

Multilevel Monte Carlo path simulation

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Outline

Long-term objective is faster Monte Carlo simulation of path dependent options to estimate values and Greeks.

Several ingredients, not yet all combined:

- multilevel method
- quasi-Monte Carlo
- adjoint pathwise Greeks
- parallel computing on NVIDIA graphics cards

Emphasis in this presentation is on multilevel method

Generic Problem

Stochastic differential equation with general drift and volatility terms:

$$dS(t) = a(S, t) dt + b(S, t) dW(t)$$

We want to compute the expected value of an option dependent on $S(t)$. In the simplest case of European options, it is a function of the terminal state

$$P = f(S(T))$$

with a uniform Lipschitz bound,

$$|f(U) - f(V)| \leq c \|U - V\|, \quad \forall U, V.$$

Simplest MC Approach

Euler discretisation with timestep h :

$$\widehat{S}_{n+1} = \widehat{S}_n + a(\widehat{S}_n, t_n) h + b(\widehat{S}_n, t_n) \Delta W_n$$

Estimator for expected payoff is an average of N independent path simulations:

$$\widehat{Y} = N^{-1} \sum_{i=1}^N f(\widehat{S}_{T/h}^{(i)})$$

- weak convergence – $O(h)$ error in expected payoff
- strong convergence – $O(h^{1/2})$ error in individual path

Simplest MC Approach

Mean Square Error is $O(N^{-1} + h^2)$

- first term comes from variance of estimator
- second term comes from bias due to weak convergence

To make this $O(\varepsilon^2)$ requires

$$N = O(\varepsilon^{-2}), \quad h = O(\varepsilon) \quad \implies \quad \text{cost} = O(N h^{-1}) = O(\varepsilon^{-3})$$

Aim is to improve this cost to $O(\varepsilon^{-p})$, with p as small as possible, ideally close to 1.

Note: for a relative error of $\varepsilon = 0.001$, the difference between ε^{-3} and ε^{-1} is huge.

Standard MC Improvements

- variance reduction techniques (e.g. control variates, stratified sampling) improve the constant factor in front of ε^{-3} , sometimes spectacularly
- improved second order weak convergence (e.g. through Richardson extrapolation) leads to $h = O(\sqrt{\varepsilon})$, giving $p = 2.5$
- quasi-Monte Carlo reduces the number of samples required, at best leading to $N \approx O(\varepsilon^{-1})$, giving $p \approx 2$ with first order weak methods

Multilevel method gives $p = 2$ without QMC, and at best $p \approx 1$ with QMC.

Other Related Research

- In Dec. 2005, Ahmed Kebaier published an article in *Annals of Applied Probability* describing a two-level method which reduces the cost to $O(\varepsilon^{-2.5})$.
- Also in Dec. 2005, Adam Speight wrote a working paper describing a very similar multilevel use of control variates.
- There are also close similarities to a multilevel technique developed by Stefan Heinrich for parametric integration (*Journal of Complexity*, 1998)

Multilevel MC Approach

Consider multiple sets of simulations with different timesteps $h_l = 2^{-l} T$, $l = 0, 1, \dots, L$, and payoff \hat{P}_l

$$\mathbb{E}[\hat{P}_L] = \mathbb{E}[\hat{P}_0] + \sum_{l=1}^L \mathbb{E}[\hat{P}_l - \hat{P}_{l-1}]$$

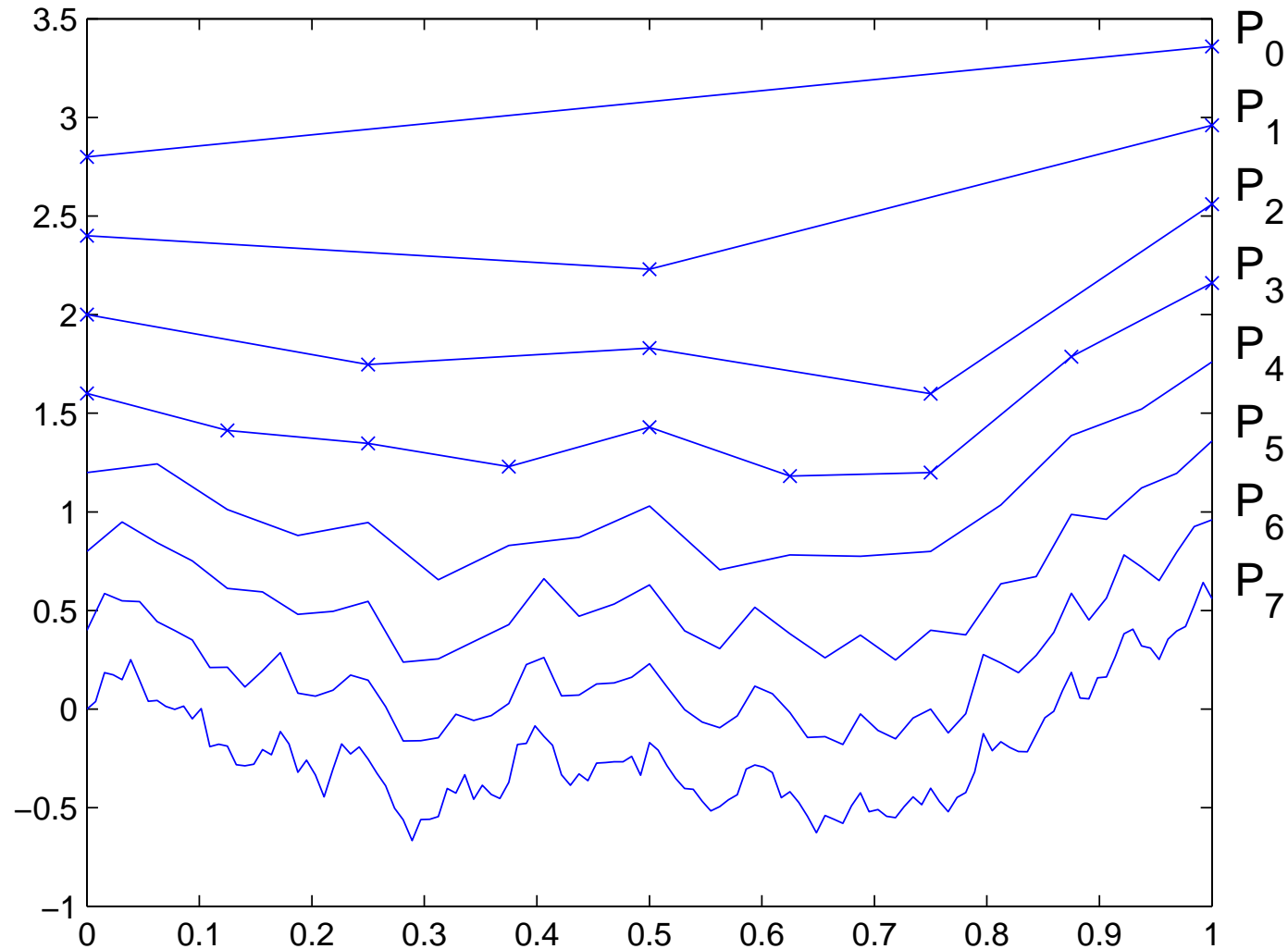
Expected value is same – aim is to reduce variance of estimator for a fixed computational cost.

Key point: approximate $\mathbb{E}[\hat{P}_l - \hat{P}_{l-1}]$ using N_l simulations with \hat{P}_l and \hat{P}_{l-1} obtained using same Brownian path.

$$\hat{Y}_l = N_l^{-1} \sum_{i=1}^{N_l} \left(\hat{P}_l^{(i)} - \hat{P}_{l-1}^{(i)} \right)$$

Multilevel MC Approach

Discrete Brownian path at different levels



Multilevel MC Approach

Using independent paths for each level, the variance of the combined estimator is

$$\mathbb{V} \left[\sum_{l=0}^L \hat{Y}_l \right] = \sum_{l=0}^L N_l^{-1} V_l, \quad V_l \equiv \mathbb{V}[\hat{P}_l - \hat{P}_{l-1}],$$

and the computational cost is proportional to $\sum_{l=0}^L N_l h_l^{-1}$.

Hence, the variance is minimised for a fixed computational cost by choosing N_l to be proportional to $\sqrt{V_l h_l}$.

The constant of proportionality can be chosen so that the combined variance is $O(\varepsilon^2)$.

Multilevel MC Approach

For the Euler discretisation and a Lipschitz payoff function

$$\mathbb{V}[\hat{P}_l - P] = O(h_l) \quad \Longrightarrow \quad \mathbb{V}[\hat{P}_l - \hat{P}_{l-1}] = O(h_l)$$

and the optimal N_l is asymptotically proportional to h_l .

To make the combined variance $O(\varepsilon^2)$ requires

$$N_l = O(\varepsilon^{-2} L h_l).$$

To make the bias $O(\varepsilon)$ requires

$$L = \log_2 \varepsilon^{-1} + O(1) \quad \Longrightarrow \quad h_L = O(\varepsilon).$$

Hence, we obtain an $O(\varepsilon^2)$ MSE for a computational cost which is $O(\varepsilon^{-2} L^2) = O(\varepsilon^{-2} (\log \varepsilon)^2)$.

Multilevel MC Approach

Theorem: Let P be a functional of the solution of a stochastic o.d.e., and \hat{P}_l the discrete approximation using a timestep $h_l = M^{-l} T$.

