The One Percent Per Week TQQQ Trading Strategy:

MY EQUATION

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The One Percent Per Week TQQQ Trading Strategy:

MY EQUATION

In **The One Percent Per Week TQQQ Trading Strategy: MY EQUATION**, I explore its use and describe the inner workings of the ***One Percent Per Week*** (OPPW) strategy trading the TQQQ ETF, elaborating on its properties and potential forecasting abilities.

A portfolio strategy's long-term return outlook is usually vague when expressed in mathematical terms. As Yogi Berra once said, and more than once: "It's tough to make predictions, especially about the future". That quote certainly resonates when looking at the outcome of future stock prices.

Even if you have a future value formula to calculate the return on your investment, looking forward or backward, you will still have to determine the unknown future growth rate that will apply.

Without some context, a mathematical formula might be just a formula and not enough. Regardless, at times, we can have exceptional scenarios where portfolio equations do apply.

In my prior articles and papers, based on this strategy's trading history, I presented what this particular strategy is telling us. Not only can it tell us what it did in the past, which it does, but it can also say, in general terms, how it will behave in the future.

As if stating that a trading strategy will behave in the future as it has in the past. It is more than hinting that the strategy's past might be the best information source for what it might do in the future.

Based on reasonable assumptions, we can approximate the long-term outcome of the OPPW strategy. It should lead us in a worthwhile direction and give us the ability to determine the average probable outcome of the strategy for a number of years forward. A forward Monte Carlo simulation over hundreds of iterations should help determine those probable and expected outcomes.

MY TQQQ PORTFOLIO EQUATION

The TQQQ portfolio equation of interest, as presented before.[1]

$$\bar{e} \cdot (1+\gamma)^N \cdot f_0 \cdot \prod_1^N \cdot (1 \pm r_i) = \bar{e} \cdot (1+\gamma)^N \cdot f_0 \cdot (1+\bar{r}_+)^{N-\lambda} \cdot (1-\bar{r}_-)^{\lambda} \qquad (1)$$

1 See my list of articles, papers, and book.

the above equation with no leverage ($\gamma = 0$) can be reduced to:

$$\bar{e} \cdot f_0 \cdot \prod_{1}^{N} \cdot (1 \pm r_i) = \bar{e} \cdot f_0 \cdot (1 + \bar{r}_+)^{N-\lambda} \cdot (1 - \bar{r}_-)^{\lambda} \quad (2)$$

If N, the number of trades, is sufficiently large, then the equation can provide long-term return averages on its trading positions. Being long-term return averages ($\bar{r}_+$ and $\bar{r}_-$), they could persist beyond their realized results at time t.

The portfolio metrics of a simulation generating N trades could see those metrics maintained for an added ν trades. Projecting forward the future value of your portfolio as long as ν is also within reasonable reach.

I presented the above equations before, for instance, in my free book: **Gain Your Financial Freedom** where you will see the impact of adding and removing 10 or 20 trades over the 15-year testing period.[2]

Table #1: List Of Variables Used

Variable	Description	Origin Of Value
$\bar{e}$	average exposure rate	from simulation result
f_0	initial trading capital	your initial capital
γ	leveraging factor	calculated after sim
N	number of trades	from simulation result
λ	number of losing trades	from simulation result
$N - \lambda$	number of winning trades	from simulation result
ν	number of added trades after reaching N	for forward estimates
$\bar{g}$	portfolio's growth rate	from simulation result
$\pm r_i$	return for trade i	from simulation result
$\bar{r}_+$	average percent win on winning trades	from simulation result
$\bar{r}_-$	average percent loss on losing trades	from simulation result
t	long-term trading interval	you determine

In my article: **One Percent Per Week Strategy: SOME TRADING HABITS**, I projected forward for one year using equation (2) above by simply increasing the trade exponents by ν in the same proportions as achieved over the previous 15 years.

The problem with such a projection is that we will not know until the following year if those projections have stood the test of time. Even if you make a forward projection, you cannot assure yourself that it will happen. It is a reasonable assumption.

Nonetheless, the above-cited article[3] did illustrate the outcome of a 9-month walk forward where the portfolio metrics stayed stable over that extended period, even though the strategy had no idea of what was coming its way.

[2] The book describes the inner workings of this interesting strategy; take the time to read it.

[3] **One Percent Per Week Strategy: SOME TRADING HABITS**.

My Wealth-Lab 8 (WL8) program version trading procedures have not changed since May 2024, and the weekly return variations for the coming 9 months were unpredictable. Yet, it maintained its steady objective of generating a 1% portfolio return per week over those 9 added months.

Such a projection has also been made last September in my article: **Make Your First $\$$50M Before You Retire** where in Figure #1, the 780-week forecast (for February) came in at $\$87$ million. In my last article, **One Percent Per Week Strategy: SOME TRADING HABITS**, after reaching that 780-week milestone, the simulation reached $\$86$ million on February 21, 2025. An impressive estimate, since last September 2024, there was no way to assure anyone that that forecast might hold. It was just an estimate, an expected future outcome calculated using equation (2).

The question arises: is the number of trades (780) sufficient for some of those averages to reach the status of sustainable long-term averages?

In most statistical problems, a sample of about 30 elements is often considered sufficient to have statistically significant averages. Most often, reaching about 500 samples might be viewed as an overreach and more than enough to make a case.

Equation (2) can be modified to make those forecasts relatively easy. Especially if the long-term averages tend towards the long-term averages we seek. We might only need to add ν trades to the existing N trades with the same proportion and distribution as the achieved average portfolio metrics over those N trades.

Thereby using the strategy's past trading history and behavior to explain its forward-looking outcome.

THE *ONE PERCENT PER WEEK* PROPERTIES

My version of the OPPW strategy has interesting properties, especially when trading TQQQ, a 3x-leveraged ETF. Due to its high weekly profit targets, the program will not work so well with non-leverage, low-volatility stocks or ETFs. My program version seeks volatility; it is not running away from it.

TQQQ will be more volatile than the average market benchmarks. That is a given. The OPPW strategy trades a 3x-leveraged ETF based on QQQ. We have no leveraging fees, only the ETF's annual management fees (0.98%/year). Our trades last at most one week, and close to half of them less.

If QQQ has an estimated long-term annual growth rate of 15%, we should expect that TQQQ would aim for a 45% yearly compounding rate of return.

Using TQQQ, prices will swing more than the general market. It is part of the very nature of this ETF.

As a long-term trader trading TQQQ over the short term (one-week trades), we seek the higher volatility this ETF can bring, even knowing how volatile it can be. A 3% one-week price move in QQQ will push TQQQ to a 9% one-week return. The reverse is also true; a QQQ -3% one-week decline should translate into a -9% one-week price drop for TQQQ.

So, be ready to swing up and down. We seek higher overall growth rates, and TQQQ can deliver in that department.

Here is my point: if you want higher returns, you should not shy away and try to avoid larger price variations. How is that going to help you achieve higher returns than your favorite average market benchmark? All your trade profits or losses ($X = \sum_1^N \pm x_i$) are measured based on their price variations.

You will be dealing with unknown probability measures, future outcomes, and a high degree of randomness. We do not know with any certainty what the market will do tomorrow, next week, or next year, for that matter. But we do know the market's long-term average.

We do know that over the long run, the US market tends to rise slowly over time ($\sim$10%). But for this, you need a long-term view of the market. Nothing assures you that the market will increase by $\sim$10% next year. However, over 20+ years, you can easily achieve that goal as your potential average and expected outcome unfolds.

That is the problem you need to face head-on. Nonetheless, suppose you are ready to stay the course for 15 to 20+ years; you could easily envision reaching that minimal $\sim$10% compounded return simply by buying SPY, DIA, or QQQ and holding for the duration.

As expressed many times in recent articles, that should not be enough, especially since you have methods that could bring you much higher long-term returns.

THE TQQQ TRADING STRATEGY'S STATISTICS

Let's start with a copy of the trade distribution from my previous article.[4] All trades (782) fell in one of the four trade types displayed below with the accompanying statistics.

Based on those results, if you took a trade, you had a 17.26% chance of reaching your profit target or better, while you had a 19.94% chance of having a losing trade.

You had a 51.65% chance of generating a profit and 19.94% of having a losing trade. You also had a 28.38% chance of generating nothing at all (Type-C trades).

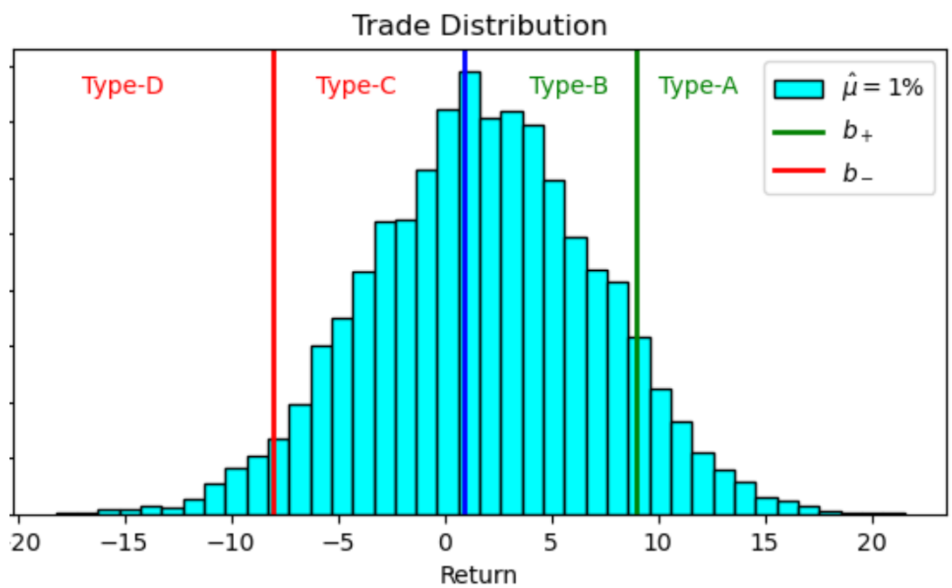
[4] Refer to **One Percent Per Week Strategy: Trade Distribution**.

