1. Introduction

In my first paper, published in March 2012, I discussed the how's and the why's for creating the Combo-MF model. This model combines the End-Of-Days signals from two other independent sources: VSTpro and 20DMF. In my second paper, published on July 12, I expanded my trading strategy by adding three new models: for trading the PM MF, the XLB MF and the XLI MF. I also enhanced the signals from these models by combining them with the status of the 20DMF.
The results from these four models are looking promising. For back testing these models I used MF signals from July 30, 2007 until July 12, 2012. No stop-loss strategy was used for these preliminary numbers. I subtracted 0.5% from the result of each trade to account for trading fees and taxes. I used leveraged ETFs for the Combo-MF (QLD and TQQQ from March 2010), no leverage for the GDX MF and leverage for the XLB and XLI MF (UYM resp. UXI). For these tests I gave each model 25% of the available equity for each trade. The results per model are:

Model	Winners	Losers	Cumul%	Compound%	CAGR
Combo-MF	36	37	410.92	2139.71	87.25
GDX	59	40	338.63	1869.42	82.46
XLB	53	32	490.34	6315.29	131.55
XLI	65	30	359.54	2466.81	92.47

Trading this strategy with a starting equity of $ 10,000.00 would result in $ 337,338.06 with a maximum draw-down of 17.38%. This strategy as a whole has a CAGR of 103.75%.
Implementing a stop-loss strategy could further reduce the risks per trade. The reason is simply because without stop-loss a possible very sharp decrease of prices (or increase when holding a short position) could deliver a nasty loss when a signal change is imminent.
Further enhancing the possible gains of the strategy could be achieved with the implementing of position sizing. Up until now, I used a fixed 25% portion of the available equity to trade for each model in my back tests. Not all models have equal performances. At certain moments specific models significantly outperform other models. An intelligent system is needed to allocate the right portion of the available funds to the models that performed the best at a certain time.

2. Stop-loss strategy

The stock market is difficult to predict. Although statistics and certain patterns deliver a relative sense of security, the stock market can jump very quickly in the not forecasted direction. A stop-loss strategy is to protect the position if things go wrong.
There are lots of possible stop-loss scenarios. Because I wanted something that is not subjective, I have chosen a volatility based approach. Other methods based on trend lines and/or pivot levels are not my cup of tea. A volatility based stop-loss can use the Average True Range as measurement of risk. If the ATR is high, then the odds for large price changes in the right (or wrong) direction are larger compared to when the ATR is low. In differently literature about trading strategies, a multiple of ATR is used as stop-loss delimiter. I did not prefer using an arbitrary value so I performed a large series of back tests to find the right ATR multiple for each model. I wanted the ATR multiple to be depended on the performance of the model at a certain moment in time, that is why a sliding window of 250 periods was used. This window is roughly a year of data. For each window I calculated the performance of a model with ATR values ranging from 1 to 4 with increments of 0.1. I decided to use ATR(3) because this volatility sensor reacts quickly to a change in the trend. Jose Silva uses also an ATR(3) for his VSTpro strategy. I did test ATR(20) as Pascal Willian uses this value for certain calculations. My back tests showed that ATR(3) works better than ATR(20); ATR(3) delivers higher returns with lower risk.
I used the Ulcer Performance Index (UPI) as measurement of performance. The UPI is the division of the return of a model by the Ulcer Index (UI). UI measures the depth and duration of the drawdown's. Because the draw-down's are squared, the lower the drawdown, the lower the UI will be. The squaring effect penalizes large drawdown's proportionately more than small drawdown's. UPI was, in my opinion, the best measurement to find the best stop-loss scenario.

