Option Valuation Models: Tuning and Performance

Joseph Muslu
Northeastern University
Khoury College of Computer Sciences | D'Amore McKim School of Business
360 Huntington Avenue, Boston, MA 02115
muslu.jo@northeastern.edu

Abstract

Option Valuation Models: Tuning and Performance

This paper documents a process used to evaluate the effectiveness of options pricing models. In the field of quantitative finance, various valuation models derived from the fields of mathematics and statistics are used to model the prices of stock options based on a variety of factors. These include information surrounding the options contract such as the strike price and days until expiry, behavior of the underlying stock as the standard deviation of the assets returns over a given time period, and broader market conditions such as the risk free rate to ensure no arbitrage conditions are met (the idea that there should exist no opportunity for risk-free profits in an efficient market).

The models presented in this paper are the Black Merton Scholes (BSM) and Heston models. The models presented in this paper exist as stochastic differential equations that can be transformed and solved. BSM can be solved analytically through closed form solutions by setting boundary conditions in an equation similar to the physics heat equation (Black Merton Scholes). Heston requires semi-closed form solutions with integration that can be solved in a variety of methods. The method used here involved conversion of Heston into the frequency domain via fourier methods into a characteristic function, numerical integration, and conversion back into an interpretable solution again via fourier methods. Fast fourier transformation for integration may generally be favored but for these purposes numerical methods via Gauss-Laguerre integration on 144 points were found to be sufficient.

The parameters used to tune these models and market prices used to evaluate them in options pricing are derived from data that originates in Bloomberg terminal excel API. The options data is completely sourced from Bloomberg, the historical price data of the underlying stock is

sourced from Bloomberg in the short term and for all longer expiry options, and Yahoo finance python wrapper (yfinance) for longer term price history on options with shorter term option expiration. The Risk Free Rate data is sourced from the US treasury API.

The tech stack used in this project was Python (Libraries: pandas, numpy, QuantLib, re, os, datetime, finance, concurrent.futures, requests, matplotlib), Excel, Bloomberg (Bloomberg Query Language excel API), Git, PowerQuery. There was also preparation to use the northeastern discovery Linux HPC, and performed tests on it, but ultimately not used in the final calculations due to bottlenecks within the amount of data that could be sourced from the Bloomberg API, rendering it necessary.

The models were used in a trading simulation on end of day options data through March 31st, 2025 to April 11th, 2025, within a subsample of contracts that met specific market liquidity guidelines. The findings illustrate that the Heston models performed better than the BSM model with return on investments of -4.15% for BSM, 24.4% on Heston with a moments based parameter estimation and 69.12% on Heston with GARCH-inspired (Generalized Auto Regressive Conditional Heteroskedasticity) parameter estimation. These results can also be attributed to the more conservative valuations adjusting the trading strategies, with BSM having 67 trades, Heston moments approach having 24 trades, and Heston GARCH having 20 trades. The results suggest that the more granular volatility parameters in the Heston models allow for more profitable trading strategies that are better at forward modeling the decay of the options prices to avoid purchasing overvalued options.

1 Data Sourcing

This section focuses on the sourcing of options data and what exactly is needed, as well as reiterations of what options contracts are. There will be explanations geared toward an audience with primarily non-finance backgrounds; we will assume familiarity with intermediate to beginner computer science and programming knowledge as well as statistics. This section will also discuss the parameters and strategies outlined in the queries and the obstacles.

1.1 Options Defined

Stocks represent partial ownership of a company and can be sold and purchased in individual parts called shares. Publicly traded companies have their stocks available in publicly traded exchanges or through brokerages. These stocks tend to increase in value over time, and the primary ways that money is made through stocks (also known as equities) are through capital appreciation and gains (which is buying at a lower market price and selling stock at a higher market price) or alternatively through the payments of cash sums to shareholders through dividends.

An options contract, also known as a type of stock derivative, gives the owner the right but not the obligation to either purchase or sell a lot (100 shares) of stock within a certain date range at a predetermined price within any point of time in American options expiration. For example, an investor might purchase a call option on Company XYZ with a strike price of $50 expiring in three months. This gives the investor the right to purchase 100 shares of XYZ at $50 per share anytime before the expiration date, regardless of the stock's current market price. A Call option is denoted by the right to purchase at a certain price and a Put option denoted by the right to sell.