Table #1: Trade Statistics – February 8th, 2025

Trade Type	Trade Outcome	Trade Result	# Trades	≈ Percent Of Total	Reason Position Sold	Average # Trades/Year
A	Positive	$>= 7\%$	135	≈ 17.26%	Above Profit Target	9.0
B	Positive	$> 0 < 7\%$	269	≈ 34.39%	On Friday's Close	17.9
C	Zero	$= 0$	222	≈ 28.38%	Break Even	14.8
D	Negative	< 0	156	≈ 19.94%	Losing Positions	10.4
		Total →	782			

The 51.65% hit rate is very close to a heads or tails game, coming in at 50/50. The trade distribution below expresses the point. Returns have a raggy bell-shaped distribution, usually with fat tails and centered on its mean.

Figure #1:Trade Distribution.



(**Click here to enlarge**)

Any program testing for randomness in time series could not conclude that this was not a random-like phenomenon.

The only reason you have a 51.65% win rate is because it comes from the long-term upside bias found in US stock market averages. Such an upside bias is also expected to continue in the coming years.

From such observations, we can put forward how this time series behaved in the past, as if quasi-randomly, and it might also be how it will behave in the future.

The trading strategy's future will resemble its past.

Looking at the return distribution of this strategy, you would get something like Figure #1 above, which would resemble a lot of other trading strategy's distributions if they had that number of trades. This bell-shaped distribution is quasi-normal, and its shape derives from the high number of randomly generated elements.

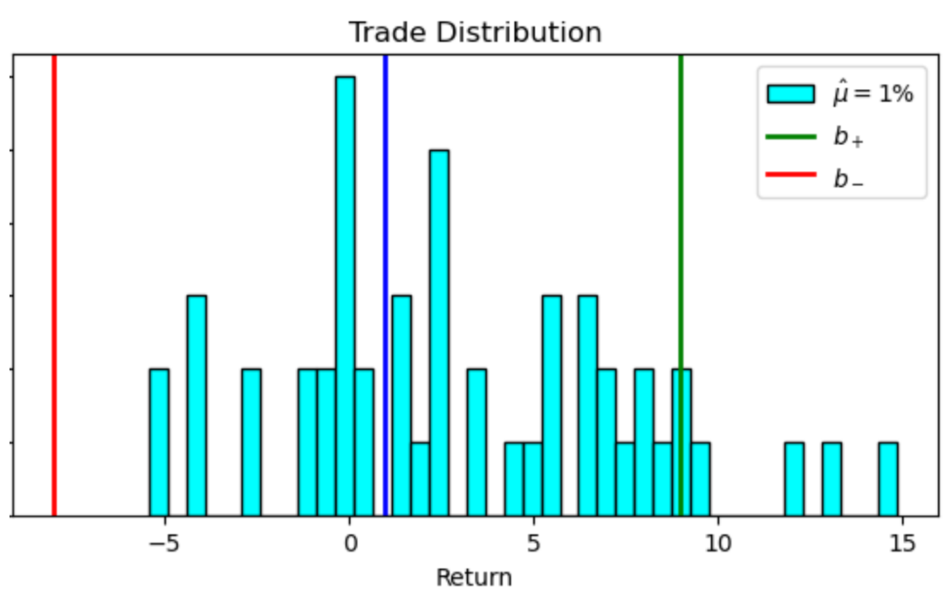
Adding more trades will even smooth out the distribution, getting it closer to a normal distribution. Market return distributions usually exhibit higher kurtosis, skewness, and fat tails; the reason I use the term quasi-normal.

I separated the chart in Figure #1 into four sections, as in Table #1 above. The barriers $(\pm b_{\pm})$ would change for every distribution but stay near where they are drawn. The reason is simple: the more you add trades, the more the standard deviation will tend to the distribution's long-term values.

From the strategy's result, I defined the four trade types as presented in Table #1 and Figure #1.

We could not express these things if the trade distribution were for a low number of trades. We could not determine from Figure #2 below what would be the long-term distribution, even though we know it would tend to some quasi-normal distribution resembling a bell-shaped curve as in Figure #1.

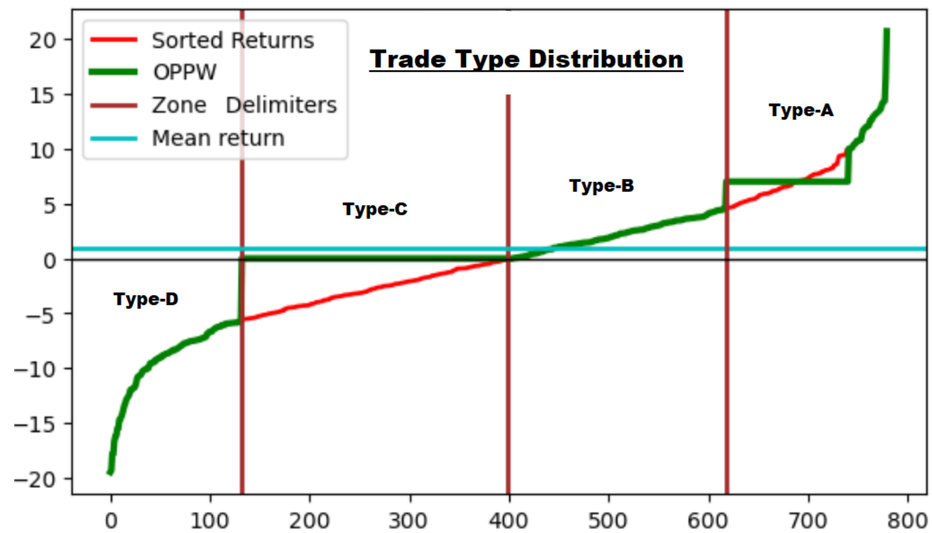
Figure #2: Trade Distribution With A Small Number Of Trades



(**Click here to enlarge**)

In my article, **One Percent Per Week Strategy: Trade Distribution**, Figure #3 showed the same data as in Figure #1 but ordered by return where the outcomes of the trading rules were superimposed on the chart.

Figure #3: Sorted Return: Trade Distribution.



(**Click here to enlarge**)

Type-B and Type-D trades, in Figure #3, were not impacted the same as the other two trade types by the applied trading rules.

Whatever the random-like process they might have come from, the program did not alter their outcomes; both closed on Friday's closing price. Whatever the percentage gain or loss, it was the recorded and achieved return.

You got in on the week's first trading day and got out at the closing price on Friday, whatever the outcome. We could classify those trades as a variation of a buy-and-hold, but only holding for one week, thereby giving the same up-and-down returns as the buy-and-hold would.

There was no technical advantage in those two types of trade that would generate more than the market's average, except for its 3x-leverage QQQ scenario. Your expected outcome was, notwithstanding, 3 times the weekly price variation, up or down. And for a general market with an upward bias, it should be beneficial overall.

Trades of Type-A and Type-C are where the trading rules changed the impact (follow the green line in Figure #3). The break-even rule produced the horizontal green line at the zero mark (Type-C), while the profit target generated the horizontal portion of Type-A trades. Both position types are usually closed before Friday's close.

In trades of Type-A, the profit target % set an upside limit to the trades crossing the profit target. They would be liquidated at the profit target's price since all those trades were sell-limit orders already waiting in the books.

Type-C trades have become the most interesting, at least for me.

They produce absolutely nothing: no gains and no losses. Except they do make a significant contribution to the strategy. They do not cancel out Type-B trades.

In Figure #1, with its quasi-normal distribution, we would have about as many trades making a profit as there would be losing money and in about the same proportions (the win rate is only 51.65% after all).

Let's give numbers to Figure #1.

We have: $(1 + \bar{r}_+)^{N-\lambda} \cdot (1 + \bar{r}_-)^{\lambda} = z$, this is the factor to be applied to the invested capital.[5] With an average return per trade $\bar{r} = | \pm 0.07|$, $N = 780$, and $\lambda = 390$ ($\lambda/N = 0.50$), we would have: $z = (1 + 0.07)^{390} \cdot (1 - 0.07)^{390} = 0.1472$.

We could easily conclude the quasi-normal distribution, with its high number of trades, would destroy our portfolio. We would have to find better trading strategies or use more profitable methods.

It is our interference with this quasi-normal distribution
that will make a difference.
Our trading rules will give us a solid and positive edge.

MY GENERIC LITTLE CARD GAME (MGLCG)

Let's design a game based on an ordinary deck of 52 cards. Black, you win, and red, you lose the card number as a percentage of your ongoing stake.

We put our stake on the table, pick a card, and have the face value number as the percentage gain or loss.

The range of outcomes will be from -13% to +13%, with a zero mean. Each with the same probability: $1/26$.

One might think that this game would give you a zero expectancy. If each outcome, black or red card, has equal probability (50/50), we could average out the positive and negative returns to $\pm 7\%$[6].

If we played 780 hands, we would get the same equation as for z above.

We get a game of chance, which, by "our" design, would make us lose the game and bad since we would be left with only 14.72% of our original stake, whatever it was. You would have lost over the long term (780 plays) -85.28% of our initial capital.

[5] From (2), we have total outcome: $F(t) = \bar{e} \cdot F_0 \cdot z$.

[6] The average of the sum of those returns: $\frac{\sum_1^{13} r_i}{13} = 0.07$

That would be a bad game for anyone. It would be a bad card game, just as it would for a stock market game.

So, you opt to interfere with the game itself and change the playing rules and their outcomes.

You set a rule that the cards numbered 6 to 10 will be counted as 0.08. The average would still be 0.07. And if you applied this in the above equation, you would get: $z = (1 + 0.07)^{390} \cdot (1 - 0.07)^{390} = 0.1472$, the same answer as above. You gained no advantage and are still left on the wrong side of this game.

The average for the 5 rates is $((0.06 + 0.07 + 0.08 + 0.09 + 0.10)/5 = 0.08)$. You would have thought we would have had an edge, but in this new design, not so much. Your modifications to the rules had literally no impact.

So, you opt again to redesign your game and set that if the card is red, meaning it has a losing percentage, you will assign zero to the cards between 0.0 and -0.09. Your bet is returned intact if a red card is below 10. So, instead of losing -1% to -9% of your stake on those bets, you get your money back and suffer no loss.

By changing the game, you get: $z = (1 + 0.07)^{390} \cdot (1 - 0.03538)^{390} = 228,357.63$.

That is now a winning game. If we had a slight hedge like a win rate of 51.65%, it would again change the game.

