

# Discrete Dynamic Programming Models for Pricing Asian Exotic Options

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## Abstract

This report presents a discrete dynamic programming (DP) approach to price arithmetic-average Asian exotic options under European, Bermudan, and American exercise styles. The method explicitly models early-exercise flexibility and path dependence through a two-dimensional state space in spot price and running average. The framework integrates Gauss–Hermite quadrature for expectation computation, Monte Carlo validation for convergence studies, and detailed analysis of exercise boundaries, early-exercise premiums, and multi-style sensitivity overlays. Results confirm the theoretical hierarchy  $V_{Euro} \leq V_{Berm} \leq V_{Amer}$  and demonstrate the DP model’s accuracy and robustness across key parameters such as volatility, strike, interest rate, and averaging frequency.

## 1 Introduction

Asian options are path-dependent derivatives whose payoffs depend on the average price of the underlying asset over a monitoring period. By averaging over multiple observations, they reduce exposure to short-term volatility and are commonly used in structured financial products and corporate hedging.

Traditional pricing approaches—such as closed-form approximations or Monte Carlo simulation—struggle to efficiently handle early exercise features (as in Bermudan or American variants). Discrete Dynamic Programming (DP) provides a natural solution framework: it recursively computes continuation and exercise values across a discretized  $(S, A)$  state grid. This recursive structure captures optimal stopping behavior and facilitates transparent convergence control via spatial and temporal discretization.

The goal of this work is to develop, validate, and interpret a DP-based solver capable of pricing Asian options of multiple styles and to assess its numerical stability, early-exercise behavior, and sensitivity to key parameters.

## 2 Mathematical Framework

We consider an arithmetic-average Asian option under a standard risk-neutral process. The model discretizes both the underlying spot  $S$  and the running average  $A$  on finite grids.

### 2.1 Underlying Dynamics

The risk-neutral dynamics of the underlying are discretized as:

$$S_{t+\Delta t} = S_t e^{(r-q-\frac{1}{2}\sigma^2)\Delta t + \sigma\sqrt{\Delta t}Z}, \quad (1)$$

where  $r$  is the risk-free rate,  $q$  is the dividend yield,  $\sigma$  is volatility, and  $Z \sim \mathcal{N}(0, 1)$ .

### 2.2 Arithmetic Average Update

At each monitoring step,

$$A_{t+\Delta t} = \frac{kA_t + S_{t+\Delta t}}{k+1}, \quad (2)$$

where  $k$  denotes the number of past observations included in the running average.

### 2.3 DP Recursion

Let  $V_n(S, A)$  denote the option value at discrete step  $n$ . The backward recursion is:

$$V_n(S, A) = \begin{cases} e^{-r\Delta t} \mathbb{E}[V_{n+1}(S', A')], & \text{(continuation)} \\ \max\{\Phi(S, A), e^{-r\Delta t} \mathbb{E}[V_{n+1}(S', A')]\}, & \text{(exercise)} \end{cases} \quad (3)$$

where  $\Phi(S, A)$  is the intrinsic payoff (e.g.,  $\max(K - A, 0)$  for a put). The expectation is computed via Gauss–Hermite quadrature using pre-tabulated nodes and weights, offering high accuracy for Gaussian integrals.

### 2.4 Boundary and Terminal Conditions

At maturity,  $V_T(S, A) = \Phi(S, A)$ . For sufficiently large or small  $S$  or  $A$ , boundary conditions are imposed such that  $V(S, A)$  tends to intrinsic payoff limits. The backward recursion is performed from  $t = T$  to  $t = 0$ .

### 3 Numerical Validation: Convergence Study

To establish correctness, the DP model is validated against Monte Carlo (MC) pricing for European Asian options. We examine sensitivity to grid resolution in  $S$  and  $A$ , and quadrature accuracy via  $K_{gh}$  nodes.