If there exist independent estimators \hat{Y}_l based on N_l Monte Carlo samples, and positive constants $\alpha \geq \frac{1}{2}$, β , c_1 , c_2 , c_3 such that

$$i) \mathbb{E}[\hat{P}_l - P] \leq c_1 h_l^\alpha$$

$$ii) \mathbb{E}[\hat{Y}_l] = \begin{cases} \mathbb{E}[\hat{P}_0], & l = 0 \\ \mathbb{E}[\hat{P}_l - \hat{P}_{l-1}], & l > 0 \end{cases}$$

$$iii) \mathbb{V}[\hat{Y}_l] \leq c_2 N_l^{-1} h_l^\beta$$

iv) C_l , the computational complexity of \hat{Y}_l , is bounded by

$$C_l \leq c_3 N_l h_l^{-1}$$

Multilevel MC Approach

then there exists a positive constant c_4 such that for any $\varepsilon < e^{-1}$ there are values L and N_l for which the multi-level estimator

$$\hat{Y} = \sum_{l=0}^L \hat{Y}_l,$$

has Mean Square Error $MSE \equiv \mathbb{E} \left[\left(\hat{Y} - \mathbb{E}[P] \right)^2 \right] < \varepsilon^2$

with a computational complexity C with bound

$$C \leq \begin{cases} c_4 \varepsilon^{-2}, & \beta > 1, \\ c_4 \varepsilon^{-2} (\log \varepsilon)^2, & \beta = 1, \\ c_4 \varepsilon^{-2 - (1-\beta)/\alpha}, & 0 < \beta < 1. \end{cases}$$

Milstein Scheme

The theorem suggests use of Milstein scheme —
better strong convergence, same weak convergence

Generic scalar SDE:

$$dS(t) = a(S, t) dt + b(S, t) dW(t), \quad 0 < t < T.$$

Milstein scheme:

$$\hat{S}_{n+1} = \hat{S}_n + a h + b \Delta W_n + \frac{1}{2} b' b \left((\Delta W_n)^2 - h \right).$$

Milstein Scheme

In scalar case:

- $O(h)$ strong convergence
- $O(\varepsilon^{-2})$ complexity for Lipschitz payoffs – trivial
- $O(\varepsilon^{-2})$ complexity for Asian, lookback, barrier and digital options using carefully constructed estimators based on Brownian interpolation or extrapolation

Milstein Scheme

Key idea: within each timestep, model the behaviour as simple Brownian motion conditional on the two end-points

$$\begin{aligned}\widehat{S}(t) &= \widehat{S}_n + \lambda(t)(\widehat{S}_{n+1} - \widehat{S}_n) \\ &\quad + b_n \left(W(t) - W_n - \lambda(t)(W_{n+1} - W_n) \right),\end{aligned}$$

where

$$\lambda(t) = \frac{t - t_n}{t_{n+1} - t_n}$$

There then exist analytic results for the distribution of the min/max/average over each timestep.

Results

Geometric Brownian motion:

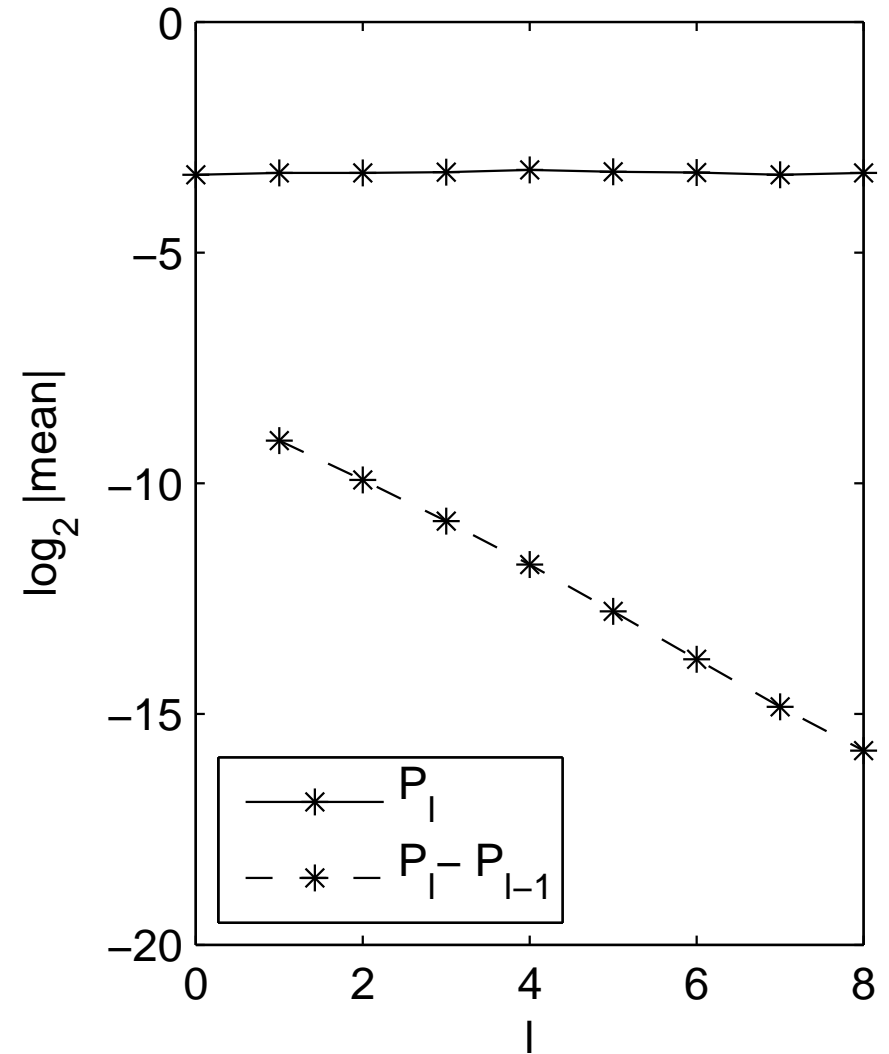
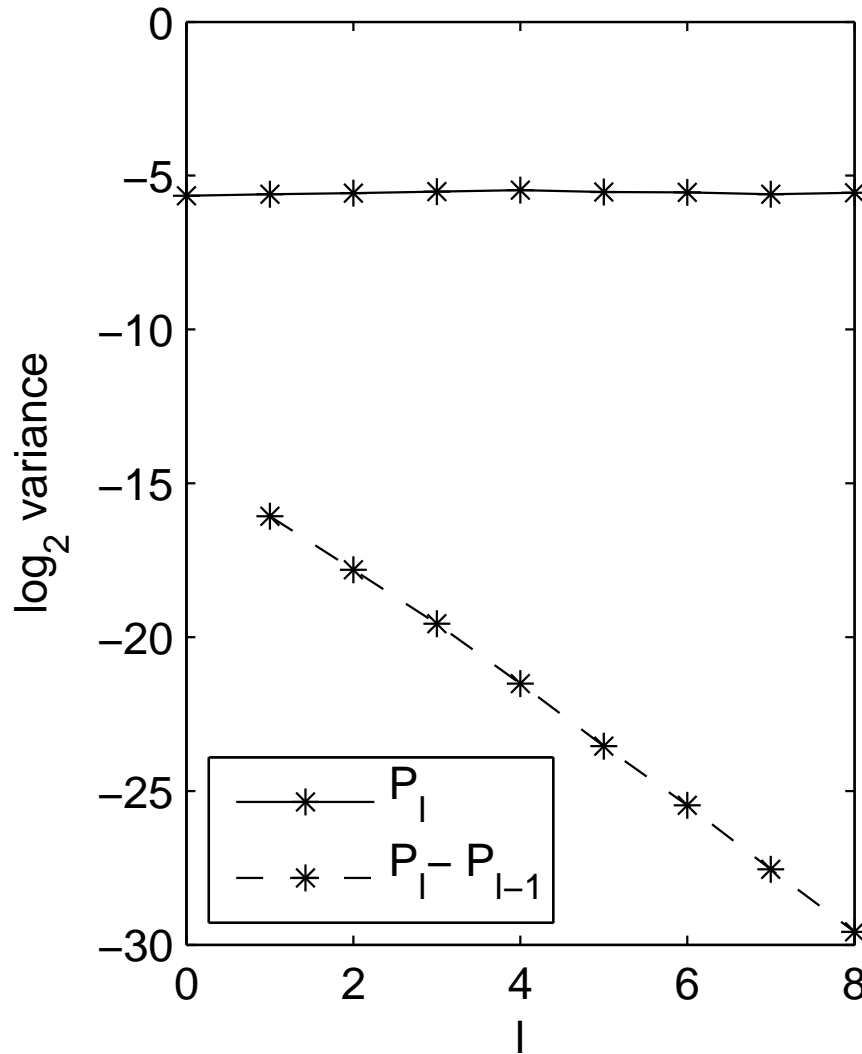
$$dS = r S dt + \sigma S dW, \quad 0 < t < T,$$

with parameters $T=1$, $S(0)=1$, $r=0.05$, $\sigma=0.2$

- European call option: $\exp(-rT) \max(S(T) - 1, 0)$
- Asian option: $\exp(-rT) \max\left(T^{-1} \int_0^T S(t) dt - 1, 0\right)$
- Lookback option: $\exp(-rT) \left(S(T) - \min_{0 < t < T} S(t)\right)$
- Down-and-out barrier option: same as call provided $S(t)$ stays above $B=0.9$

