NC STATE UNIVERSITY

iSoftStone Information Technology (Group) Co., Ltd. Stock Analysis

Project Report

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Project Goal

The purpose of this project is to conduct a Monte Carlo simulation of the movement of the closing stock price of iSoftStone Information Technology (Group) Co., Ltd. in a 14-day trading period under the Jump Diffusion Geometric Brownian Motion model:

$$dS_t = \mu S_t dt + \sigma S_t dW_t + S_t dJ_t$$

The stochastic differential equation has solution:

$$S_t = S_0 \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t\right)\prod_{i=1}^{N_t}(1 + J_i)$$

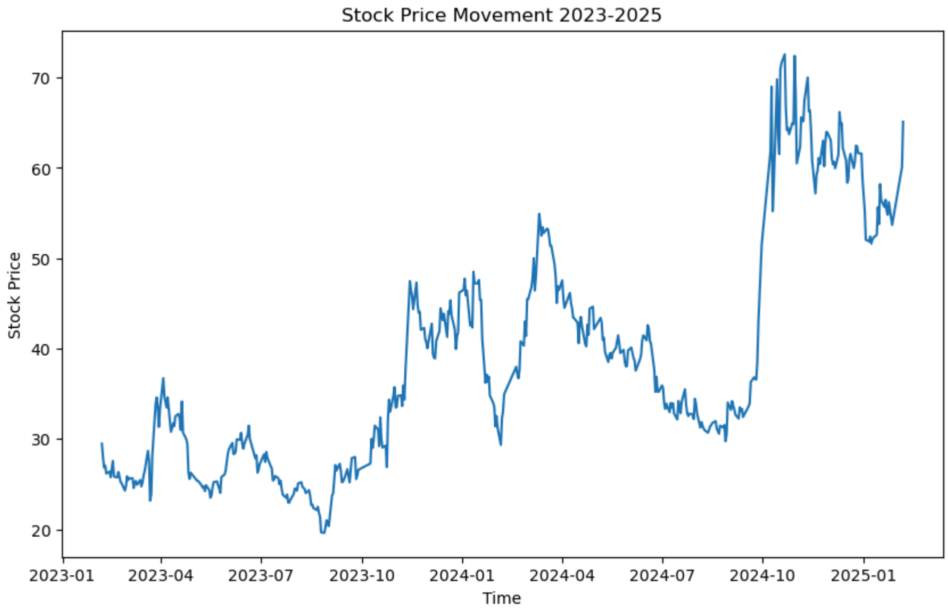
where:

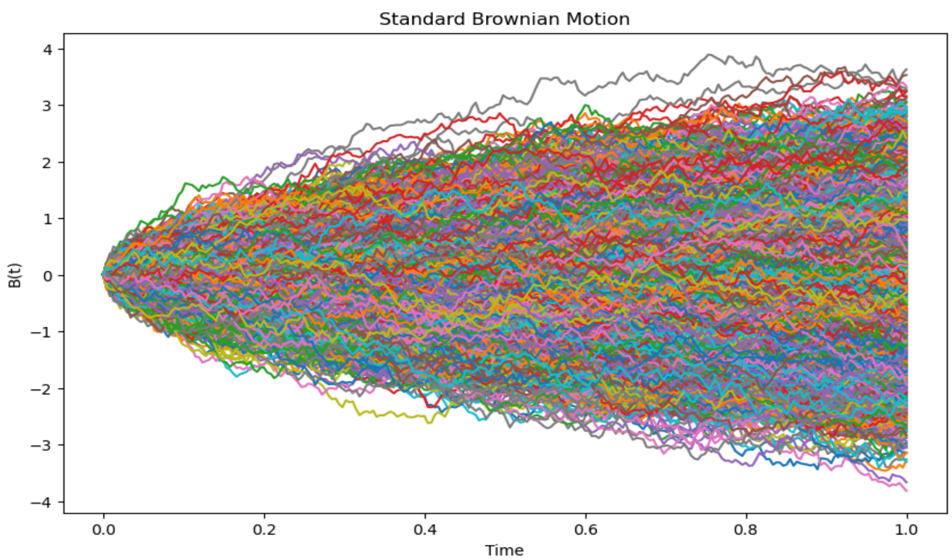
- $\mu - \frac{\sigma^2}{2}$ accounts for the drift and volatility.
- N_t is the number of jumps up to time t.
- $J_i = e^{Y_i} - 1$ represents the jump sizes.

