Numerical Project Summary

"The Constant Elasticity of Variance Model: Implementation and Comparison"

Executive Summary

This project implements numerical methods for pricing options under the Constant Elasticity of Variance (CEV) model, which generalizes Black-Scholes by allowing volatility to depend on the stock price level. We derive and implement the Crank-Nicolson finite difference scheme, establish the relationship between CEV and CIR processes, and compare results with Black-Scholes solutions when δ = 1.

1. Introduction and Model Framework

The CEV model extends Black-Scholes by introducing price-dependent volatility through: - Stock dynamics: $dS(t) = rS(t)dt + \sigma S(t)^{\delta} dW(t)$ - Option price: $\Pi(t) = e^{-(-r(T-t))u(t)}$

Key advantages over Black-Scholes: - Captures volatility smile/skew observed in markets - Models leverage effect (negative correlation between price and volatility) - More realistic for assets with volatility clustering - Better pricing for out-of-the-money options

Applications: - Option pricing with implied volatility surfaces - Risk management and portfolio optimization - Forecasting asset price distributions - Pricing exotic derivatives and structured products

2. Mathematical Development

Exercise 6.27: CEV-CIR Connection

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Given parameters: - a = 2r/(\delta-1) - b = \sigma 2(2\delta-1)/(2r) - c = -2\sigma(\delta-1) - \theta = -1/(2(\delta-1))
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Proof: Shows that if X(t) follows the CIR process: $dX(t) = a(b - X(t))dt + c\sqrt{X(t)}dW(t)$

Then $S(t) = X(t)^{\theta}$ solves the CEV equation with $S_0 = x^{\theta}$

This connection enables using CIR techniques for CEV option pricing.

3. Numerical Implementation

Partial Differential Equation

The CEV pricing PDE: $-\partial_t u + rx \partial_x u + (\sigma 2/2)x^{(2\delta)} \partial_x^2 u = 0$

With boundary conditions: - Terminal: u(T,x) = max(x-K, 0) for calls - Lower: u(t,0) = 0 - Upper: $u(t,X) = X - Ke^{-(t-t)}$

Crank-Nicolson Scheme

Combines forward and backward Euler methods for unconditional stability:

 $u^{(n+1)_i} = (\Delta t/4)[rx_i(forward + backward derivatives) + \sigma^2 x^{(2\delta)_i/(\Delta x)^2}(forward + backward second derivatives)] + u^n_i$

Implementation parameters: - Spatial grid: M = 100 points - Time steps: N = 1000 - Grid spacing: Δt = T/N, Δx = X/M

4. Results and Validation

Comparison with Black-Scholes ($\delta = 1$)

When δ = 1, CEV reduces to Black-Scholes: - Implemented exact Black-Scholes formula for validation - Maximum absolute error function computes discrepancies - Results: ~45 mismatched values out of 1000 time steps

Error Sources and Mitigation

Numerical errors: - Discretization error $(O(\Delta t^2 + \Delta x^2))$ for Crank-Nicolson) - Boundary condition approximations - Round-off errors in matrix operations

Improvements: - Finer grids reduce discretization error - Adaptive mesh refinement near strike - Higher-order finite difference schemes

Performance Metrics

Time Steps	Error Count	Computation Time
N=1000	~45	Fast
N=20	~37	Very Fast
	N=1000	

5. Key Insights

Model Selection Criteria: - Use CEV when volatility smile is pronounced - Black-Scholes sufficient for at-themoney, short-term options - CEV essential for exotic options and long maturities

Computational Trade-offs: - CEV requires numerical methods (no closed form for general δ) - Black-Scholes offers analytical solutions but limited realism - Crank-Nicolson provides good stability-accuracy balance

6. Conclusions

Successfully implemented CEV model pricing with Crank-Nicolson method, demonstrating its superiority over Black-Scholes for capturing market volatility dynamics. The CEV-CIR relationship provides theoretical foundation while numerical implementation offers practical pricing capability.

Interview Questions with Detailed Answers

Q1: What is the main advantage of the CEV model over Black-Scholes?

Answer: Captures volatility smile/skew observed in real markets. δ < 1 increases volatility as price decreases (leverage effect), improving pricing for far-from-the-money and long-maturity options.

Q2: Explain the significance of the δ parameter in the CEV model.

Answer: Controls price-volatility relationship: δ =1 recovers Black-Scholes, δ <1 creates leverage effect, δ >1 increases volatility with price. Empirical equity $\delta \approx 0.5$ -0.8 produces negative skew.

Q3: How does the Crank-Nicolson method ensure stability in solving the CEV PDE?

Answer: Averages implicit and explicit schemes, second-order accurate in time, unconditionally stable for any $\Delta t/\Delta x^2$ ratio, critical for variable coefficients $x^{\wedge}(2\delta)$.

Q4: What is the connection between CEV and CIR processes, and why is it important?

Answer: $S(t)=X(t)^{\theta}$ with X(t) CIR solves CEV. Provides theoretical validation, allows CIR techniques for simulation/numerical pricing, and gives economic interpretation.

Q5: How would you handle boundary conditions for different option types?

Answer: European calls: u(0)=0, $u(X)=X-Ke^{(-r(T-t))}$; puts: $u(0)=Ke^{(-r(T-t))}$, u(X)=0. American: check early exercise each node. Barrier: special conditions at barrier.

Q6: What are the main sources of error in your implementation, and how would you reduce them?

Answer: Discretization error (O($\Delta t^2 + \Delta x^2$)), boundary truncation, round-off. Reduce via finer grids, adaptive mesh, sparse matrix solvers, Richardson extrapolation.

Q7: When would you choose CEV over other volatility models like Heston or SABR?

Answer: CEV is simpler, captures smile, good for single-asset options with price-volatility correlation. Heston/SABR better for multi-asset, term structure, or volatility derivatives.

Q8: How does the error comparison with Black-Scholes validate your implementation?

Answer: δ =1 reduces to Black-Scholes; ~95% agreement confirms correctness. Discrepancies near strike/boundaries expected from discretization.

Q9: What modifications would you make for production deployment?

Answer: Sparse matrices, parallel computing, adaptive time-stepping, automatic grid refinement, caching, error handling, Greeks calculation.

Q10: How would you calibrate the CEV model to market data?

Answer: Estimate δ from implied volatility skew, optimize σ and δ using nonlinear least squares weighted by vega, apply constraints and cross-validation, recalibrate regularly, monitor parameter stability.