strategy, or group of strategies, much as in the same way a regular strategy may actively trade stocks, going long or short from time to time. One distinction is that a meta-strategy will rarely, if ever, actually "short" an underlying strategy – at most it will simply turn the strategy off (reduce the position size to zero) for a period.

In this post I look at a meta-strategy that developed for a client's strategy in S&P E-Mini futures. What is extraordinary is that the underlying strategy was so badly designed (not by me!) and performs so poorly that no rational systematic trader would likely give it a second look – instead he would toss it into the large heap of failed ideas that all quantitative researchers accumulate over the course of their careers. So this is a textbook example that illustrates the power of meta-strategies to improve, or in this case transform, the performance of an underlying strategy.

## The Strategy

The Target Trader Strategy ("TTS") is a futures strategy applied to S&P 500 E-Mini futures that produces a very high win rate, but which occasionally experiences very large losses. The purpose of the analysis if to find methods that will:

1) Decrease the max loss / drawdown
2) Increase the win rate / profitability

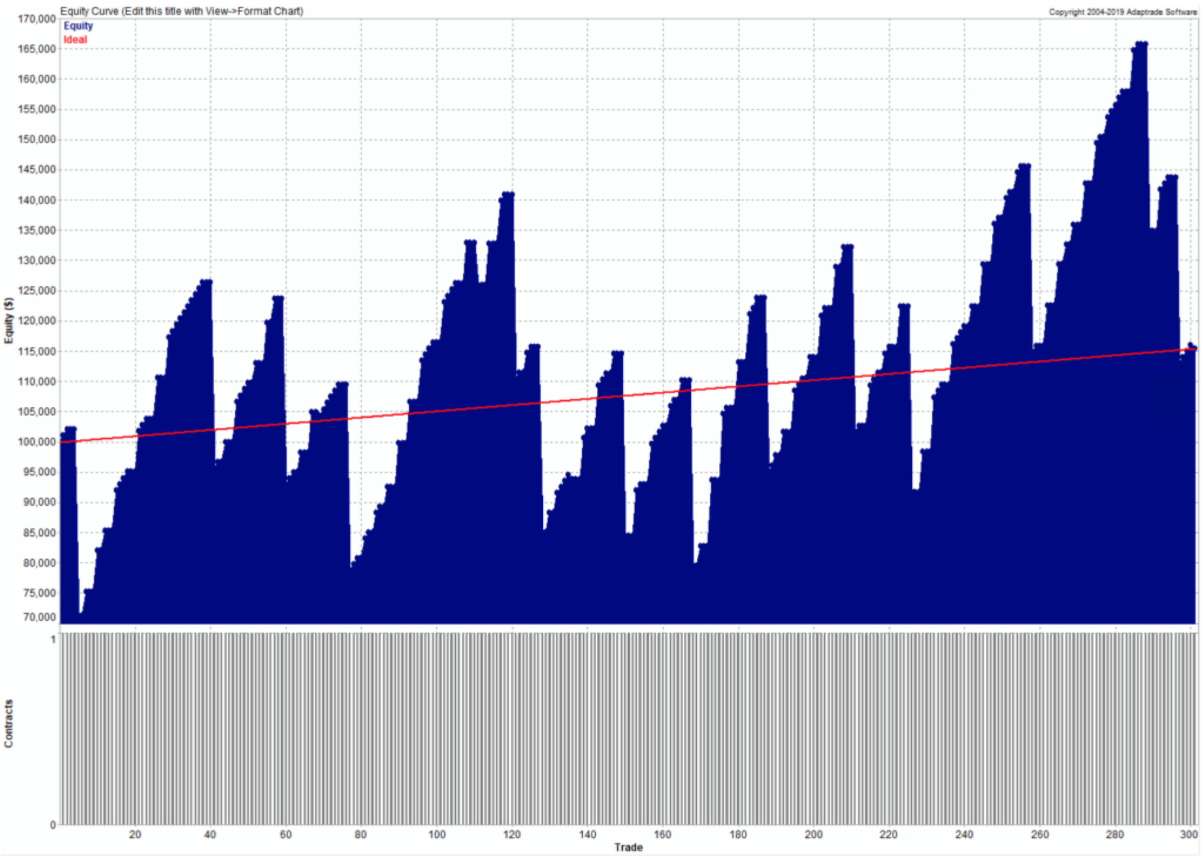
For longs the standard setting is entry 40 ticks below the target, stop loss 1000 ticks below the target, and then 2 re-entries 100 ticks below entry 1 and 100 ticks below entry 2

