Bayesian Recovery following the fall of Mjolnir – Myth Inspired Approach

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Introduction

In Norse mythology, the fall of Mjolnir, Thor's almighty hammer was never considered a symbol of defeat but a harbinger of powerful resurgence. Similarly, in technical analysis of stocks prices, the *Hammer* candlestick serves a similar purpose. When appears during a downtrend, it signals a potential reversal and hints towards a near exhaustion of the bearish trend and an imminent bullish resurgence.

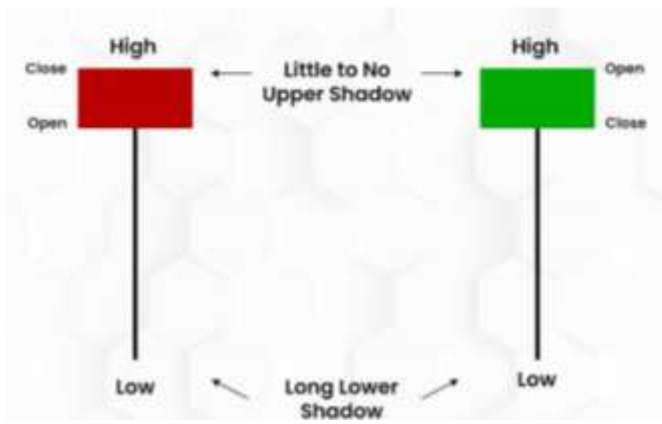
The formation of *Hammer* indicates that sellers drove prices lower but at the end being overpowered by the buyers, metaphorically a battle reminiscent of Thor reclaiming the Mjolnir after a fall. Traders interpret *Hammer* as a shift in sentiment from bearish to bullish, when followed by a strong confirmation, i.e. higher volumes, cluster of hammers, or support from market etc.

With all the dramatic scenarios around the *Hammer,* the pattern is relatively rare. Various quantitative analyses that cover millions of historical price bars suggest that valid hammers occur in only 1-2% of all candlestick patterns. A study that analyzed over 4 million candles across two decades, found *Hammer* formations in just 1.1% of cases. In major indices like the S&P 500, the rate hovers around 2.5%, slightly higher in small-cap indices such as the Russell 2000 (3.2%). This rarity enhances the pattern's perceived reliability, very much like Mjolnir, it is not often seen, but its appearance carries weight.[1]

The project adopts a Bayesian approach focusing on the post-hammer price behavior with probability distribution of returns over the next 20 candles followed by the observance of a valid hammer. I used *Markov Chain Monte Carlo (MCMC)* method, the *Hamiltonian Monte Carlo (HMC) algorithm*, to estimate the posterior distribution of expected gains, incorporating both prior beliefs and observed market data for a comparatively conservative stock "ITC", *(India Tobacco Company Limited)*. For this short study, I focused on the maximum possible gains in the next 20 candlesticks after observing a *Hammer*, which typically ignores the drawdown through the price movement, but at the same time also highlights the concept of patience and the power of a valid hammer, that even if there is a drawdown the occurrence of the pattern is still impactful if it results in gains.

Keywords: Hammer, Candlesticks, MCMC, *Hamiltonian Monte Carlo (HMC)*, drawdown.

Mjolnir- The Almighty Hammer Candlestick – Background & Motivation



A candlestick pattern is a movement in prices shown graphically on a candlestick chart that some traders believe can helps in identifying repeating patterns of a particular market movement. The credit for developing the candlestick charting goes to *Munehisa Homma (1724-1803)*, who was a rice merchant from Sakata, Japan and traded in the *Dojima Rice market* in *Osaka* during the *Tokugawa*

Shogunate and the pattern was popularized by Steve Nison in 1850s.[2]

The Hammer Candlestick pattern in a single candlestick patter and it is characterized having a small real body and long lower shadow (wick) at least twice the length of real body and with almost no or very small upper shadow (wick). The small body of hammer emerges after a significant drop in price. A hammer is valid, if it appears at the bottom of a downtrend. The longer lower shadow indicates that the stock nose-dived at the open only to rebound significantly by the close. The slim real body signifies indecision with prices stabilization after the recovery.