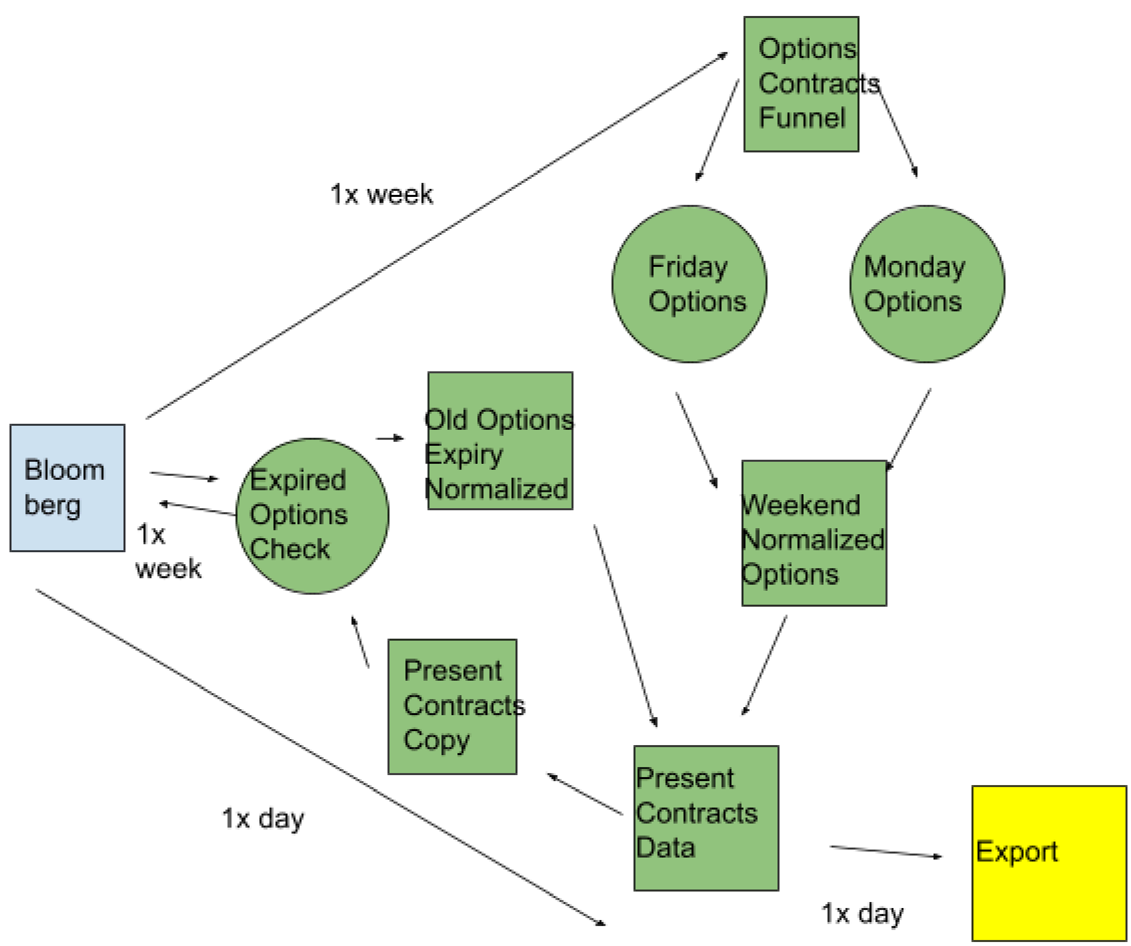
A characteristic of options contracts is volume. Volume is not exclusive to options and also exists in equities, and it represents the total amount of an asset that has been traded during a time period. For the purpose of this paper, volume refers to the amount of options contracts of a specific option that were traded in the trading day; this helps assess liquidity by showing how many willing participants are buying or selling an option. Another characteristic of options contracts is open interest. Open interest is the amount of contracts for a specific options contract that have not expired or been exercised yet but are held by owners. Open interest provides insight into the liquidity and interest level in a particular options contract. When a new options contract is created (one party buys and another sells), open interest increases by one. When an options contract is closed (either through offsetting transactions, expiration, or exercise), open interest decreases by one. Unlike volume, which tracks activity during a specific period, open interest represents the total outstanding contracts at a given point in time. High open interest indicates significant market interest in a particular options contract and typically corresponds with higher liquidity, making it easier to enter or exit positions at favorable prices.

The assumption is that for trading purposes, liquidity is a good thing. However, there are some other factors to keep in mind. While very high volume can be good for liquidity, if there are not many contracts outstanding relative to that volume, there is a potential that the contract is being traded many more times than it's being held overall in a given day. Sometimes this can be a bad thing because market participants are buying and selling the contract not with intention to hold it but instead with intention to resell it in very short time frames and profit off of being the liquidity provider in the markets. This is primarily done by institutions with billions of dollars at their disposal and computing systems that can place transactions under seconds and even milliseconds. In order to avoid this, it is better to have less volume relative to the amount of open interest; however, there's a balance to still have enough volume for proper liquidity. Based on this, we put some parameters in place to help only look at options with an open interest greater than or equal to 1,000 and volume greater than or equal to 500, as well as the requirement of the option to possess an open interest to volume ratio between or equal to 0.3 to 0.7. This helps filter out market-made options where the chances of finding improperly valued options is much lower.

1.2 Bloomberg Excel Pipeline

The first step in pricing options contracts has to be sourcing the options contracts to price. Based on the parameters that were discussed previously, specifically open interest greater than or equal to 1,000, volume greater than or equal to 500, and open interest to volume ratio between 0.3 to 0.7, we were able to set up Bloomberg query statements. Northeastern University provides access to Bloomberg terminals with a student license that allows students the ability to access data directly from the Bloomberg terminals and onto Excel files through an Excel API that allows formulas and queries to pull data directly from the terminal. The Excel commands are set up to take inputs from multiple cells within the spreadsheet to run Bloomberg query formulas. The beginning column of the spreadsheet had the tickers of every single stock on the NASDAQ stock exchange.