For shorts the standard is entry 80 ticks above the target. stop loss 1000 ticks above the target, and then 2 re-entries 100 ticks above entry 1 and 100 ticks above entry 2

For both directions its 80 ticks above/below for entry 1, 1000 tick stop, and then 1 re entry 100 ticks above/below, and then re-entry 2 100 ticks above/below entry 2

## Strategy Performance

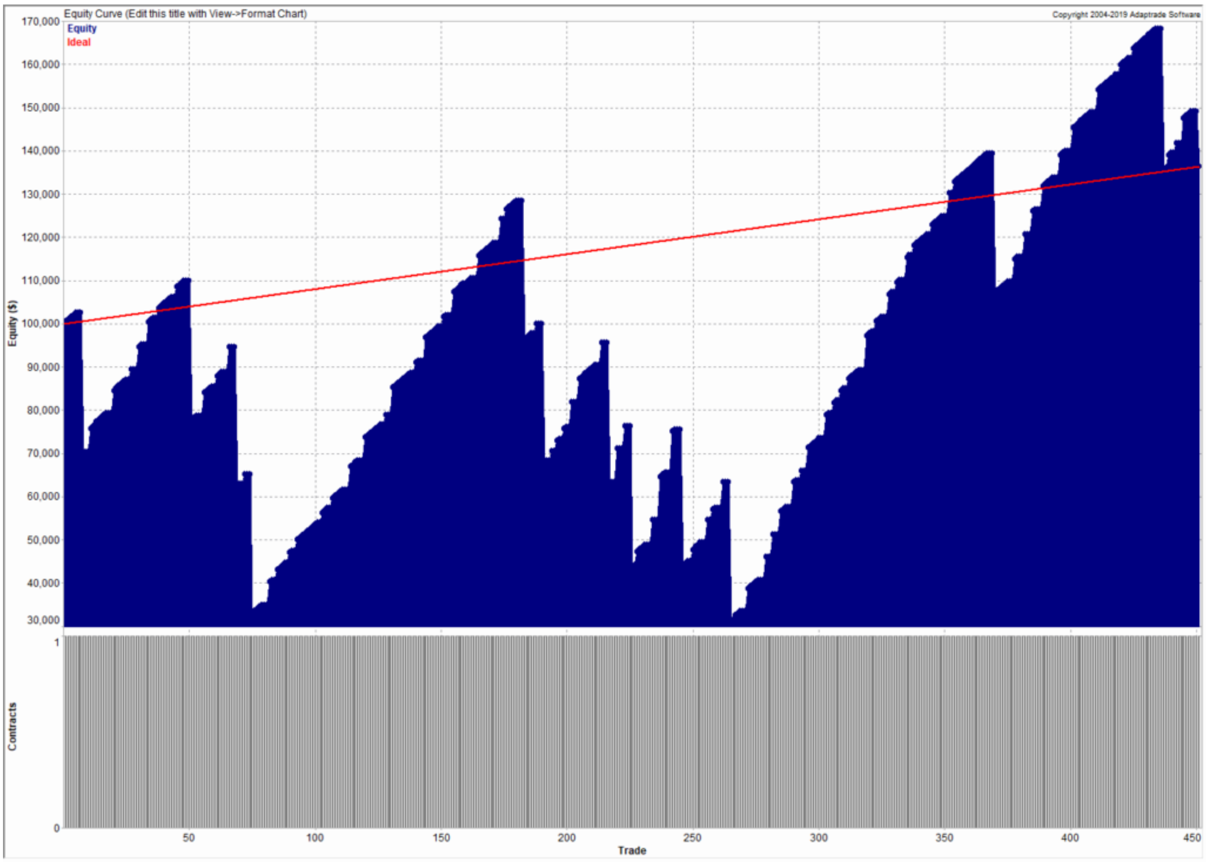
The overall performance of the strategy over the period from 2018 to 2020 is summarized in the chart of the strategy equity curve and table of performance statistics below.
These confirm that, while the win rate if very high (over 84%) there strategy experiences many significant drawdowns, including a drawdown of -$61,412.50 (-43.58%). The total return is of the order of 5% per year, the strategy profit factor is fractionally above 1 and the Sharpe Ratio is negligibly small. Many traders would consider the performance to be highly unattractive.