#### 3.1 Convergence vs Grid Parameters

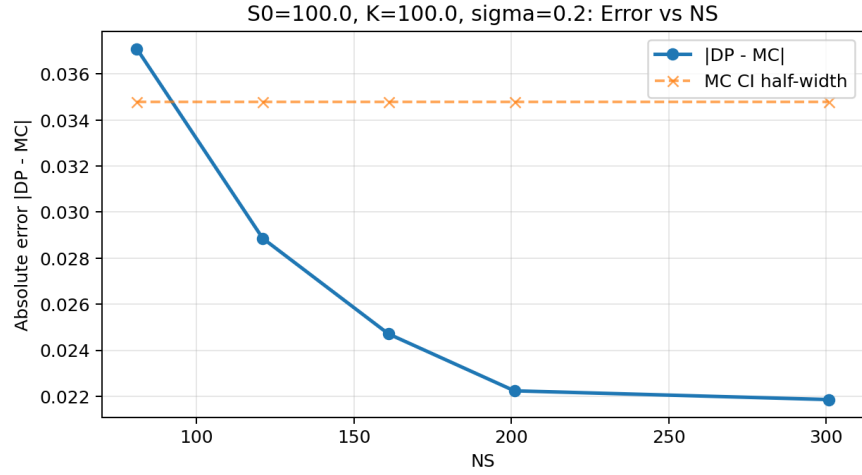


Figure 1: Convergence with increasing number of spot grid points ( $N_S$ )

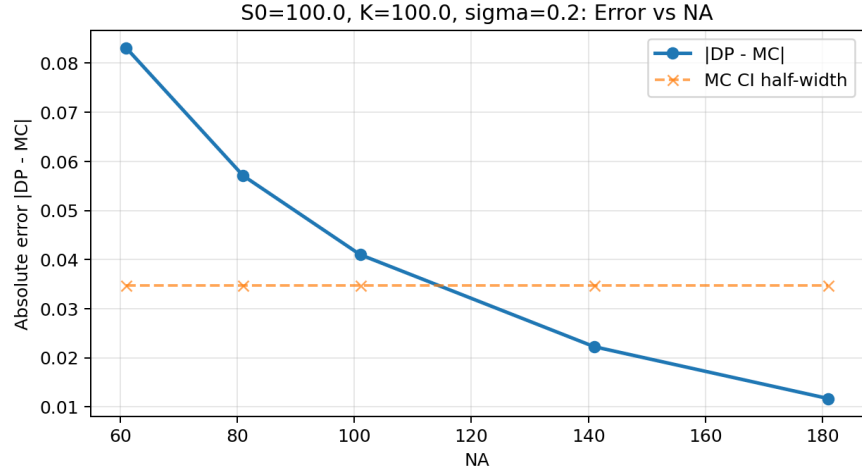


Figure 2: Convergence with increasing number of average grid points ( $N_A$ )

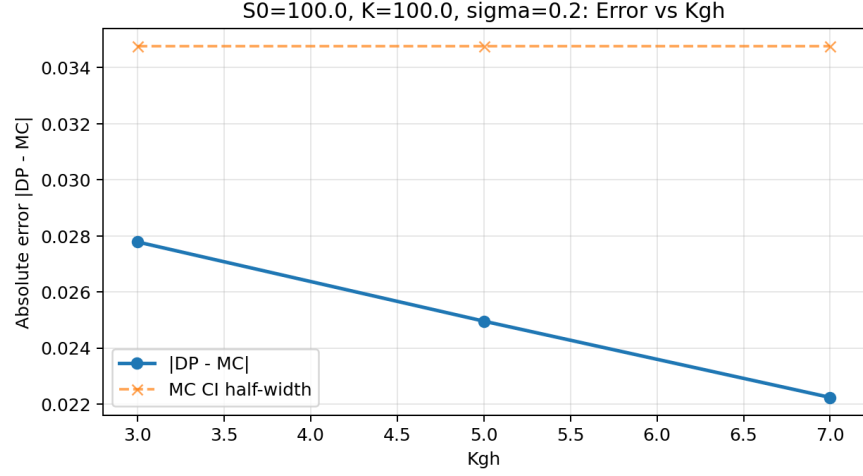


Figure 3: Convergence with increasing number of Gauss-Hermite nodes ( $K_{gh}$ )