These query requests can only take in a certain amount of data before they time out. To handle this, 10 separate queries were run in parallel for sections of NASDAQ tickers in groups of around 250 companies each and the underlying options contracts that fit the parameters. For clarification, there can be hundreds of options contracts for a single stock, but the parameters helped ensure the data collected was not too much for the API license. There are limits to how many queries can be done on a given Bloomberg terminal in a given day. There is a limit of a few thousand independent contract or equity queries and a more general limit of cells being populated by around 500,000 a day. To make sure that API limitations are not a problem, these stricter parameters were chosen. Specifically, end-of-day options and underlying stock behavior was used for a variety of reasons because the data could only be sourced by being at the computers at the Bloomberg terminals. It also allowed for the use of the adjusted closing price query for the underlying stock, adjusted for any dividend payments that may be paid and added to the price of the assets. Another characteristic of these options contracts that had to be navigated is that parameters could change, and if they constantly changed, then options would not be monitored consistently, to allow for price pattern tracking. In order to get around this, a process was used in which a query was done on Friday for all the options in the market that fit the parameters and a query was done on Monday for the same parameters. The options contracts that appeared only on both days moved through the system to be evaluated. Additionally, old options from the previous week that were deemed monitorable by the parameters and had not expired from the previous week were also outer merged with the new contracts to continue to keep track of them. Once the options were in the system, the prices and relevant statistics could be queried daily. To summarize, new contracts were rotated in at the beginning of the trading week, and those contracts were monitored daily with new additions or removals by the beginning of the next trading week. This also worked particularly well as it is very common for options contracts to expire on Fridays. This whole process is outlined in the figure. Power Query was used for the weekend consolidation, and a VBA script for inner join, and BQL to assess the expiry. The exports were made to Git.



2 Parameter Estimation and Model Pricing

This section will describe the methodologies used to tune the options pricing models as well as the conceptual functions and theories behind them. A variety of algorithms and statistical techniques will be mentioned but not explained fully. This section assumes previous knowledge of calculus and statistics.

2.1 Black Scholes and Merton

The Black-Scholes (Black-Merton-Scholes can be also used interchangeably) equation models the price of an option as a stochastic differential equation which can be solved with inputs of price and price sensitivity values. Specifically, the Black-Scholes equation is known as the foundation of all other option pricing equations and was developed in 1973. Parameters of the Black-Scholes equation include the underlying asset price, strike price, time to expiration, risk-free interest rate, and volatility, which is calculated as the standard deviation of returns. This differs from the Heston equation that also models the price of an option as a stochastic differential equation. The Heston model extends the Black-Scholes framework by incorporating stochastic volatility. While the Black-Scholes model assumes constant volatility, the Heston model recognizes that volatility itself fluctuates over time and exhibits clustering behavior. The Heston model includes several key parameters that give it greater flexibility in modeling real-world option prices. The initial variance parameter represents the starting volatility level of the underlying asset at the beginning of the modeling period. This is paired with a long-term variance parameter, also called the mean reversion level, which represents the average variance that the process tends toward over time. The model includes a mean reversion rate that controls how quickly variance returns to its long-term average. Higher values indicate faster mean reversion, while lower values show that volatility takes longer to normalize after shocks. This reflects the empirical observation that market volatility tends to spike quickly but often decays slowly. Another important parameter is the volatility of variance. This determines how much the variance process itself fluctuates around its mean-reverting path. Higher values create more erratic volatility patterns that can better capture extreme market conditions. The correlation parameter represents the relationship between asset returns and changes in volatility. In equity markets, this correlation is typically negative, known as the leverage effect, meaning that decreases in asset price tend to coincide with increases in volatility. This negative correlation helps the model produce the volatility skew commonly observed in options markets. The Heston model's additional parameters allow it to capture important market phenomena not accounted for in the Black-Scholes model, including volatility clustering, volatility smiles and skews in options markets, the leverage effect, and fat-tailed return distributions that better match empirical observations. These improvements make the Heston model particularly valuable for pricing options in markets where volatility is known to be dynamic and where the Black-Scholes assumptions about constant volatility are too restrictive.

2.1 Parameters For The Models

All options pricing models rely on several common market parameters. The strike price is the predetermined price at which the option holder can execute their contract, while the spot price represents the current market price of the underlying asset at calculation time. These two parameters determine whether an option is in-the-money, at-the-money, or out-of-the-money. For call options to be profitable, the strike price should be below the spot price, allowing the holder to buy at the lower strike and sell at the higher market price. For put options, profitability occurs when the strike price exceeds the spot price. Options also incorporate expiration dates as a parameter, which is annualized along with other statistical values. Our models use risk-free rates from treasury instruments (bonds, notes, or bills) that match the option's expiration timeframe. Dividend yields were set to zero since Bloomberg closing prices are already dividend-adjusted, and the short two-week trading period makes dividend payouts negligible for most contracts.

The Black-Scholes model employs volatility to represent expected price fluctuations of the underlying asset, calculated from historical price data using the standard deviation of log returns. In our implementation, we used a mirrored approach where the volatility calculation period matches the option's time to expiry. For instance, an option expiring in 10 days would use the past 10 days of stock performance to calculate volatility.

Heston models introduce more sophisticated parameters to model volatility. The initial variance parameter represents the starting point for the stochastic volatility process (equivalent to square initial volatility). Long-term variance indicates the level that variance reverts to over time. Mean reversion speed controls how quickly variance returns to its long-term average. Volatility of volatility determines how much the variance itself fluctuates. Correlation defines the relationship between price movements and variance, typically negative for equity options to capture the leverage effect.

The Heston Moments approach implements a practical method of moments estimation using the statistical properties of historical returns. Rather than using complex maximum likelihood estimation, the code directly leverages daily variance for both initial and long-term variance parameters. For mean reversion speed, the function analyzes the skewness of returns, applying a formula that scales with absolute skewness magnitude. This captures the financial intuition that more skewed return distributions tend to revert more quickly to their mean. Similarly, kurtosis, which measures the tailedness of the distribution, determines the volatility of the volatility parameter.

