Your Stock Trading Portfolio Destroyer

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We are constantly bombarded with the notion of investing in the stock market for the long term. The quest is often to build a significant investment or retirement fund. But, we also see the risk involved in "playing" the markets.

Early on, we learn that nothing is guaranteed and that there is much randomness in all those price moves. But you still have to make the best of it since you know that some long-term stockholders make a fortune. All the super-rich have significant stock holdings.

In **Your Stock Trading Portfolio Destroyer**, I will attempt to present the other side of the coin and also cover a part of why you need a positive edge in trading for the long term. Explore the negative side and show that total randomness in stock prices can destroy your stock trading portfolio, whether you like it or not. It will not be something you can escape either unless you opt to do something about it.

In my previous article, **Stock Trading Strategy Alpha Generation**, I used a geometric Brownian motion (GBM) as a long-term model for stock prices and portfolios. I will use it again for this demonstration.

Unsurprisingly, the above article concluded that you needed some alpha generation to outperform market averages. Without it, a stock trading portfolio could be doomed, and that, from the start, no less (refer to Chart #14 in the above-cited article for an example).

You could run hundreds of simulations of that chart and get the same answer repeatedly. Chart #14 is not an aberration but something close to the average outcome under those variables having no alpha generation.

In my last article **You Will Earn Every Penny You Make**, eight investment scenarios were considered, each with increasing growth rates $\bar{g}$. The case was a matter of choice as to the alpha level ($\bar{g} = \bar{r}_m + \alpha_1 + \alpha_2 + \cdots$) you could select since all were easily feasible, including the two most accessible scenarios producing no alpha.

The immediate problem would have been the tools needed to reach the higher alpha levels. In this case, the tools and programs were provided. You had either simple investment decisions to execute or select one of the free programs to do the job at the level you wanted.

Perhaps the most critical factor was not finding how to do it since solutions were provided but finding the initial capital. You were left with finding, on top of the capital, the determination and perseverance to carry out your selected plan. Let's dive in.

The Stochastic Equation

We often use a stochastic equation to represent the chaotic and quasi-random nature of stock price movements. You can find its equation plastered everywhere:

$$\frac{dS}{S} = \mu dt + \sigma dW \tag{1}$$

where μ is the return component, and σdW the random side of the equation.

If we used a simple regression line of an ordinary time series, we would have:

$$F(t) = rdt + \sum_{1}^{N} \epsilon_i \tag{2}$$

where ϵ_i is an IID with an estimated cumulative mean tending to zero, E $\left[\frac{\sum_1^N \epsilon_i}{N}\right] \to 0$.

The first part of equation (1) is easy; it is the slope of the regression line over the period under study. You have an example in Figure #1 in **There Is Always A Better Retirement Fund - Part II** where the 220-year market average had a mean return of $\mu = 6.9\%$.

We could estimate that in the future, the market should continue over the long term to achieve about the same results, give or take a few points. You could reduce the stock selection to something like SPY with its 500 stocks to improve on the overall market's outcome. It should raise the long-term return to SPY's average of about 10% compounded.

Improving the outcome of your future portfolio will require exceeding that long-term average; otherwise, buying an index fund would have at least assured you that you would get close to that long-term average.

A single decision and you would get closer to a long-term compounded return of $\sim$10%. Trillions are invested in index funds that follow that simple principle.

If you do not know you can beat them or are not assured you will, then at least join them and get that market average.

There is always this other thing: you could do better. Not just as a wish but as actually doing better.

Detrending The Stochastic Equation

Removing the trend in the above stochastic equation (1) will leave you with the random component: $F(t) - \mu dt = \sigma dW$.