We get: $z = (1 + 0.07)^{403} \cdot (1 - 0.03538)^{377} = 878,968.34$. It's quite an improvement in the game with a tiny advantage.

With the above win rate of 51.65%, we could also project forward for another 52 hands with the probable outcome: $z = (1 + 0.07)^{430} \cdot (1 - 0.03538)^{402} = 2,219,431.71$.

Simply by changing the playing rules, we transformed our card game into a monumental winner. If you added one more year under the same playing conditions, you would have: $z = (1 + 0.07)^{457} \cdot (1 - 0.03538)^{427} = 5,604,157.58$.

Would you play such a card game? Note that we only calculated the multiplying factor and have not provided the total outcome. Here it is again: Total profit: $X = F_0 \cdot z$, for any of the card game scenarios above.

In our little card game, we know the odds for any back play just as we know for any forward play. Stating that the past statistics for this game are the same as its future statistics.

You could project forward for as many plays as you want and quickly determine the outcome, whether it be with or without a slight upside bias, as the above examples demonstrate.

It leaves a question: where would you find that slight edge in this card game? Since we are setting the playing rules, let's introduce two black jokers in the deck of cards with a count the same as the average outcome of 0.07. It would give an edge of $28/54 = 0.5185$, close to the 51.65% edge demonstrated in the WL8 simulation over those 15 years.

Our rules of engagement in the above card game make us win. And if you look closer at the math, you should realize that as the number of hands increases, you will be more and more unable to lose the game. You will still have only 51.85% of hands on the winning side.

It is almost the same thing we did with the OPPW trading procedures. You can see the same type of boundaries ($\pm b$) in Figures #1 and #3.

- No casino will ever offer you a card game as designed above.
  They know they will lose.
- But, here is the kick in the butt; you can design such a game in the stock market game, and with ease.
- As a matter of fact, you have the **One Percent Per Week** trading strategy as a demonstration that you can do it.
- The program is even free. Technically, you have no remaining excuses except the lack of capital. The strategy takes less than 5 minutes per week to execute by hand and a few microseconds using your computer. So it is hard to say you do not have the time.

I also put forward that it is not the only stock trading strategy that can do it. There are many, many more.

As someone said before:

Something that works in practice can be shown to work in theory.

LOOKING AT THE FUTURE

We can analyze the past and determine how a stock trading system works. We get statistics to help us determine probabilities to set trading rules.

In the case of the OPPW strategy, these are set based on stopping times. For instance, if it does, a position is closed during the week the first time it hits its profit target. The same goes for the first rebound to break even after closing a day with a loss or reaching Friday's close.

Our analysis of the past data does not give us any assurance we might need to go forward. We have 240+ years of market data, and still, most stock market participants, on average, have a hard time exceeding market benchmarks.

It is not a new phenomenon; it has been so for decades. We should expect it will also be the same for decades to come.

That is not good news for the small investor. It implies that, on average, all they have available to choose from might turn out to just be average. It has been shown, over decades, that the expected outcome would be close to about 10%.

If you had made that forecast 50 years ago, it would have been the same: your expected outcome then would still have been that ~10% CAGR.

Look at the long-term average performance of traditional money managers (over 15+ years). You will find that most have had returns of about ~10% ±5%. As soon as you speak averages, you should expect half your sample to be below average, just as half might be above. That is the expected and usual outcome from any average.

Oftentimes, we have to make assumptions based on too little data. For instance, as demonstrated above, too few trades will not provide reliable long-term statistics; at least, that should not be expected to (see Figure #2).

What should you expect if all you are offered has a long-term 10% expectancy or about?

You could not foresee Figure #1 or Figure #3 from Figure #2. It is with the larger number of trades that our trade statistics are expected to tend to their long-term averages, another example of the Law of large numbers, which can apply here.

It should not deter you from the task at hand, which is building your investment/retirement fund at the highest speed possible, and a long-term 10% compounded return should not be enough.

We are playing a compounded return game ($\prod_1^N (1 \pm r_i)$), and that growth rate is a major component of our future value formula: $F(t) = F_0 \cdot (1 + \bar{g})^t$.

The OPPW trading strategy is not the only one that can help you in your quest to achieve financial freedom. There are many more. But they all require your participation. No play, no gain, and no loss. However, no play will not outpace inflation: $F(t) = F_0 \cdot (1 - 0.03)^{20} = 0.5437 \cdot F_0$, a -45.62% decline in buying power. You would get a -59.9% should you wait 10 more years.

You cannot leave your cash idle; it will depreciate whether you like it or not.

A TRADING STRATEGY TO THE RESCUE

This OPPW trading strategy and many others say you need to be in the game for a long time, 15+ years, and more.

The surprising thing might be that my program version of the OPPW trading strategy shows that it might be sufficient to participate for a long time to win this game and win big.

You will need a worthwhile trading program. You have it, and it is free. [7]

You have the code and all the trading procedures for the strategy. You have everything in hand.

You have all the math that will justify the strategy's long-term outcome.

What you now need is more understanding, time, and working capital.

The simulations have shown that this strategy worked quite well in the past. We are now concerned about its future. How will it do?

We are left with the big question: **Will it work as well in the future**?

That is the real question. In fact, it is the only question that matters.

A SIMULATED TRADING UNIVERSE

We can use past market data to simulate future scenarios where we carry forward the knowledge acquired from what has been.

Stating that the future market conditions might just be a continuation of what was.

For instance, we could take the results of Table #1 and design a quasi-random-like trading environment that would operate on the same statistics as gathered from the strategy's past trading behavior. We could use the average portfolio metrics provided in the WL8 simulation.

The OPPW trading strategy has about the same structure and principles as the little card game. Based on the playing rules of that card game, we could easily predict what will come out of it over a large number of plays. We have an equation for it, as expressed above.

The probabilities that applied over the WL8 simulation data could also apply in the

[7] Link to my version of the **program code**.

future, as in the above card game or a game of heads or tails.

We could simulate a future game of cards based on the same probabilities where you would not know if the next return is up or down or what the return value might be, positive or negative.

For the card game, you would have a return range between -13% to 13%. We would have a chart similar to Figure #3 with the gaming rules applied.[8]

The defining zones would still separate the trade types but with fuzzy boundaries ($\sim b_{\pm}$). And looking into the future, we would not know where those boundaries would fall. Nonetheless, they would look like as shown in Figure #3.

In the future, the math for the card game will not change. The game would have the same probabilities looking back as looking at the future. Each simulation would be different, and each sequence of plays would remain unpredictable.

The MGLCG card game would provide past probability statistics to help calculate future probability outcomes. But we would know the probability of each move in advance and make our bets based on those statistics.

Furthermore, we know we would win just by playing the game. The question of how much we could win would depend on how many hands we would play.

Based on Table #1, where we have the statistics on the trade distribution for the OPPW, we could use a random number generator to determine the outcome of each play. Then, distribute the plays according to their outcomes. A simple series of if statements could do the job.

The Python program below can simulate as many future or past scenarios as you wish. We should remember that with low numbers of trades N, the distribution of returns will resemble Figure #2. With a larger number, like $N = 780$ (15 years), you will get a chart resembling Figure #1. Following the same playing rules, sorting Figure #1 by return outcomes gives a chart looking like Figure #3.

With such a program, as the number of trades increases, we will see each type of trade nearing its expected long-term average. For instance, as the trades increase, Type-A trades will tend to be 17.26% of total trades for $N = 780$, as given in Table #1. The same goes for the other types of trades. Overall, the code will explain the WL8 simulation results and the outcome of equation (2) as shown in Figures #4 and #5 below.

[8] Both the green and red lines would be linear. However, the general curve structure would be the same, with the same trade type distribution.

Figure #4: Simulation Code Based On The WL8 Portfolio Metrics.

```
a, b, c, d, t = 0, 0, 0, 0, 0
# Trade Type Percent Distribution
A, B, C, D = 0.1726, 0.3439, 0.2840, 0.1994
N = 780  # 15 years

for i in range(0, N):
    rand = np.random.uniform()
    t+=1
    if rand > 0.8294:
        a+=1
    elif rand > 0.4825:
        b+=1
    elif rand > 0.1997:
        c+=1
    else:
        d+=1
# Using my portfolio equation on WL8 simulation metrics
TotalValue = 0.52 * 100000 * ((1.082)**a * (1.0301)**b * (1+0.0)**c * (1-0.0596)**d)
print(f"Total Value:  $ {TotalValue:0,.0f} ") # portfolio estimate.

Total Value:  $ 89,667,396
```

(**Click here to enlarge**)

We can use the WL8 portfolio statistics to recompose a new trading series based on the distribution of trade type. Due to the large number of trades, the simulated data would tend to be near the WL8 long-term simulation portfolio metrics. Furthermore, we could do many simulations to explore the average outcome over a large number of simulations.[9]

We can replicate the WL8 portfolio based on randomly selected trade types. We could make future estimates based on the same principles and randomly generate as many future outcomes as we like. It would be a Monte Carlo method, with each simulation taking a different path, independent of its past or future for any of the taken positions.

The outcomes would relate to the original scenario by their expected portfolio metrics. However, with every simulation, you would get different results, as if simulating a real future based on your trading rules, which would remain the same.

You could not predict the outcome of any trade, whether for next week's outcome or a year forward. You could not even predict if the strategy would keep the same trade distribution it had in the WL8 portfolio's original scenario.

My version of the OPPW strategy represents only one occurrence, as was provided in prior articles. And since the program has not changed since May 2024, we are still dealing with the same time series of events with a program using the same trading procedures.

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[9] The same as doing some simulations using a Monte Carlo method but with randomly generated trade types.

Just as we could use the card game (MGLCG) and make as many simulations as we like based on the percent outcome distribution, we could do the same with the OPPW portfolio metrics using the code in Figure #4 above. Every simulation would give a different answer, some better and some worse, as should be expected.

Nonetheless, making 100 such simulations would give us something like a Monte Carlo simulation, even if none of the trades would depend on the trade before or after any of those trades or portfolios. In a second, we could have the outcome of a portfolio with its 780 trades, and again, we could not predict the result or the sequence of trades of this time series. You would have positive and negative scenarios entirely depending on the outcome of the random number generator.

The simulation program in Figure #4 would have to follow its code, and give the total value for each simulation.