### 3.2 Interpretation

Error decreases monotonically with finer spatial discretization ( $N_S, N_A$ ) and higher quadrature order ( $K_{gh}$ ). The average grid resolution ( $A$  dimension) contributes more to accuracy due to its role in representing path-dependence. Beyond  $K_{gh} = 5$ , quadrature error stabilizes, confirming that primary bias arises from grid discretization rather than numerical integration. The DP results remain within the Monte Carlo 95% confidence interval, validating both numerical and probabilistic consistency.

## 4 Bermudan Option: Early-Exercise Frontier

For Bermudan options, early exercise is permitted at discrete time steps. At each monitoring point, we compute the optimal exercise region where  $\Phi(S, A) > e^{-r\Delta t}\mathbb{E}[V_{n+1}]$ .

### 4.1 Visualizing the Frontier

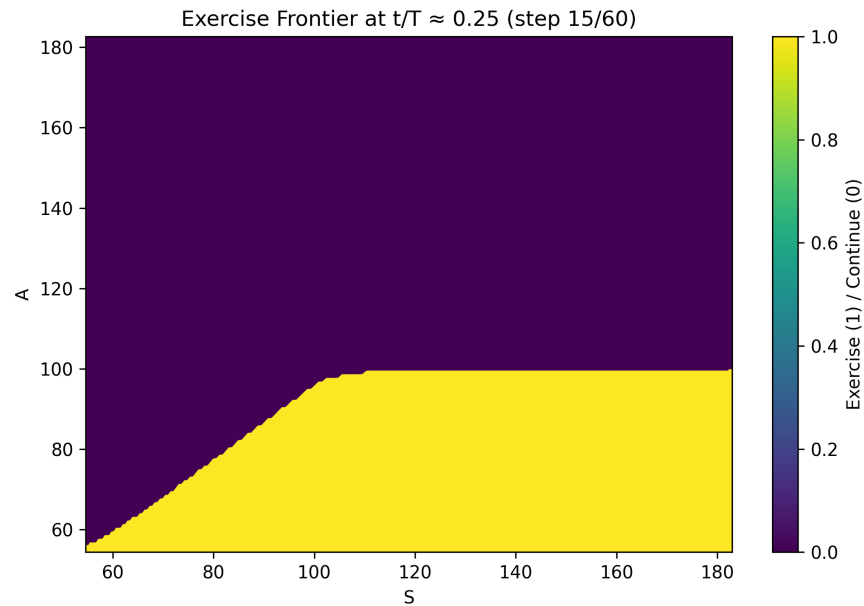


Figure 4: Exercise frontier at 25% maturity