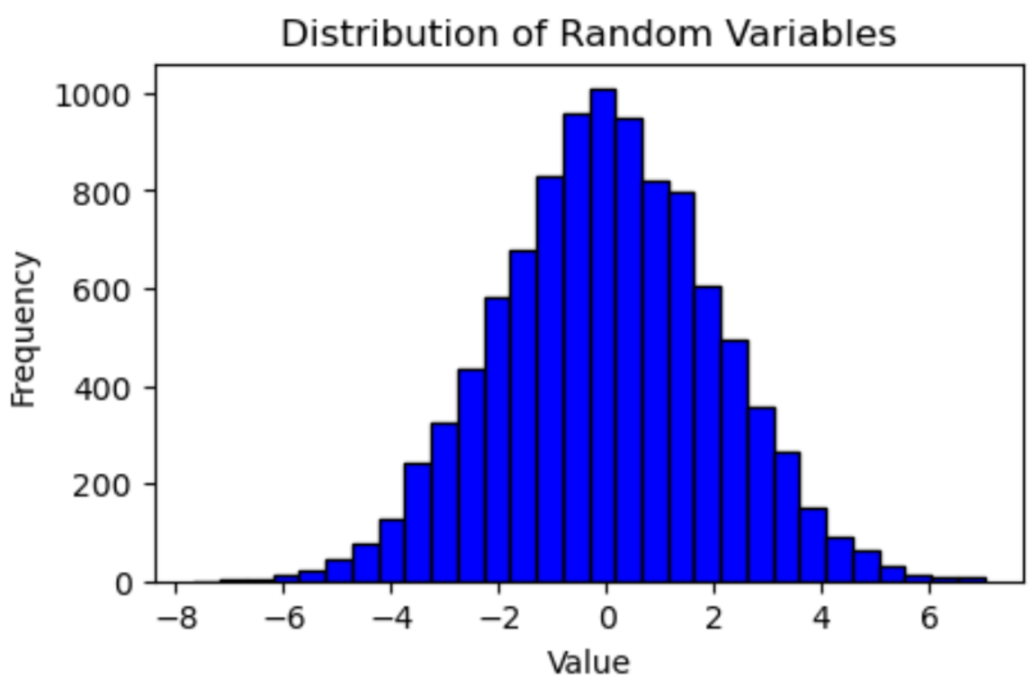
We already know that in σdW, you have a Wiener process with a zero-mean scaled by σ and that its mean also tends to zero $\left[\frac{\sum_1^N \sigma dW_i}{N}\right] \to 0$.

There is no artificial intelligence that can help you with this one. No one has yet broken the code to predict the outcome of the next flip of a fair coin.

After thousands of years, no one came up with: here is the solution. Some have tried, but they all cheated. The next flip of a fair coin still has a 50% probability.

The only place artificial intelligence could have any meaning in long-term trading is in the stock selection process, the trade segmentation, and the trading methods used. These impact μdt, even more so if your trading techniques include some alpha generation $(\mu + \alpha)dt$. The market can provide you with $\mu = \bar{r}_m$ easily, but you are the one needed to provide the excess return, the added alpha, to outperform.

Chart #1: A Normal distribution



(*Click here to enlarge*)

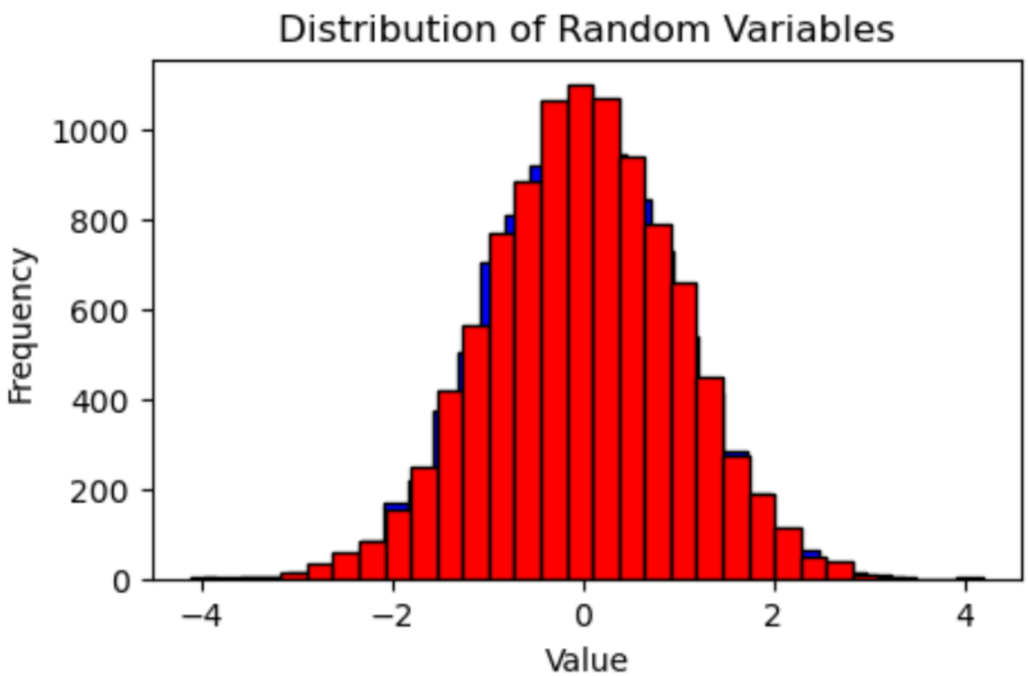
It's a common practice to use a normal distribution to represent the random component of a stochastic equation, and for good reason. If any trend remains in the data, it would be captured by the trend component of the equation, often obtained using the OLS method to get the linear regression. It leaves us with variables that behave almost randomly and unpredictably as a reasonable data representation.