| Performance Summary | |
|---|---|
| **MSA2018-2020Both.msa** | |
| Position Sizing: | None |
| No. Contracts: | From input data |
| Starting Equity: | $100,000.00 |
| Equity High | $165,700.00 |
| Equity Low | $71,262.50 |
| Net Profit | $15,387.50 |
| Total Additions | $0.00 |
| Total Withdrawals | $0.00 |
| Final Equity | $115,387.50 |
| Account Return | 15.39% |
| Total Trades | 301 |
| Pct Wins | 84.05% |
| Max Shares | 1 |
| Max $ Win | $4,750.00 |
| Ave $ Win | $1,787.15 |
| Max Consec Wins | 33 |
| Max $ Loss | ($11,500.00) |
| Ave $ Loss | ($9,099.22) |
| Max Consec Losses | 3 |
| $ Win/Loss Ratio | 0.1964 |
| Ave $ Trade | $51.12 |
| Ave % Trade | 0.2548% |
| Max $ Drawdown | ($61,412.50) |
| Max % Drawdown | 43.58% |
| Prof Fact | 1.035 |
| Ret/DD Ratio | 0.3531 |
| Mod Sharpe Ratio | 0.07134 |

*Long Trades*

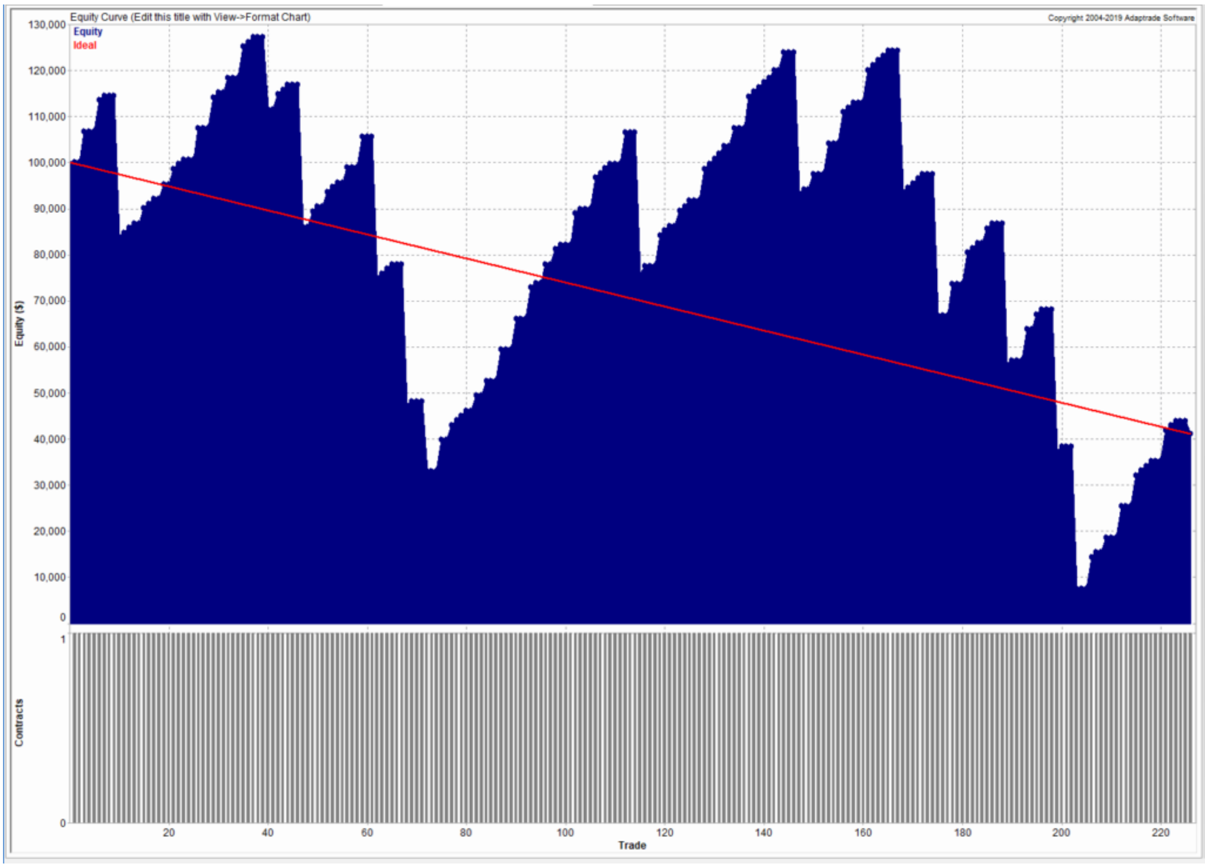
We break the strategy performance down into long and short trades, and consider them separately. On the long side, the strategy has been profitable, producing a gain of over 36% during the period 2018-2020. It also suffered catastrophic drawdown of over -$97,000 during that period:


Equity Curve (Edit this title with View->Format Chart)
Copyright 2004-2019 Adaptrade Software
Equity
Ideal
Equity ($)
170,000
160,000
150,000
140,000
130,000
120,000
110,000
100,000
90,000
80,000
70,000
60,000
50,000
40,000
30,000
Contracts
1
0
50
100
150
200
250
300
350
400
450
Trade

| Performance Summary | |
|---|---|
| **MSA2018-2020Long.msa** | |
| Position Sizing: | None |
| No. Contracts: | From input data |
| Starting Equity: | $100,000.00 |
| Equity High | $168,250.00 |
| Equity Low | $30,725.00 |
| Net Profit | $36,437.50 |
| Total Additions | $0.00 |
| Total Withdrawals | $0.00 |
| Final Equity | $136,437.50 |
| Account Return | 36.44% |
| Total Trades | 451 |
| Pct Wins | 91.13% |
| Max Shares | 1 |
| Max $ Win | $4,937.50 |
| Ave $ Win | $1,062.35 |
| Max Consec Wins | 102 |
| Max $ Loss | ($12,087.50) |
| Ave $ Loss | ($10,004.69) |
| Max Consec Losses | 3 |
| $ Win/Loss Ratio | 0.1062 |
| Ave $ Trade | $80.79 |
| Ave % Trade | 0.3466% |
| Max $ Drawdown | ($97,762.50) |
| Max % Drawdown | 76.09% |
| Prof Fact | 1.091 |
| Ret/DD Ratio | 0.4789 |
| Mod Sharpe Ratio | 0.08881 |

*Short Trades*

On the short side, the story is even worse, producing an overall loss of nearly -$59,000:


Equity Curve (Edit this title with View->Format Chart)
Copyright 2004-2019 Adaptrade Software
Equity
Ideal
Equity ($)
130,000
120,000
110,000
100,000
90,000
80,000
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
Contracts
1
0
20
40
60
80
100
120
140
160
180
200
220
Trade

## Performance Summary

**MSA2018-2020Short.msa**

| | |
|---|---|
| Position Sizing: | None |
| No. Contracts: | From input data |
| Starting Equity: | $100,000.00 |
| Equity High | $127,212.50 |
| Equity Low | $7,587.50 |
| Net Profit | ($58,825.00) |
| Total Additions | $0.00 |
| Total Withdrawals | $0.00 |
| Final Equity | $41,175.00 |
| Account Return | -58.82% |
| Total Trades | 226 |
| Pct Wins | 81.86% |
| Max Shares | 1 |
| Max $ Win | $3,562.50 |
| Ave $ Win | $1,692.64 |
| Max Consec Wins | 40 |
| Max $ Loss | ($11,512.50) |
| Ave $ Loss | ($9,072.26) |
| Max Consec Losses | 3 |
| $ Win/Loss Ratio | 0.1866 |
| Ave $ Trade | ($260.29) |
| Ave % Trade | 0.5135% |
| Max $ Drawdown | ($119,625.00) |
| Max % Drawdown | 94.04% |
| Prof Fact | 0.8419 |
| Ret/DD Ratio | -0.6256 |
| Mod Sharpe Ratio | 0.07177 |

## Improving Strategy Performance with a Meta-Strategy

We considered two possible methods to improve strategy performance. The first method attempts to apply technical indicators and other data series to improve trading performance. Here we evaluated price series such as the VIX index and a wide selection of technical indicators, including RSI, ADX, Moving Averages, MACD, ATR and others. However, any improvement in strategy performance proved to be temporary in nature and highly variable, in many cases amplifying the problems with the strategy performance rather than improving them.