MLMC Results

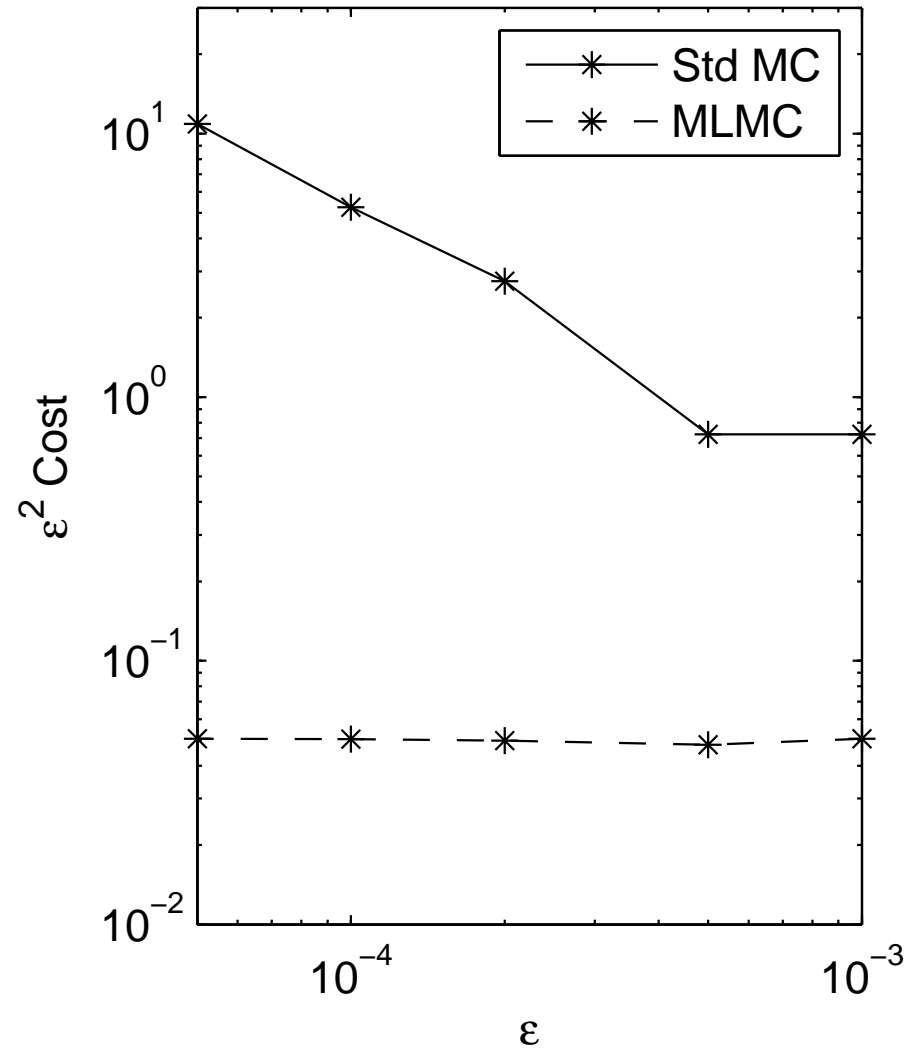
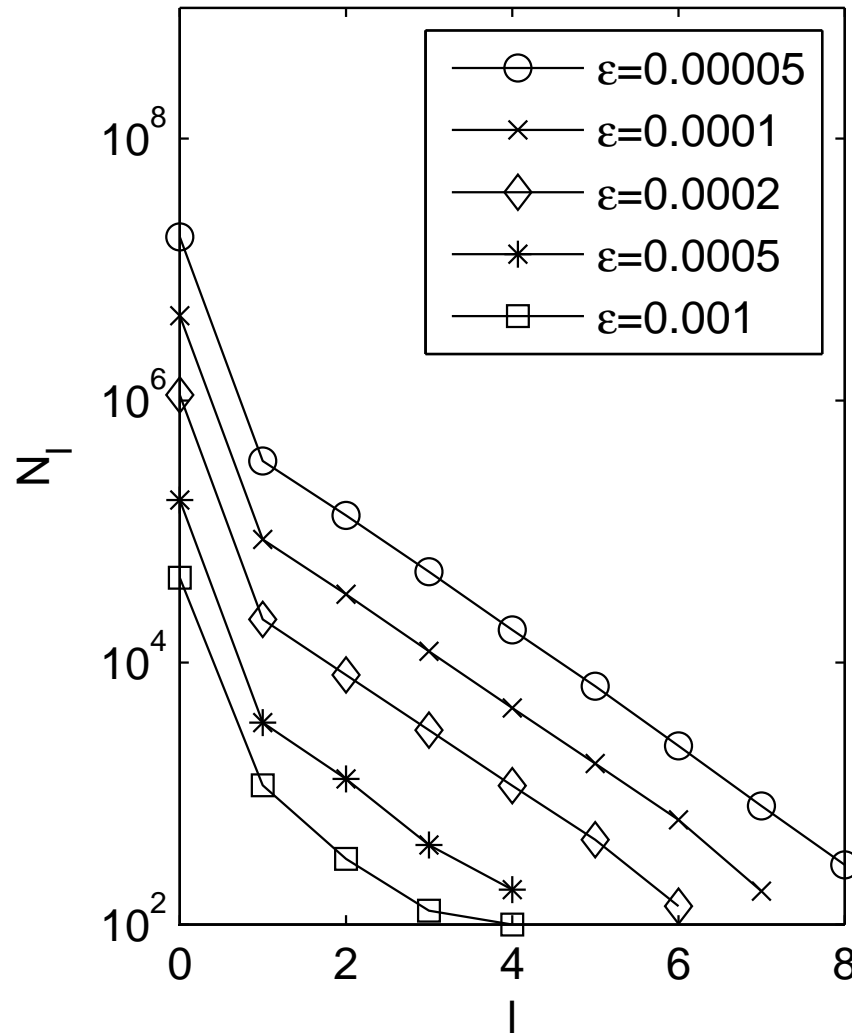
GBM: European



call

MLMC Results

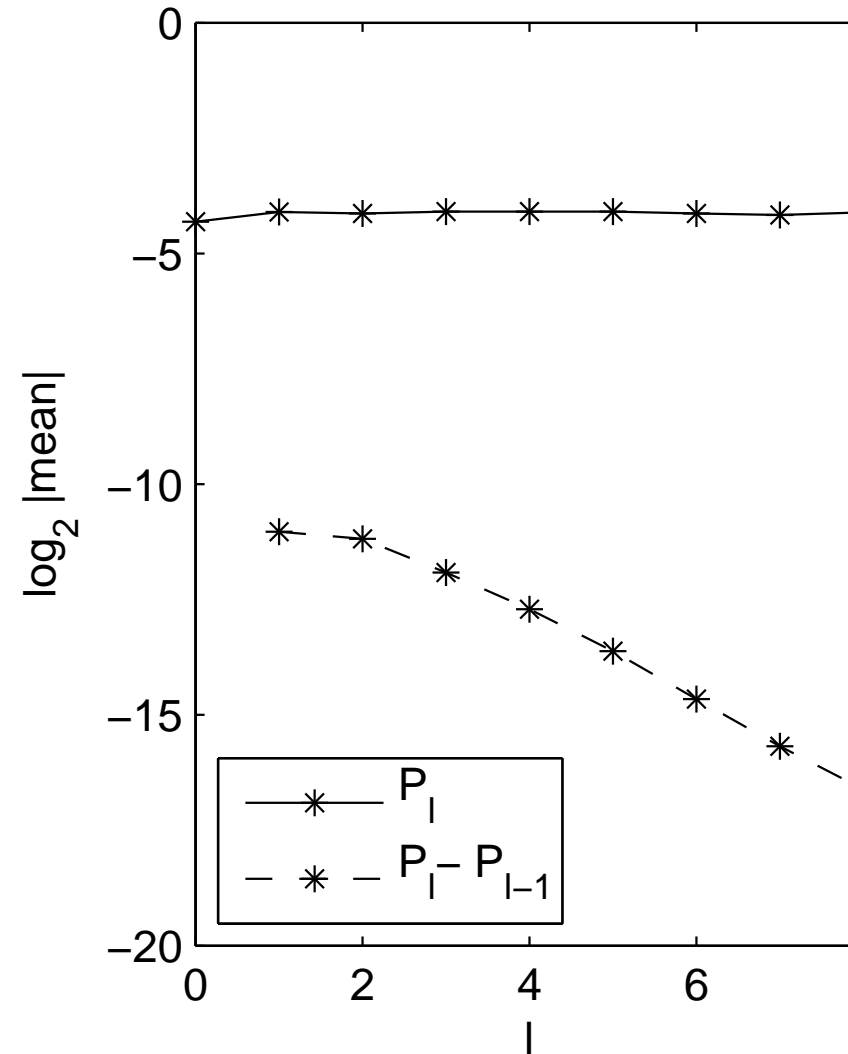
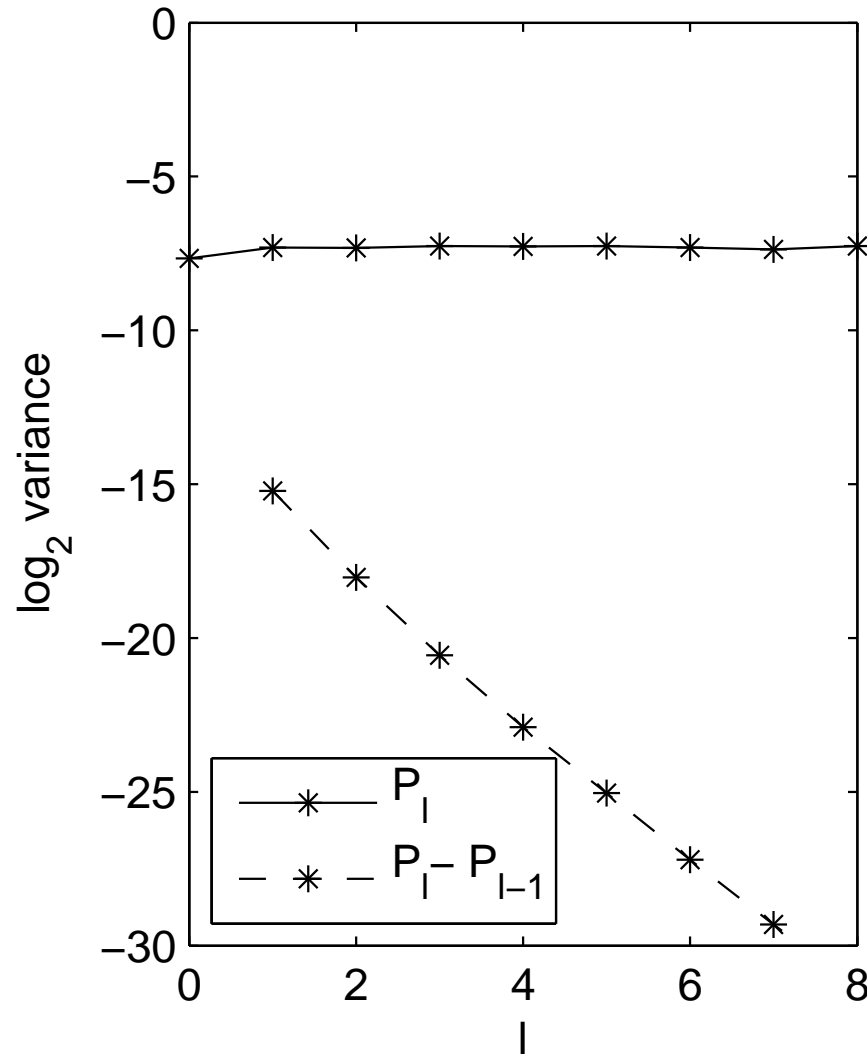
GBM: European



