# Probabilistic Formalization of a High-Volatility Stock Trading Strategy with Automation Potential

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**Abstract**

This paper formalizes a high-volatility stock trading strategy aimed at maximizing returns while managing risk. Utilizing mathematical models derived from stochastic processes and the Black-Scholes framework, the strategy assesses the probability of upward price movements in stocks demonstrating consistent upward momentum. A key component of the strategy is a 3% take profit (TP) filter, alongside risk mitigation techniques such as portfolio diversification and maintaining a cash reserve to buffer against market downturns. The strategy is divided into three phases of stock behavior—upward trend, stagnating maxima, and downward trend—with corresponding probability formulas tailored to each phase. Cumulative distance metrics $D_1$, $D_2$, and $D_3$ are introduced to quantify the momentum based on relationships between local maxima and minima, offering a comprehensive evaluation of stock movement patterns. Additionally, the strategy holds significant potential for **automation** and can be enhanced through the use of **neural network techniques**, which could improve accuracy by adapting dynamically to real-time market data. This formalization provides a robust foundation for implementing a systematic, automated trading system in high-volatility environments.

## 1 Introduction

This paper presents a formalization of the thought process behind a successful trading strategy designed for high-volatility stocks with consistent upward returns. The strategy focuses on identifying stocks that exhibit strong momentum in their price movements, while managing risk through portfolio diversification, a 3% take profit (TP) filter, and a disciplined approach to cash allocation during market downturns.

The core objective of the strategy is to take advantage of stocks with positive skewness and high volatility by employing mathematical models that quantify the probability of significant upward movements. These models are built on the

Black-Scholes framework, normal distribution properties, and stochastic processes to assess the likelihood of future gains.

In addition to momentum-based stock selection, the strategy incorporates three phases of stock price behavior: upward trend with increasing maxima, stagnating maxima, and downward trend with decreasing maxima. For each phase, a distinct probability formula is provided to assess the stock's future price movement, allowing the investor to make informed decisions about when to buy, hold, or exit positions. The formulas incorporate cumulative distance metrics $D_1$, $D_2$, and $D_3$, which measure momentum based on the stock's local maxima and minima over time.

This formalized framework is designed to systematically apply these concepts in a real-world trading environment, offering a structured approach for maximizing returns while minimizing risk in highly volatile markets.

# 2 Thought Process

## 2.1 Unconstrained Time Horizon

In the scenario where the time horizon $T_f$ is not constrained, the stock prices can be modeled as stochastic processes evolving indefinitely. Let $S_t$ represent the stock price at time $t$. Given a positive skew in the stock price distribution, the expected return $E(S_t)$ over an unbounded time horizon $T$ can be described by the integral:

$$E(S_t) = \int_{-\infty}^{\infty} s \cdot f(s)\, ds$$

where $f(s)$ is the probability density function of the stock price.

As $T$ tends to infinity, the probability that the stock price will achieve at least a certain percentage change $\delta$ approaches 1 as $\delta$ tends to zero:

$$\lim_{T\to\infty} P\left(\frac{S_T}{S_0} \geq 1+\delta\right) = 1 \quad as \quad \delta \to 0$$

This is a direct consequence of the law of large numbers and the cumulative nature of returns over time.

## 2.2 Constrained Time Horizon

When the time horizon $T_f$ is constrained, we need to consider the finite period within which the stock must achieve the desired return $\delta$. The expected return over a constrained time horizon $T_f$ is given by:

$$E(S_{T_f}) = \int_{-\infty}^{\infty} s \cdot f_{T_f}(s)\, ds$$

where $f_{T_f}(s)$ is the probability density function of the stock price at $T_f$.

The probability of the stock reaching the percentage change $\delta$ within the constrained time $T_f$ is:

$$P\left(\frac{S_{T_f}}{S_0} \geq 1+\delta\right)$$

As $T_f$ increases, this probability tends to 1, although it may not be 1 for finite $T_f$. The rate of convergence depends on the skewness $\mu$ and volatility of the stock price distribution $\sigma$.