The second approach proved much more effective, however. In this method we create a meta-strategy which effectively "trades the strategy", turning it on and off depending on its recent performance. The meta-strategy consists of a set of rules that determines whether or not to continue trading the strategy after a series of wins or losses. In some cases the meta-strategy may increase the trade size for a sequence of trades, at times when it considers the conditions for the underlying strategy to be favorable.

The result of applying the meta-strategy are described in the following sections.

*Long & Short Strategies with Meta-Strategy Overlay*

The performance of the long/short strategies combined with the meta-strategy overlay are set out in the chart and table below.
The overall improvements can be summarized as follows:

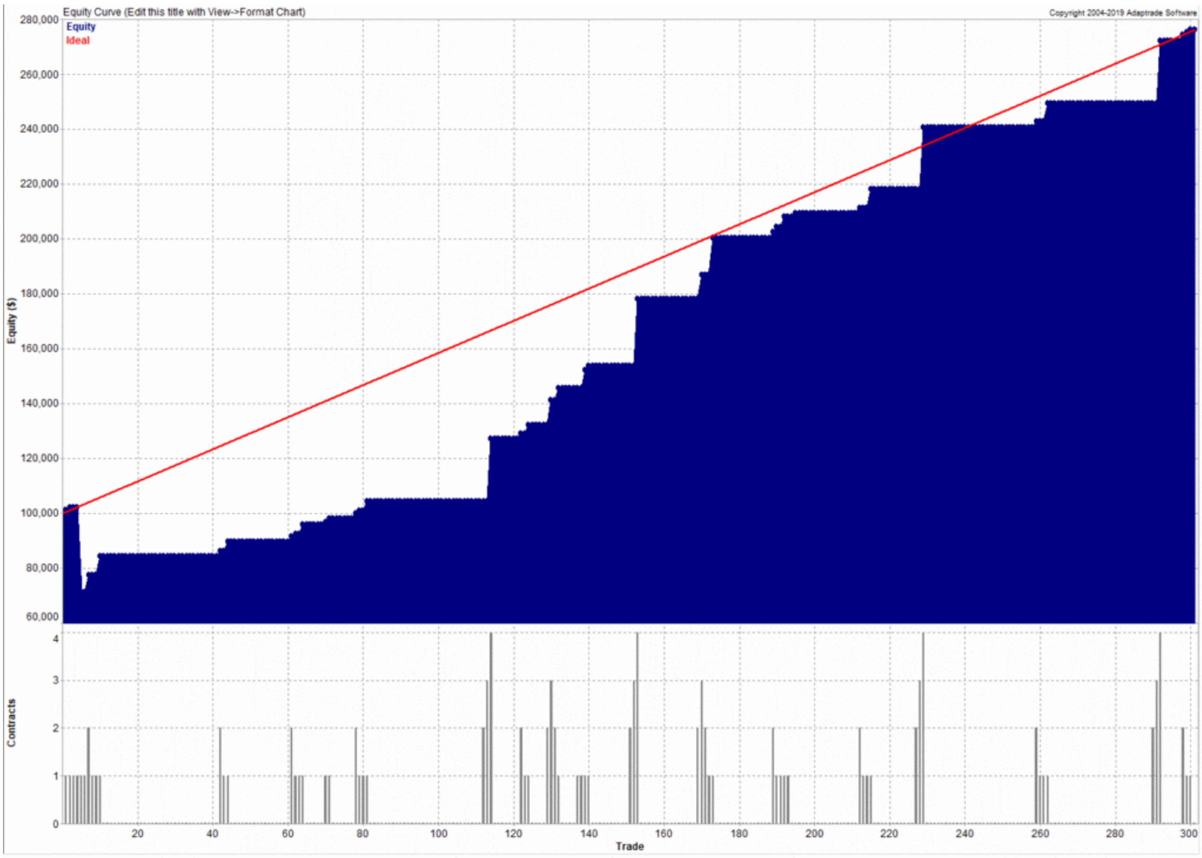
- Net profit increases from $15,387 to $176,287
- Account return rises from 15% to 176%
- Percentage win rate rises from 84% to 95%
- Profit factor increases from 1.0 to 6.7
- Average trade rises from $51 to $2,631
- Max $ Drawdown falls from -$61,412 to -$30,750
- Return/Max Drawdown ratio rises from 0.35 to 5.85
- The modified Sharpe ratio increases from 0.07 to 0.5