It implies selling pressure is weakening, and bulls are taking control. A single hammer isn't always reliable, but back-to-back or multiple consecutive hammers strengthen the signal and indicate the decline could be ending. *For confirmation, traders watch for increased volume on the hammer candle and look for follow-through buying pressure on the next candle.*

"Much like Mjolnir, the Hammer candlestick is rare but a potent symbol of strength and resilience, appearing after significant turmoil, and capable of heralding a powerful recovery."

Motivation & Scope of Study

The almighty *Hammer* candlestick has been discussed extensively in trading literature, and most of the available work focuses on qualitative descriptions or heuristic backtesting with rigid rules. However, market evaluations are probabilistic in nature and price behavior after a Hammer is influenced by a various factors such as market sentiment, macroeconomic events, volume anomalies, or institutional activities. Hence, the understanding of post-Hammer movement requires a probabilistic framework that not only considers historical evidence but also allows for uncertainty and variability in outcomes.

Having considerable interest in candlestick patterns and their beauty of being able to predict price movements, I was particularly interested to apply Bayesian Approach to validate if the occurrence of the hammer candlestick does really give better returns than random candlesticks. Further, the technical analysis in financial markets always walks the line between art and science and relies heavily on the visual patterns and I thought of strengthening the belief based on Bayesian modelling.

For the study, I have only chosen the Hammer as a focus candlestick (due to time restraints), and then compared it to other random candlesticks. However, this study can be expanded to collate other candlesticks and perform a hierarchical analysis for the different candlesticks patterns.

The primary motivation behind this study is to approach the Hammer pattern not merely as a binary signal (i.e., trend reversal or not), but to quantify the likelihood and distribution of future returns in a probabilistic manner. Instead of asking "Does a Hammer always lead to a price rise?", this study asks ***"What is the probability distribution of returns after a Hammer, and how confident can we be in expecting gains?"***

To answer this question, I adopted Bayesian inference approach using Hamiltonian Monte Carlo (HMC) sampling to estimate posterior distribution of maximum potential gains over the next 20 candlesticks followed by a hammer candlestick pattern.

The focus on *ITC (India Tobacco Company Limited)* is deliberate, it's a large-cap, relatively stable stock with limited speculative noise, thus allows effect of Hammer's presence in a cleaner environment.
The scope of this study is thus centred on:

- Identification of valid Hammer candlesticks from the historical daily ITC stock price data (data from 03-01-2000 till 22-04-2025, *sourced through yfinance*).
- Measuring the maximum price increase in the next 20 candles after a Hammer.
- Estimating a posterior distribution of these returns using MCMC sampling.
- Interpreting the outcome in terms of probability, credibility intervals, and real-world trading implications.
- Understanding drawdowns within the 20-bar window to acknowledge risk along with potential reward.

Note: Further, the study provides the analysis for 5 & 10 period window along with the 20 period window analysis.

Data Collection & Preprocessing

Data Overview

The dataset used in this study comprises daily closing price data for ITC Limited, retrieved using the *yfinance* Python package. The timeframe spans from January 3, 2000, to April 22, 2025. The raw data includes standard financial metrics such as Open, High, Low, Close, Adjusted Close, and Volume. The dataset includes **6,277** daily candles.

Hammer Detection

The rules I used to identify the hammer are as follows:

- The Body Size of candle <= 0.33 * Range of Candle (i.e size of candle)
- Lower Shadow >= 2 x Size of the Real body,
- Upper Shadow should be very small or negligible.
- Lower Shadow >= 2 x Upper Shadow
- The Hammer must appear after a preceding downtrend (the lowest of the candle being the lowest price in the previous 5 candles).

Further, the constraint, Low [Candle = Hammer] < Low [Previous 5 Candles], was used to detect that the identified hammer is a valid hammer, occurring in a downtrend.

This identifies **108** valid Hammer Candles.

Performance Metrics

For each hammer pattern, I calculated price returns for each of the three time periods, [5, 10, 20], which indicates weekly, biweekly and monthly (almost) returns.

Here, I have used only the maximum price reached within the next periods to calculate the gains, and minimum low price for losses, to reflect upon the potential take-profit opportunities and the loss cases.