The outcome should be similar to the WL8 simulation in the article: **One Percent Per Week Strategy: Trade Distribution**.

We can observe the trade type distribution. What a trade type wins or loses is taken or given to the other types. The randomness of the draw controls this distribution. You do not know which week will gain or lose trades, but you know the total number of trades will remain the same, in this case, 780 weekly trades.

The simulation outcome of Figure #4 did not depart much from the WL8 simulation (see Figure #5 below). Figure #4 can attest that output was randomly generated according to equation (2).

We could do thousands of these simulations using the code in Figure #4. We could add another `for loop` to iterate the requested any number of times. Doing so would bring in more valuable information. For instance, it could provide the most expected outcome of such simulations. Those thousand simulations could give us a better idea of where this strategy's mean is going and where its most expected value might be.

In the simulations below (Figure #6), the trade distribution, even under random selection, produces something similar to the WL8 program. Yet, Figure #6 was randomly generated and followed equation (2).

Figure #6 presents the outcome of 100 simulations based on the Figure #4 code but shows only one in ten of these iterations. The objective was only to have a shorter list. However, The given average is for the 100 simulations, not just the 11 shown.

Each simulation is a one-of-a-kind occurrence with no assurance that it will be ”the” outcome in the future. Stating that your future path will be unique and unpredictable every step of the way. Except for the expected long-term outcome. The simulations give you an idea of the range of these simulations, including their expected long-term average performance level.

Figure #5: 15 Year Simulation From The WL8 Program.

Metrics Report | Equity Curve

Select ScoreCard: Basic ScoreCard

	Strategy	Benchmark (Q...
Summary		
Starting Capital	100,000.00	100,000.00
Profit	86,642,514.88	1,120,534.25
Profit %	86,642.51%	1,120.53%
Profit Per Bar	15.21	14.83
APR	56.86%	18.11%
Std Dev of Annual Ret...	159.94%	20.72%
Exposure	52.18%	99.99%
Maximum Exposure	99.91%	100.00%
EAR	108.98%	18.12%
Alpha (α)	32.17	-
Beta (β)	1.39	-
Sharpe Ratio	1.27	0.97
Sortino Ratio	2.19	1.59
WL Score	49.62	11.66
Slope of Equity Curve	14,661.89	259.34
Interest, Commission...		
Commission Paid	0.00	0.00
Cash Interest Received	0.00	0.00
Margin Interest Paid	-0.00	-0.00
Maximum Margin Used	1.00	1.00
Dividends Received	0.00	0.00
Total Currency Adj	0.00	0.00

Metrics Report | Equity Curve

Select ScoreCard: Basic ScoreCard

	Strategy	Benchmark (Q...
Positions		
Position Count	784	1
Avg Profit	110,513.41	1,120,534.25
Avg Profit %	1.02%	1,120.86%
Profit Factor	1.63	-
Payoff Ratio	1.66	-
Avg Bars Held	3.36	3,780.00
Avg Trades Per Month	8.66	0.01
Avg Bars Held as % of...	0.09	99.97
Largest Bars Held as %...	0.13	99.97
NSF Position Count	0	0
NSF Ratio	0.00	0.00
Drawdown		
Max Drawdown	-22,726,223.93	-333,824.80
Max Drawdown Date	10/26/2023	12/28/2022
Max Drawdown %	-54.47%	-35.62%
Max Drawdown % Date	7/6/2010	12/28/2022
Recovery Factor	3.81	3.36
Profitable Positions		
Count	405	1
% Profitable	51.66%	100.00%
Avg Profit	555,450.37	1,120,534.25
Avg Profit %	4.53%	1,120.86%
Average Bars Held	3.05	3,780.00
Unprofitable Positions		
Count	379	0
% Unprofitable	48.34%	0.00%
Avg Loss	-364,946.93	-
Avg Loss %	-2.72%	-
Avg Bars Held	3.69	-

(**Click here to enlarge**)

Figure #6: 100 Simulations Based On Figure #4 Code (15 Years).

```
  Total: $  1,288,227,073    Sim #:   1
  Total: $  1,287,209,561    Sim #:  10
  Total: $  2,357,574,724    Sim #:  20
  Total: $     45,404,091    Sim #:  30
  Total: $    244,206,911    Sim #:  40
  Total: $    158,561,981    Sim #:  50
  Total: $    263,649,016    Sim #:  60
  Total: $    592,551,778    Sim #:  70
  Total: $    235,538,713    Sim #:  80
  Total: $  1,121,227,323    Sim #:  90
  Total: $    495,721,959    Sim #: 100

Average: $    730,445,494
```

(**Click here to enlarge**)

Your response could be: if I do enough of those future simulations, could I not average them out and get an estimate of the average outcome? The answer is yes. It is the main reason for generating Figure #6 above.

We could do the same for one thousand simulations of the WL8 scenario, all based on the Figure #4 code and equation (2).

Figure #7 gives such a series of simulations. Each is independent of the others, but all operate on the code in Figure #4. Figure #7 shows only 1 in 50 of those simulations. At the bottom of the chart, you have the average for the 1000 simulations. The chart gives an idea of the wide range of outcomes. Note that the average for those 1000 simulations is more than desirable and should align more with the expected result.

Figure #7: 1000 Simulations Based On Figure #4 Code (15 Years).

```
  Total: $    482,860,928    Sim #:    1
  Total: $  1,475,979,421    Sim #:   50
  Total: $  1,138,373,161    Sim #:  100
  Total: $    436,379,859    Sim #:  150
  Total: $    840,198,876    Sim #:  200
  Total: $    153,282,620    Sim #:  250
  Total: $    965,363,770    Sim #:  300
  Total: $     75,210,190    Sim #:  350
  Total: $     67,622,075    Sim #:  400
  Total: $    212,509,329    Sim #:  450
  Total: $    732,367,521    Sim #:  500
  Total: $  1,283,415,667    Sim #:  550
  Total: $  1,309,813,428    Sim #:  600
  Total: $ 10,684,121,501    Sim #:  650
  Total: $     58,604,712    Sim #:  700
  Total: $    103,970,541    Sim #:  750
  Total: $  1,280,734,274    Sim #:  800
  Total: $    215,784,242    Sim #:  850
  Total: $  1,171,113,252    Sim #:  900
  Total: $    119,595,242    Sim #:  950
  Total: $    313,832,339    Sim #:1,000

Average: $    833,876,038
```

(**Click here to enlarge**)

I would get similar results if I ran the Python code again and again, 1000 simulations at a time. I would get similar averages over the 1000 simulations. Should you doubt that assertion, Figure #8 is another run of the same program under the same conditions.

I did not push further. I thought it was not necessary. Even a smaller number of trials would be sufficient to make the point. However, should you want to make more trials, you have the code in Figure #4.

You already have two runs of 1000 simulations, each taking a different path and having every trade type randomly selected.

Figures #7 and #8 might not look pretty, but they did the job.

Figure #8: Another 1000 Simulations Based On Figure #4 Code (15 Years).

Total: $	148,924,738	Sim #:	1
Total: $	2,289,908,899	Sim #:	50
Total: $	96,213,947	Sim #:	100
Total: $	185,697,144	Sim #:	150
Total: $	497,649,334	Sim #:	200
Total: $	1,292,186,183	Sim #:	250
Total: $	1,048,537,440	Sim #:	300
Total: $	367,692,888	Sim #:	350
Total: $	681,220,378	Sim #:	400
Total: $	810,413,642	Sim #:	450
Total: $	139,263,342	Sim #:	500
Total: $	141,814,246	Sim #:	550
Total: $	188,953,637	Sim #:	600
Total: $	361,364,386	Sim #:	650
Total: $	146,242,515	Sim #:	700
Total: $	279,402,276	Sim #:	750
Total: $	743,636,421	Sim #:	800
Total: $	1,306,013,959	Sim #:	850
Total: $	508,996,076	Sim #:	900
Total: $	321,629,892	Sim #:	950
Total: $	3,471,307,531	Sim #:	1,000
Average: $	853,581,880		

(**Click here to enlarge**)

You have two groups of 1000 simulations; all the results of the Python code of Figure #4. All 2000 outcomes are different, as should have been expected.

The 2000 simulations averaged over 800 million, far exceeding the WL8 simulation results. We have some entries near the WL8 results, but most are far from the WL8 expected average.

The data in Figures #7 and #8 suggests that the WL8 outcome might have been on the low side of estimates or that the variance is much more significant than anticipated.

It all depends on the return sequence from the random number generator. Which side would be favored more than expected by the trade-type statistics, positive or negative returns? The outcome of a random process remains random whether we like it or not.[10]

Nonetheless, Figures #7 and #8 are telling. I did not find it a surprise. I have stated before, in prior articles, that if we made future estimates based on the strategy's trade distribution, we would get higher results.

All the simulations were according to the equation (2). Figure #5 corroborates the outcome of Figure #4, which uses the portfolio's average simulation metrics.

---

[10] Review my book: **Gain Your Financial Freedom** where equation (2) is shown with adding and removing trades.

The strategy operates in a compounding return environment with a unique feature (Type-C trades) that might produce nothing but that nonetheless more than saves the day.

We are dealing with an exponential function as presented in equations (1) and (2). So, we expect that the lowest portfolio values will be at the beginning of the return sequence, while the highest will be near the end of the portfolio value series in the region approaching N.

Moreover, since we deal with exponential curves, the overall average will tend to increase as the portfolio value increases. Adding more trades will only push these averages higher.

THE OTHER FUTURE, THE ONE BEYOND THE SIMULATIONS

All the above simulations represented some past scenarios of what might have been. What we are often missing is a look forward at what our trading strategies could do going forward.

What could be the result if we projected 5 years in the future?

Going beyond the first 15 years presented in all the above simulations was easy. I modified the Figure #4 code to add 5 years to the simulation. It was sufficient to increase the number of trades ($N = 780 + 260$), giving it 5 more years of doing the same things as it did in the first 15 years.

Figure #9: Another 1000 Simulations Using Same Code Over 20 Years.