call

MLMC Results

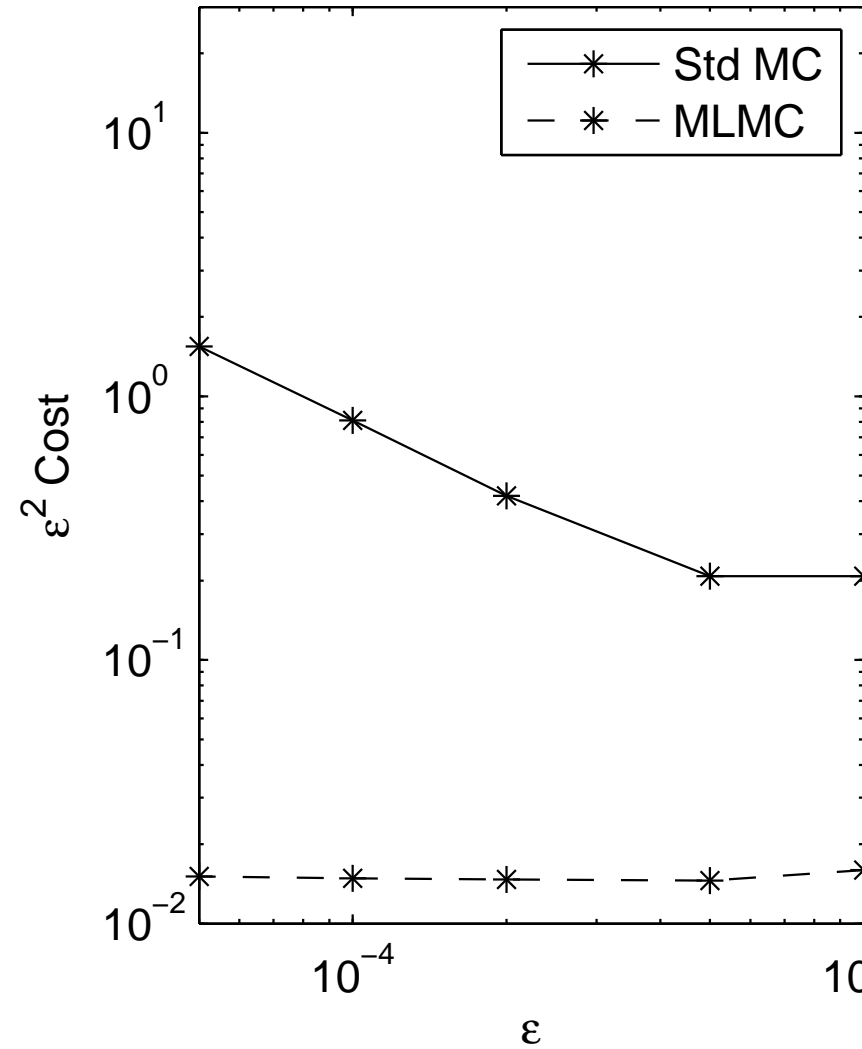
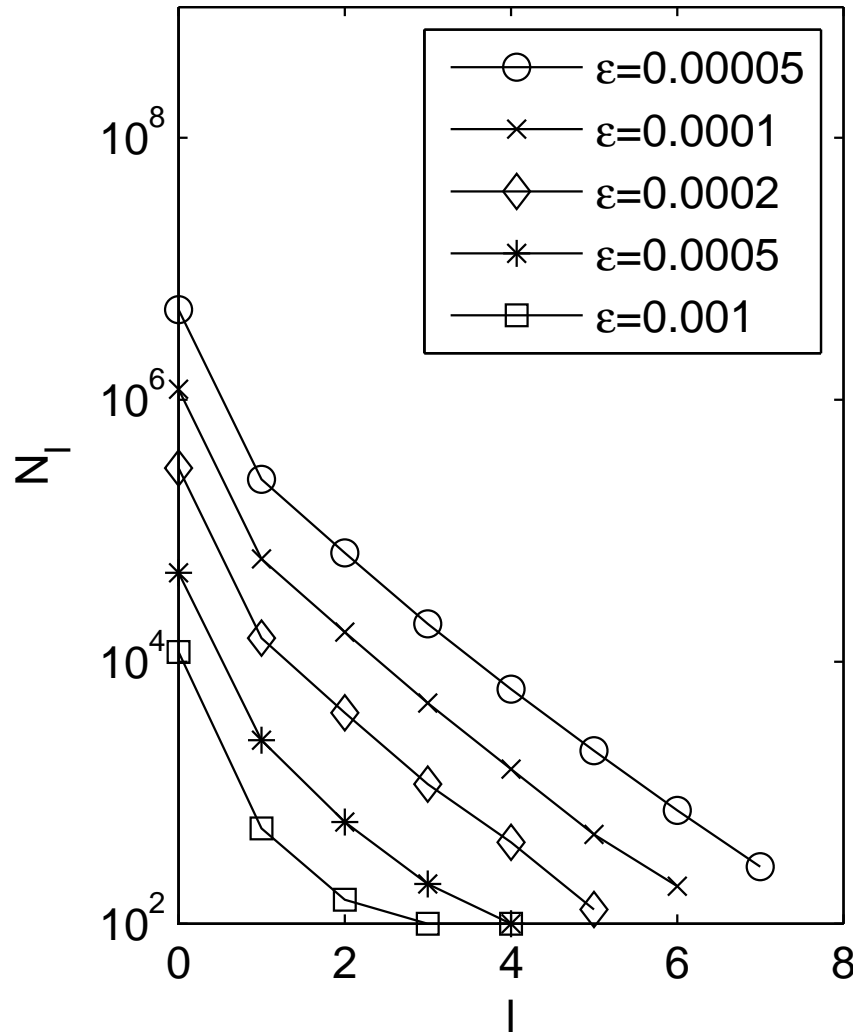
GBM: Asian