However, it's important to note that the random component of price movements doesn't strictly adhere to a normal distribution. The normal distribution does not explain 'fat' tails, unexpected outliers, high kurtosis, and high skewness levels. Yet, it remains a fairly reasonable representation of the data close to the mean.

The above chart represents a normal distribution with a mean of zero and a standard deviation σ of 1.0. You could request thousands of similar charts; they would all come close to the one displayed in Chart #1. You have the Python code to generate such charts at the end of the article.

To make the point, Chart #2 below has two such distributions on the same chart using the same parameters.

Chart #2: Two Similar Normal Distributions



(*Click here to enlarge*)

There are differences between those two distributions, as should be expected. Nonetheless, you would not be able to predict which would have the highest bar, but you could, knowing one, determine the vicinity of the other or others. The height of the red bar would get close to the height of the blue bar. You could request thousands of these replicates, and they would all look alike.

As stated earlier, the above two charts represent σdW, with a mean of zero and a sigma σ of 1.0.

We can look at σdW as the distribution of trade returns or the profit or loss on each trade $\pm x_i$.

You technically expect not to make any money based on σdW. What you gain on one side is lost on the other. And therefore, the sum of variations tends to zero: $\sum_i^N \sigma dW_i \rightarrow 0$. The same as any error term on a series of random variables: $\sum_1^N \epsilon_i \rightarrow 0$. As such, the random component could not do any harm: the sum of a multitude of random stuff tending to zeros is still zero.

A normal distribution of returns like σdW does not help a portfolio in the stock market game. Every positive bar in those charts has a negative one of the same size. It means that a +10% bar has a -10% counterpart. And that is bad.

Ignoring all the others, this could give $\cdots(1+0.10)\cdots(1-0.10)\cdots = 0.99$. This mirror return $\pm\%$ would also apply to every positive bar in the above charts. To extend the principle, we could have as part of a chain of returns:

$$\cdots(1+0.12)\cdot(1+0.11)\cdot(1+0.10)\cdots(1-0.10)\cdot(1-0.11)\cdot(1-0.12)\cdots = 0.9639$$

The more we put in return bars, the more the outcome would decline. With 100 such series, we would have: $(1.12 \times 1.11 \times 1.10 \times 0.9 \times 0.89 \times 0.88)^{100} = 0.0254$.

That is not tending to the same zero as before. This one will effectively destroy your portfolio.

Before, the zero outcome did not change your investment portfolio, but now, with 600 trades, it was reduced to 2.54% of its original value simply because you traded. It is not a zero-sum game anymore.

Therefore, σdW can do much harm, even more so if you use leverage. The above series of returns with 3x leverage would give 0.00001639, which is not desirable.

From Charts #1 and #2, we can easily observe the symmetry of the curve around the mean. And each positive return has its match on the negative side. Folding the bell curve at its mean is sufficient to see its mirror image of $\pm r_i\%$.