The GARCH-inspired approach doesn't implement a traditional GARCH(1,1) model with maximum likelihood estimation of parameters based on the time series. Instead, it approximates volatility clustering over the previous 252 days by analyzing how variance itself varies over time, with a hardcoded mean reversion parameter of 2.0. The function calculates variance across multiple overlapping windows of returns (typically 20 days wide), then measures the standard deviation of these variance estimates. This captures the essence of volatility clustering periods where volatility itself becomes volatile without requiring computationally intensive GARCH fitting. Both approaches incorporate the leverage effect by using a fixed correlation parameter of -0.7, representing the well-documented phenomenon where equity prices and volatility typically move in opposite directions, falling prices tend to coincide with rising volatility, creating an asymmetric response that standard Black-Scholes cannot capture.

2.2 Using the Models To Price Options

The code implements two sophisticated mathematical approaches for pricing options. The Black-Scholes-Merton model uses an analytical closed-form solution derived from a partial differential equation that originates from the geometric Brownian motion stochastic differential equation. In the implementation, this is handled by QuantLib's AnalyticEuropeanEngine, which directly applies the closed-form formula without numerical approximations. The BSM solution connects option prices to the normal probability distribution through the N(d1) and N(d2) terms, making it computationally efficient while being constrained by its assumptions of constant volatility and log-normal price distribution. For the Heston model variants (both HNGAR and HNMOM), the code employs QuantLib's AnalyticHestonEngine with a specifically defined integration order of 144 points. This engine implements a semi-analytical approach using Fourier transform methods. The code sets up a HestonProcess object with parameters that define how variance evolves (initial variance, long-term variance, mean-reversion speed, volatility of volatility, and correlation), which creates the two-dimensional system tracking both price and variance evolution. The solution method converts the option pricing problem to the frequency domain using Fourier transforms, working with the characteristic function rather than directly with probabilities. The integrationOrder = 144 parameter indicates that Gauss-Laguerre quadrature with 144 points is used to numerically evaluate the resulting integral before transforming back to obtain the final price. This specific numerical integration technique was chosen for its accuracy in handling the semi-infinite integration range that appears in the Heston pricing formula. While both HNGAR and HNMOM variants use identical solution methods in the code, they differ in how their model parameters are calibrated and estimated, as evidenced by the separate parameter sets passed to the same price_with_heston function. These results are saved and outputted as new columns on the existing data.

3 Trading Simulation

This section describes the performance of the different models in the trading environment that was created. It also explains the trading environments themselves and the conditions for purchases and trades, what was measured, and some relevant figures.

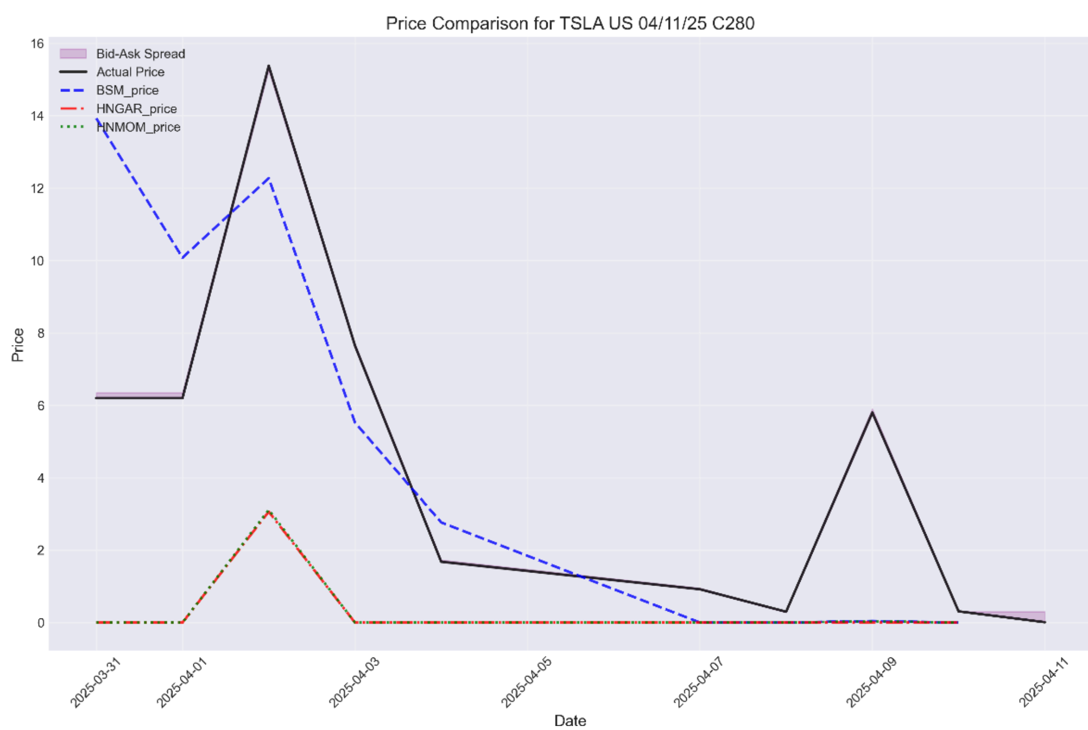
3.1 Trading Environment

By now, the data collected includes option bid and ask prices as well as the last price sold of an option for each relevant day for around 60 contracts from the first week, 4 contracts over both weeks, and 25 contracts over just the second week. The data also includes the estimated prices from the models. Based on the actual prices and the model estimated prices, we conduct a trading simulation.