For each model I ran back tests with the different ATR multiplier values and this for the complete 5 year of available data in a sliding window of 250 periods that moved forward one month at a time. The ATR multiplier with the highest UPI was chosen for the month after the sliding window. I did these calculations for each model separate and also separated for long and short trades. These back tests showed that the direction of a trade made a huge difference with a fixed ATR multiplier. I also determined a different ATR multiplier for the initial stop-loss and another one for the trailing stop-loss.
The result of these back tests was the optimal ATR multiplier for each model at a certain time separated for long and short trades. Because of the sliding window, it only started working from roughly one year after the start of available data. I compensated this by using the same stop-loss settings from period 251 (July 25, 2008) for the first 250 periods.
The results per model after implementing the stop-loss strategy are:

Models	**Winners**	**Losers**	**Stop-loss**	**Cumul%**	**Compound%**	**CAGR**
Combo-MF	50	41	35	382.83	2052.98	85.77
GDX	64	50	27	334.93	1846.37	82.02
XLB	54	38	14	491.34	6427.11	132.36
XLI	66	41	17	315.24	1435.52	73.52

The end result of trading this strategy is an amount of $ 303,547.22 with a max drawdown of 18.03%. At first sight these results are not so promising as before the implementation of the stop-loss strategy. However, I needed a stop-loss definition to move further in the direction of position sizing because I wanted a position sizing technique that makes trades for each model relative to the risk involved for that model at that time. Relative in the way that certain models are more sensible to risks than others at certain situations in the market.

3. Using margin

Margin lets the trader borrow money from his broker to buy more securities using other securities as collateral. This increases the available amount per trade. The broker sets the margin requirements. I am trading with Interactive Brokers. IB has set the margin requirements for a single ETF at 25%, for a double leveraged ETF at 50% and for a triple leveraged ETF at 90%. This enables me to trade with 2.2857 times my available equity when using QLD, GDX, UYM and UXI or 1.8605 times the equity when trading with TQQQ, GDX, UYM and UXI.
Trading with margin increases significantly the results mostly due to the compounding effect of reinvesting the acquired trading results. Using margin enables me to obtain an end equity of € 5,007,311.28 with exact the same trading signals as in the previous chapter. This is a multiplication of 16 when compared to using no margin. Very significant! I have calculated for each trade the outstanding interests that have to be paid to the broker and deducted these interests from the trading result. The negative factor when using margin are the larger drawdown's. The trading results are much more blown up and this leads to temporary larger drawdown's. According to the back tests with this use of margin delivers a max drawdown of 51.52%. Psychologically very difficult!

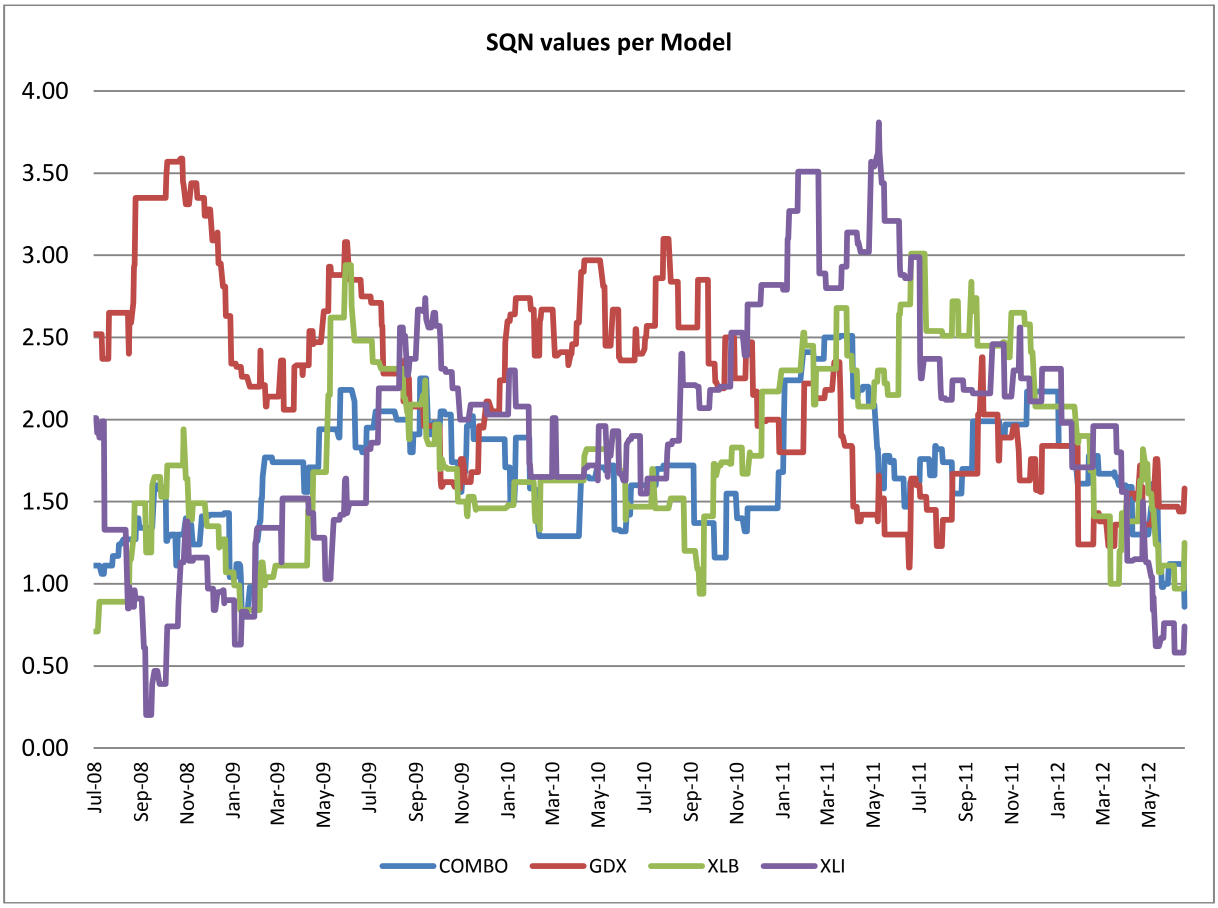
4. Performance based portfolio distribution