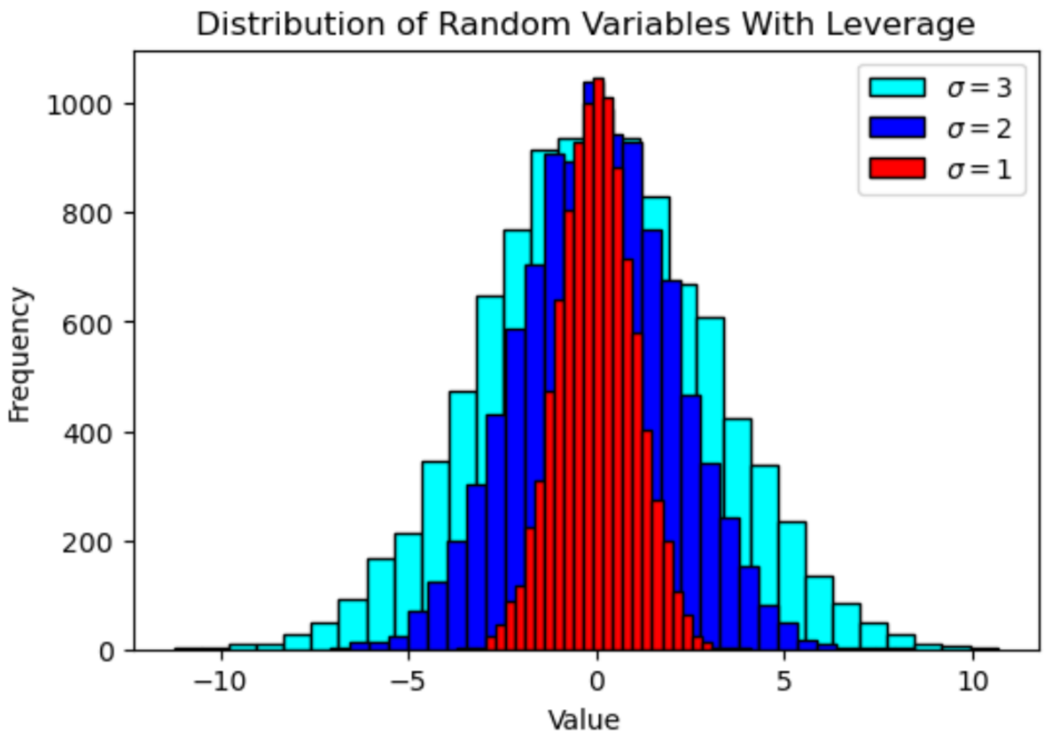
Using Leverage

Using leverage increases the dispersement of the random variables, as illustrated in Chart #3 below. Using 2x or 3x leverage will make the impact more visible the more you trade. The mean for all three distributions is still zero.

In Chart #3, the red normal distribution is the same as in Chart #2 and uses the same data.

Going for the 3x-leverage plot, you are almost assured that the random component of the stochastic equation will destroy your stock portfolio if you have a lot of trades. Your initial capital could end up with $0.00001639 \cdot F_0$. You would not be ahead by any measure. A million dollars would shrink to $\$$16.39.

Chart #3: Three Normal Distributions With 1x, 2x, 3x Leverage



(*Click here to enlarge*)

So, what should you do? **For one thing, change your game**.

The Return Of *μdt*

To change the game and win, you must look at the other component of the stochastic equation: μdt. Otherwise, be prepared to fail.

You must literally force μdt to compensate for everything.

It also means that you will be trading over what is effectively a straight line over the long term with random-like variations. You will deal with a future stochastic equation with an unknown mean and unknown sigma.