option

MLMC Results

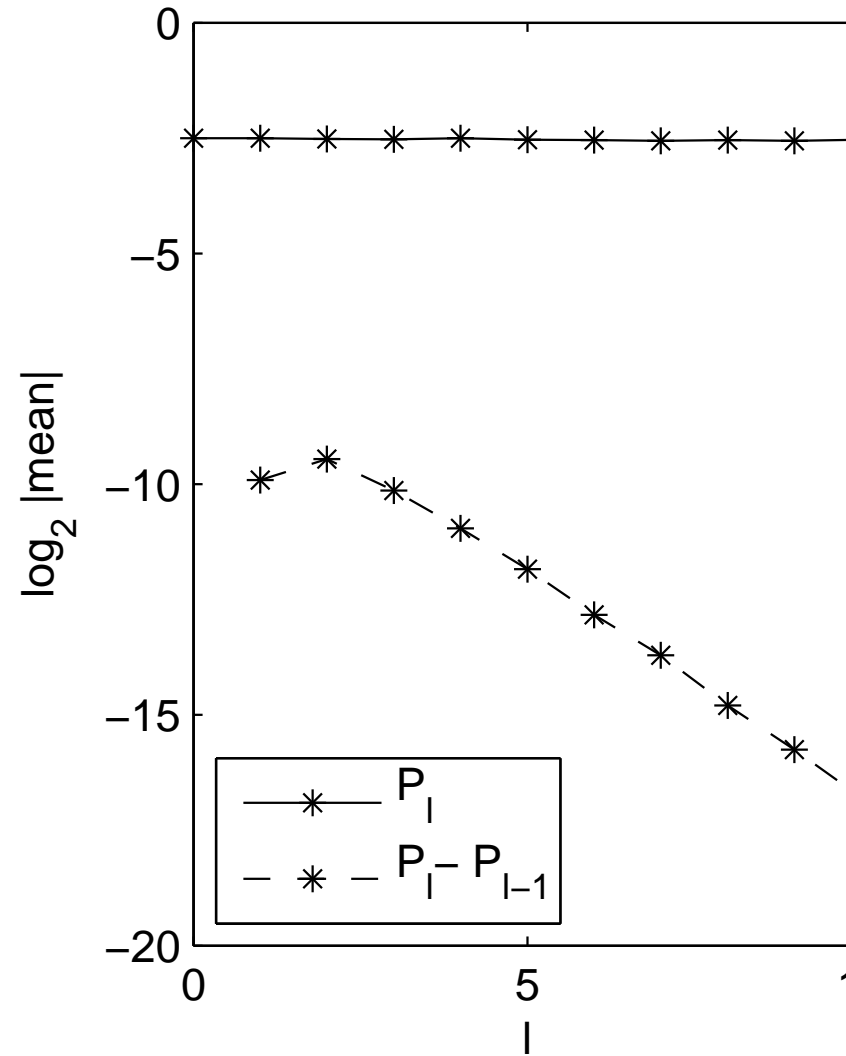
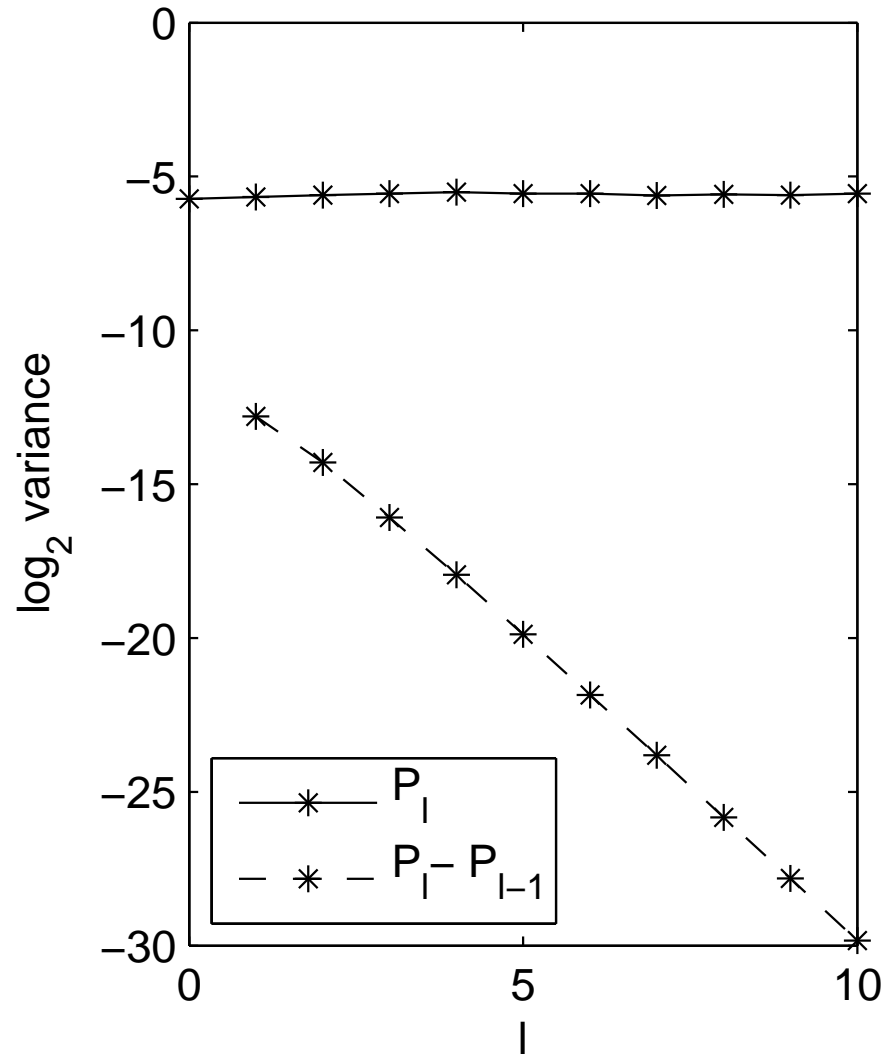
GBM: Asian



option

MLMC Results

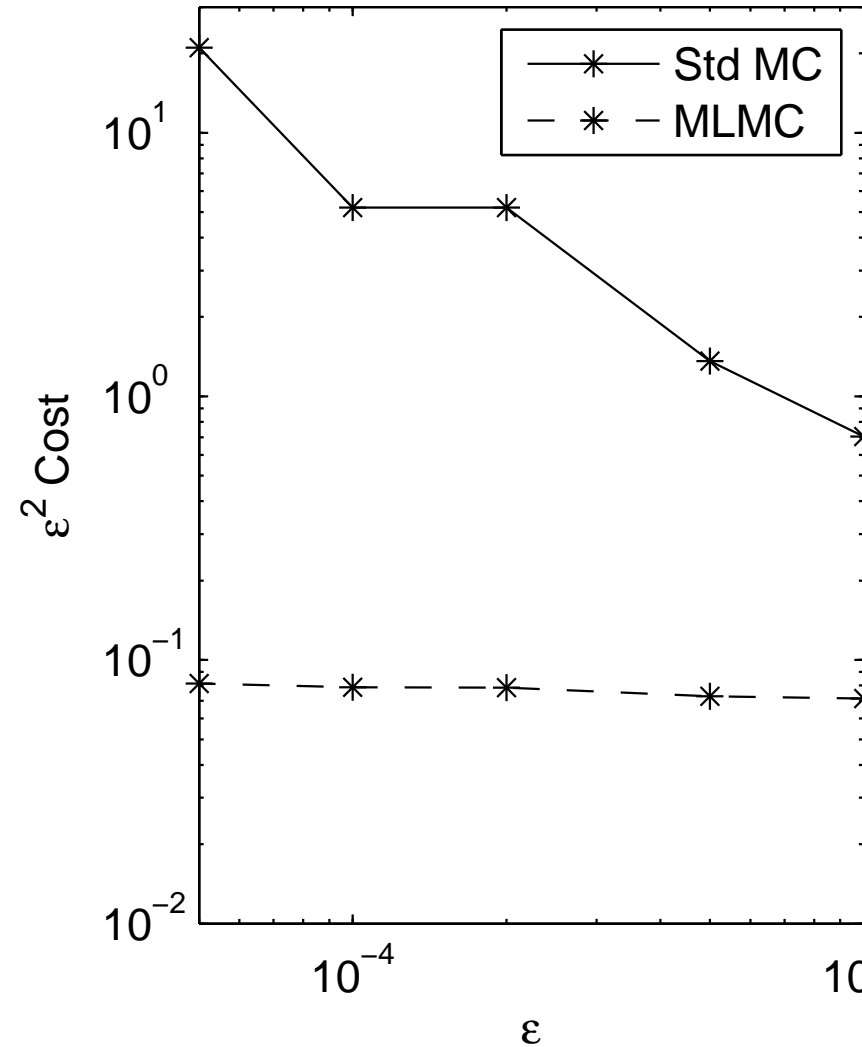
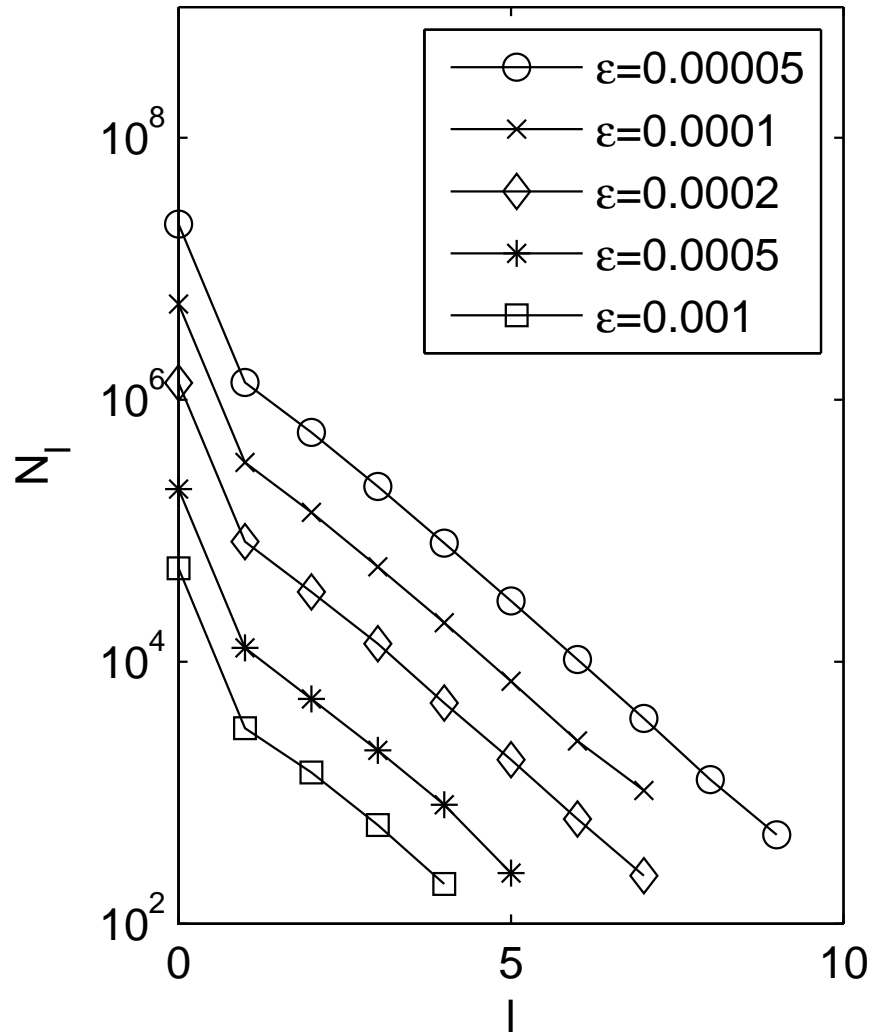
GBM: lookback