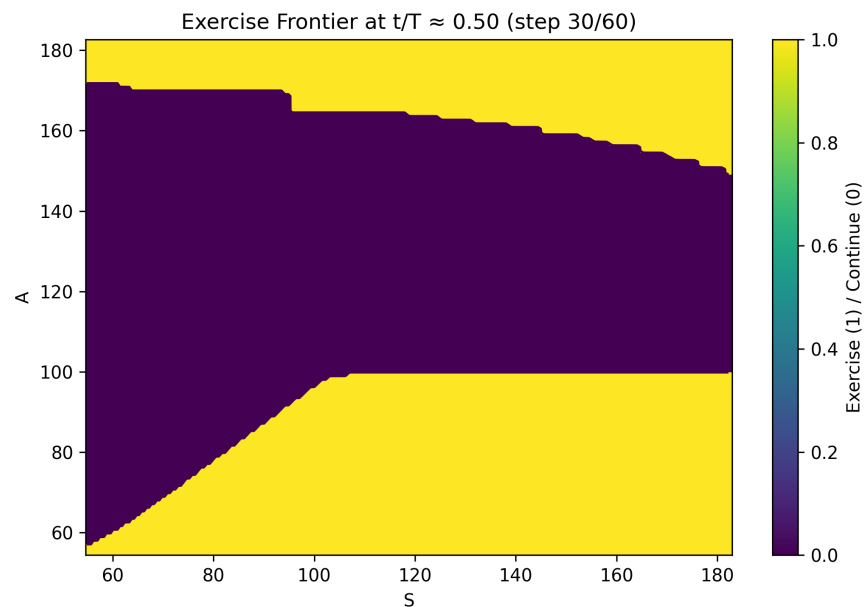


Figure 5: Exercise frontier at 50% maturity

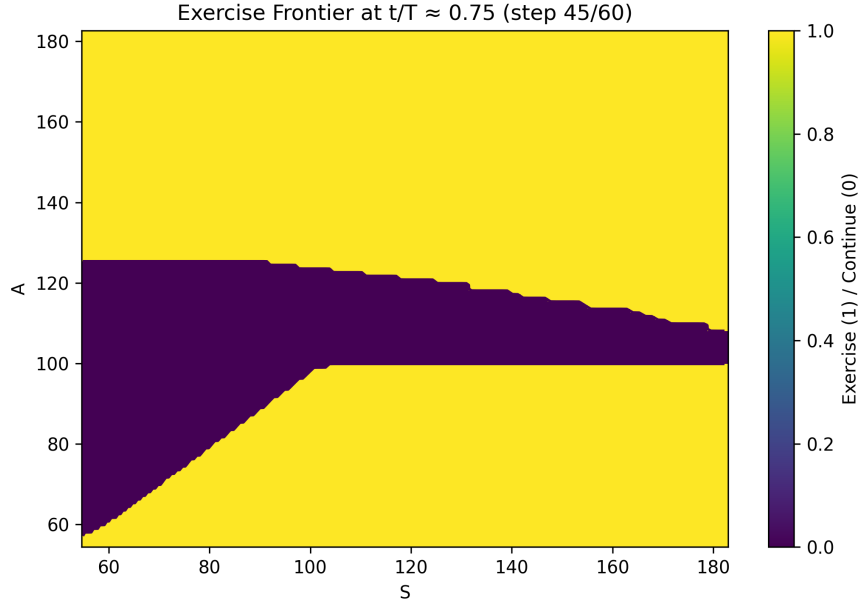


Figure 6: Exercise frontier at 75% maturity

## 4.2 Interpretation

The yellow region represents the **exercise zone**, and the purple region denotes **continuation**. The frontier shifts inward as time progresses, showing that the optimal exercise region expands closer to maturity. The boundary is upward sloping: higher running averages  $A$  require larger  $S$  to justify immediate exercise, as the expected future payoff diminishes with increasing  $A$ . This pattern captures the natural trade-off between *intrinsic value* and *time value* in early-exercise behavior.

## 5 Early-Exercise Premium Analysis

We define the early-exercise premium as:

$$\text{Premium} = V_{Berm/Am} - V_{Euro}.$$

This premium quantifies the added value of early exercise flexibility.