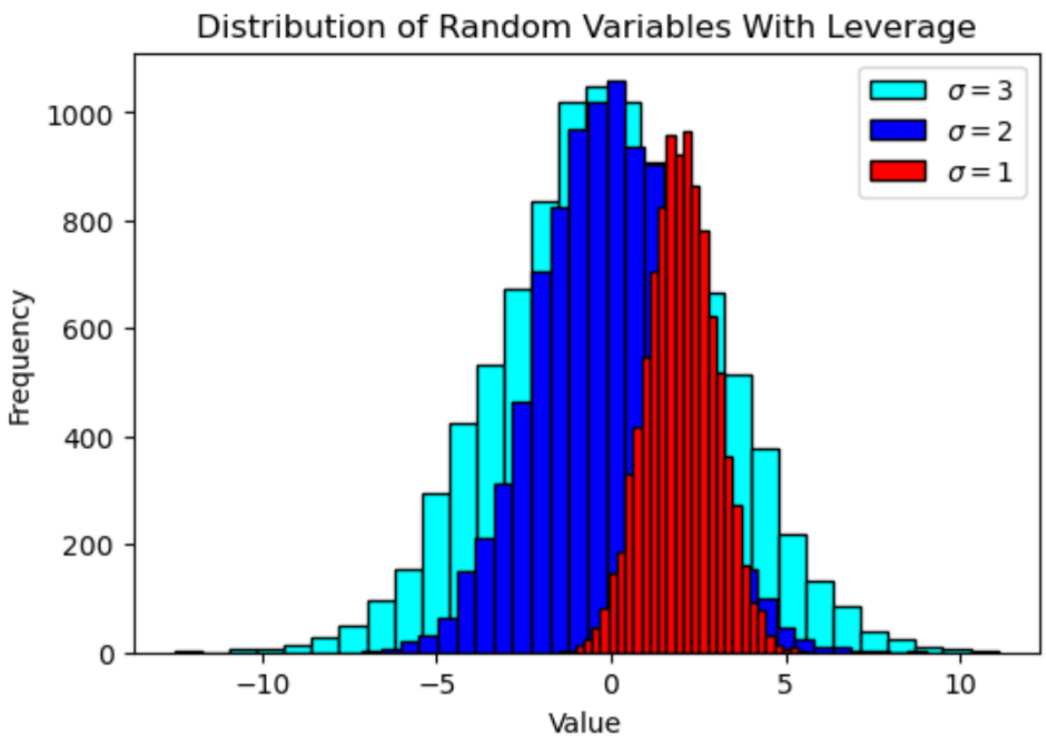
Since you will not get any help from the random component of the equation $-$ which will attempt to destroy your portfolio over the long run, and the other component is a straight line $-$ what are you to do?

That is simple: you trade over the straight line. And since it is a straight line, you can enter a trade any time and hold your position for the long term or do its equivalent.

We regain control of our portfolio by adding back μdt to the equation. With it, we can now move the mean of the random component. As the red bars show in Chart #4, most of the returns are above zero, with its mean at 2.0. It creates a return imbalance in favor of positive returns.

In Chart #4 below, the red distribution without its mean displacement would give back the same curve as in charts #1, #2, and #3.

Chart #4: One Distribution With Mean Displacement



(*Click here to enlarge*)

It did not change σdW. It only shifted the mean of σdW higher by the value of μdt.

You can get your long-term μdt by buying a market proxy such as SPY. And if your trading is reasonable, meaning that it follows common sense, you should be able to grab that long-term return rate without much effort. Already, just buying and holding SPY would do the job. But your objective should be to do better, which is also easy.

You need to create this imbalance between winning and losing trades. It is not that difficult. For example, look at Figure #2 in the last simulation using the **One Percent Per Week** trading strategy **YOUR Stupendous Retirement Fund**, where the 14.4-year CAGR exceeded 50%.