Note that $N_t \sim Pois\ (\lambda t)$, where λ is the estimated price jumps per year using criteria $\mu_{log\ return} + 3\sigma_{log\ return}$, i.e, any daily log returns satisfy the mean plus 3 times the standard deviation would count as a price jump, and $Y_i \sim N(\mu_j, \sigma_j^2)$, where μ_j is the mean of the log return of the jump days and σ_j^2 is the variance of the log return of the jump days.

Process

First, plotting the graph of the stock price from 02/06/2023 to 02/06/2025 (487 observations).





Graph of the Standard Brownian Motion (10,000 paths).

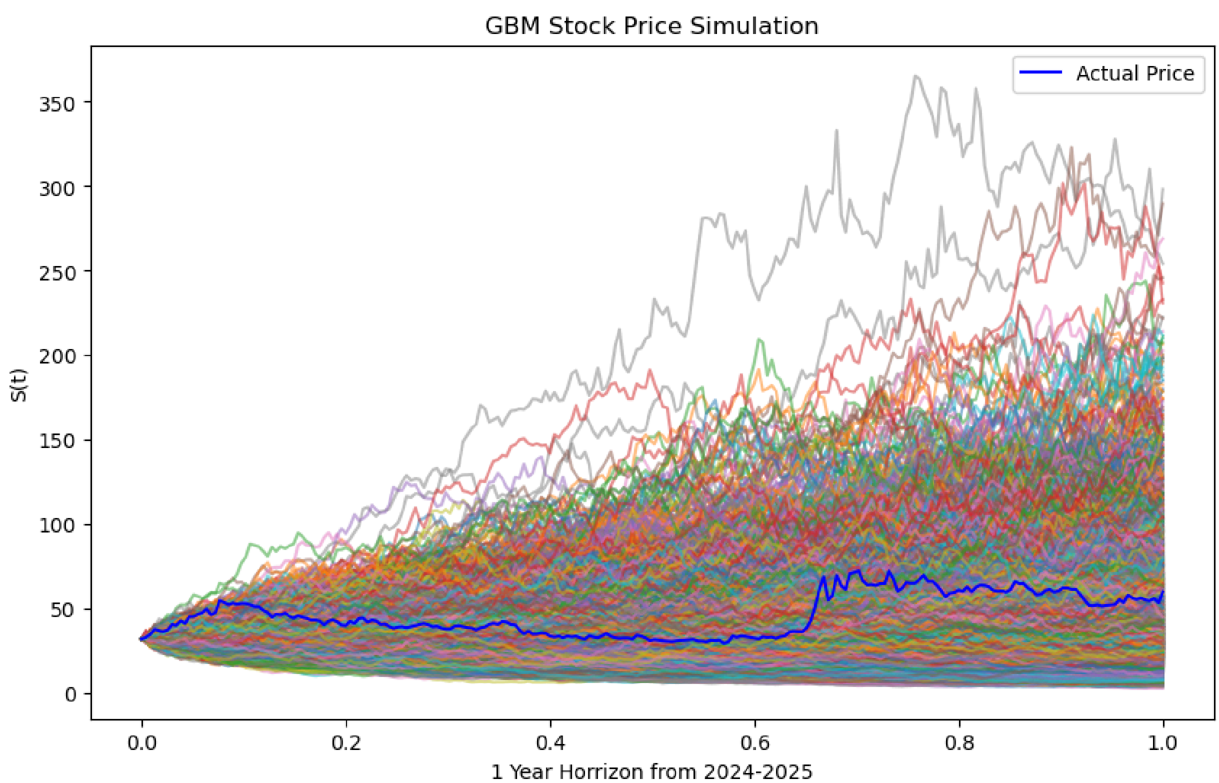
The Brownian Motion was originally used to describe the random movement of particles in a liquid or gas. Scientists had later discovered that the stock price follows a similar movement, and this will be the base assumption of the model in this project.