### 5.1 Parameter Variation Studies

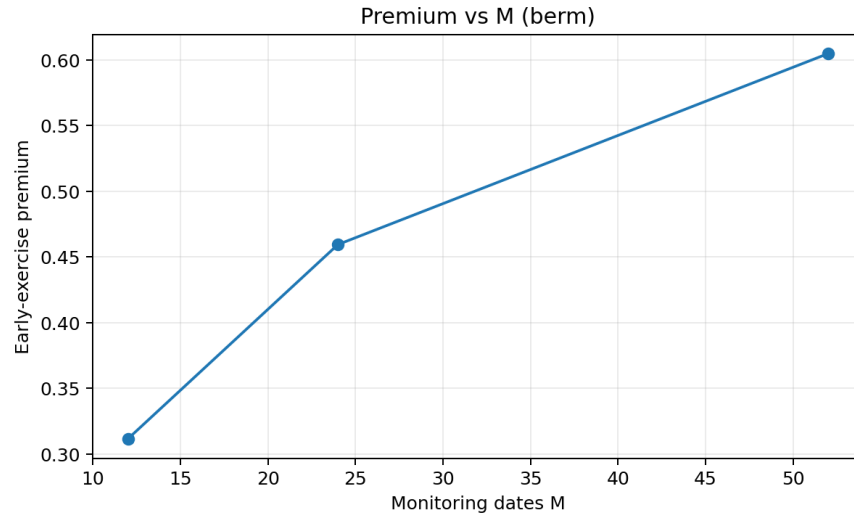


Figure 7: Premium vs number of monitoring steps ( $M$ )

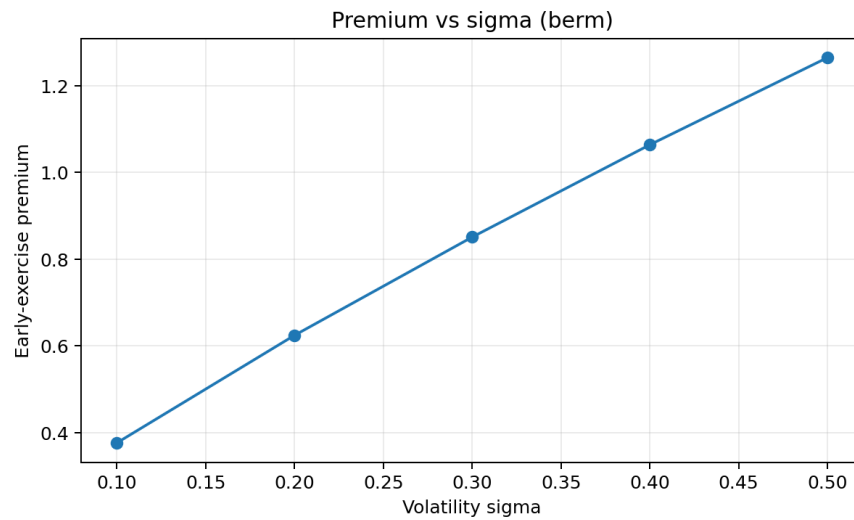


Figure 8: Premium vs volatility ( $\sigma$ )

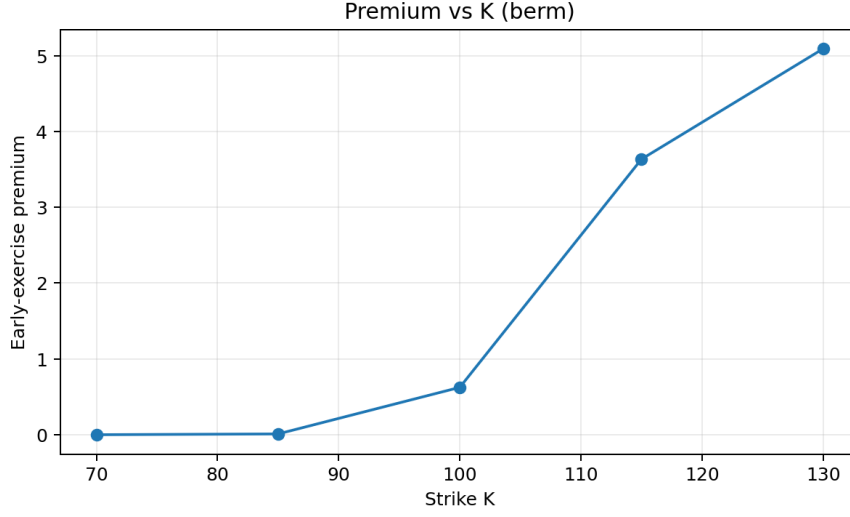


Figure 9: Premium vs strike ( $K$ )

## 5.2 Interpretation

The variable  $M$  represents the number of averaging or monitoring dates. Here we set  $M = N$ , implying that averaging occurs at every DP time step. Increasing  $M$  smooths the payoff distribution, reducing volatility in the running average and leading to smaller early-exercise gains. Premiums increase with volatility  $\sigma$ , as uncertainty enhances optionality and thus the benefit of flexible exercise. As strike  $K$  increases (deep in-the-money for puts), the premium rises sharply since the immediate payoff dominates. These results align with theoretical intuition and confirm numerical stability.