Taken together, these are dramatic improvements to every important aspect of strategy performance.

There are two key rules in the meta-strategy, applicable to winning and losing trades:

Rule for winning trades:
After 3 wins in a row, skip the next trade.

Rule for losing trades:
After 3 losses in a row, add 1 contract until the first win. Subtract 1 contract after each win until the next loss, or back to 1 contract.


Equity Curve (Edit this title with View->Format Chart)
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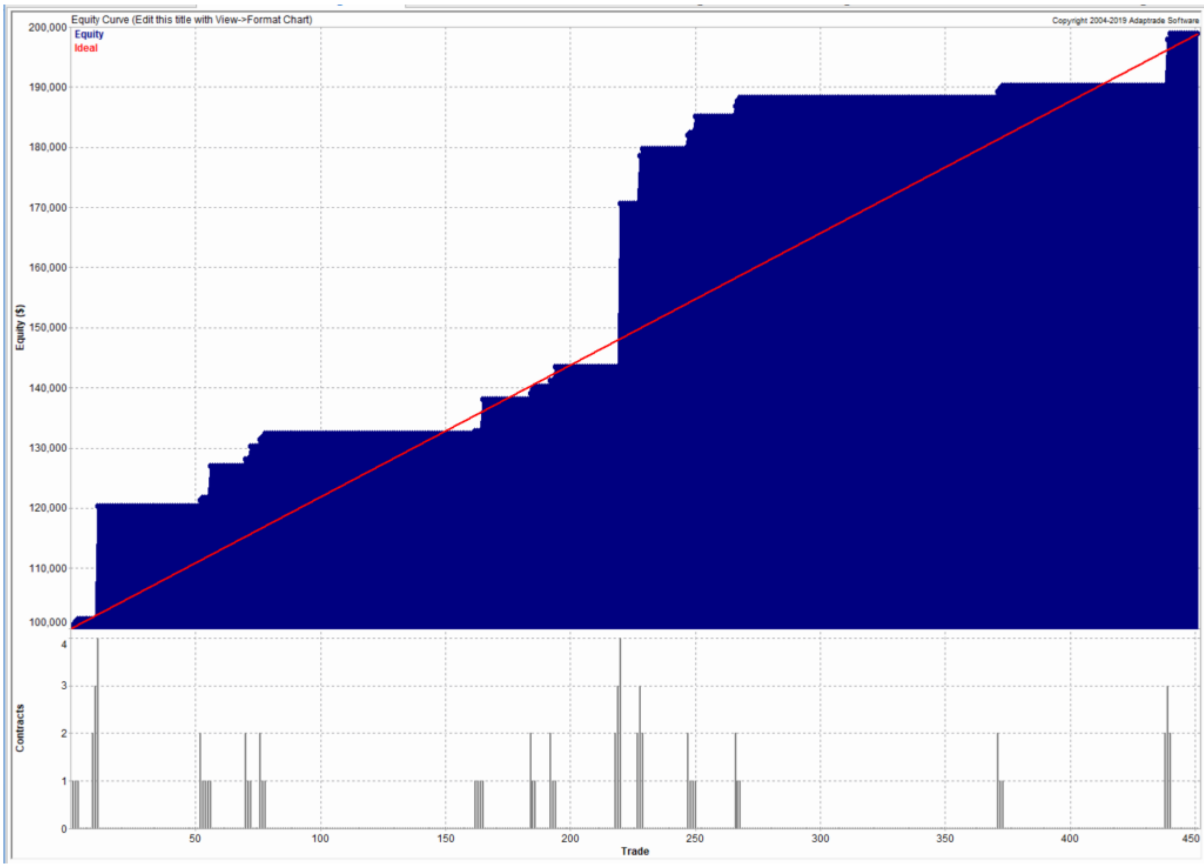
Equity
Ideal
Equity ($)
280,000
260,000
240,000
220,000
200,000
180,000
160,000
140,000
120,000
100,000
80,000
60,000
Contracts
4
3
2
1
0
20
40
60
80
100
120
140
160
180
200
220
240
260
280
300
Trade