### 2.3 Portfolio Portions Division

Consider a portfolio that allocates 10% of its value to cash, with the remaining 90% divided equally across $n$ different asset classes. The 10% cash allocation serves as a buffer for risk reduction, as cash is not subject to market volatility. The portfolio's total value $P$ can be expressed as:

$$P = 0.1P + \sum_{i=1}^{n} w_i P$$

where $w_i = \frac{0.9}{n}$ represents the weight of each asset. The cash portion remains constant during market fluctuations, providing stability and liquidity, while the diversification across $n$ assets reduces the overall portfolio risk. According to modern portfolio theory (Markowitz, 1952), diversification reduces the variance of portfolio returns, thus minimizing risk. The portfolio variance $\sigma_P^2$ is given by:

$$\sigma_P^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2\sum_{i<j} w_i w_j \sigma_{ij}$$

where $\sigma_i^2$ is the variance of asset $i$, and $\sigma_{ij}$ is the covariance between assets $i$ and $j$. By diversifying across $n$ assets, we reduce the impact of any single asset's volatility on the overall portfolio risk.

### 2.4 3% Take Profit Filter

The take profit (TP) filter is applied to all stocks under analysis, requiring a constant percentage gain of 3% in a single day for the stock to be considered for investment during that day. The 3% TP condition can be modeled as a threshold $\delta = 0.03$. A stock is considered for investment if:

$$\frac{S_{t+1}}{S_t} \geq 1+\delta$$

### 2.5 Cash Investment in a Market Depression

During a market downturn, if none of the stocks hit the designated 3% TP filter, keeping cash becomes a more viable strategy. Since cash retains its value while other assets depreciate, it is less risky to hold cash in a bear market. Cash provides liquidity and preserves capital during periods of high market volatility, allowing the investor to avoid losses and reinvest when the market conditions improve.

# 3 Probability Formulas for Stock Cycle Phases

This section introduces the three phases of stock behavior, each with its own distinct probability formula and risk evaluation method based on local maxima and minima. The formulas in each phase help assess the probability of specific movements—such as achieving a positive percentage gain or surpassing the last local maxima.

## 3.1 Stock Selection Method

The stock selection method involves a 3-month lookback period to analyze the stock's price behavior. The key indicator is whether the stock's local maximas keeps increasing consistently over time, indicating high probability of continued upward momentum. Let $S_{t_i}^{max}$ denote the local maxima at time $t_i$. A stock exhibits positive momentum if:

$$S_{t_1}^{max} < S_{t_2}^{max} < S_{t_3}^{max}$$

where $t_1 < t_2 < t_3$. The probability of further upward movement is higher if the stock recently hit the 3% TP filter and is trading below the previous local maxima.

The following probability equations were created using the properties of the cumulative distribution function (CDF) of the normal distribution, given the drift $\mu$ and volatility $\sigma$ of the stock. Using the Black-Scholes framework, the probability of hitting the TP filter $\delta$ is:

$$P(\delta) = \Phi\left(\frac{\ln(1+\delta) - (\mu - \frac{1}{2}\sigma^2)}{\sigma}\right)$$

where $\Phi$ is the CDF of the standard normal distribution.

## 3.2 Phase 1: Upward Trend with Increasing Maxima

In this phase, the stock is on a steady upward climb, and local maxima are generally increasing. The goal is to calculate the probability that the stock price will achieve a certain positive percentage change $\delta$.

$$P(S_{t+\Delta t} \geq S_t * (1+\delta)) = \Phi\left(\frac{\ln(1+\delta) - \left(\mu - \frac{\sigma^2}{2}\right)\Delta t - \alpha D_1}{\sigma\sqrt{\Delta t}}\right)$$

**Intuition:** This formula computes the probability that the stock will increase by a **positive percentage change** $\delta$. The formula uses the log-normal property of stock price behavior and focuses on the distance from the current price to the desired percentage increase. The inclusion of $D_1$, which quantifies the momentum from previous maxima, reinforces the probability that this positive gain will occur if momentum is strong. Here $\alpha$ is a scaling factor that adjusts the influence of $D_1$.

#### 3.2.1 Definition of $D_1$:

$$D_1 = \sum_{i=1}^{k-1} w_i \cdot \left( \ln\left(\frac{M_i}{M_{max}}\right) + \ln\left(\frac{M_i}{m_i}\right)\right)$$

**Intuition for $D_1$:**

- The weighting scheme $w_i = \frac{1}{i}$ where $i$ is the index of the local maxima in the time series, starting from the most recent one, ensures that more recent local maxima have **greater influence** on the overall momentum calculation than older maxima.
- $D_1$ represents the **distance from the highest maximum observed in the trend** The first term $\ln\left(\frac{M_i}{M_{max}}\right)$ calculates how far the current maxima are from the overall maximum within the reverse passage of time. The second term $\ln\left(\frac{M_i}{m_i}\right)$ captures the distance between maxima and the nearest local minima, which signals upward momentum after dips.
- If $D_1$ is large, it suggests strong upward momentum, which increases the probability of the stock hitting the desired percentage gain.