## 6 Sensitivity Overlay: European, Bermudan, and American Options

The solver enables simultaneous comparison across exercise styles. For each varying parameter—volatility, strike, rate, and averaging frequency—the three style values satisfy:

$$V_{Euro} \leq V_{Berm} \leq V_{Amer}.$$

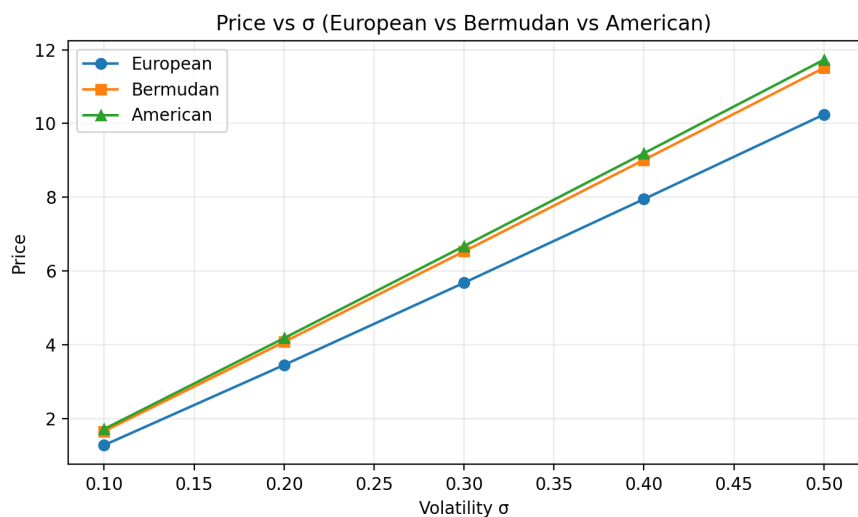


Figure 10: Option price vs volatility

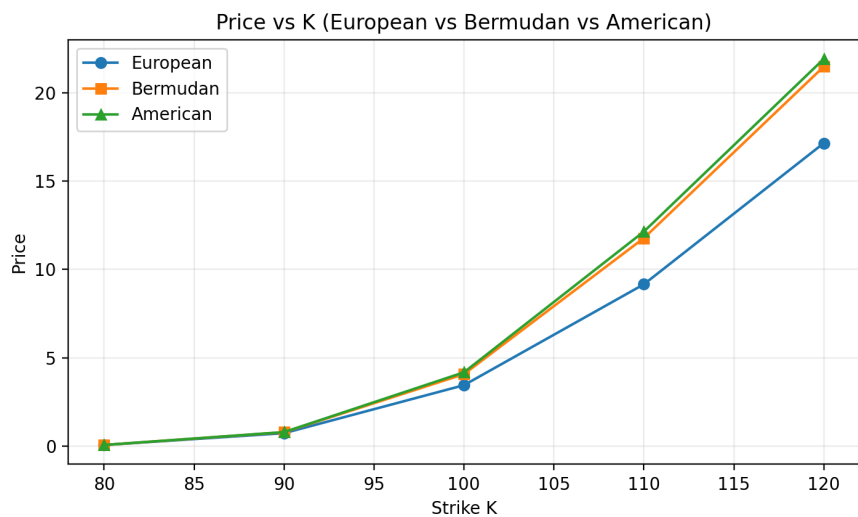


Figure 11: Option price vs strike

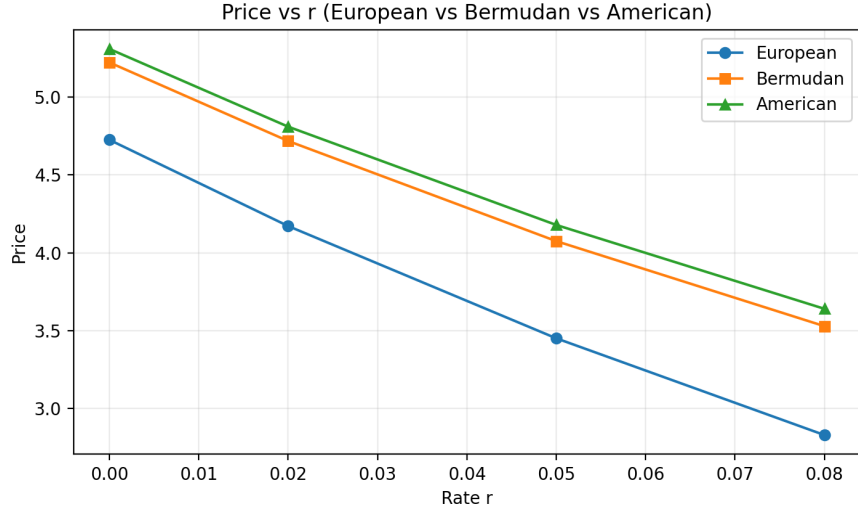


Figure 12: Option price vs interest rate

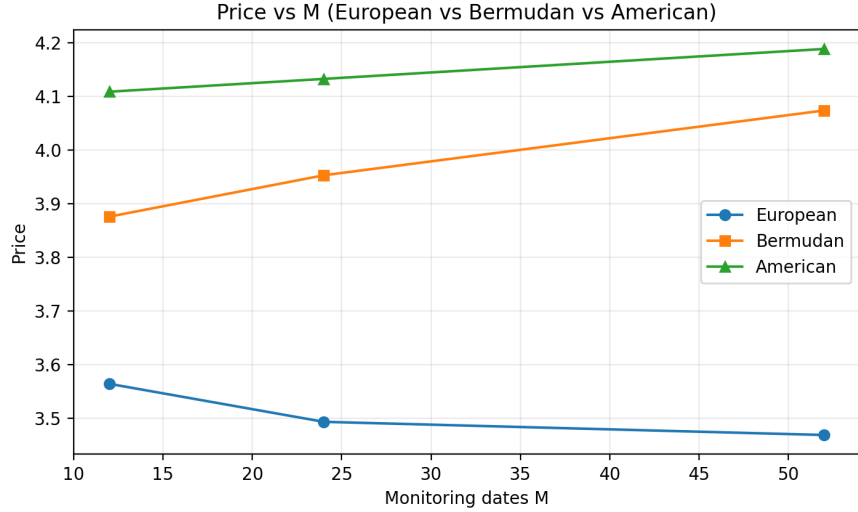


Figure 13: Option price vs monitoring frequency ( $M$ )

## 6.1 Interpretation

Volatility  $\sigma$  increases the value of all option styles, but the incremental gain is largest for American options. Increasing  $K$  reduces option value (typical put behavior), and higher interest rate  $r$  slightly reduces discounted payoffs. As averaging frequency increases, all prices converge due to reduced path volatility. The consistent ranking of  $V_{Euro} < V_{Berm} < V_{Amer}$  across all sensitivities confirms correct implementation of exercise flexibility.

## 7 Conclusion and Future Work

The discrete DP framework successfully models Asian options with early exercise flexibility. The solver shows strong convergence to MC results, realistic early-exercise boundaries, and theoretically consistent sensitivities. Future improvements include:

- Adaptive non-uniform grids for finer resolution near the exercise frontier.
- Parallelization of DP recursion for high-dimensional state spaces.
- Integration of neural regression to approximate continuation values (Deep DP).
- Extension to multi-asset basket options and stochastic volatility models.

## References

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- Carverhill, A. (1992). Discrete time models for option pricing. *Journal of Economic Dynamics and Control*, 16(2), 273–298.