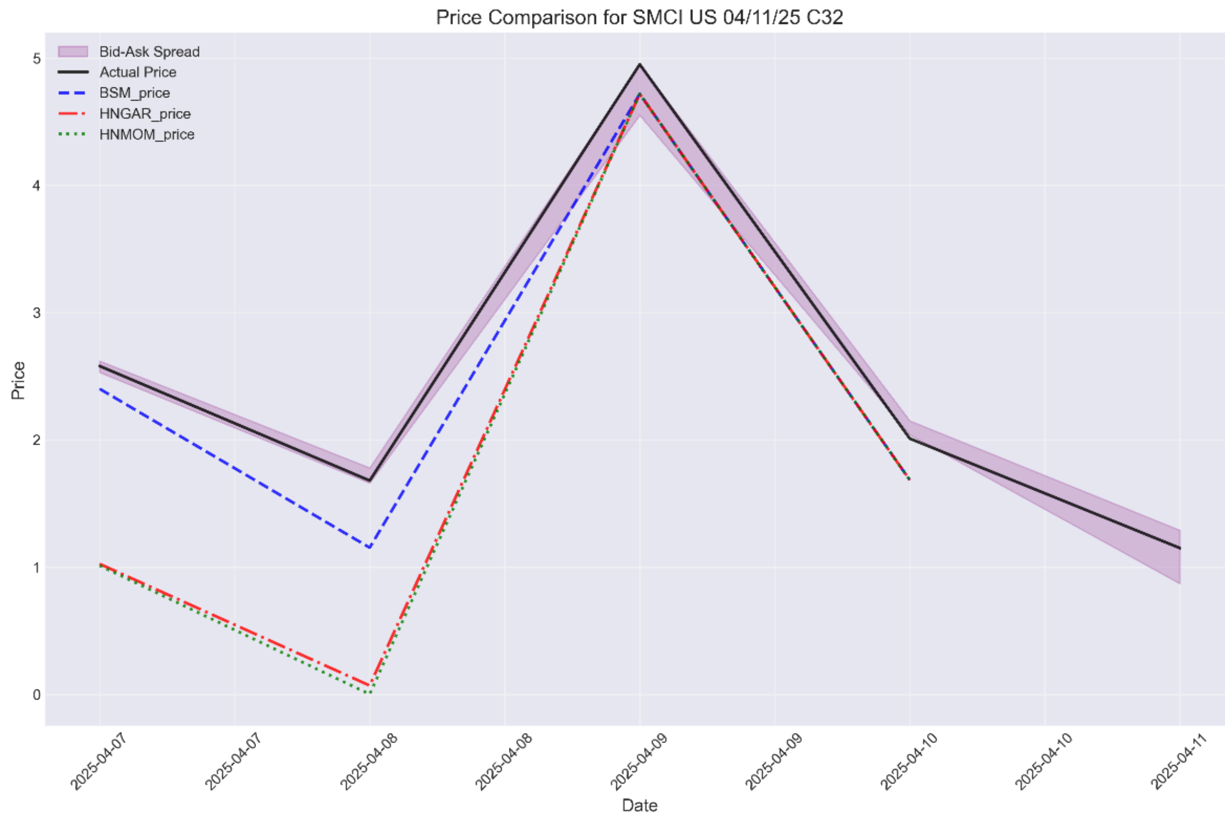
For price data clarification: bid price is the highest price you can instantly sell a contract for, ask is the lowest price someone is selling their contract for, the spread is the distance between them, the midpoint is halfway between bid and ask, and the last price is the most recent price the option sold for. In our trading simulation, all entry transactions are at $100 as a simplification, even though some options can be worth more (purchasing fractions for simplifaction). Whenever a model evaluates an option price to be above or equal to the current ask for a day, it takes a position in the contract, if it doesn't already have one. If the model says the option price is below the current price, it is sold at the bid price if already holding a position; otherwise, nothing happens. If the model price is within the spread and not already held, it will set a bid at today's midpoint, filled tomorrow at today's midpoint if tomorrow's midpoint is below or equal to today's. If the model price is within the spread and a position is already held, it will set an ask at today's ask, filled tomorrow at today's ask if tomorrow's ask is below or equal to today's ask. If an option is expiring while held, it's valued at the last price sold; if not expired and held, it's valued at the midpoint.

3.2 Results

To better understand the simulation, the price behavior of options and the model predictions were plotted for each individual option over the time periods that it was available to purchase. Over 100 plots were created, but for simplicity, we'll focus on the most relevant or interesting plots that best show how each of these models perform. Additionally, there are visualizations for how the models performed in the trading simulation over time. There are four visualizations for this in total: one to track each individual model and how it's using its capital and how it's performing, as well as one plot that compares all of the performance of the models against each other in terms of return on investment percentage (ROI).