Total: $	14,656,874,621	Sim #:	1
Total: $	4,983,781,967	Sim #:	50
Total: $	11,880,809,102	Sim #:	100
Total: $	753,465,236	Sim #:	150
Total: $	11,092,246,382	Sim #:	200
Total: $	9,227,383,245	Sim #:	250
Total: $	2,767,069,235	Sim #:	300
Total: $	4,191,230,988	Sim #:	350
Total: $	4,359,129,378	Sim #:	400
Total: $	37,919,970,249	Sim #:	450
Total: $	15,639,852,313	Sim #:	500
Total: $	18,033,749,942	Sim #:	550
Total: $	22,564,107,991	Sim #:	600
Total: $	30,133,710,405	Sim #:	650
Total: $	61,201,905,294	Sim #:	700
Total: $	11,940,877,497	Sim #:	750
Total: $	1,447,981,282	Sim #:	800
Total: $	783,248,014	Sim #:	850
Total: $	13,953,180,065	Sim #:	900
Total: $	7,009,742,732	Sim #:	950
Total: $	1,057,518,099	Sim #:	1,000

Average: $ 18,133,502,676

(**Click here to enlarge**)

Figure #9 is another simulation covering 1000 simulations with an added 5 years.

We are interested in the last line, which is the average of those 1000 simulations.

An interesting question might be: which scenario would you not take?

The OPPW trading strategy is impressive. All the presented scenarios obeyed equation (2), which explicitly is a compounding return equation based on the WL8 portfolio metrics in Figure #5.

You can make it big, as I have said many times, but it is all up to you. Do not take this for granted. Do your homework, and verify it all. You need to have the conviction and determination to stay the course. It is all in your hands.

I transformed a stock trading strategy into a quasi-casino game (MGLCG) where the odds are definitely in your favor (Refer to equation (2) and Figure #3). What is required in this compounding betting system is that you play for the long haul.

Playing a 3x-leveraged ETF scenario will be volatile. You will have ups and downs. Based on Table #1, you will still have, on average, about 20% losing trades (1 in 5) and 28% generating absolutely nothing (Type-C trades). So, yes, the ride will be bumpy.

But the overall return will be worthwhile and more than compensate for whatever the uneasy ride you might have. In the end, every dip will be recuperated and exceeded. It is the outcome of a random walk on an exponential curve.

The market, in general, will not change that much over the coming years. By that meaning, it will continue to fluctuate up and down as if sailing in a tumultuous sea of variance.

With its compounding feature, equation (2) assures you that you will not get down to zero and that, with time, you will always make new highs portfolio-wise. TQQQ is based on QQQ, and this gives it its prospects. QQQ will rise in the future, and so will TQQQ. In a way, the TQQQ strategy is making a long-term bet on America and that there will be more prosperity in the future, not less.

Regardless, this strategy needs to become your game, your method of play. As I have said before, you can easily override the trading procedures anytime and at any time. If you do not think prices might go up next week, let that week pass by. You are not in the market over weekends.

You have no obligation to take a trade on the first trading day of the week. Not only that, but you can also add new trading procedures to the code if you want to. One change I highly recommend is adding more downside protection, such as procedures to reduce the impact of Type-D trades.

Any money you do not lose in trading is money in the bank.

OTHER SCENARIOS TO CONSIDER

I performed simulations over 15 years of randomly generated data based on the WL8 portfolio metrics trading the TQQQ ETF. I extracted the statistics of the strategy's trading behavior and classified the trading procedures by types of outcomes. Due to the large number of trades, those trade-type statistics could serve as persistent long-term averages.[11]

Figure #9 even ventured 5 years forward, looking at what might be the estimated average outcome based on the same trade distribution metrics as all the other presented simulations. All simulations following equation (2) as given in the program code in Figure #4.

Equation (2) deals with the usual average portfolio metrics given in our WL8 simulations. Most often, strategies lack the number of executed trades, as illustrated in Figure #2 above. With a larger number of trades, we might assume that some of those portfolio metrics approach their long-term averages, which can serve as probable and sustainable trends.

Stating that a strategy with a large number of trades might behave in the future as it did in the past.

We can advance this, especially if all the trades are quasi-randomly distributed. And this is exactly what the Python program in Figure #4 does.

We have 4 trade types, but the boundaries are not what might have been a 0.25 expectancy for each. From Table #1, the trade type distribution is concentrated in the Type-B and Type-C trades (some 62.77%). That is close enough to the 66%, within $\pm\sigma$ of a normal distribution.

Due to the long-term upward bias in stock prices, we have, from Table #1, trades of Type-B at 34.69% exceeding trades of Type-C (28.38%). It also corroborates the +1% average return per trade of the distribution (see Figure #3, the horizontal cyan line).

With our inability to predict with certainty what next week's outcome will be, we are forced to take all the bets as if quasi-randomly generated. We know we will have one of the four trade types by the close every Friday, whatever happens during the week. We do not know in advance which trade type will prevail. It is the reason for taking all the bets in the first place.

[11] This was presented in the articles: **One Percent Per Week Strategy: Some Trading Habits**, and **One Percent Per Week Strategy: Trade Distribution**.

Notwithstanding, it should not stop anyone from overriding the program and injecting our view into the trading process. After all, it will be your money that will be on the line. And stepping aside once in a while will not make that much of a difference. If you step aside from what could be a Type-C trade, there would be no loss at all; already, that represents some 28.38% of trades.

I wanted to extract long-term portfolio averages using the code in Figure #4. I could easily add or subtract simulation years and add more simulations. You have 52 trades per year; therefore, to add one year to a simulation, you increase N by 52, and job done.

To have more than the 1000 simulated scenarios, add more. In the following simulations, I will go with 10,000 simulations at a time and display multiples of 500 to show some of the variations in outcome.

None of the simulations will be the same, and none will be repeatable since no starting seed is used. Every trade sequence in any of the simulations will be different, independent of their past, future, or siblings. Each simulation is taking its own path. Each has its own series of gains and losses.

Figure #10: 10,000 Simulations over the 15 years of simulated data.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.
 Total: $     190,669,620  Sim #:     1  (A: 136, B: 251, C: 231, D: 162)  CAGR:  65.46 %
 Total: $     215,218,349  Sim #:   500  (A: 117, B: 289, C: 220, D: 154)  CAGR:  66.80 %
 Total: $   1,371,815,458  Sim #: 1,000  (A: 133, B: 282, C: 224, D: 141)  CAGR:  88.72 %
 Total: $     433,226,902  Sim #: 1,500  (A: 143, B: 258, C: 218, D: 161)  CAGR:  74.76 %
 Total: $     126,100,646  Sim #: 2,000  (A: 110, B: 273, C: 251, D: 146)  CAGR:  60.96 %
 Total: $     145,192,662  Sim #: 2,500  (A: 128, B: 261, C: 230, D: 161)  CAGR:  62.48 %
 Total: $      64,057,605  Sim #: 3,000  (A: 112, B: 278, C: 228, D: 162)  CAGR:  53.85 %
 Total: $      98,065,217  Sim #: 3,500  (A: 117, B: 277, C: 225, D: 161)  CAGR:  58.28 %
 Total: $     273,567,797  Sim #: 4,000  (A: 123, B: 277, C: 228, D: 152)  CAGR:  69.49 %
 Total: $     170,899,603  Sim #: 4,500  (A: 118, B: 291, C: 211, D: 160)  CAGR:  64.25 %
 Total: $     550,720,883  Sim #: 5,000  (A: 134, B: 261, C: 238, D: 147)  CAGR:  77.58 %
 Total: $     640,098,687  Sim #: 5,500  (A: 139, B: 259, C: 232, D: 150)  CAGR:  79.37 %
 Total: $     505,048,434  Sim #: 6,000  (A: 135, B: 272, C: 218, D: 155)  CAGR:  76.56 %
 Total: $   1,597,826,200  Sim #: 6,500  (A: 143, B: 273, C: 217, D: 147)  CAGR:  90.65 %
 Total: $       7,994,718  Sim #: 7,000  (A: 111, B: 254, C: 232, D: 183)  CAGR:  33.92 %
 Total: $     439,545,490  Sim #: 7,500  (A: 132, B: 267, C: 230, D: 151)  CAGR:  74.93 %
 Total: $     568,974,565  Sim #: 8,000  (A: 131, B: 268, C: 235, D: 146)  CAGR:  77.97 %
 Total: $     182,501,040  Sim #: 8,500  (A: 128, B: 277, C: 210, D: 165)  CAGR:  64.97 %
 Total: $     520,915,650  Sim #: 9,000  (A: 148, B: 253, C: 217, D: 162)  CAGR:  76.92 %
 Total: $     360,014,724  Sim #: 9,500  (A: 136, B: 260, C: 228, D: 156)  CAGR:  72.62 %
 Total: $     430,466,889  Sim #:10,000  (A: 138, B: 269, C: 213, D: 160)  CAGR:  74.69 %