### 3.3 Phase 2: Stagnating Maxima

In Phase 2, the stock's upward momentum is weakening, with local maxima showing signs of stagnation. Here, we calculate the probability that the stock will surpass the most recent local maximum $M_{last}$, which indicates whether upward momentum can be regained.

$$P(S_{t+\Delta t} \geq M_{last}) = \Phi\left(\frac{\ln\left(\frac{M_{last}}{S_t}\right) - \left(\mu - \frac{\sigma^2}{2}\right)\Delta t - \alpha D_2}{\sigma\sqrt{\Delta t}}\right)$$

**Intuition:** This formula calculates the **probability of surpassing the most recent local maximum** in a phase where the stock has lost some of its upward momentum. The focus is on whether the stock can break through the stagnation. The term $D_2$ plays a key role here in evaluating the weakening of upward momentum.

### 3.3.1 Definition of $D_2$:

$$D_2 = \sum_{i=1}^{k-1} w_i \cdot \left( \ln\left(\frac{M_i}{M_{i+1}}\right) + \ln\left(\frac{M_i}{m_i}\right) \right)$$

**Intuition for $D_2$:**

- $D_2$ measures how **stagnant or small the gains are between successive maxima**. The term $\ln\left(\frac{M_i}{M_{i+1}}\right)$ becomes small or close to zero when the maxima stop increasing significantly. The overall momentum weakens, and if $D_2$ is small, it indicates a higher probability of the stock struggling to surpass the last local maximum.
- If $D_2$ is small, the stock's upward momentum is near its peak, increasing the risk of stagnation or reversal.

## 3.4 Phase 3: Downward Trend with Decreasing Maxima

In Phase 3, the stock is experiencing a downward trend, with local maxima consistently decreasing. The goal is to calculate the probability that the stock will **surpass the last local maximum** $M_{last}$, which could signal a reversal of the downward trend.

$$P(S_{t+\Delta t} \geq M_{last}) = \Phi\left( \frac{\ln\left(\frac{M_{last}}{S_t}\right) - \left(\mu - \frac{\sigma^2}{2}\right)\Delta t - \alpha D_3}{\sigma\sqrt{\Delta t}} \right)$$

**Intuition:** This formula evaluates whether the stock can **break out of the downward trend** by surpassing the last local maximum. In this phase, the stock is at high risk, but there is potential for a reversal if the local maxima begin to increase again. The term $D_3$ reflects the continued downward momentum.

### 3.4.1 Definition of $D_3$:

$$D_3 = \sum_{i=1}^{k-1} w_i \cdot \left( \ln\left(\frac{M_{i+1}}{M_i}\right) + \ln\left(\frac{M_i}{m_i}\right) \right)$$

**Intuition for $D_3$:**

- $D_3$ captures the **negative momentum** in a downward trend. The term $\ln\left(\frac{M_{i+1}}{M_i}\right)$ becomes negative when local maxima are decreasing, signaling that the stock is losing value. The second term $\ln\left(\frac{M_i}{m_i}\right)$ measures how far the stock has fallen from its local maximum to the nearest minimum.

- If $D_3$ is large, it reflects **continued downward momentum**, making it less likely that the stock will surpass the last maximum. However, if $D_3$ starts to shrink over time, it could signal that the downward trend is weakening.

# 4 Conclusion

The trading strategy presented in this paper offers a robust framework for capitalizing on high-volatility stocks that demonstrate consistent upward momentum. By systematically applying probability-based formulas that evaluate stock behavior across three distinct phases, the strategy provides a disciplined approach to stock selection, risk management, and market timing. The use of cumulative distance metrics $D_1$, $D_2$, and $D_3$ allows for an in-depth analysis of stock momentum based on local maxima and minima, giving traders the ability to assess the likelihood of future price movements with greater precision.

This strategy has significant potential for **automation**, particularly in its reliance on structured decision-making processes that can be efficiently executed by algorithmic trading systems. Furthermore, the strategy can be greatly enhanced through the integration of **neural network techniques**, which are capable of learning from large datasets and identifying complex patterns in stock price movements that may not be easily captured through traditional statistical methods. By employing neural networks to refine the probability formulas and adjust for real-time market dynamics, the strategy could be further optimized to improve accuracy and profitability in high-volatility markets.

In conclusion, the formalization of this trading strategy not only provides a solid foundation for managing high-risk stocks with consistent returns but also opens the door to more advanced techniques in the realm of automated and machine learning-driven trading systems.