| Performance Summary | |
|---|---|
| **MSA2018-2020Both.msa** | |
| Position Sizing: | None |
| No. Contracts: | From input data |
| Dependency Rule(s): | In Effect |
| Starting Equity: | $100,000.00 |
| Equity High | $276,287.50 |
| Equity Low | $71,262.50 |
| Net Profit | $176,287.50 |
| Total Additions | $0.00 |
| Total Withdrawals | $0.00 |
| Final Equity | $276,287.50 |
| Account Return | 176.3% |
| Total Trades | 301 |
| Pct Wins | 95.52% |
| Max Shares | 4 |
| Max $ Win | $14,000.00 |
| Ave $ Win | $3,234.96 |
| Max Consec Wins | 62 |
| Max $ Loss | ($11,500.00) |
| Ave $ Loss | ($10,250.00) |
| Max Consec Losses | 3 |
| $ Win/Loss Ratio | 0.3156 |
| Ave $ Trade | $2,631.16 |
| Ave % Trade | 1.692% |
| Max $ Drawdown | ($30,750.00) |
| Max % Drawdown | 30.14% |
| Prof Fact | 6.733 |
| Ret/DD Ratio | 5.848 |
| Mod Sharpe Ratio | 0.5006 |

*Long Trades with Meta-Strategy*

The meta-strategy rules produce significant improvements in the performance of both the long and short components of the strategy. On the long side the percentage win rate is increased to 100% and the max % drawdown is reduced to 0%:


Equity Curve (Edit this title with View->Format Chart)
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Equity
Ideal
Equity ($)
Contracts
Trade