Average: $     854,829,785    CAGR:  82.86 %
```

(**Click here to enlarge**)

I added more information in these simulations, especially the trade type distribution. Also provided the achieved CAGR at the end of each simulation, again showing the result for simulations multiples of 500. I was not to list all 10,000 simulations. The attention should be on the Total column and the 10,000 simulations average shown at the bottom of the chart.

If I reran the program, I would get totally different answers for all 10,000 simulations. However, my interest would still be the last line, where we have the average for the 10,000 trials and the average achieved CAGR.

Figure #11 is not that much different from Figure #10. The long-term averages persisted, as they should have. The 10,000 simulations made 7.8 million bets at the opening of the first trading day of each week. It is more than enough to state that the average outcome of such a test would be close to the statistical mean of the distribution.

Figure #11: Another 10,000 Simulations over the 15 years of data.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 15 years using randomly selected trades based on WL8 sim metrics.
 Total: $     335,939,931  Sim #:     1  (A: 138, B: 271, C: 206, D: 165)  CAGR:  71.82 %
 Total: $     789,719,281  Sim #:   500  (A: 125, B: 295, C: 214, D: 146)  CAGR:  81.90 %
 Total: $     425,088,206  Sim #: 1,000  (A: 143, B: 247, C: 234, D: 156)  CAGR:  74.54 %
 Total: $     239,107,382  Sim #: 1,500  (A: 120, B: 268, C: 246, D: 146)  CAGR:  67.97 %
 Total: $     131,527,569  Sim #: 2,000  (A: 125, B: 276, C: 213, D: 166)  CAGR:  61.41 %
 Total: $     277,757,695  Sim #: 2,500  (A: 129, B: 274, C: 219, D: 158)  CAGR:  69.66 %
 Total: $     363,689,836  Sim #: 3,000  (A: 135, B: 263, C: 226, D: 156)  CAGR:  72.74 %
 Total: $     207,419,999  Sim #: 3,500  (A: 125, B: 281, C: 213, D: 161)  CAGR:  66.39 %
 Total: $   1,800,572,248  Sim #: 4,000  (A: 135, B: 290, C: 212, D: 143)  CAGR:  92.17 %
 Total: $     398,945,731  Sim #: 4,500  (A: 118, B: 274, C: 250, D: 138)  CAGR:  73.80 %
 Total: $     261,561,796  Sim #: 5,000  (A: 122, B: 274, C: 234, D: 150)  CAGR:  68.98 %
 Total: $     106,638,046  Sim #: 5,500  (A: 135, B: 261, C: 209, D: 175)  CAGR:  59.17 %
 Total: $     151,420,216  Sim #: 6,000  (A: 117, B: 273, C: 238, D: 152)  CAGR:  62.93 %
 Total: $     426,473,761  Sim #: 6,500  (A: 131, B: 279, C: 214, D: 156)  CAGR:  74.58 %
 Total: $     381,197,841  Sim #: 7,000  (A: 136, B: 264, C: 223, D: 157)  CAGR:  73.28 %
 Total: $     422,046,425  Sim #: 7,500  (A: 136, B: 255, C: 238, D: 151)  CAGR:  74.46 %
 Total: $   2,025,603,717  Sim #: 8,000  (A: 148, B: 276, C: 205, D: 151)  CAGR:  93.69 %
 Total: $     435,114,021  Sim #: 8,500  (A: 128, B: 269, C: 236, D: 147)  CAGR:  74.81 %
 Total: $      38,506,299  Sim #: 9,000  (A: 111, B: 278, C: 222, D: 169)  CAGR:  48.72 %
 Total: $     255,054,343  Sim #: 9,500  (A: 138, B: 270, C: 203, D: 169)  CAGR:  68.70 %
 Total: $   1,094,909,252  Sim #:10,000  (A: 126, B: 293, C: 220, D: 141)  CAGR:  85.91 %

Average: $     861,861,207    CAGR:  82.96 %
```

(**Click here to enlarge**)

Nonetheless, I want to go beyond Figures #10 and #11.

The question is: What would those two charts look like if we added one year to the 10,000 simulations?

What we should expect is more of the same.

We would add 52 trades over a year, with a probable hit rate of 51.65%, just as with the WL8 simulation.

We should, therefore, expect 26.86 winning and 25.14 losing trades. It's not a significant advantage (one trade and a half over 52 weeks).

Figure #12 does put emphasis on the value of that one more year.

Figure #12: 10,000 Simulations over 16 years of randomly generated data.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 16 years using randomly selected trades based on WL8 sim metrics.
 Total: $     162,898,738  Sim #:     1  (A: 145, B: 257, C: 251, D: 179)  CAGR:  58.76 %
 Total: $     237,882,373  Sim #:   500  (A: 129, B: 304, C: 224, D: 175)  CAGR:  62.56 %
 Total: $     277,815,734  Sim #: 1,000  (A: 140, B: 280, C: 237, D: 175)  CAGR:  64.15 %
 Total: $     370,945,998  Sim #: 1,500  (A: 137, B: 277, C: 253, D: 165)  CAGR:  67.14 %
 Total: $     197,939,400  Sim #: 2,000  (A: 130, B: 291, C: 238, D: 173)  CAGR:  60.71 %
 Total: $     933,394,931  Sim #: 2,500  (A: 145, B: 291, C: 229, D: 167)  CAGR:  77.06 %
 Total: $   1,623,995,676  Sim #: 3,000  (A: 152, B: 289, C: 225, D: 166)  CAGR:  83.30 %
 Total: $     257,729,905  Sim #: 3,500  (A: 133, B: 294, C: 231, D: 174)  CAGR:  63.38 %
 Total: $     258,960,693  Sim #: 4,000  (A: 144, B: 267, C: 246, D: 175)  CAGR:  63.43 %
 Total: $   3,718,864,373  Sim #: 4,500  (A: 147, B: 295, C: 241, D: 149)  CAGR:  93.04 %
 Total: $   1,468,417,246  Sim #: 5,000  (A: 149, B: 277, C: 248, D: 158)  CAGR:  82.15 %
 Total: $   7,046,168,054  Sim #: 5,500  (A: 150, B: 292, C: 249, D: 141)  CAGR: 100.91 %
 Total: $   1,894,722,641  Sim #: 6,000  (A: 146, B: 306, C: 216, D: 164)  CAGR:  85.07 %
 Total: $   7,967,604,279  Sim #: 6,500  (A: 150, B: 292, C: 251, D: 139)  CAGR: 102.46 %
 Total: $     937,351,218  Sim #: 7,000  (A: 155, B: 277, C: 227, D: 173)  CAGR:  77.11 %
 Total: $     570,152,603  Sim #: 7,500  (A: 142, B: 301, C: 213, D: 176)  CAGR:  71.69 %
 Total: $     885,283,417  Sim #: 8,000  (A: 150, B: 278, C: 236, D: 168)  CAGR:  76.48 %
 Total: $   2,331,853,999  Sim #: 8,500  (A: 146, B: 313, C: 209, D: 164)  CAGR:  87.49 %
 Total: $     823,016,910  Sim #: 9,000  (A: 148, B: 285, C: 229, D: 170)  CAGR:  75.68 %
 Total: $   1,574,454,778  Sim #: 9,500  (A: 149, B: 298, C: 218, D: 167)  CAGR:  82.95 %
 Total: $   1,184,911,667  Sim #:10,000  (A: 143, B: 294, C: 233, D: 162)  CAGR:  79.72 %

Average: $   1,680,431,446    CAGR:  83.69 %
```

(**Click here to enlarge**)

With a 1% expected average profit per week, we should see the portfolio increase in value by some 67% since $(1+0.01)^{52} = 1.6777$. It would help to maintain the average CAGR given in Figures #10 and #11.

Figure #12 above shows the impact of adding one year to the simulation. The program did not change. All that was requested was to do the same thing it did for the prior 15 years. Adding 52 to N, the number of trades, was sufficient to do the job.

Was the added year worth it? The answer should be yes, no doubt.

It is not the beginning that matters the most; it is in the last few years that the strategy will be in operation.

The added year is at the end of a compounding return series. And that is why it is so productive.

For example, adding another year, having those 10,000 simulations over 17 years, we should also see an average increase in performance, as shown in Figure #13 below. Even the average CAGR increased a bit, just as it had in Figure #12.

The program in Figure #4 did not know the $\pm\%$ return it would get from week to week in the above simulations. However, you had expectations that, on average, the outcome would tend to its long-term averages acquired from years of accumulating data.

Figure #13: 10,000 Simulations over 17 years of randomly generated trades.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 17 years using randomly selected trades based on WL8 sim metrics.
 Total: $     302,207,797  Sim #:     1  (A: 139, B: 300, C: 263, D: 182)  CAGR:  60.22 %
 Total: $     279,740,008  Sim #:   500  (A: 147, B: 301, C: 242, D: 194)  CAGR:  59.50 %
 Total: $   1,452,025,773  Sim #: 1,000  (A: 148, B: 300, C: 268, D: 168)  CAGR:  75.72 %
 Total: $   1,351,905,963  Sim #: 1,500  (A: 170, B: 293, C: 227, D: 194)  CAGR:  74.98 %
 Total: $   5,422,485,397  Sim #: 2,000  (A: 168, B: 312, C: 226, D: 178)  CAGR:  89.88 %
 Total: $   6,705,689,454  Sim #: 2,500  (A: 169, B: 302, C: 242, D: 171)  CAGR:  92.27 %
 Total: $  10,901,840,472  Sim #: 3,000  (A: 171, B: 311, C: 232, D: 170)  CAGR:  97.84 %
 Total: $   1,924,323,620  Sim #: 3,500  (A: 143, B: 329, C: 241, D: 171)  CAGR:  78.66 %
 Total: $   8,215,633,317  Sim #: 4,000  (A: 163, B: 302, C: 259, D: 160)  CAGR:  94.58 %
 Total: $   2,445,926,982  Sim #: 4,500  (A: 159, B: 307, C: 241, D: 177)  CAGR:  81.19 %
 Total: $     565,730,646  Sim #: 5,000  (A: 149, B: 307, C: 240, D: 188)  CAGR:  66.24 %
 Total: $     359,037,108  Sim #: 5,500  (A: 141, B: 315, C: 239, D: 189)  CAGR:  61.85 %
 Total: $   3,002,959,003  Sim #: 6,000  (A: 163, B: 295, C: 253, D: 173)  CAGR:  83.39 %
 Total: $     749,570,699  Sim #: 6,500  (A: 138, B: 325, C: 243, D: 178)  CAGR:  69.02 %
 Total: $     170,324,509  Sim #: 7,000  (A: 151, B: 284, C: 250, D: 199)  CAGR:  54.91 %
 Total: $     564,535,491  Sim #: 7,500  (A: 144, B: 314, C: 241, D: 185)  CAGR:  66.22 %
 Total: $   1,620,451,223  Sim #: 8,000  (A: 162, B: 281, C: 266, D: 175)  CAGR:  76.86 %
 Total: $   1,542,007,246  Sim #: 8,500  (A: 145, B: 310, C: 261, D: 168)  CAGR:  76.34 %
 Total: $  20,267,777,068  Sim #: 9,000  (A: 174, B: 297, C: 256, D: 157)  CAGR: 105.19 %
 Total: $   8,948,389,160  Sim #: 9,500  (A: 175, B: 302, C: 233, D: 174)  CAGR:  95.56 %
 Total: $   3,666,341,950  Sim #:10,000  (A: 159, B: 302, C: 255, D: 168)  CAGR:  85.56 %

Average: $   3,101,214,860    CAGR:  83.74 %
```

(**Click here to enlarge**)

On the same principle for adding years to the simulations, we could remove some years to see what might have been the outcome if you ran the program for less than 15 years.

Figure #14 below is an example with only 14 years of simulated trades, again based on equation (2).