My trading strategy has four separate models, using different signals and different instruments. Up until now I have always divided equal the available equity and gave each model an equal share of the available funds. The performance of one model is not stable over time. Sometimes one model perform better than the others. Therefore I needed some measurement tool to gauge the relative performance of each model compared to the others. I decided to use a sliding window again and calculate for each model its performance over a certain part of time. I chose a sliding window with a time frame of 250 periods. For each model I calculated the System Quality Number (SQN). SQN is a model performance measurement designed by Van Tharp. If a certain model produces N trades in a certain time, than the SQN can be calculated by using the following formula:

*SQN = Square root(N) * Average (TradeResult) / Std dev (TradeResult)*

I preferred to use SQN instead of UPI because by using the Standard Deviation the measurement of the performance took in account the regularity of the trades. The more regular trades are, the less is the possible

drawdown. UPI focuses more on the depth and length of the drawdown's. SQN focuses more on the regularity of the trades.
I performed these calculations and moved the sliding window period per period forward in time. These calculations where done over the entire 5 years of data. Because the sliding window worked with a window of 250 periods, it only started working from roughly one year after the start of available data. I compensated this by using the same SQN values per model from period 251 (July 25, 2008) for the first 250 periods.
The values for SQN over the 5 year of data varied from 0.20 to 3.81. The following graph gives a representation of the evolution:



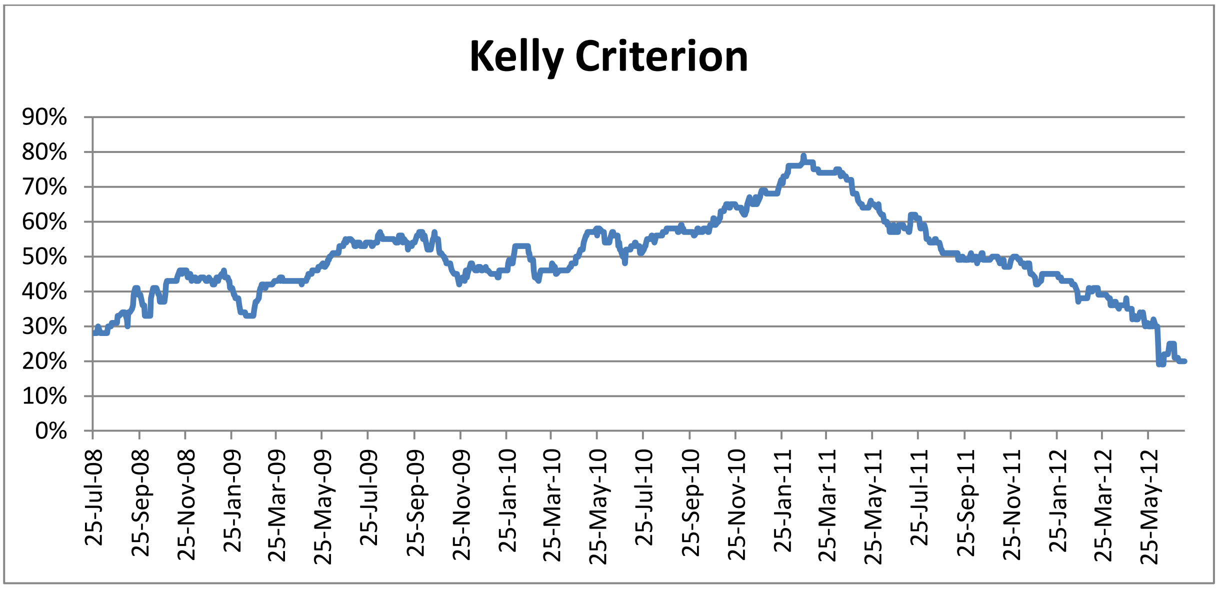
These numbers provide a logical and efficient way to qualify each model in comparison with the others. It also shows roughly when the models as a whole performed well or not. Significant is the descending performance of all the models the last 9 months!
Using the SQN values per model increased the performance of my strategy as a whole because it gave more funds to the model that performed best. The end equity of this strategy is $ 5,787,660.19. This is a CAGR of 261%. This increased performance did however produce higher draw downs along the way. At maximum value the drawdown was 85.87%. This was intolerable and I had to find a solution for this.

5. <u>Performance based risk control</u>

The strategy that I had developed used at all times all the available equity. The spread over the different models was now based on the relative performance of the models to each other. But I always was 100% invested. Because of the use of margin the total investment of the equity was in effect 228% or 186%. Quite logical that the drawdown could be huge.
The performance of the combination of the four models as a whole did vary over time. Sometimes the performance was good, sometimes not so good. I call this in sync with the market or not. To measure how much the strategy as a whole was in sync with the markets I decided to calculate the Kelly Criterion of the strategy. The Kelly criterion is a formula that helps determining the optimal risk size of a series of trades.

Kelly % = W – [(1 – W) / R]   where W = Winning probability and R = Win/loss ratio

I again used a sliding window with a window size of 250 periods. I calculated the Kelly criterion for each period over the whole 5 years of data. Because the sliding window worked with a window of 250 periods, it only started working from roughly one year after the start of available data. I compensated this by using the same Kelly criterion from period 251 (July 25, 2008) for the first 250 periods. The evolution of the Kelly Criterion is represented in the following graph:



Very clear is shown that the strategy is now not so good in sync with the markets.
Advantage of using this formula is that the risk used is depending on the performance of the strategy. This reduces the loses in the times where the strategy does not perform well.
I used this Kelly Criterion to limit the risk exposure of my trades. When Kelly Criterion was high I risked more, when Kelly was low I risked less. I Implemented this with the following formula:

Shares to buy = (available equity * model risk percentage) / (ATR(3) * ATR Multiple)