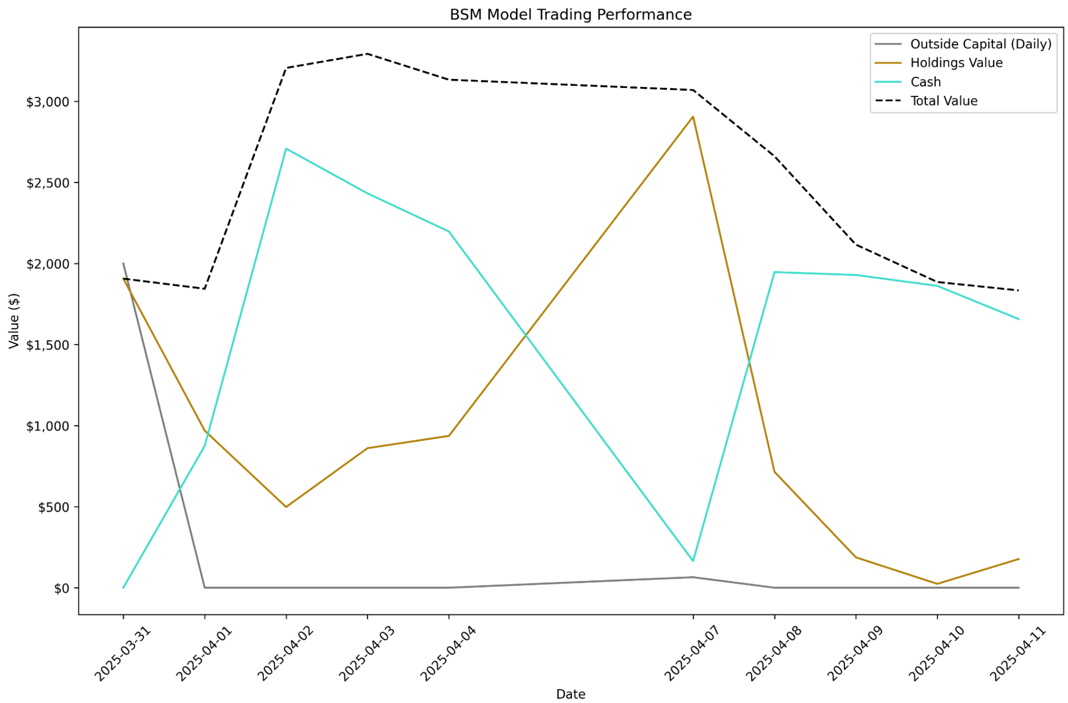
This figure shows an example of Tesla Call Options. As we can observe, the BSM model values the option highly at the beginning of the simulation which allows it to purchase the contract at ask price, and sells it shortly, as the value shoots up dramatically. This nets a healthy profit. This is the trade summary TSLA US 04/11/25 C280: $140.16 (2025-03-31 to 2025-04-02).



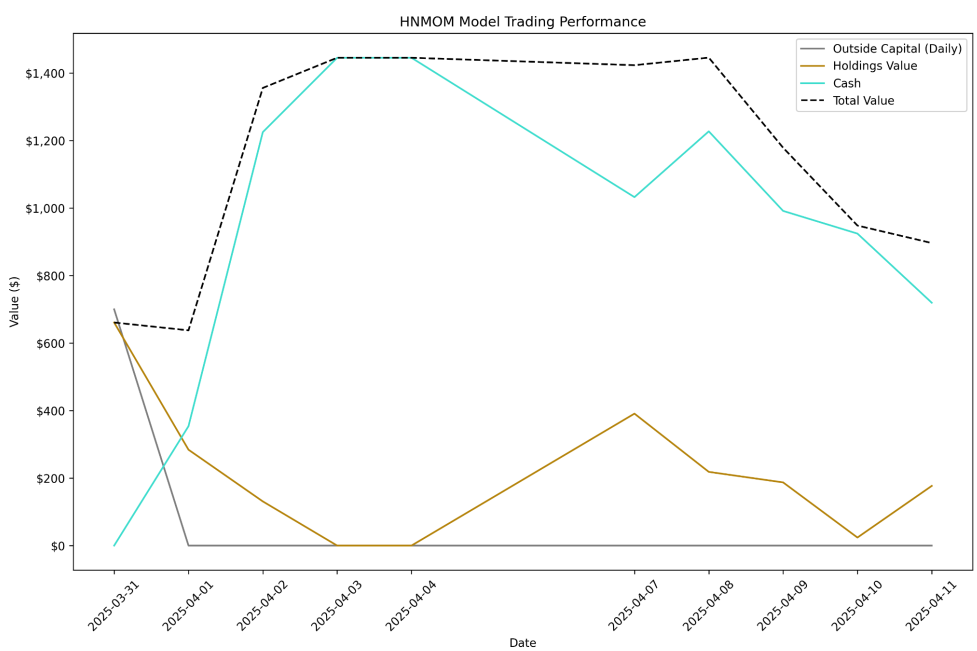
This is an example where every single model loses money. We can see the price trending upwards, but the models are not able to trade it until it starts going downward, leading to a loss. This is the trading summary SMCI US 04/11/25 C32: $-57.05 (2025-04-10 to 2025-04-10).

These plots show the individual performance of the models. Outside capital is the amount of outside capital that needs to be put in per day to make the trades happen on the given days.