If you reduced the number of years again and made those 10,000 simulations over 13 years, you would get more of the same as in Figure #14, meaning a lesser outcome and a slightly lower average CAGR.

To make the point, Figure #15 below is such a simulation over only 13 years.

We made over 60,000 simulations based on the program in Figure #4, and yet, we would be hard-pressed to find an iteration in all those 13+ year simulations that would be undesirable. Even the worst scenario would be welcomed in any portfolio. Take a look at the CAGR column in those simulations.

Even though the simulations show only 21 occurrences out of 10,000, the sample remains representative of the whole and gives us a view of its wide range of outcomes. Overall, the expected average portfolio should come close to the average shown on the bottom line of each figure.

There should be no need to restate that this strategy's trading rules are so simple you can execute them on your phone from anywhere. A few minutes a week would be sufficient to manage it all.

Figure #14: 10,000 Simulations over the 14 years of quasi-randomly trading.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 14 years using randomly selected trades based on WL8 sim metrics.
 Total: $     943,011,166  Sim #:     1  (A: 128, B: 264, C: 204, D: 132)  CAGR:  92.26 %
 Total: $      17,867,367  Sim #:   500  (A: 113, B: 224, C: 233, D: 158)  CAGR:  44.83 %
 Total: $     122,089,185  Sim #: 1,000  (A: 109, B: 287, C: 180, D: 152)  CAGR:  66.14 %
 Total: $     110,925,434  Sim #: 1,500  (A: 107, B: 258, C: 226, D: 137)  CAGR:  65.01 %
 Total: $      66,499,953  Sim #: 2,000  (A: 110, B: 268, C: 196, D: 154)  CAGR:  59.09 %
 Total: $     209,873,645  Sim #: 2,500  (A: 127, B: 245, C: 210, D: 146)  CAGR:  72.70 %
 Total: $     662,391,528  Sim #: 3,000  (A: 134, B: 232, C: 232, D: 130)  CAGR:  87.47 %
 Total: $     188,861,453  Sim #: 3,500  (A: 118, B: 255, C: 214, D: 141)  CAGR:  71.40 %
 Total: $      99,525,562  Sim #: 4,000  (A: 101, B: 262, C: 232, D: 133)  CAGR:  63.73 %
 Total: $     847,888,593  Sim #: 4,500  (A: 127, B: 261, C: 209, D: 131)  CAGR:  90.81 %
 Total: $     318,313,286  Sim #: 5,000  (A: 125, B: 254, C: 208, D: 141)  CAGR:  77.91 %
 Total: $     170,312,767  Sim #: 5,500  (A: 114, B: 258, C: 217, D: 139)  CAGR:  70.14 %
 Total: $     255,072,166  Sim #: 6,000  (A: 127, B: 235, C: 228, D: 138)  CAGR:  75.12 %
 Total: $   1,479,620,343  Sim #: 6,500  (A: 126, B: 270, C: 207, D: 125)  CAGR:  98.55 %
 Total: $     373,437,212  Sim #: 7,000  (A: 137, B: 242, C: 201, D: 148)  CAGR:  79.95 %
 Total: $     184,265,494  Sim #: 7,500  (A: 130, B: 243, C: 204, D: 151)  CAGR:  71.10 %
 Total: $     216,311,479  Sim #: 8,000  (A: 123, B: 238, C: 230, D: 137)  CAGR:  73.07 %
 Total: $     185,214,439  Sim #: 8,500  (A: 117, B: 257, C: 213, D: 141)  CAGR:  71.16 %
 Total: $   1,461,030,046  Sim #: 9,000  (A: 146, B: 233, C: 216, D: 133)  CAGR:  98.37 %
 Total: $      74,275,647  Sim #: 9,500  (A: 116, B: 262, C: 193, D: 157)  CAGR:  60.35 %
 Total: $      86,029,577  Sim #:10,000  (A: 123, B: 267, C: 172, D: 166)  CAGR:  62.04 %

Average: $     457,343,766    CAGR:  82.58 %
```

(**Click here to enlarge**)

Figure #15: 10,000 Simulations over 13 years.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 13 years using randomly selected trades based on WL8 sim metrics.
 Total: $     173,206,827  Sim #:     1  (A: 113, B: 226, C: 215, D: 122)  CAGR:  77.47 %
 Total: $      76,858,867  Sim #:   500  (A: 121, B: 225, C: 185, D: 145)  CAGR:  66.72 %
 Total: $      34,697,037  Sim #: 1,000  (A: 109, B: 228, C: 195, D: 144)  CAGR:  56.82 %
 Total: $      34,639,818  Sim #: 1,500  (A: 120, B: 207, C: 201, D: 148)  CAGR:  56.80 %
 Total: $      59,411,091  Sim #: 2,000  (A: 108, B: 226, C: 209, D: 133)  CAGR:  63.45 %
 Total: $     277,783,596  Sim #: 2,500  (A: 113, B: 244, C: 196, D: 123)  CAGR:  84.04 %
 Total: $     162,705,872  Sim #: 3,000  (A: 116, B: 247, C: 176, D: 137)  CAGR:  76.62 %
 Total: $      84,195,948  Sim #: 3,500  (A: 106, B: 241, C: 197, D: 132)  CAGR:  67.89 %
 Total: $   1,225,894,001  Sim #: 4,000  (A: 132, B: 256, C: 159, D: 129)  CAGR: 106.30 %
 Total: $     173,626,017  Sim #: 4,500  (A: 109, B: 245, C: 196, D: 126)  CAGR:  77.50 %
 Total: $     335,152,281  Sim #: 5,000  (A: 131, B: 217, C: 198, D: 130)  CAGR:  86.71 %
 Total: $     647,369,953  Sim #: 5,500  (A: 125, B: 251, C: 172, D: 128)  CAGR:  96.41 %
 Total: $     136,551,912  Sim #: 6,000  (A: 112, B: 231, C: 206, D: 127)  CAGR:  74.25 %
 Total: $      89,794,625  Sim #: 6,500  (A: 108, B: 242, C: 192, D: 134)  CAGR:  68.72 %
 Total: $      70,524,130  Sim #: 7,000  (A: 118, B: 228, C: 186, D: 144)  CAGR:  65.62 %
 Total: $     441,921,967  Sim #: 7,500  (A: 124, B: 247, C: 174, D: 131)  CAGR:  90.73 %
 Total: $     183,688,305  Sim #: 8,000  (A: 117, B: 236, C: 192, D: 131)  CAGR:  78.27 %
 Total: $      70,527,426  Sim #: 8,500  (A: 108, B: 238, C: 194, D: 136)  CAGR:  65.62 %
 Total: $      41,719,032  Sim #: 9,000  (A: 119, B: 218, C: 190, D: 149)  CAGR:  59.06 %
 Total: $     208,769,375  Sim #: 9,500  (A: 114, B: 240, C: 195, D: 127)  CAGR:  80.04 %
 Total: $     554,458,310  Sim #:10,000  (A: 119, B: 241, C: 198, D: 118)  CAGR:  94.08 %

Average: $     246,809,163    CAGR:  82.37 %
```

(**Click here to enlarge**)

For sure, the market will swing up and down, often throwing us curve balls and surprises of all types, like black swans with gaps up and down.

But all of it does not matter so much if your trading strategy can survive over the long haul.

Any downside damage is limited to the price variation over one week. There is a time limit on all those trades.

All you can get is the percent variation over a single week. Every Friday, at the close, you are back in cash.

At a minimum, all these simulations show we have to put in the time.

You are on a compounding return curve and your average long-term CAGR counts. The future value formula: $F_0 \cdot (1 + \bar{g})^t$ still applies; $\bar{g}$ and t are major components in the outcome.

Again, it is not your beginning CAGR that matters; it is the overall CAGR you will reach at time t, whether in 10, 15, 20, or more years.

Even a 10-year scenario would be welcomed. It should produce less than over the 13, 14, 15, 16, 17, and 20 years. Nonetheless, it would still be enviable for any investor hoping to build a retirement fund. See Figure #16 below, which will make the point with its 10-year simulation.

Figure #16: 10,000 Simulations over the 10 years of data.

```
WL8 Sim $      86,642,514  Sim Feb. 21   (A: 135, B: 269, C: 222, D: 156)  CAGR:  56.86 %

# of Sims: 10,000 over 10 years using randomly selected trades based on WL8 sim metrics.
 Total: $      36,802,704  Sim #:     1  (A:  86, B: 173, C: 174, D:  87)  CAGR:  80.55 %
 Total: $       6,131,049  Sim #:   500  (A:  87, B: 170, C: 147, D: 116)  CAGR:  50.92 %
 Total: $       3,752,044  Sim #: 1,000  (A:  88, B: 157, C: 156, D: 119)  CAGR:  43.69 %
 Total: $       6,464,247  Sim #: 1,500  (A:  82, B: 183, C: 140, D: 115)  CAGR:  51.72 %
 Total: $       9,489,500  Sim #: 2,000  (A:  88, B: 180, C: 137, D: 115)  CAGR:  57.66 %
 Total: $       6,637,342  Sim #: 2,500  (A:  89, B: 157, C: 163, D: 111)  CAGR:  52.12 %
 Total: $       9,366,359  Sim #: 3,000  (A:  82, B: 181, C: 149, D: 108)  CAGR:  57.46 %
 Total: $      12,489,041  Sim #: 3,500  (A:  86, B: 178, C: 149, D: 107)  CAGR:  62.05 %
 Total: $      18,709,233  Sim #: 4,000  (A: 100, B: 171, C: 134, D: 115)  CAGR:  68.74 %
 Total: $      17,837,090  Sim #: 4,500  (A:  82, B: 182, C: 158, D:  98)  CAGR:  67.93 %
 Total: $       8,834,162  Sim #: 5,000  (A:  79, B: 187, C: 146, D: 108)  CAGR:  56.54 %
 Total: $      19,274,183  Sim #: 5,500  (A:  80, B: 192, C: 149, D:  99)  CAGR:  69.24 %
 Total: $      21,556,406  Sim #: 6,000  (A:  89, B: 176, C: 154, D: 101)  CAGR:  71.14 %
 Total: $      78,825,350  Sim #: 6,500  (A:  94, B: 194, C: 137, D:  95)  CAGR:  94.83 %
 Total: $      17,045,563  Sim #: 7,000  (A:  75, B: 197, C: 151, D:  97)  CAGR:  67.17 %
 Total: $     178,204,945  Sim #: 7,500  (A:  89, B: 212, C: 135, D:  84)  CAGR: 111.39 %
 Total: $      43,744,678  Sim #: 8,000  (A:  99, B: 165, C: 159, D:  97)  CAGR:  83.69 %
 Total: $      18,241,656  Sim #: 8,500  (A:  85, B: 181, C: 153, D: 101)  CAGR:  68.31 %
 Total: $      57,296,987  Sim #: 9,000  (A:  91, B: 185, C: 152, D:  92)  CAGR:  88.72 %
 Total: $      95,518,865  Sim #: 9,500  (A:  97, B: 178, C: 157, D:  88)  CAGR:  98.61 %
 Total: $       5,719,593  Sim #:10,000  (A:  88, B: 165, C: 151, D: 116)  CAGR:  49.88 %

Average: $      33,166,372    CAGR:  78.68 %
```

(**Click here to enlarge**)

We have to go for what counts.