Bayesian Inference

To quantify the posterior distribution of the mean return (μ) and standard deviation (σ) for each horizon, I used the following steps:

1. Bayesian modeling via PyMC that uses Hamiltonian Monte Carlo sampling using No-U-Turn Sampler (NUTS).
2. A Normal Likelihood with weakly informative priors.

For robustness, I have also attempted to fit Student-t distributions and skewed-normal distribution for comparison.

Reported Metrics

- Posterior mean (μ) and standard deviation (σ)
- 95% Highest Density Interval (HDI) for μ
- Probability that μ > 0
- 95% Value-at-Risk (VaR) and Expected Shortfall (ES)
- Comparison of Hammer vs. Baseline average gains

Model

After the data preprocessing the hammer identification analysis, I choose the Bayesain model for analysis as explained below.

The objective is to estimate the true average return following a Hammer candlestick pattern over future horizons (5, 10, and 20 trading days), while accounting for uncertainty in the observed outcomes.

This is formalized as estimating the posterior distributions of:

μ: the mean return following a Hammer

σ: the standard deviation (volatility) of those returns

<u>Establishing the Prior</u>:

I used a weakly informative prior to reflect uncertainty while keeping the model numerically stable:

$$\mu \sim \mathcal{N}(0.01, 0.1)$$

$$\sigma \sim \text{Half-Normal}(0.1)$$

i.e. gains centred around 1% with a considerate variation of ± 10%. Further, the volatility is considered to be positive only with majority of its mass concentrate below 10%, expecting a moderate variation in gains.

<u>Likelihood Function</u>:

After plotting the distribution of gains followed by a valid hammer, I see that the distribution is almost normal with a slight skewness in the data towards the right. So, I modelled the likelihood with a normal distribution also

$$y_i \sim \mathcal{N}(\mu, \sigma), \qquad i = 1, 2, ..., N$$

and, $$L(\mu, \sigma) = \Sigma^{N}_{i=1} \mathcal{N}(y_i \mid \mu, \sigma)$$

where:

y_i : the observed return after a Hammer pattern; μ : unknown average return; σ : unknown volatility

Posterior Inference:

Using the Bayes' Theorem I combined the prior beliefs and observed data:

$$P(\mu, \sigma \mid y) \propto P(y \mid \mu, \sigma) * P(\mu) * P(\sigma)$$

I used the Markov Chain Monte Carlo (MCMC) with the No-U-Turn Sampler (NUTS) {HMC} to draw samples from the posterior.

~ 4 chains

~ 1,000 tuning steps

~ 2,000 posterior samples per chain (8,000 total draws)

~ Convergence assessed via R-hat (~1.000) and effective sample size (ESS > 4,000)

Summary Metrics from Posterior

For each horizon, I have derived the following parameters :

- Posterior mean and 95% HDI of μ
- Probability(μ > 0): chance of positive expected return
- Value-at-Risk (VaR): 5th percentile of return
- Expected Shortfall (ES): average return in worst 5% scenarios

Results & Interpretation

Overall Statistics:

- 108 hammer patterns were identified
- Mean gain after 20 days: 6.16%
- Median gain: 4.65%
- Win rate (positive gains): 98.1%

Model Analysis:

- Three probability distributions were fitted: Normal, Student-t, and Skewed-normal
- The Normal distribution was determined to be the best fit based on Mean Squared Error (MSE)

Baseline Comparison:

- Baseline mean gain (excluding periods with hammer patterns): 16.65%
- Hammer patterns underperformed the baseline by 10.49% (63% relative underperformance)
- However, hammer patterns had a better win rate (98.1% vs 90.1%)

Bayesian Probability:

- 100% probability of *positive* mean return according to the Normal model

Prior Sensitivity Analysis:

- Different prior assumptions were tested, showing the robustness of results
- Results remained consistent for *positive returns* across different prior specifications

Interpretation of Results

Model Selection

The analysis fitted three different models to the data:

- **Normal distribution**: Simplest model, assumes symmetric returns
- **Student-t distribution**: Accounts for potential outliers with heavier tails
- **Skewed-normal distribution**: Accounts for asymmetry in returns

The Normal model was selected as the best fit based on having the lowest MSE (Mean Squared Error) of 3.83e-08, significantly better than the other models.