Jump Diffusion GBM Simulation After 02/06/2024 (2023 Parameters)

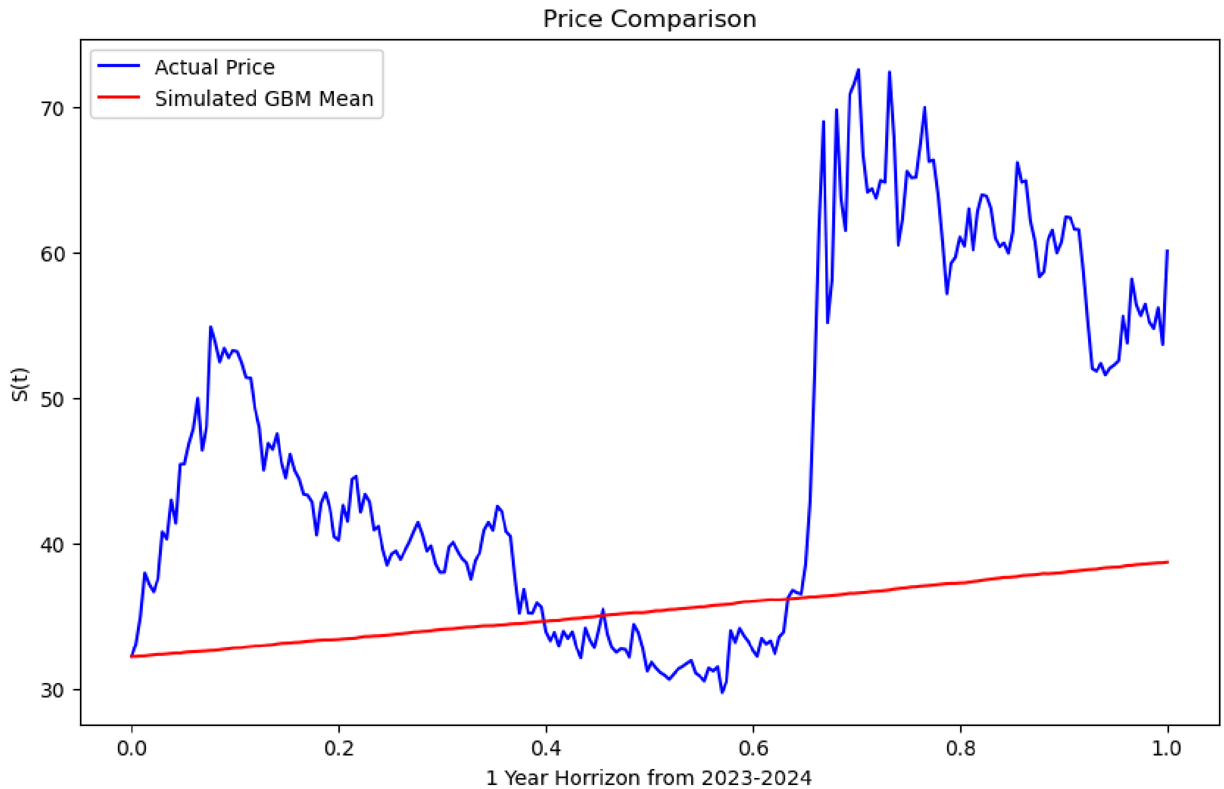
The goal is to first first simulate the paths of the stock prices on the period of 2024-2025, then compare it to the actual price movement. If statistically feasible, the model will be used to generate the movement of the new unknown stock price movement after 02/06/2025.

The first step is to calculate the total drift (mean of log returns) and total volatility (standard deviation of log returns) of 2023 and use these parameters to model the price movement in 2024.

The data has $\mu_{2023} = 9\%$ and $\sigma_{2023} = 0.78$. It shows that iSoftStone Information Technology (Group) Co., has a high volatility but a low return rate, indicating the poor performance of the equity. Usually, a high volatility (more risk) leads to a high return rate. Now, integrating these parameters into the jump diffusion model and generate 10,000 paths of the closing stock price from $32.25 (the price on 02/06/2024):