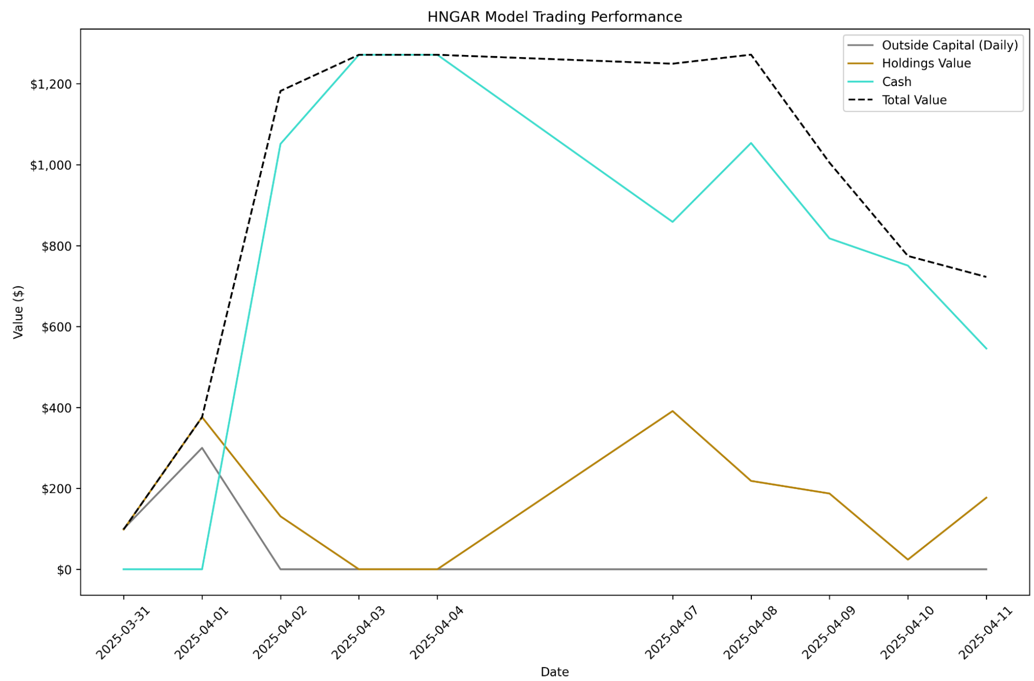
Black Scholes:



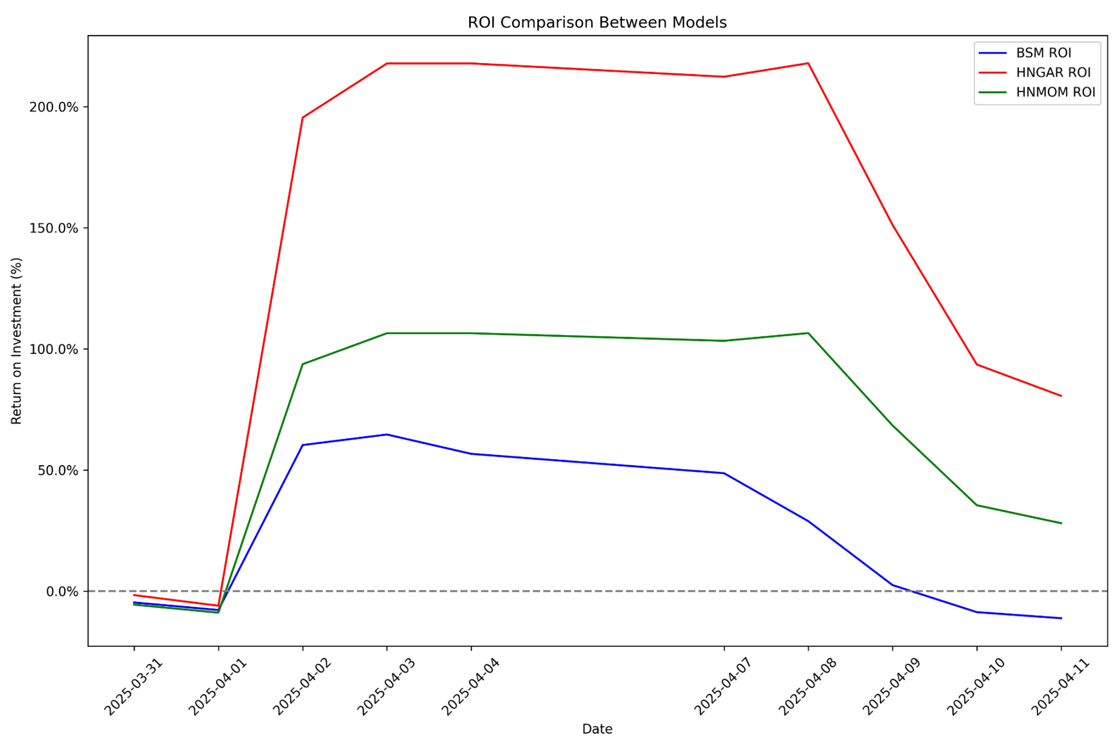
Heston Moments Approach:



Heston GARCH inspired:



All of the models relative to each other in ROI:



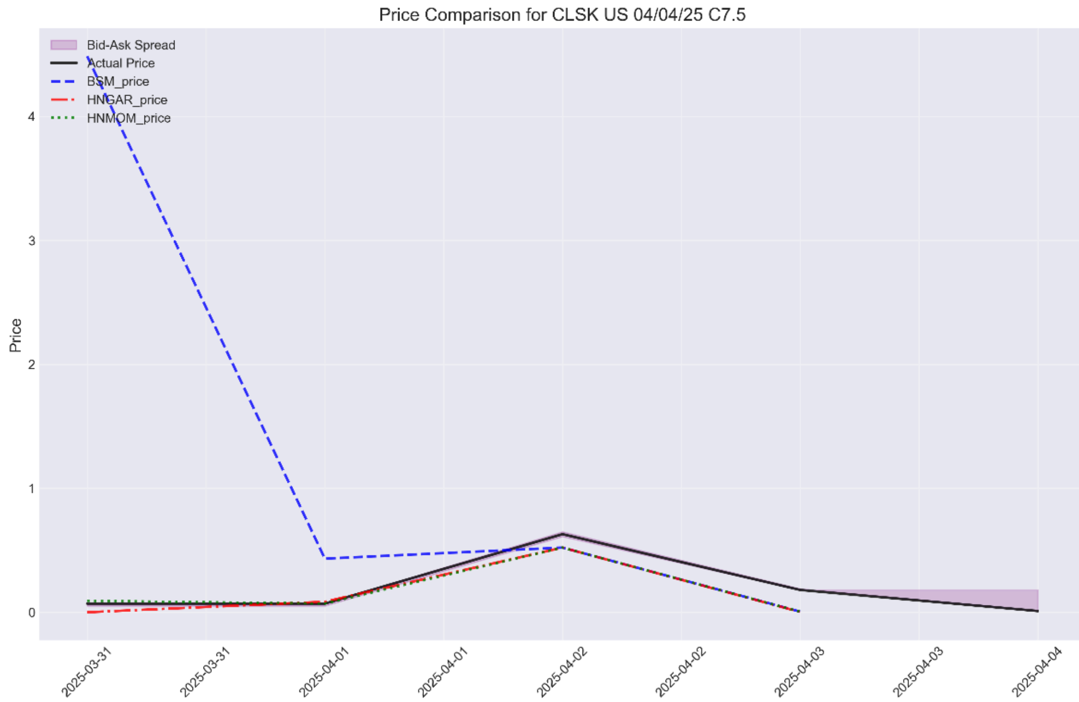
Some additional statistics in the trading include these.

BSM Model: Total trades: 67 with a win rate of 19.40%. The biggest gain was $771.43 and the biggest loss was $-98.99. Average win (winners only) was $122.88 while average loss (losers only) was $-33.86. The total money outside invested was $5000.00 with a final value of $4792.40. Maximum single-day investment reached $2300.00. Total profit was $-207.60, yielding a return on investment of -4.15%. The most profitable trade was CLSK US 04/04/25 C7.5 at $771.43, while the least profitable was SMCI US 04/11/25 P30 at $-98.99.

HNGAR Model: Total trades: 20 with a win rate of 15.00%. The biggest gain was $771.43 and the biggest loss was $-98.99. Average win (winners only) was $291.71 while average loss (losers only) was $-32.51. The total money outside invested was $500.00 with a final value of $845.61. Maximum single-day investment reached $500.00. Total profit was $345.61, yielding a return on investment of 69.12%. The most profitable trade was CLSK US 04/04/25 C7.5 at $771.43, while the least profitable was SMCI US 04/11/25 P30 at $-98.99.

HNMOM Model: Total trades were recorded with a win rate of 8.33%. The biggest gain was $771.43 and the biggest loss was $-98.99. Average win (winners only) was $397.67 while average loss (losers only) was $-27.22. The total money outside invested was $900.00 with a final value of $1119.56. Maximum single-day investment reached $700.00. Total profit was $219.56, yielding a return on investment of 24.40%. The most profitable trade was CLSK US 04/04/25 C7.5 at $771.43, while the least profitable was SMCI US 04/11/25 P30 at $-98.99.

Something additional to note is that all 3 options models captured the same most profitable trade which can be shown here. This likely played a strong role in the profitability in the models, and afterwards the more conservative stochastic volatility models preserved this amassed capital better with much less trades than BSM. Without this point the results may have been different. But this is normal for options trading where one contract can have significant gains



Price Comparison for CLSK US 04/04/25 C7.5
Bid-Ask Spread
Actual Price
BSM_price
HNGAR_price
HNMOM_price
Price
4
3
2
1
0
2025-03-31
2025-03-31
2025-04-01
2025-04-01
2025-04-02
2025-04-02
2025-04-03
2025-04-03
2025-04-04

Sources

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. Journal of Political Economy, 81(3), 637-654.

Bloomberg. (2023). Options Valuation and Risk Management. Bloomberg Terminal Documentation.

Chicago Board Options Exchange. (2022). The CBOE Volatility Index - VIX. CBOE White Paper.

Fidelity. (2022). Understanding Options Pricing. Retrieved from https://www.fidelity.com/learning-center/investment-products/options/options-pricing-basics

Heston, S. L. (1993). A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options. The Review of Financial Studies, 6(2), 327-343. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=210009

Hull, J. C. (2002). Options, Futures, and Other Derivatives (5th ed.). Prentice Hall.

Investopedia. (2023). Options Greeks: Delta, Gamma, Theta, Vega, and Rho. Retrieved from https://www.investopedia.com/trading/getting-to-know-the-greeks/

Investopedia. (2023). Understanding the Black-Scholes Model. Retrieved from https://www.investopedia.com/terms/b/blackscholes.asp

Merrill Lynch. (2022). Options Strategy Guide. Merrill Lynch Wealth Management.

TD Ameritrade. (2023). Options Trading Basics. Retrieved from https://www.tdameritrade.com/investment-products/options/options-trading-basics.html