The Apparent Contradiction

I found an interesting contradiction in the results:

1. Hammer patterns show a near-guaranteed positive return (*98.1% win rate*)
2. But they significantly underperform the baseline (*6.16% vs 16.65%*)

This suggests that while hammer patterns do predict positive price movements, they actually predict smaller positive movements than would be expected without the pattern.

Risk Metrics

The Value-at-Risk (VaR) and Expected Shortfall (ES) metrics provide insights into downside risk:

- 95% VaR: 0.0529 (5.29%) - This means there's a 95% chance the return won't fall below 5.29%
- 95% ES: 0.0507 (5.07%) - The average loss expected in the worst 5% of cases

Prior Sensitivity

The analysis tested different prior beliefs to check if they would significantly affect the results. The consistency across different priors indicates the findings are robust and driven by the data rather than initial assumptions.

Conclusion

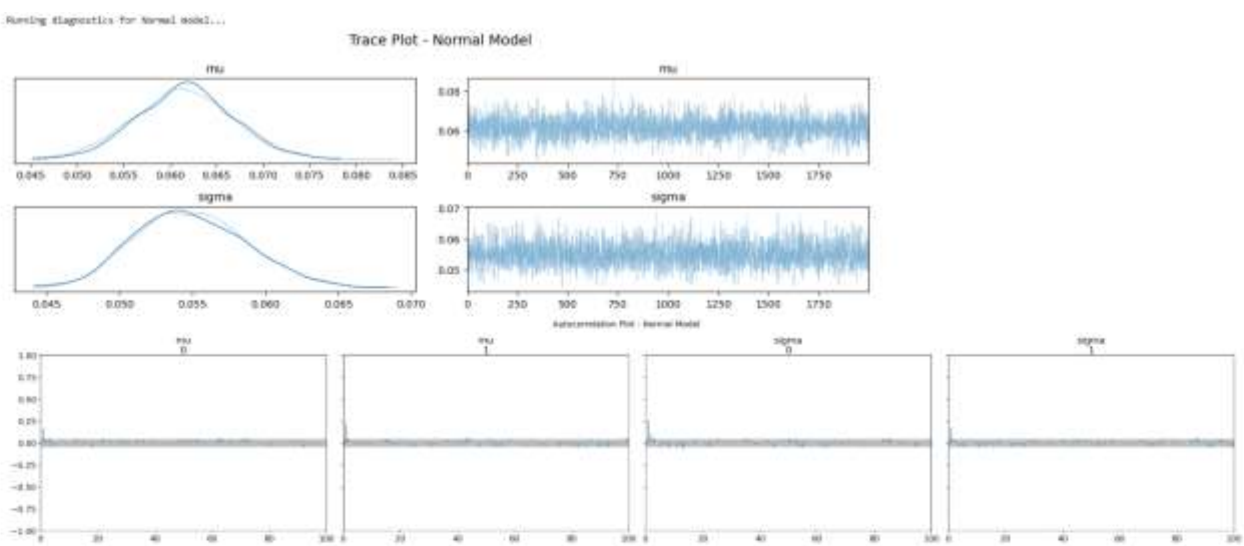
"NO SIGNIFICANT EDGE found for hammer patterns in this dataset". Even though hammers showed positive returns but they didn’t show any significant edge over other candles. This is also due to the fact that the study focussed on limited characteristics and didn’t account a very large dataset, and further there are other bullish reversal candlestick patterns too that have not been accounted for in this study.

Model Outputs, Plots, and Tables

```
Total hammer patterns found: 108

Analyzing 20-day gains after hammer patterns (n=107)...
Mean gain: 0.0616
Median gain: 0.0465
Positive gains: 98.1%
Running Bayesian analysis for 20-day gains...

--------------------------------------------------
Fitting and analyzing NORMAL model...
--------------------------------------------------
```

Progress	Draws	Divergences	Step size	Grad evals	Sampling Speed	Elapsed	Remaining
	3000	0	0.67	3	1483.34 draws/s	0:00:02	0:00:00
	3000	0	0.67	3	731.32 draws/s	0:00:04	0:00:00

```
Sampling ... 100% 0:00:00 / 0:00:00

Normal Model Summary:
         mean      sd  hdi_3%  hdi_97%  mcse_mean  mcse_sd   ess_bulk  \
mu     0.0615  0.0052  0.0515   0.0711     0.0001   0.0001  2632.0997
sigma  0.0549  0.0038  0.0482   0.0620     0.0001   0.0001  2528.6851

        ess_tail   r_hat
mu     1997.7191  1.0017
sigma  2454.6272  1.0003
Probability of positive mean return: 100.00%
95% Value-at-Risk: 0.0529
95% Expected Shortfall: 0.0507
```



Fitting and analyzing STUDENT-T model...