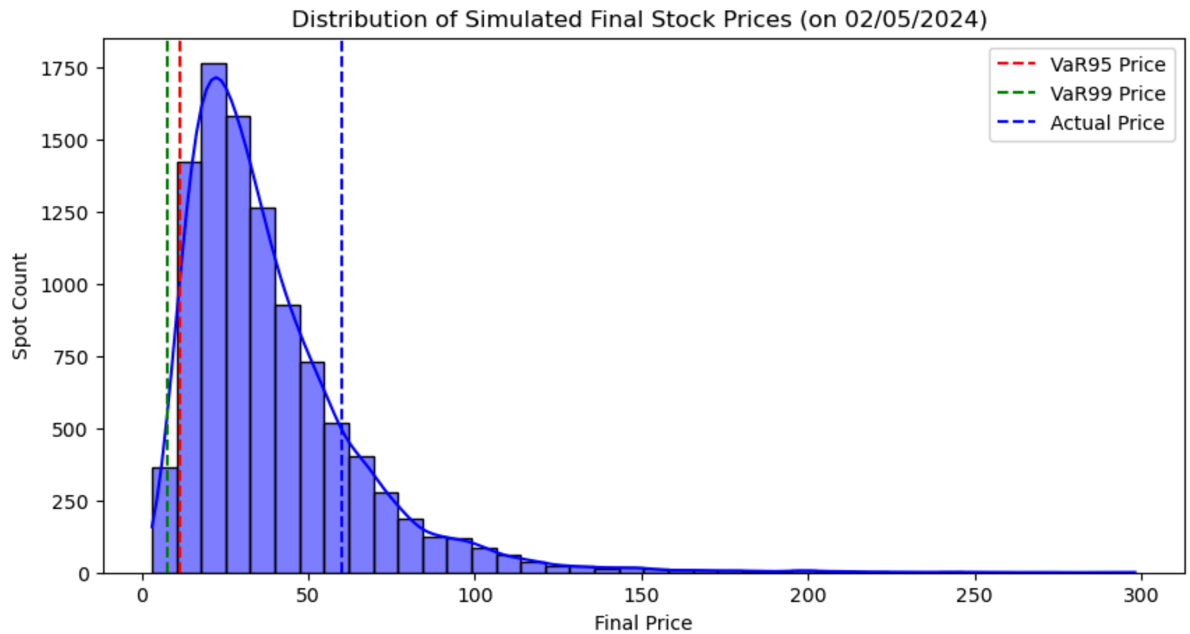
The blue line above represents the actual stock price movement in the year of 2024, and all other lines are the simulated paths of the stock prices.