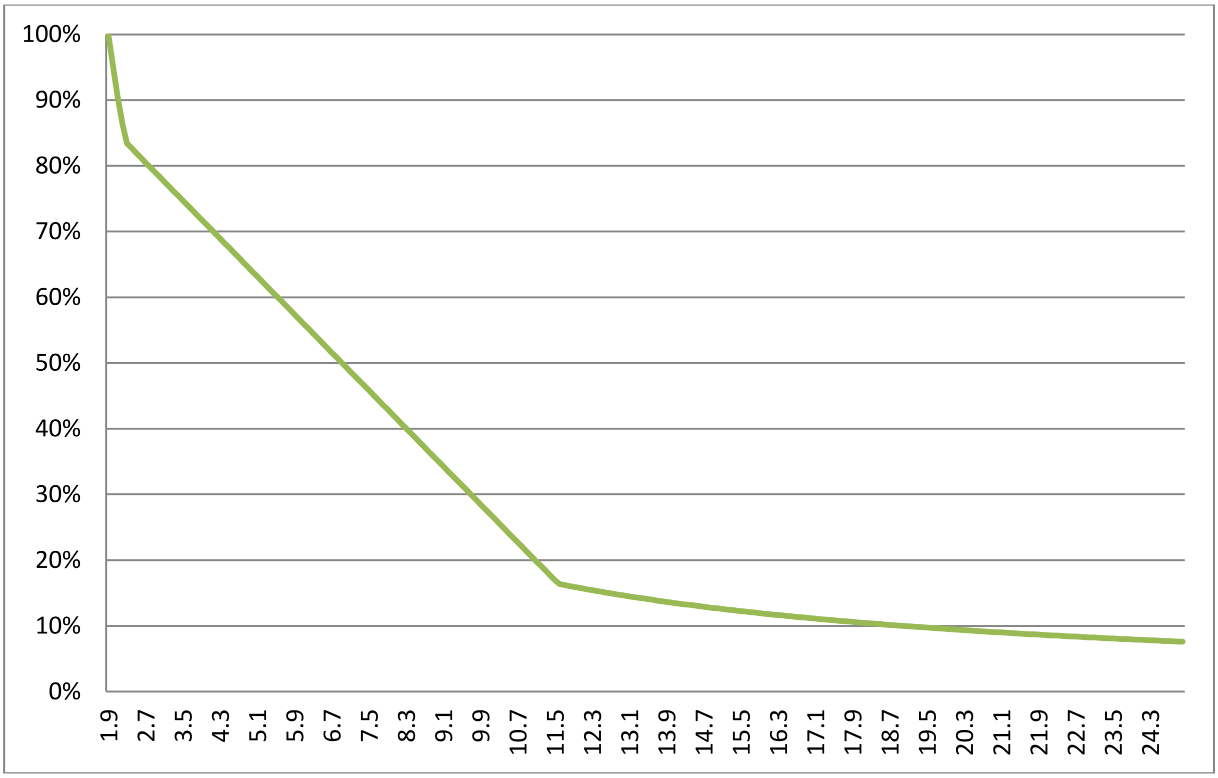
Around the Kelly Criterion is a lot of discussion. There are more opponents then proponents. The Formula is based on pure mathematics originally developed for reducing the bandwidth of telecommunication channels. The discussing is whether the formula is actually effective in the stock market. I think it is.
Among the followers of the formula is also the discussion whether to use Full Kelly or Partial Kelly. Full Kelly is defined as using the same percentage that the formula calculates. If the Kelly Criterion is for instance 50% then the total risk of the trades made by the strategy should be 50% when using Full Kelly. Half Kelly is using only 25% maximum risk if Kelly Criterion is 50%.
I performed back test for different partials of the Kelly Criterion. The smaller the partial of the Kelly Criterion, which I called the “Kelly Multiple”, the lower the results and the draw downs. Here are the results:

Kelly Multiple	**Equity**	**Max DD**
0.5	2,606,725	70.12
0.6	3,799,021	80.24
0.7	4,654,680	84.22
0.8	5,216,364	86.97
0.9	5,647,298	89.92
1.0	5,881,110	91.01

I had found a way to control the draw downs but it was not entirely satisfactory. The draw downs where still too high.

6. Drawdown avoiding bet control

It is clear that the strategy performed better at times and worse at other times. The better the performance, the higher the result and the lower the drawdown. The inverse was also true: the meager the performance, the lower the results and the higher the drawdown. I decided to use a deduction of the bet size depending on the drawdown the strategy produced at a certain time. The higher the drawdown, the smaller the bet size. The relationship between bet size deduction and drawdown could be linear of exponentially. I decided to use a mix. I called this factor the "NoFear" number. The NoFear number is the value of drawdown that starts a linear/exponential deduction of the bet size. A graph representing the NoFear 1.9 is shown below:



In this graph is shown that when the drawdown is less than 1.9%, there is no deduction of the bet size. When the drawdown is for instance 10%, the bet size is only 28%.
I now had two independent formulas to control the result/risk ratio. I decided to perform back tests with ranges of values of both variables to discover the optimal values. In these back tests I used a range for the Kelly Multiple from 0.5 to 1.0 and a range for NoFear from 1.5 to 2.0. For each combination I calculated the Sharp Ratio. The Sharp Ratio is another measurement of the performance of a trading strategy in relationship with the possible risk. I used a simplified version of the Sharp Ratio. I divided the result of the strategy expressed by the cumulative trade percentage by the standard derivation of the trade percentages.