option

MLMC Results

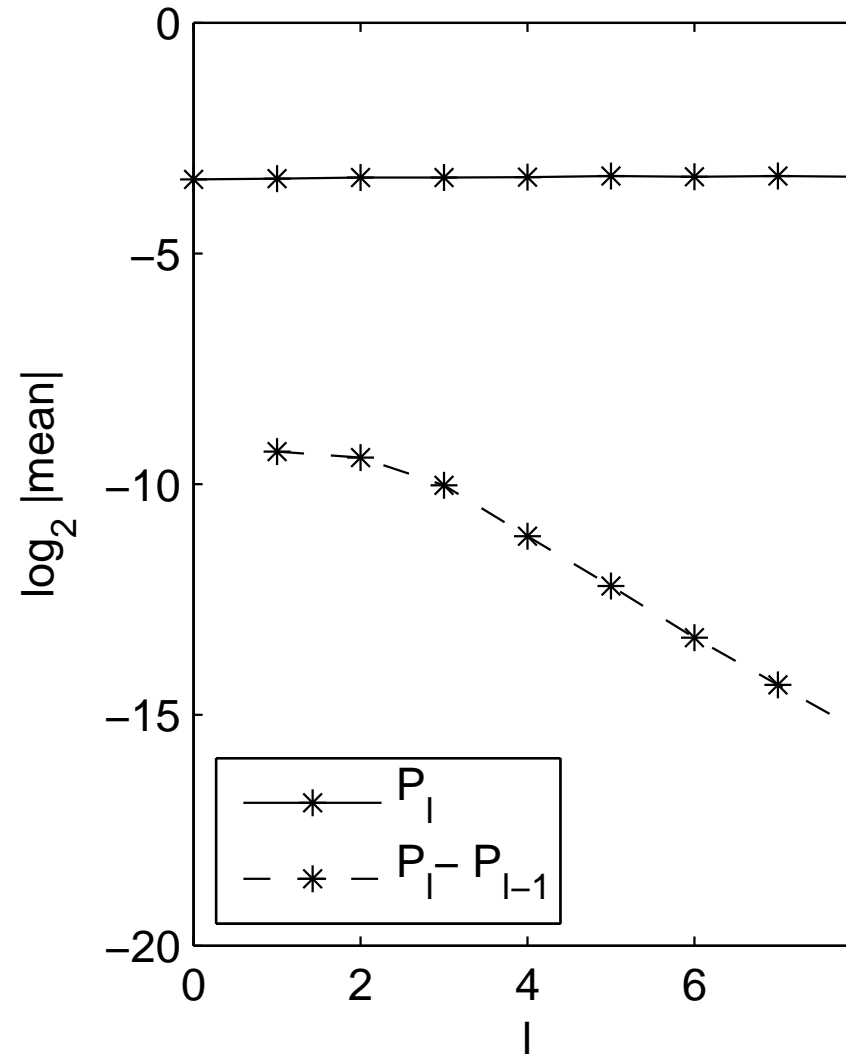
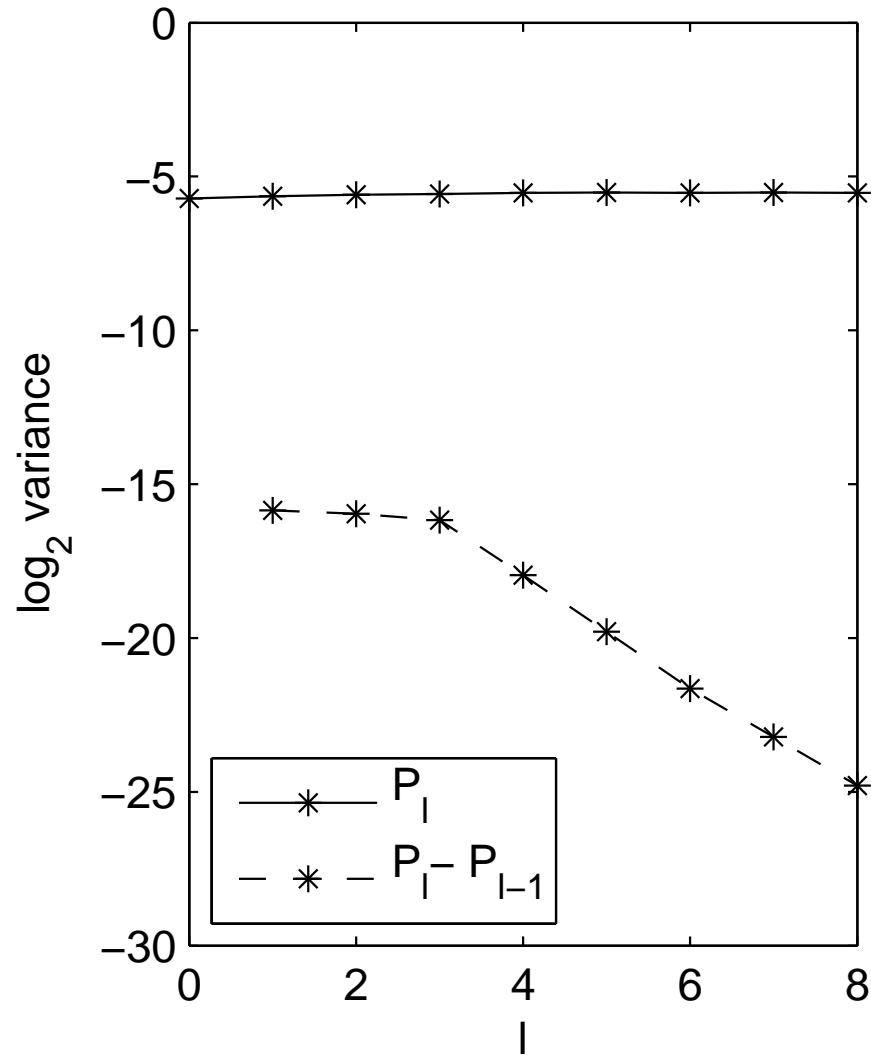
GBM: lookback