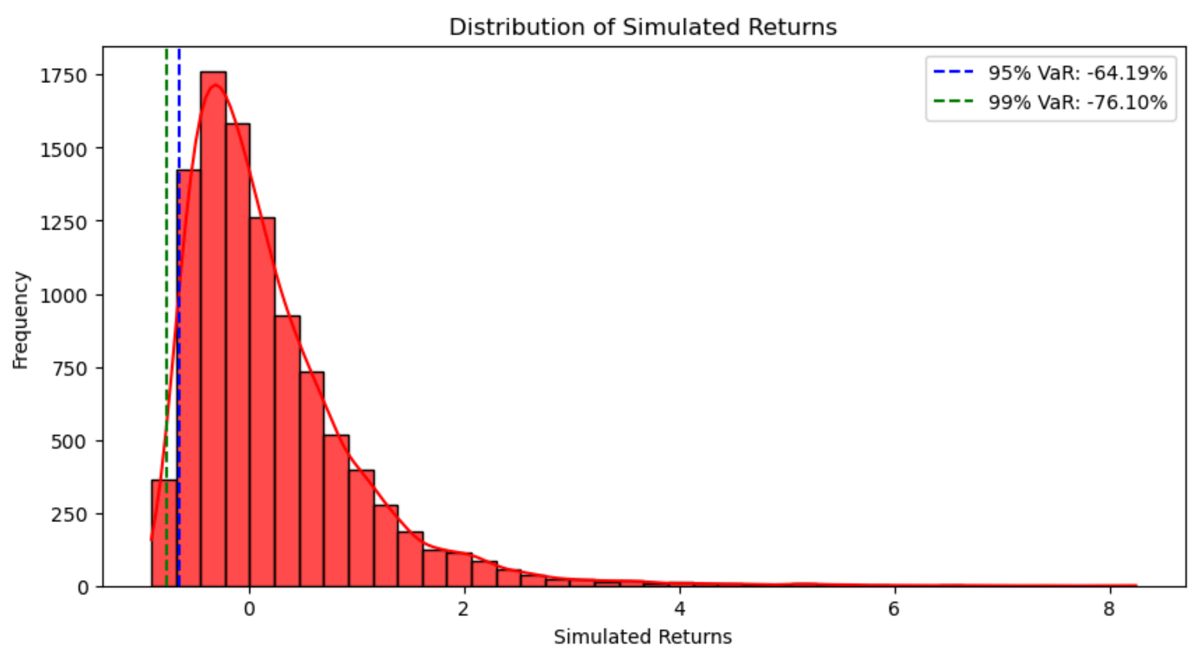


The above image is the actual stock price movement v.s. the expected value of price on the simulated path. Note that the mean plot converges to a straight line.This is because $\mu_{2023} = 9\%$ is relatively small. The actual stock price follows this mean line, indicating a **bullish** signal in the next period. This is based on the mathematical formula for the expected value:

$$\mathbb{E}[S_t] = S_0 \exp\left(\left(\mu + \lambda(e^{\mu_J + \frac{1}{2}\sigma_J^2} - 1)\right) t\right)$$

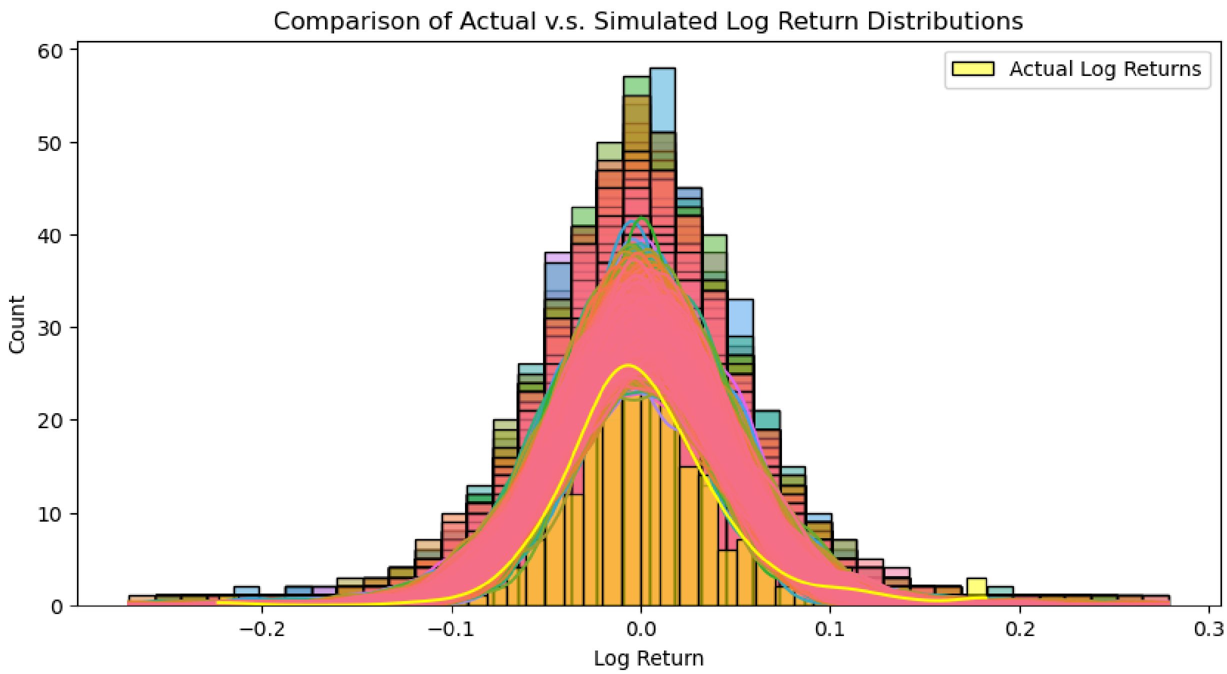
A more clear visual representation of the statistics of the simulated paths could be presented:





Verifying the Model's Viability

To test out that the model is statistically viable, the idea is to plot out the distribution of the actual log returns v.s. the simulated daily log returns. There are 10,000 paths, and 238 trading days from 02/06/2024 to 02/06/2025. So the graph will have 10,000 graph overlaps and a total count of 238 for each data set collection. In order to obtain the optimal result, repeatedly tuning the parameters is required.