KellyMultiple	NoFear	Sharp
0.5	1.5	29.44
0.5	1.6	29.54
0.5	1.7	29.40
0.5	1.8	28.52
0.5	1.9	28.21
0.5	2.0	27.28
0.6	1.5	30.02
0.6	1.6	29.01
0.6	1.7	28.73
0.6	1.8	28.82

0.6	1.9	28.11
0.6	2.0	26.64
0.7	1.5	29.45
0.7	1.6	29.36
0.7	1.7	29.50
0.7	1.8	29.01
0.7	1.9	27.81
0.7	2.0	26.51
0.8	1.5	30.05
0.8	1.6	30.32
0.8	1.7	30.11
0.8	1.8	29.24
0.8	1.9	28.26
0.8	2.0	27.98
0.9	1.5	30.63
0.9	1.6	30.55
0.9	1.7	30.20
0.9	1.8	29.79
0.9	1.9	28.83
0.9	2.0	27.95
1.0	1.5	28.70
1.0	1.6	30.70
1.0	1.7	30.28
1.0	1.8	29.57
1.0	1.9	28.26
1.0	2.0	27.17

The (simplified) Sharp Ratio gave me the indication to the optimal parameters to use for the KellyMultiple and NoFear. The highest Sharp Ratio 30.70 was achieved with a KellyMultiple of 1.0 (= Full Kelly) and a Nofear of 1.6.

7. Adding a boost

While performing the seemingly endless back tests, I noticed that certain models performed differently at times usually called bull or bear markets. I decided to investigate this.
For each model I separated the trades by direction and by BullBear qualification. I used as determination of bear or bull the location of the 50MA relative to the 200MA. If the 50MA was above the 200MA I considered that model to be bullish. When to 50MA was below the 200MA I considered that model to be bearish. For clarity: bull or bear was not a measurement if the model was performing good or bad. A model could be better or worse performing in bear condition than in bull condition. I wanted to find out.
Here are the results for the models Combo-MF and XLI:

Model	Direction	BullBear	Cumul%
Combo	Long	Bull	64.70
	Long	Bear	146.59
	Short	Bull	69.11
	Short	Bear	102.46

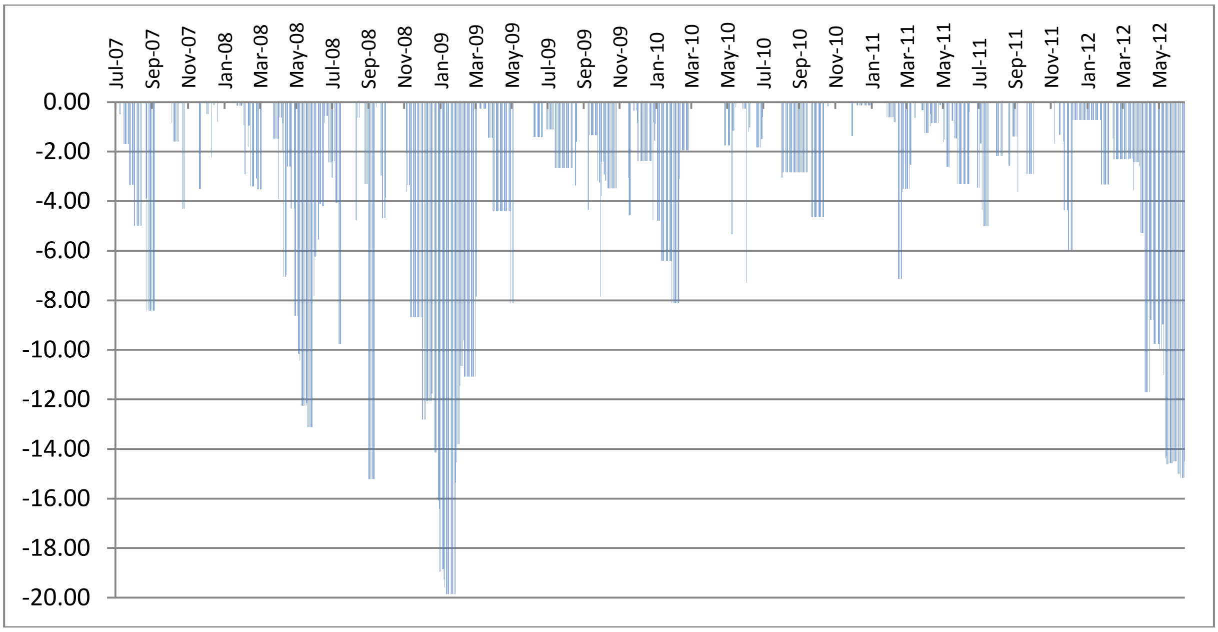
Model	Direction	BullBear	Cumul%
XLI	Long	Bull	54.34
	Long	Bear	132.03
	Short	Bull	37.67
	Short	Bear	91.19