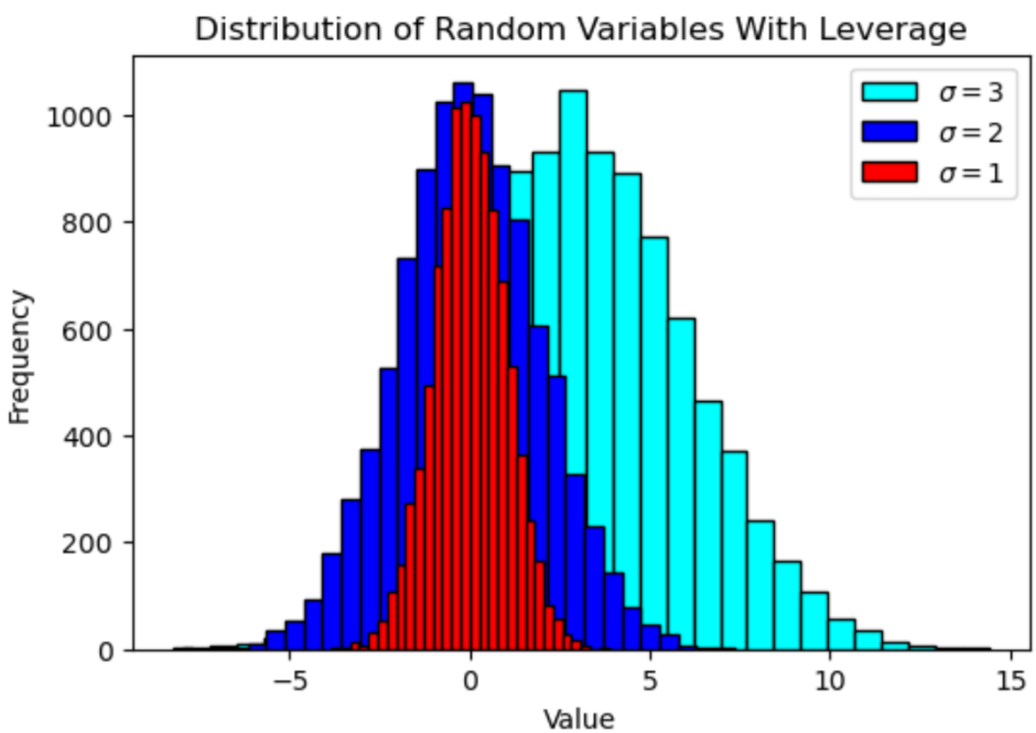
The TQQQ trading strategy had three simple rules: buy on Monday at the open, sell on the 7% or 8% profit target, or liquidate at Friday's close at the latest. The percent return on the average winning trade was 4.53%, while losing trades averaged -2.65%.

Chart #4 illustrates the impact of bypassing the destructive nature of σdW in a trading environment. It did not require extraordinary trading methods, nor did it require artificial intelligence or sentiment analysis. Buying and holding SPY would have been sufficient.

All you have at hand to displace the outcome of σdW is the slope of μdt. In the **One Percent Per Week** program, it was sufficient to execute the profit target at a higher percent setting than the average loss per losing trade. The strategy would benefit even in a 50% hit rate situation, which it did.

Nothing complicated was required. Even the one percent bump was productive because it increased the average spread between the average percent win per winning trade and the average percent loss per losing trade. Any other such method could also improve the outcome.

Chart #5: Mean Displacement Of Leveraged Scenario

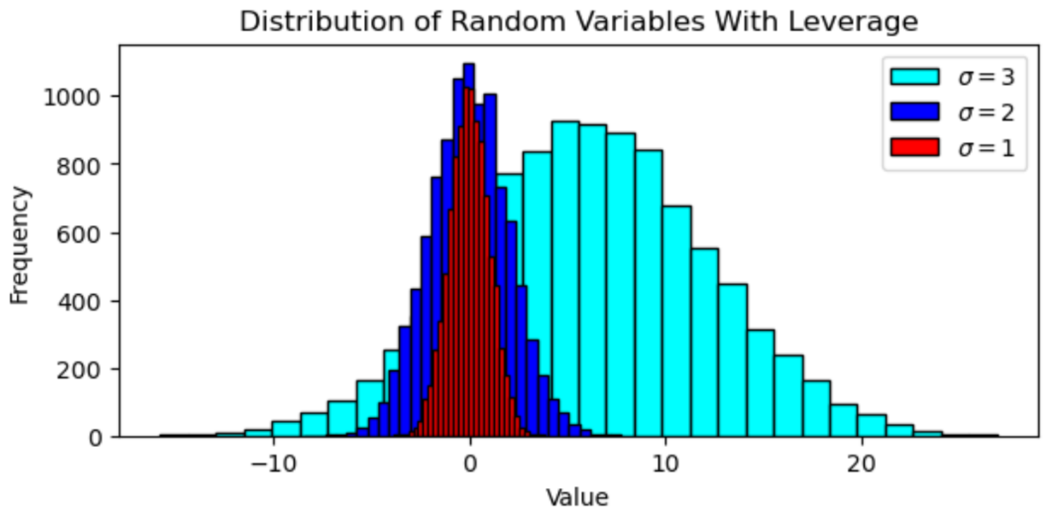


(*Click here to enlarge*)

It is this trade imbalance that we need to generate. It does not matter how, only that it is generated somehow.