The tuned jump diffusion parameters are $\lambda = 0.35\lambda_{estimated\ 2023}$, $\mu_{log\ return} = 0.35\mu_{log\ return\ 2023}$, and $\sigma_{log\ return} = 0.35\sigma_{log\ return\ 2023}$. Plotting the histogram of the data with tuned parameters plugged into the equation, observe that the yellow curve (the Kernel Density Estimation (KDE) line of the actual daily log returns) overlaps the KDE curves of the simulated distributions, showing the similarity between the simulated result and the actual result.

To further verify the accuracy, a KS test was performed and had the following results:

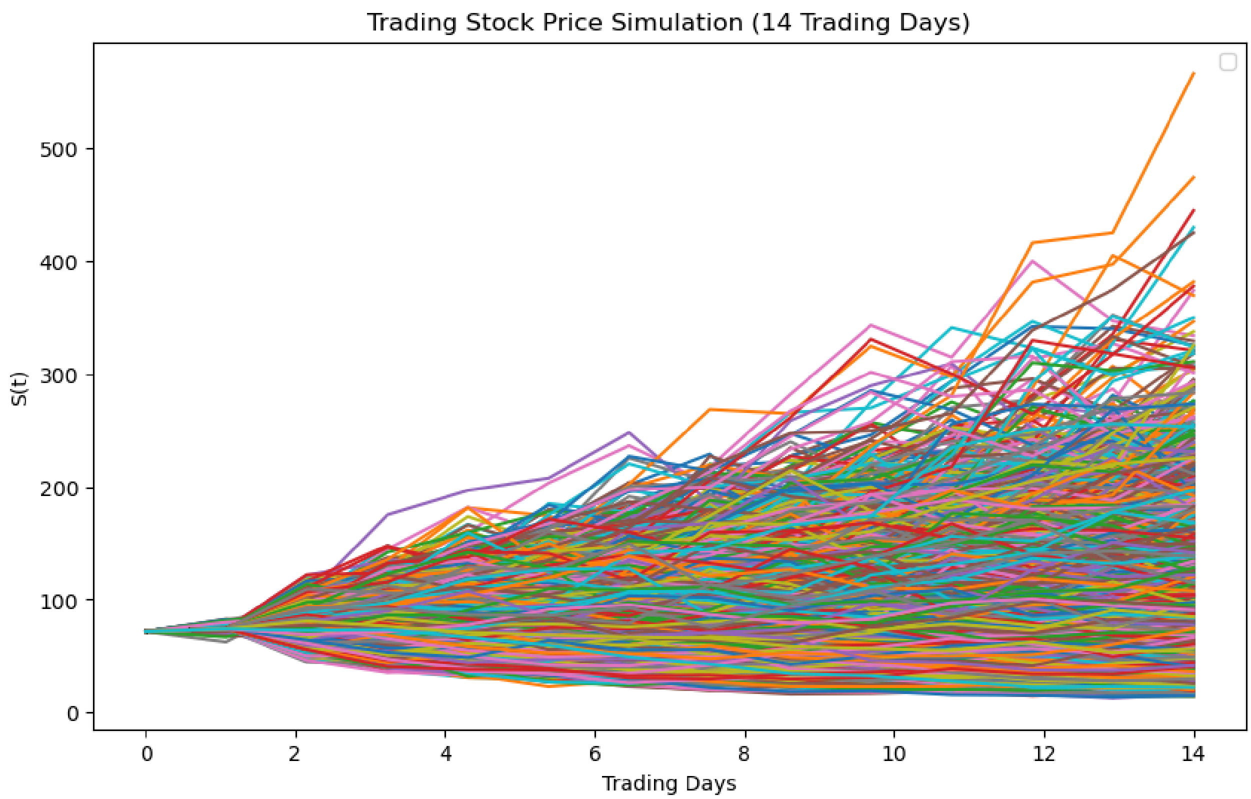
KS Statistic: 0.0572, P-value: 0.4104

Fail to reject null hypothesis: **The distributions are similar.**

The graph of 'Comparison of Actual v.s. Simulated Log Return Distributions' and KS Test indicates that the Jump Diffusion GBM model is **fairly accurate** and could be used for simulation purposes. For the actual trading simulation (new unknown period), new parameters $\lambda = 0.4\lambda_{estimated\ 2024}$, $\mu_{log\ return} = 0.4\mu_{log\ return\ 2024}$, and $\sigma_{log\ return} = 0.4\sigma_{log\ return\ 2024}$ are being applied to the model due to the fact that the stock is in a bullish period with more potential jumps.