Progress	Draws	Divergences	Step size	Grad evals	Sampling Speed	Elapsed	Remaining
━━━━━━━━━━━━━━━━	3000	0	0.55	3	727.10 draws/s	0:00:04	0:00:00
━━━━━━━━━━━━━━━━	3000	0	0.43	7	339.59 draws/s	0:00:08	0:00:00

Sampling ... ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 100% 0:00:00 / 0:00:00

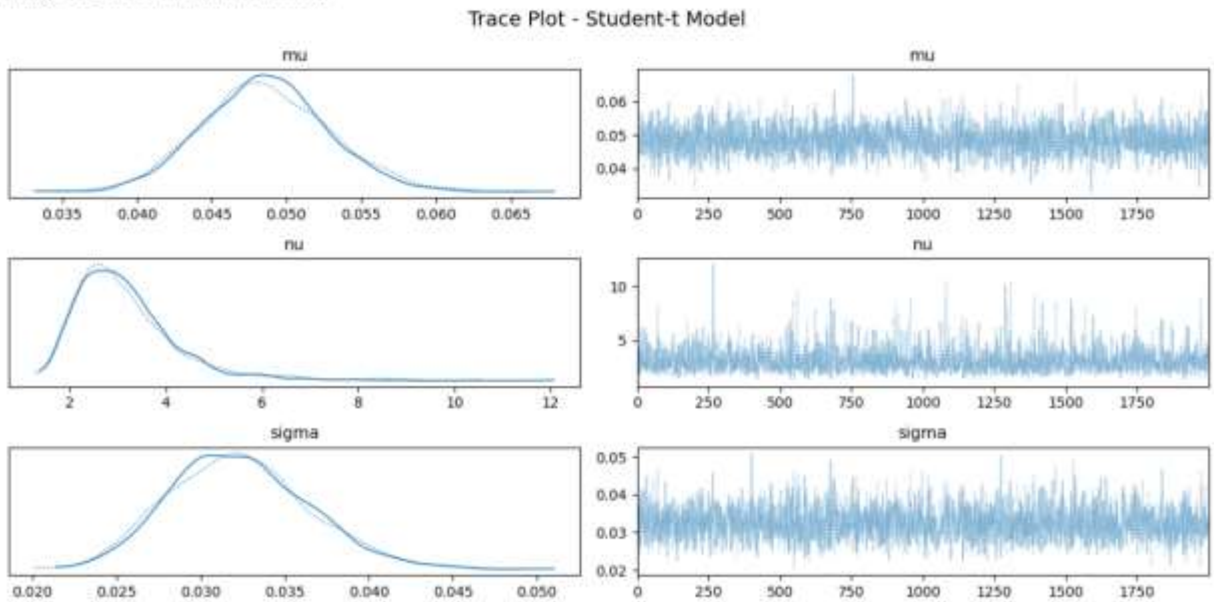
Student-t Model Summary:

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk \
mu	0.0486	0.0042	0.0412	0.0568	0.0001	0.0001	2243.5987
sigma	0.0324	0.0042	0.0250	0.0405	0.0001	0.0001	2124.8122
nu	3.1578	1.1065	1.5457	5.0756	0.0266	0.0422	2013.5551

	ess_tail	r_hat
mu	2238.4667	1.0007
sigma	2334.7792	1.0008
nu	1901.4531	1.0001

Probability of positive mean return: 100.00%
95% Value-at-Risk: 0.0419
95% Expected Shortfall: 0.0403

Running diagnostics for Student-t model...