For the models GDX and XLB there was no significant difference between bull and bear nor between long or short. For the Combo-MF and XLI models there was! It was significant that trades started when the model in

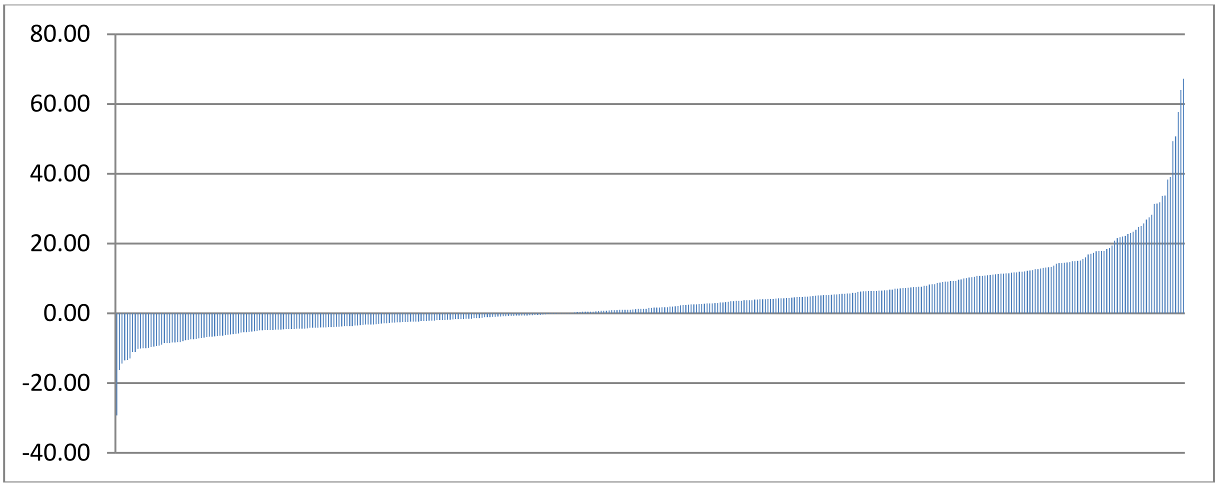
question was in bear condition where performing better then when in bull situation. The direction of the trade did not matter. I decided to use this and apply a boost to the bet size by implementing something I called a Turbo. I would double, triple or more the bet size for the model if the model was at the start of the trade in bear condition. I did this only for the Combo-MF and XLI model. I performed the back tests from section 6 again with different Turbo factors ranging from 1 to 4 for the Combo-MF and XLI models. As I expected: larger Turbo factors would produce higher returns with also higher draw downs. By controlling the initial bet size with the KellyMultiple and controlling the drawdown with the NoFear factor I could find the optimal values for my parameters. It turned out to be to use a four times Turbo for the Combo-MF and XLI model with a KellyMultiple of 0.9 and a NoFear factor of 1.6. These settings produced an ending equity of $ 5,569,571.11 with a max drawdown of 28.42. This is a CAGR of 259% !
If the maximum acceptable drawdown should be not higher than for instance 20% than the parameters are:

- KellyMultiple = 0.6
- NoFear = 2
- No turbo for Combo-MF
- 4x Turbo for XLI

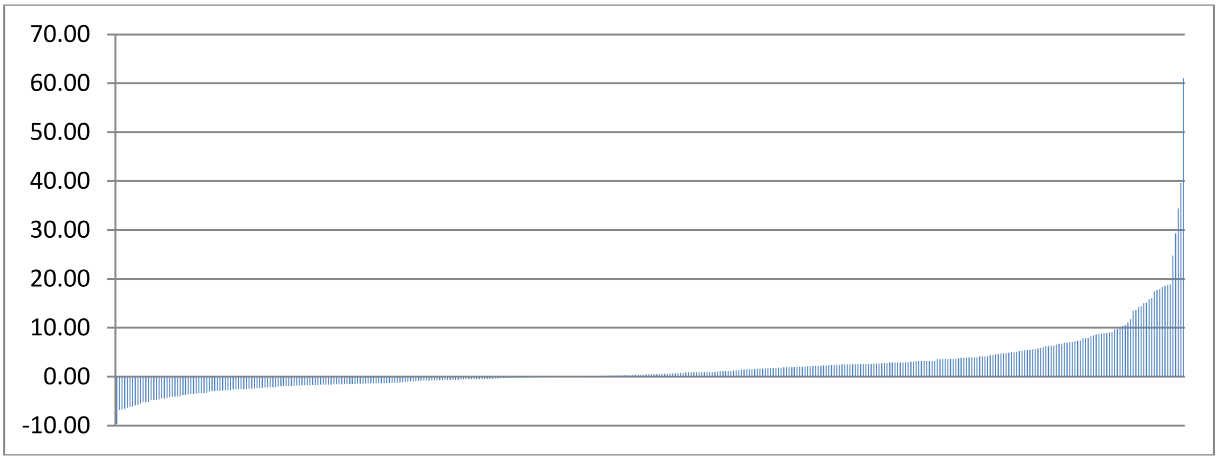
This gives an end equity of $ 2,104.653.62 with a max drawdown of 19.85%. This is still a CAGR of 194.80%
The evolution of the drawdown is shown in the following graph:



The original signals produces trades with results that vary between -29.21% and 67.20%.



Through the use of most optimal risk management, the results of the trades are more effectively. The range of the trading results are from -9.70% to 61.07%



8. Putting everything together

My daily routine consists of looking at the signals given by the four models. They determine if a new trade should be opened. It also determines if an ongoing trade should be closed.
I calculate the ideal stop-loss values for each model and each trading direction.
Next I calculate the SQN for each model for the past 250 periods. The current Kelly Criterion for the past 250 periods is also calculated.
Both numbers enable me to calculate to position size for each model separated. The KellyMultiple limits my maximum exposure. The NoFear factor helps control the drawdown as it will reduce in an effective manner the risk for each trade when the current drawdown is too high.
Determination of bear/bull status for the Combo-MF and XLI model helps me to boost the possible results.
The research in finding the ways how to apply these different parameters in an effective manner have taken me roughly 4 months fulltime work of programming and running countless tests.

9. Conclusion

I started out with a trading strategy that followed the signals from two independent sources. This strategy delivered a CAGR of 103% with a maximum drawdown of 17,38%. This was without any stop-loss settings and using always full 100% of the available funds with an equal position size for all models.
I added margin and risk control through the Kelly Criterion. I made it intelligent and agile with the KellyMultiple and NoFear Factors. Through detection of bull or bear status I can boost the performance of certain models.
Now I have a strategy that delivers me a CAGR of 259% with a drawdown of max 28.4%. This is 16 times the original performance without any change to the original signals!
There are many books about position size strategies. Some writers recommend putting more effort in a sound position size management then looking for the ideal entry and exit signals.
My back tests have proven this to be right.