Jump Diffusion GBM Simulation for trading

Assuming an extremely short trading period of 14 trading days after 02/06/2025, the goal is to use the tuned model to capture the potential trend and make rational decisions. Simulate 10,000 paths of the stock prices of this unknown period using the calculated parameters: $\mu_{2024} = 70\%$ and $\sigma_{2024} = 0.72$ (note: the return rate is extremely high is 2024, showing the well performance of the equity), the result is:



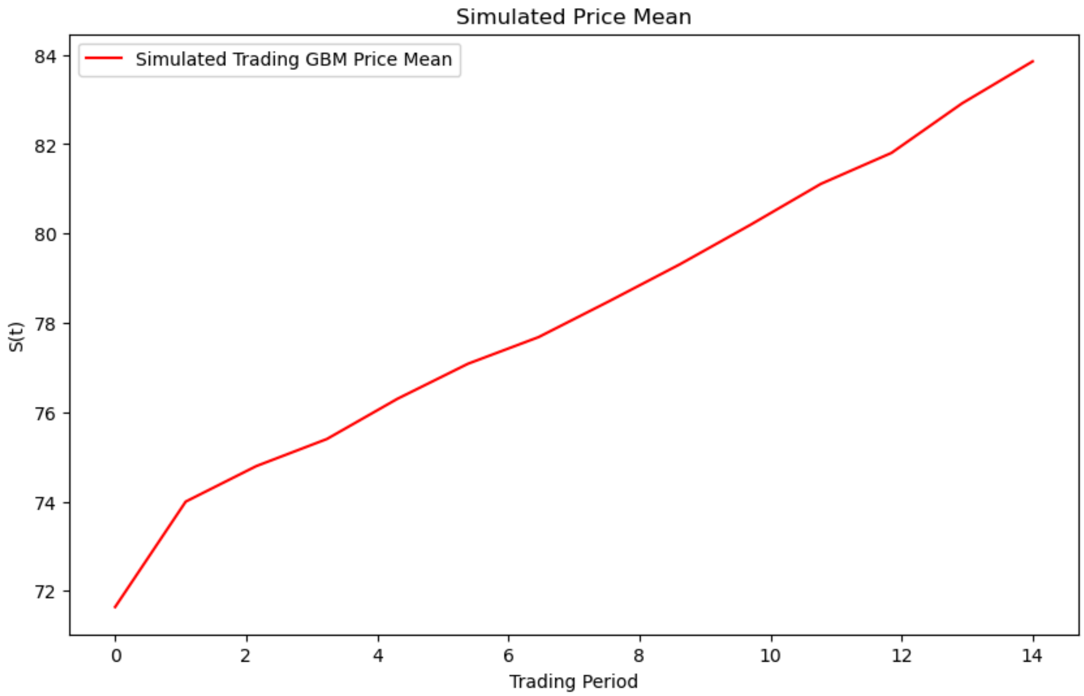
Model Applications

1. Expected Future Price Trends

If the mean price trends higher, bullish signal → Consider long positions.

If the mean price trends lower, bearish signal → Consider shorting or hedging.

Wide confidence intervals → High uncertainty → Use risk management strategies.