My version of the OPPW trading strategy is not unique. There are many more.

You can improve this strategy to make it even more productive. One interesting path would be reducing the impact of the Type-D trades, even if they only represent 20% of the trades. It also implies that 80% of trades will not harm your portfolio. Nonetheless, only 51.65% of those trades are expected to generate a profit.

It is simple. As I mentioned more than once, do your homework. Take the time to verify every aspect of this trading strategy. It should serve as a good starting point. Keep an eye on your long-term objectives; they can be met. At least you can start with an example to work with that can do the job. Also, trying to improve this strategy should not be that difficult.

OVER THE BEGINNING YEARS

I also wanted to see how the strategy would evolve over the years. So, I made the following simulations, starting from year one and adding one year at a time.

Figure #17: 10,000 Simulations per year with cumulative average portfolio values.

10,000 Simulations By Years		
Year	Portfolio Value	Average CAGR (%)
0	100,000	
1	98,978	-1.02
2	188,747	37.39
3	366,383	54.16
4	694,567	62.34
5	1,314,041	67.39
6	2,525,654	71.29
7	4,908,618	74.41
8	9,127,739	75.81
9	17,771,487	77.82
10	33,088,035	78.64
11	64,512,098	80.06
12	121,740,057	80.77
13	235,456,331	81.71
14	458,373,780	82.61
15	854,466,474	82.86
16	1,628,488,544	83.33
17	3,092,092,967	83.71
18	5,831,631,221	83.98
19	11,183,655,712	84.38
20	22,246,559,452	85.08

Each line on this chart is the average of 10,000 simulations based on equation (2).

(**Click here to enlarge**)

In the above scenarios (Figure #17), for each year, I made 10,000 simulations while increasing the number of years. I did not intend to present 20 more charts like those above, so I only recorded the last line, which gave the overall average expected profit and the achieved CAGR (over those 10,000 simulations).

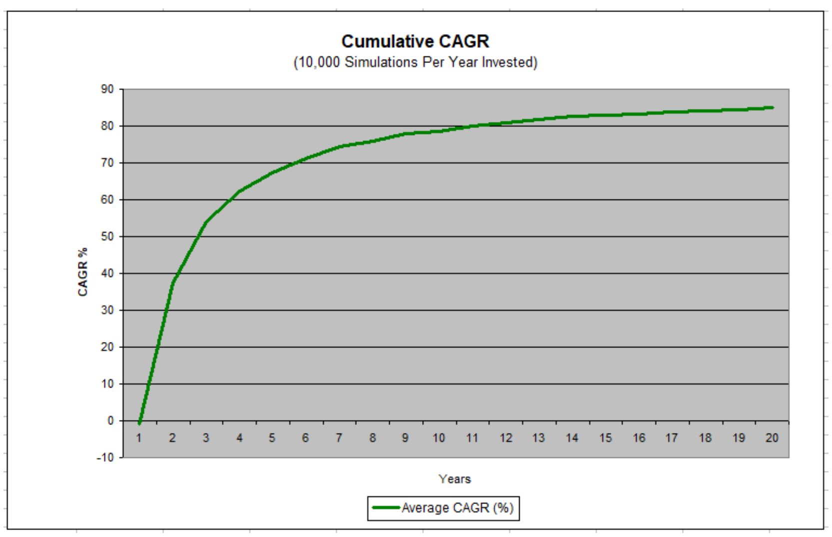
What is remarkable in Figure #17 is the CAGR column increasing year-over-year. Year 1 started with a negative average return, small but still negative. That was a surprise, but it should have been ”almost” expected.

Over one year, the strategy is expected to have only one trade and a half advantage. The expected hit rate would still be 51.65%. However, with the second year, things improved return-wise; from there, the strategy never looked back.

As we were adding years to the strategy in Figure #4, the overall CAGR increased. Figure #18 below is a visualization of the CAGR column in Figure #17. This chart states it is a good idea to stay on course for one more year, no matter which year you are on.

You have an exponentially growing portfolio.

Figure #18: 10,000 Simulations per year cumulative.



(**Click here to enlarge**)

Figures #17 and #18 are revealing. The average increase year-over-year in Figure #17 is about 90%. Sure, the CAGR appears to take off and slow down with years, but it operates at such a high level that it makes it even more remarkable. A stock trading strategy operating over 20 years at this level is outstanding.

I see my version of this trading strategy as amazing. It requires little time and can generate long-term returns way above the market’s long-term averages. All that is needed is to follow the simple trading recipe provided.

It is all based on my equation (2) for this trading strategy. I pushed the machine into a quasi-random trading environment. From the 15-year WL8 portfolio metrics, I used its long-term averages as a basis for these trading simulations.

The worst thing a trading strategy has to survive is a randomly generated long-term series of price variations. In this case, I was able to show that equation (2) prevailed even over 20 years of random-like price fluctuations where we could not, from week to week, predict what the profit or loss would be, if any.

In Figure #18, the green line appears smooth; it is the expression of the average for up to that year. We should see a vertical line with 10,000 dots for each year up to year 20.

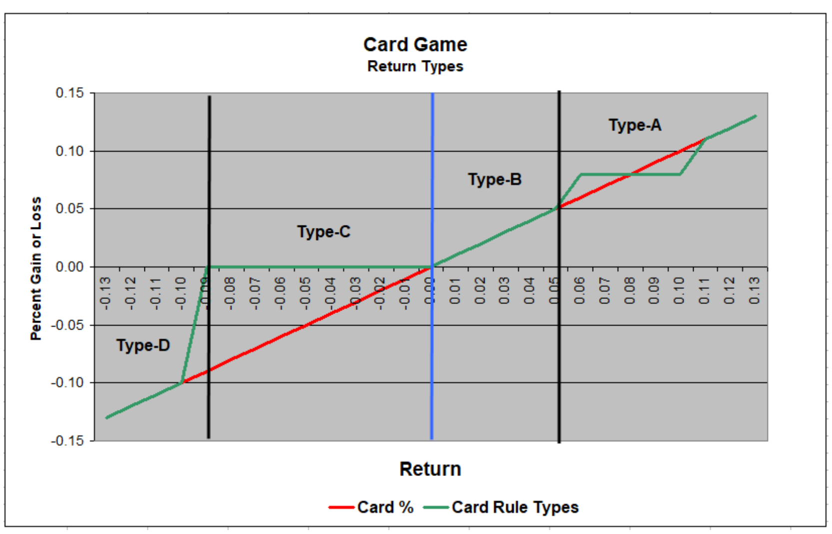
Each year, we get a bell-shaped curve with its highest density centered on the green line. There would be about 51.65% of dots above the green line and the rest below it. Even with that slight edge, the results are more than remarkable.

It is not because this strategy is free that it is not worth it. All I want to say is that you can make it and make it big. It is all in your hands.

ONE MORE THING

Remember the generic card game (MGLCG) I designed in the beginning? Figure #19 represents the play's distribution. Each return is selected at random (expecting 50% positive and 50% negative). The playing rules transformed the outcome of the expected red line into that of the expected green line. The chart is similar to Figure #3, with the same distribution for its trade types.

Figure #19: Generic Card Game Hand Types.



(**Click here to enlarge**)

In the card game (MGLCG), with its play statistics, we could determine the game's performance either before or after a number of plays. All the probabilities could be predetermined before engaging in the game.

Anyone could use the statistics of the game to predict its most expected future outcome. We had percent move limits, just as the trading strategy had percent time limits (at most one week).

If the card game statistics and its game equation can be used to predict its future outcome, then why, using the same methods, should we not be able to apply the same technique using equation (2)?

Notice that in the card game, you cannot lose if you play a sufficiently high number of hands, and that limit is not in the thousands but in the few hundred and even less.

I used the same structure as equation (2) for the card game and set the exposure to 1.0 ($\bar{e} = 1.0$). It was expected all future plays would respond to the same equation as its past distribution. We have the same phenomenon taking place in the TQQQ trading strategy.

The trading rules of my version of the TQQQ trading strategy will apply in the future just as they did in the past. And equation (2), which stood for the 15-year representation of the WL8 simulation, should also survive for a few more years. For more on the trade distribution, refer to my free book: **Gain Your Financial Freedom**.

Figure #18 tells you that persevering and maintaining the course over the long haul is the way to go, and Figure #17 puts a value on those efforts, as expressed by all those 156 million trades required to make that chart.

We all dream of having enough money for when we will retire. We are usually ready to make sacrifices and save some money for our old age. But we also find it hard to make our savings prosper in a meaningful way.

The demonstrated strategy's structure has nothing extraordinary. But, it does show much higher expectations than average benchmarks. And as Figure #18 shows, it has an expected high and rising CAGR.

The above gives you the means to reach your goal faster and with ease. The best thing you can do to help yourself, your family, and your country is to get excessively rich. You will also be able to help others along the way.

Don't make it that in 15 years from now, all you would be able to say is: ”I could have done that”. You might not have known some 15 years ago that you could, but now you do.

This paper showed you can do it. You are given the tools to make it happen, even the program code, to realize your long-term objectives. You are left with finding the initial capital to make it happen. And to provide the time, determination, and perseverance to carry it all out. Take the time to study this strategy and verify to your satisfaction if this tool is suitable for you. In the end, whatever the risks implied, it is in your hands.

I wish you the best retirement ever.