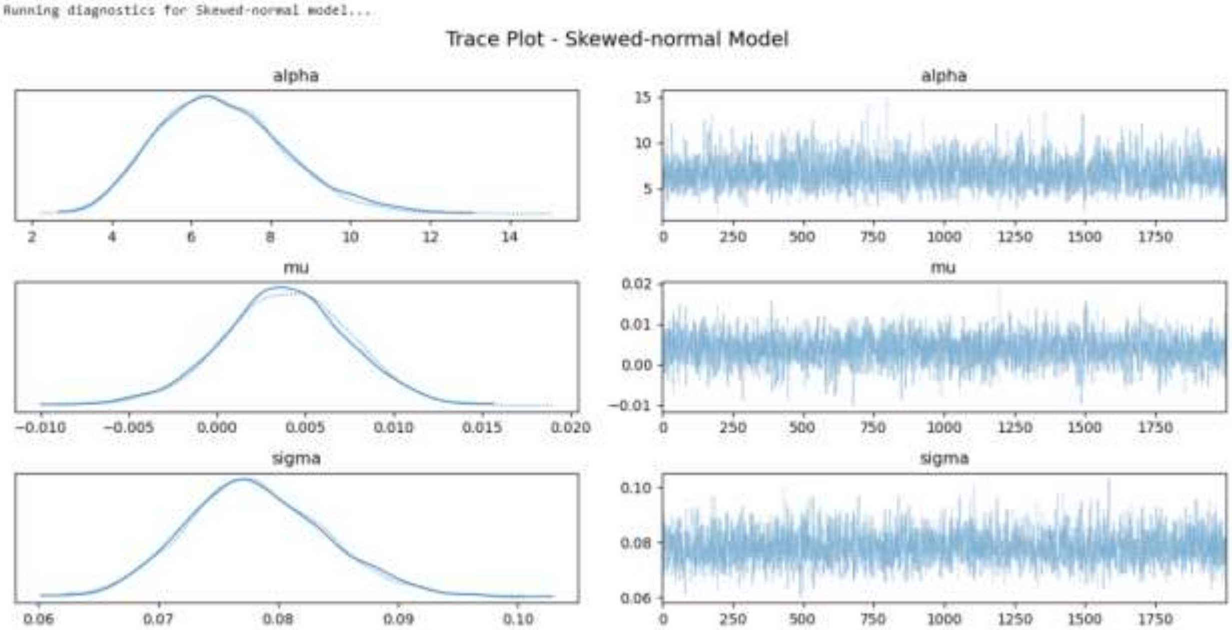


```
--------------------------------------------------
Fitting and analyzing SKEWED-NORMAL model...
--------------------------------------------------
```

Progress	Draws	Divergences	Step size	Grad evals	Sampling Speed	Elapsed	Remaining
	3000	0	0.52	7	741.17 draws/s	0:00:04	0:00:00
	3000	0	0.55	7	364.76 draws/s	0:00:08	0:00:00