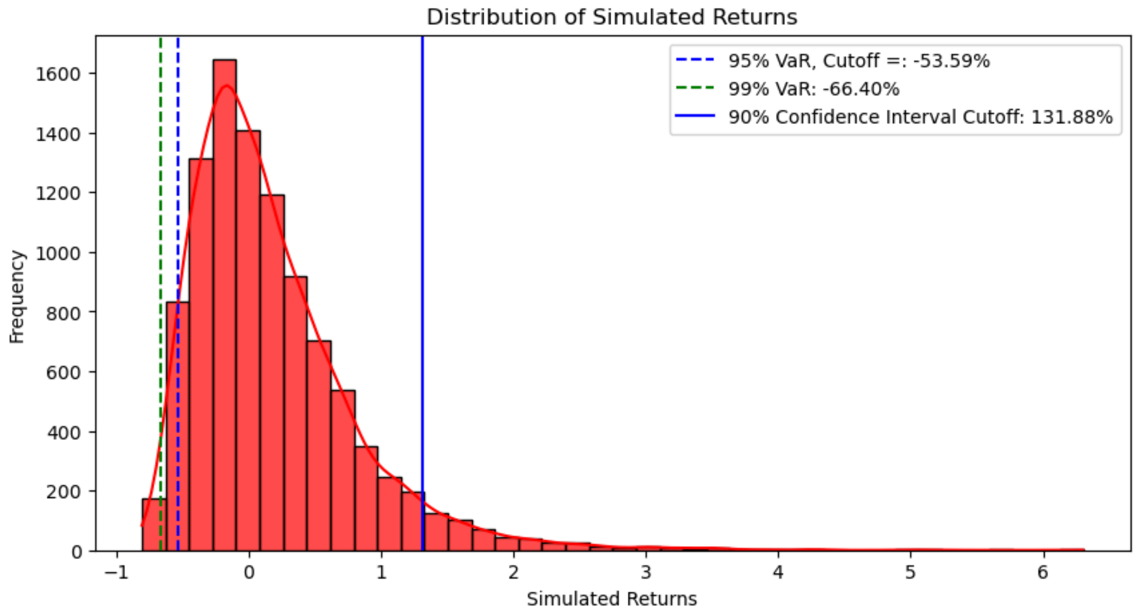


Investment Suggestion: **Long Position**

2. Computing VaR (Risk of Loss)

If VaR is high, implement hedging strategies (protective puts, stop-loss orders).

If VaR is low, the stock is relatively stable, so a larger allocation may be justified.



Interpreting the image: 95% VaR of return: the stock has 5% of chance resulting in a loss of more than 53.39%. 99% VaR of return: the stock has 1% of chance resulting in a loss of more than 66.40%. 90% Confidence Interval [-53.59%, 131.88%] (known as CI, the region between the 2 blue lines): 90% of the simulated stock returns fall within this range.

Investment Suggestion: **high risk of price fluctuations, seek for hedging options.**

3. **Assess Risk (Volatility)**

If volatility is high, but price is trending up, consider options strategies (covered calls).

If volatility is low, a long-term directional position (buy-and-hold) may be ideal.

Simulated Volatility: 0.1363

Comment: The 14 day volatility of the daily log return is relatively low, but now, DeepSeek's positive news caused the price to increase drastically. When the price of an asset skyrockets (experiences a sharp upward movement), it is possible to observe high daily log returns with low volatility.

Investment Suggestion: **Long Position with option strategies of high volatility**

4. **Detect Tail Risk (Extreme Losses)**

   Skew < 0 → More downside risk → Reduce position size or hedge.

   Kurtosis > 3 → Fat tails (more extreme moves) → Use tail-risk hedging (deep OTM options).

Skewness: -0.0646

Kurtosis: 0.2140

Investment Suggestion: **reduce position size and diversify the portfolio**

5. **Portfolio Allocation Strategy (Sharpe Ratio)**

   Annualized Sharpe Ratio > 1 → Good risk-adjusted return → Consider larger allocation.

   Annualized Sharpe Ratio < 0.5 → Low risk-adjusted return → Diversification is needed.

Expected Daily Return: 0.28%

Daily Volatility: 0.14

Daily Sharpe Ratio: 0.02

Expected Annualized Return: 65.57%

Annualized Volatility: 31.76

Annualized Sharpe Ratio: 0.31

Investment Suggestion: **high risk, diversify the portfolio**

Future Work

To enhance portfolio analysis, a comprehensive evaluation of additional stocks within the portfolio should be conducted, utilizing the Markowitz Portfolio Optimization model to identify the ideal investment combination that balances risk and return. Machine learning techniques should be incorporated to explore the underlying causes of price fluctuations by uncovering complex patterns and relationships in the data, and the analysis should be expanded to include more microeconomic factors, such as company-specific metrics, and macroeconomic factors, such as interest rates and inflation, to provide a holistic view of the drivers behind price changes. To improve model accuracy, a significantly larger number of simulation paths (e.g., 200,000+) should be generated, and the analysis should be extended to cover more historical periods with richer datasets. Additionally, integrating more trading signal indicators, such as the Bollinger Bands method and the MACD line crossing method, will provide robust tools for identifying potential buy and sell opportunities. By combining these strategies, a more sophisticated and accurate framework for portfolio optimization and market analysis can be achieved.

End of the Report