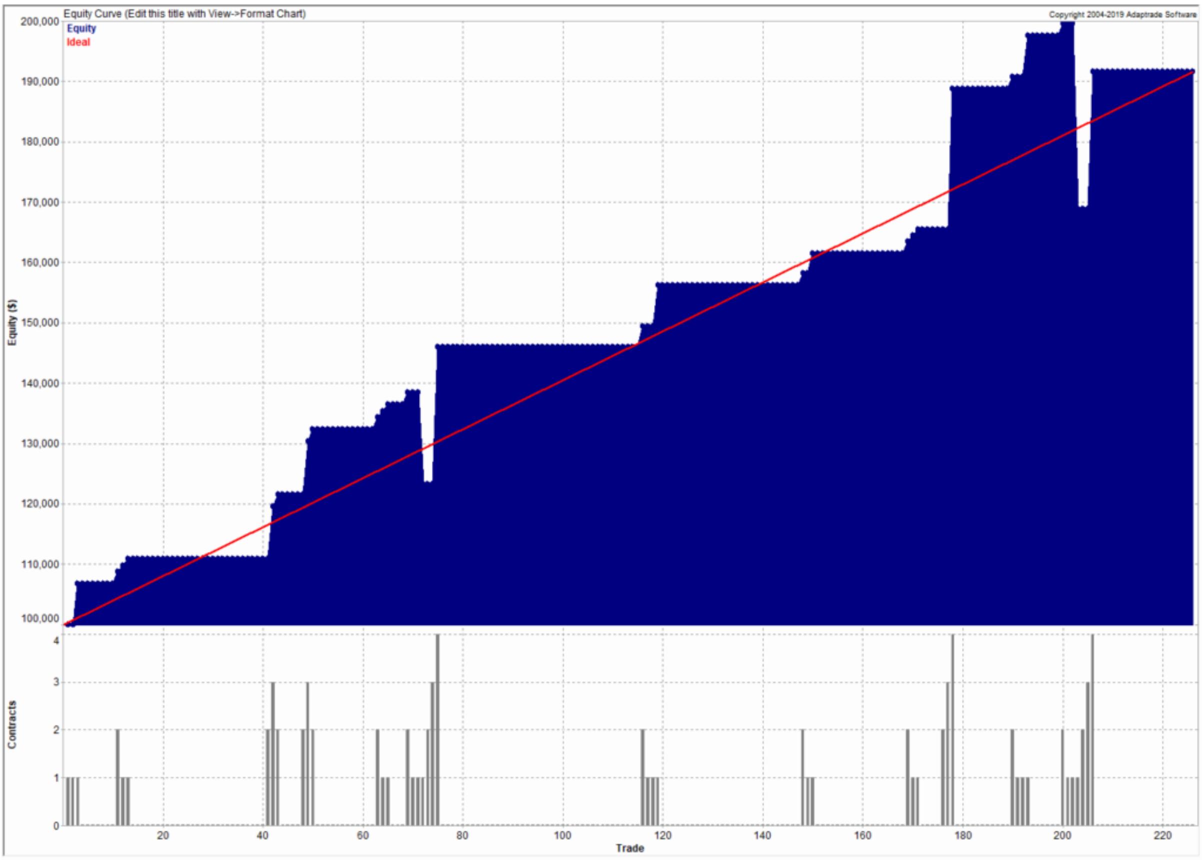
## Performance Summary

**MSA2018-2020Long.msa**

| | |
|---|---|
| Position Sizing: | None |
| No. Contracts: | From input data |
| Dependency Rule(s): | In Effect |
| Starting Equity: | $100,000.00 |
| Equity High | $198,912.50 |
| Equity Low | $100,000.00 |
| Net Profit | $98,912.50 |
| Total Additions | $0.00 |
| Total Withdrawals | $0.00 |
| Final Equity | $198,912.50 |
| Account Return | 98.91% |
| Total Trades | 451 |
| Pct Wins | 100.0% |
| Max Shares | 4 |
| Max $ Win | $19,750.00 |
| Ave $ Win | $2,150.27 |
| Max Consec Wins | 46 |
| Max $ Loss | $0.00 |
| Ave $ Loss | $0.00 |
| Max Consec Losses | 0 |
| $ Win/Loss Ratio | 100.0 |
| Ave $ Trade | $2,150.27 |
| Ave % Trade | 1.572% |
| Max $ Drawdown | $0.00 |
| Max % Drawdown | 0.000% |
| Prof Fact | 100.0 |
| Ret/DD Ratio | 100.0 |
| Mod Sharpe Ratio | 0.5988 |

*Short Trades with Meta-Strategy*

Improvements to the strategy on the short side are even more significant, transforming a loss of -$59,000 into a profit of $91,600:


Equity Curve (Edit this title with View->Format Chart)
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Equity
Ideal
Equity ($)
Contracts
Trade

## Performance Summary

**MSA2018-2020Short.msa**

| | |
|---|---|
| Position Sizing: | None |
| No. Contracts: | From input data |
| Dependency Rule(s): | In Effect |
| Starting Equity: | $100,000.00 |
| Equity High | $199,575.00 |
| Equity Low | $100,000.00 |
| Net Profit | $91,612.50 |
| Total Additions | $0.00 |
| Total Withdrawals | $0.00 |
| Final Equity | $191,612.50 |
| Account Return | 91.61% |
| Total Trades | 226 |
| Pct Wins | 86.96% |
| Max Shares | 4 |
| Max $ Win | $14,250.00 |
| Ave $ Win | $3,437.19 |
| Max Consec Wins | 21 |
| Max $ Loss | ($11,487.50) |
| Ave $ Loss | ($7,645.83) |
| Max Consec Losses | 3 |
| $ Win/Loss Ratio | 0.4496 |
| Ave $ Trade | $1,991.58 |
| Ave % Trade | 1.551% |
| Max $ Drawdown | ($30,737.50) |
| Max % Drawdown | 15.40% |
| Prof Fact | 2.997 |
| Ret/DD Ratio | 5.948 |
| Mod Sharpe Ratio | 0.4712 |

## Conclusion

A meta-strategy is a simple, yet powerful technique that can transform the performance of an underlying strategy. The rules are often simple, although they can be challenging to implement. Meta strategies can be applied to almost any underlying strategy, whether in futures, equities, or forex. Worthwhile improvements in strategy performance are often achievable, although not often as spectacular as in this case.