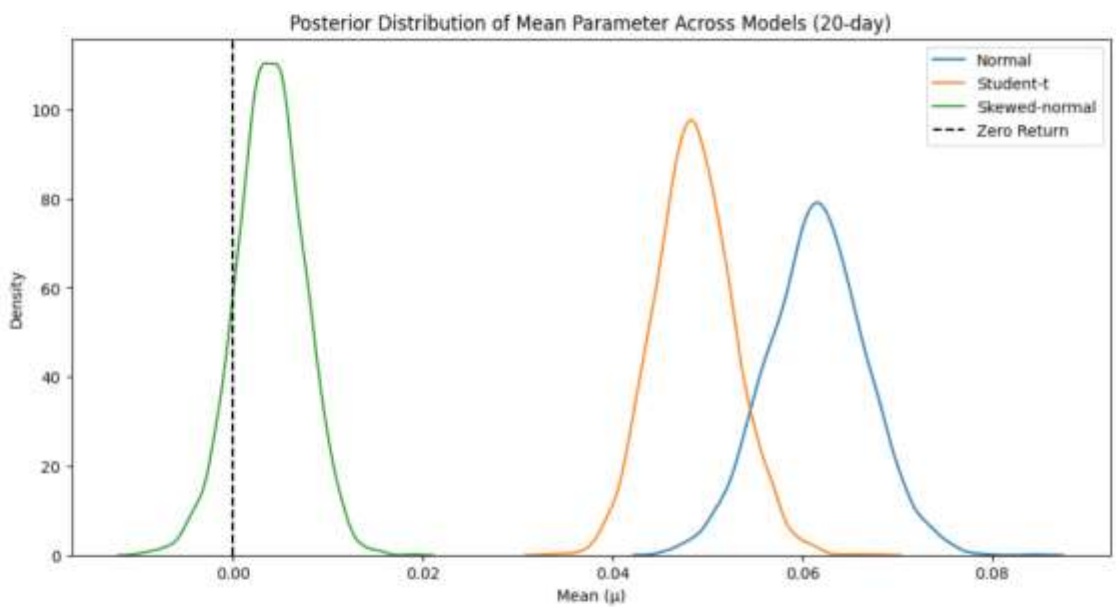
```
Sampling ... ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 100% 0:00:00 / 0:00:00

Skewed-normal Model Summary:
         mean      sd  hdi_3%  hdi_97%  mcse_mean  mcse_sd   ess_bulk  \
mu     0.0039  0.0036 -0.0029   0.0106     0.0001   0.0001  2157.9061
sigma  0.0782  0.0058  0.0674   0.0888     0.0001   0.0001  2361.0176
alpha  6.7775  1.6199  3.7975   9.7105     0.0327   0.0299  2567.1406

        ess_tail   r_hat
mu     2463.4766  1.0003
sigma  2744.9992  1.0007
alpha  2362.2007  1.0003
Probability of positive mean return: 86.65%
95% Value-at-Risk: -0.0020
95% Expected Shortfall: -0.0039
```

```
Running diagnostics for Skewed-normal model...
```



Model Comparison Stats:

```
Model Comparison:
          Model           MSE       MAE  P(μ > 0)
0        normal  3.830115e-08  0.000196    1.0000
1     student-t  1.711874e-04  0.013084    1.0000
2  skewed-normal  1.502360e-05  0.003876    0.8665
Best model based on MSE: normal

Calculating baseline statistics for comparison...

20-day baseline statistics (clean baseline, n=5243):
Mean gain: 0.1665
Median gain: 0.0507
Positive gains: 90.1%
Excluded 1030 candles from baseline (hammers + subsequent 10 days)

Comparison - Hammer vs Clean Baseline (20-day):
Hammer mean: 0.0616
Baseline mean: 0.1665
Difference: -0.1049 (-63.0% relative)

--- Parameter Comparison Across Models (20-day) ---
              Mean (μ)  Std Dev (σ)  DoF (ν)  Skewness (α)  P(μ > 0)    MSE  \
normal          0.0615       0.0549      NaN           NaN    1.0000  0.0000
student-t       0.0486       0.0324   3.1578           NaN    1.0000  0.0002
skewed-normal   0.0039       0.0782      NaN        6.7775    0.8665  0.0000

                  MAE
normal         0.0002
student-t      0.0131
skewed-normal  0.0039
```



--- Prior Sensitivity Comparison ---					
Prior	Mean Estimate	Std Dev Estimate	Prob Positive Return	95% VaR	95% ES
weakly_informative	0.0616	0.055	1	0.053051	0.050782
more_informative_mean_positive	0.0615	0.0549	1	0.052584	0.050173
more_informative_mean_negative	0.0614	0.055	1	0.0528	0.050512
narrow_sigma	0.0614	0.0547	1	0.052657	0.050437
wide_sigma	0.0616	0.055	1	0.052582	0.050564

=== ANALYSIS CONCLUSIONS ===

For 20-day horizon:

• Hammer patterns showed 6.16% average gain
• Clean baseline (excluding hammers and 10 days after) was 16.65% average gain
• Edge from hammer pattern: -10.49%
• Best fitting model: Normal
• Hammers underperformed the baseline by 63.0%
• Win rate: 98.1% for hammers vs 90.1% baseline
• Bayesian probability of positive expected return (Normal Model): 100.0%

Trading recommendation:
NO SIGNIFICANT EDGE found for hammer patterns in this dataset

References

[1] https://www.strike.money/technical-analysis/hammer-candlestick-pattern

[2] https://en.wikipedia.org/wiki/Candlestick_pattern