We could further amplify the imbalance as in Chart #6 below, where leverage is applied. The contrast is even more evident if we compare the outcome to the previous results, especially the other two scenarios, which remained with a zero mean. Will you push your machine to that level of volatility since returns will swing all over the place?

Chart #6: 3x-Leveraged Scenario



(*Click here to enlarge*)

The TQQQ program results in a long sequence of $\pm\%$ returns (753). But the TQQQ portfolio, even with its drawdowns, will not drop to zero. It is a fully invested fixed fraction strategy. Positions increase as the portfolio rises and decrease as its value falls.

What counts is the overall sequence in the series of returns: $F(t) = F_0 \cdot \prod_1^N (1 + r_i)$. In Chart #6, it favors the upside.

We could do 100 million simulations using the Monte Carlo method with no replacements based on the above product formula, get different paths each time, but always end with the same value. It makes the path of your future trading strategy irrelevant; only the start and finish will matter. Will you quit the game while you are ahead or not?

In the TQQQ strategy, as presented in the last simulation made, you had 753 trades in that sequence of returns with an overall average of 1.03% per position taken (see Figure #2 in: **Welcome To YOUR Stupendous Retirement Fund** for other details).

It emphasizes the importance of the drift component in the stochastic equation (1) since strategies are doomed without it. It leaves you with the only way to outperform the average market return is to bring some alpha into your game. It also means you need a positive edge capable of propelling your average return above the average market return.

It is not only μdt that you need. It is $(\mu + \alpha_1 + \alpha_2 + \cdots)dt$ which again you could also leverage as: $F_{(t-1)} \cdot (\mu + \alpha_1 + \alpha_2 + \cdots)dt$ as in the mentioned TQQQ strategy. Using the product function presented above, we would have $F(t) = F_0 \cdot \prod_1^N (1 + r_i + \bar{\alpha}_1 + \bar{\alpha}_2)$.

But all these moves are choices you have to make.

My point is that you can do it. You could even do it by hand using your cellphone, making it possible to trade from anywhere in the world.

The TQQQ trading rules, as described above, are very simple. A few minutes a week is all that is required, so it should not interfere with your other tasks or obligations.

You use and improve your best trading strategy until you find a better one. There is always a better one. The only important decision is yours. It remains a matter of choice.

Here is the code used to make the above charts.

Figure #1: Python Program Code

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# Generate random data
d1 = np.random.normal(loc=0, scale=3, size=10000)
d2 = np.random.normal(loc=0, scale=2, size=10000)
d3 = np.random.normal(loc=0, scale=1, size=10000)

# Figure size
plt.figure(figsize=(7, 3))  # Width: 7 inches, Height: 3 inches

# Create histogram
plt.hist(d1, bins=30, color='cyan', edgecolor='black', label='$\sigma = 3$')
plt.hist(d2, bins=30, color='blue', edgecolor='black', label='$\sigma = 2$')
plt.hist(d3, bins=30, color='red',  edgecolor='black', label='$\sigma = 1$')

# Add titles and labels
plt.title('Distribution of Random Variables')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.legend()

# Show plot
plt.show()
```

(*Click here to enlarge*)   *The program is simple, courtesy of Copilot.*

Related Papers and Articles:

You Will Earn Every Penny You Make

Stock Trading Strategy Alpha Generation

There Is Always A Better Retirement Fund - Part II

There Is Always A Better Retirement Fund

Welcome To YOUR Stupendous Retirement Fund

The One Percent a Week Stock Trading Program: **Part VII**, and **Part VIII**

The One Percent a Week Stock Trading Program: **Part V**, and **Part VI**

The One Percent a Week Stock Trading Program: **Part III**, and **Part IV**

The One Percent a Week Stock Trading Program: **Part I**, and **Part II**

The Long-Term Stock Trading Problem: **Part I**, and **Part II**

The MoonPhaser Stock Trading Program

Anticipating A Stock Portfolio's Long-Term Outcome

The Big Open Project

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Self-Managed Retirement Funds

Make Yourself A Glorious Retirement Fund

The Age Of The Individual Investor

QQQ To The Rescue

Take the Money and Keep it – II

Use QQQ - Make the Money and Keep IT