option

MLMC Results

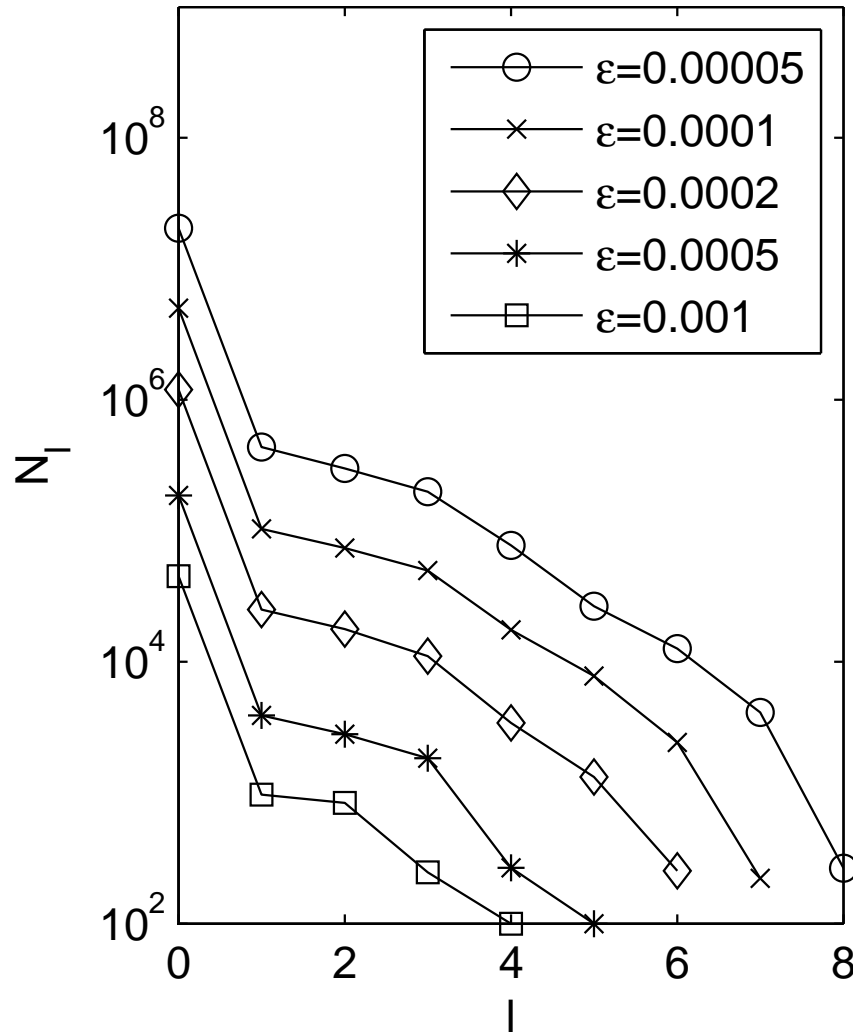
GBM: barrier



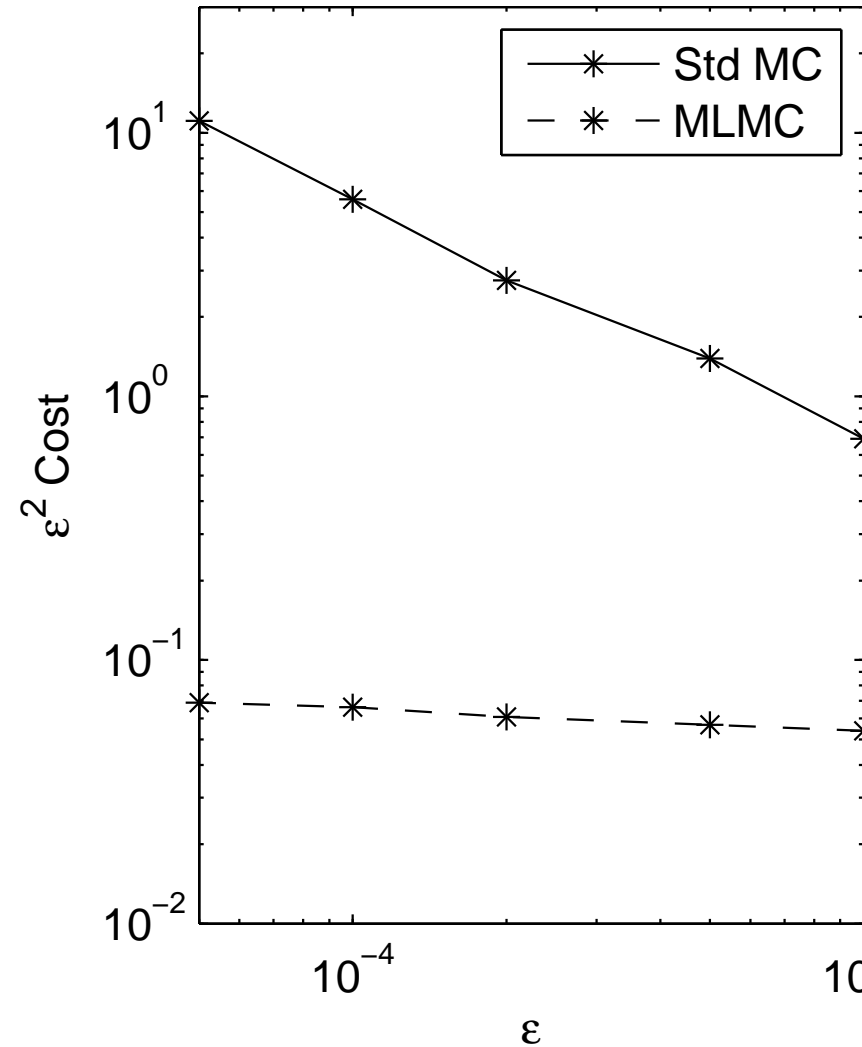
option

MLMC Results

GBM: barrier



option



Milstein Scheme

Generic vector SDE:

$$dS(t) = a(S, t) dt + b(S, t) dW(t), \quad 0 < t < T,$$

with correlation matrix $\Omega(S, t)$ between elements of $dW(t)$.

Milstein scheme:

$$\begin{aligned} \widehat{S}_{i,n+1} &= \widehat{S}_{i,n} + a_i h + b_{ij} \Delta W_{j,n} \\ &\quad + \frac{1}{2} \frac{\partial b_{ij}}{\partial S_l} b_{lk} \left(\Delta W_{j,n} \Delta W_{k,n} - h \Omega_{jk} - A_{jk,n} \right) \end{aligned}$$

with implied summation, and Lévy areas defined as

$$A_{jk,n} = \int_{t_n}^{t_{n+1}} (W_j(t) - W_j(t_n)) dW_k - (W_k(t) - W_k(t_n)) dW_j.$$

Milstein Scheme

In vector case:

- $O(h)$ strong convergence if Lévy areas are simulated correctly – expensive
- $O(h^{1/2})$ strong convergence in general if Lévy areas are omitted, except if a certain commutativity condition is satisfied (useful for a number of real cases)
- Lipschitz payoffs can be handled well using antithetic variables
- Other cases may require approximate simulation of Lévy areas

Results

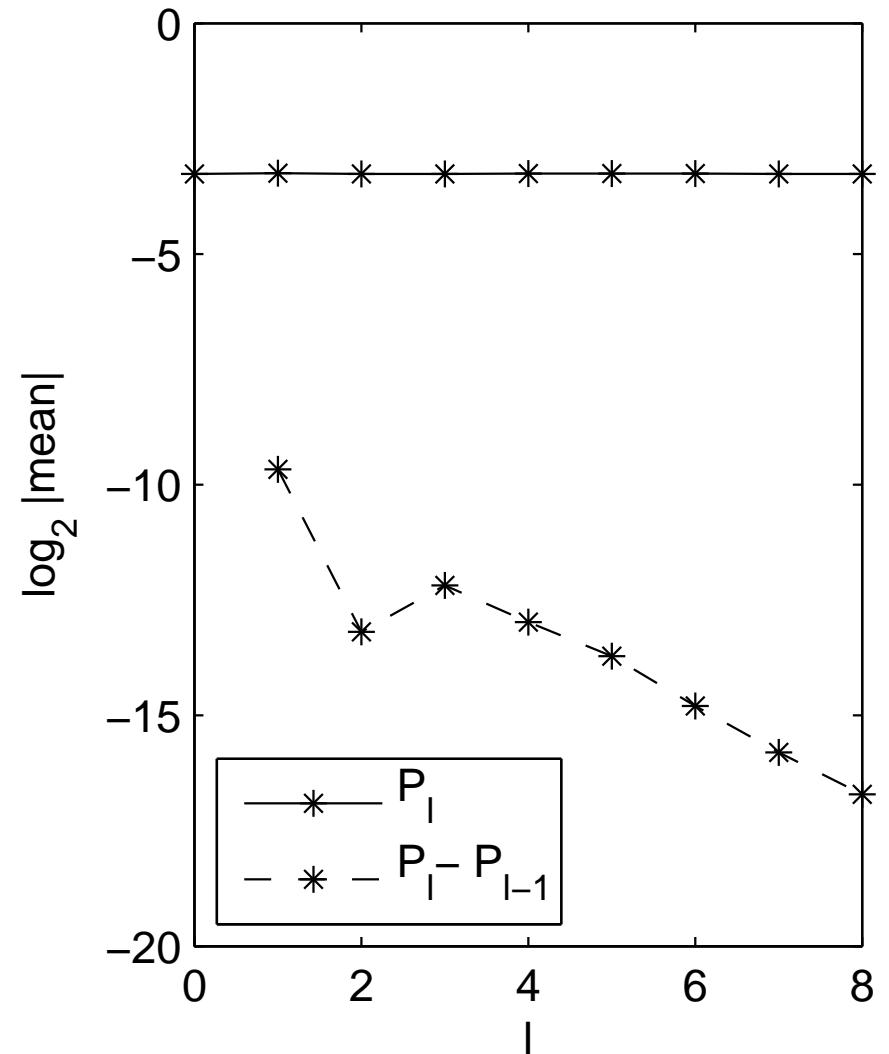
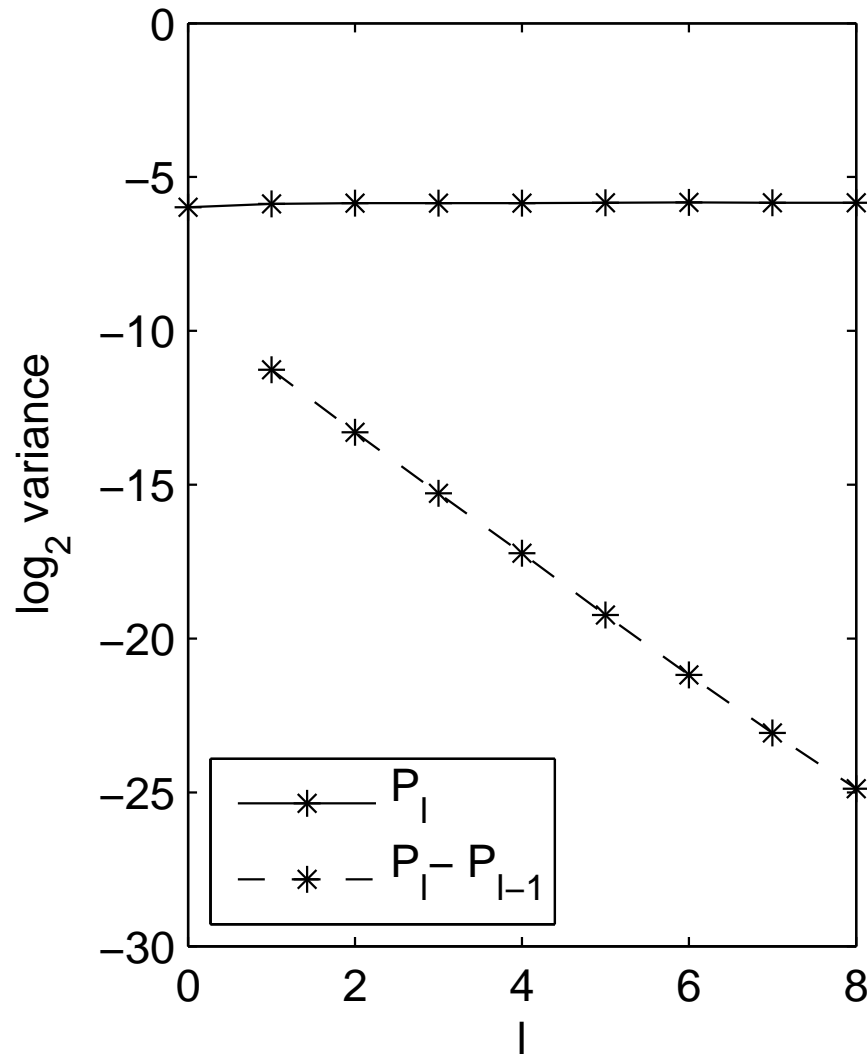
Heston model:

$$\begin{aligned}dS &= r S dt + \sqrt{V} S dW_1, & 0 < t < T \\dV &= \lambda (\sigma^2 - V) dt + \xi \sqrt{V} dW_2,\end{aligned}$$

$$\begin{aligned}T &= 1, & S(0) &= 1, & V(0) &= 0.04, & r &= 0.05, \\ \sigma &= 0.2, & \lambda &= 5, & \xi &= 0.25, & \rho &= -0.5\end{aligned}$$

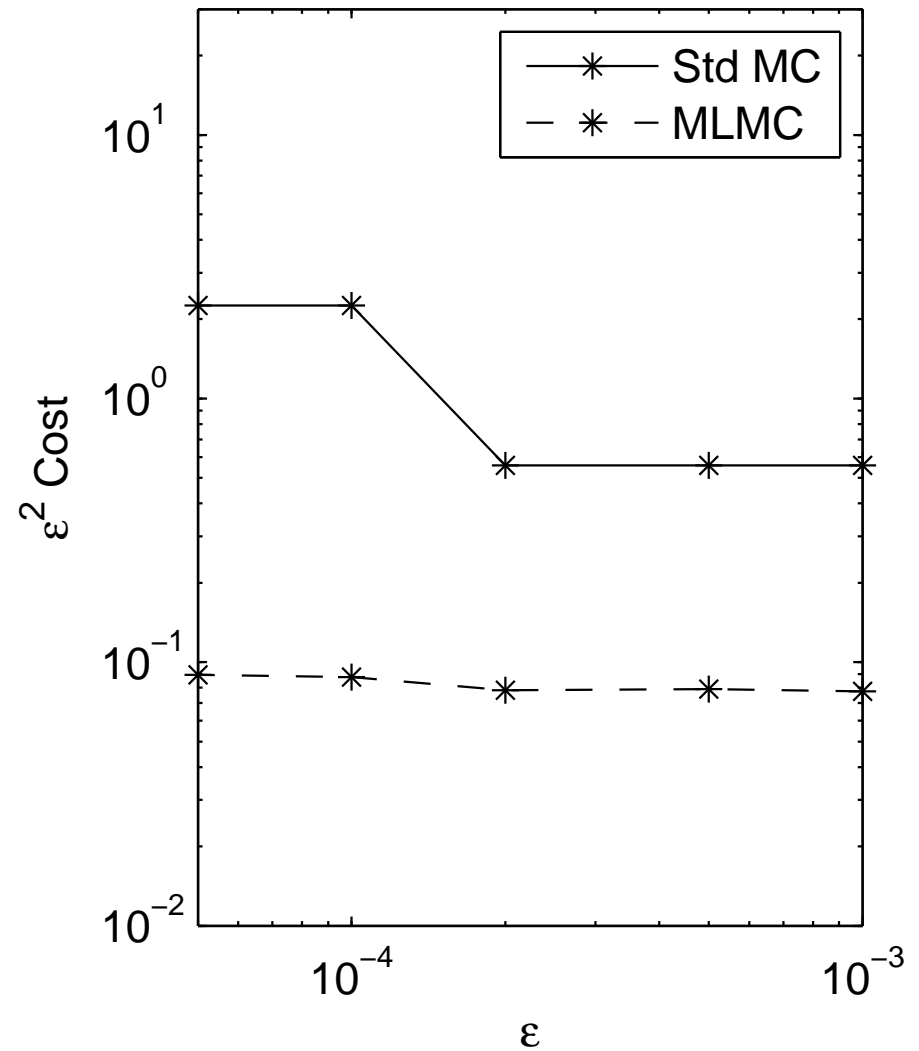
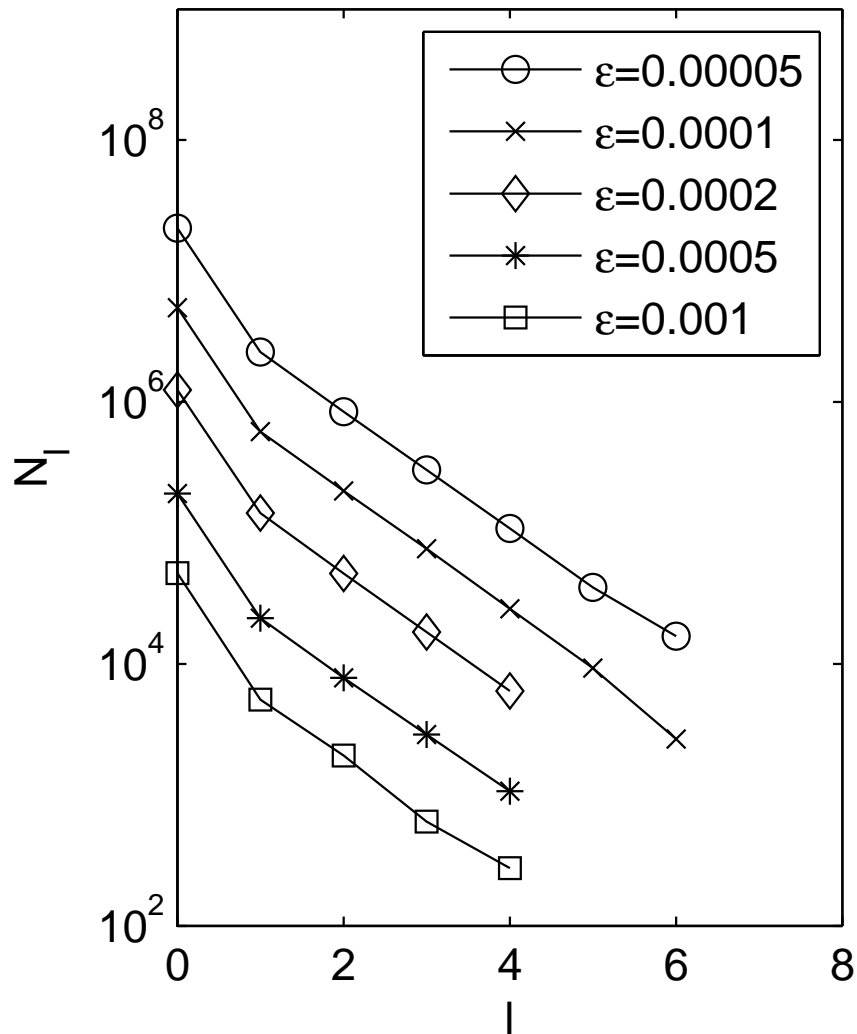
MLMC Results

Heston model: European call



MLMC Results

Heston model: European call



Quasi-Monte Carlo

- well-established technique for approximating high-dimensional integrals
- for finance applications see papers by l'Ecuyer and book by Glasserman
- Sobol sequences are perhaps most popular; we use lattice rules (Sloan & Kuo)
- two important ingredients for success:
 - randomized QMC for confidence intervals
 - good identification of “dominant dimensions” (Brownian Bridge and/or PCA)

Quasi-Monte Carlo

Approximate high-dimensional hypercube integral

$$\int_{[0,1]^d} f(x) \, dx$$

by

$$\frac{1}{N} \sum_{i=0}^{N-1} f(x^{(i)})$$

where

$$x^{(i)} = \left[\frac{i}{N} z \right]$$

and z is a d -dimensional “generating vector”.

Quasi-Monte Carlo

In the best cases, error is $O(N^{-1})$ instead of $O(N^{-1/2})$ but without a confidence interval.

To get a confidence interval, let

$$x^{(i)} = \left[\frac{i}{N} z + x_0 \right].$$

where x_0 is a random offset vector.

Using 32 different random offsets gives a confidence interval in the usual way.

Quasi-Monte Carlo

For the path discretisation we can use

$$\Delta W_n = \sqrt{h} \Phi^{-1}(x_n),$$

where Φ^{-1} is the inverse cumulative Normal distribution.

Much better to use a Brownian Bridge construction:

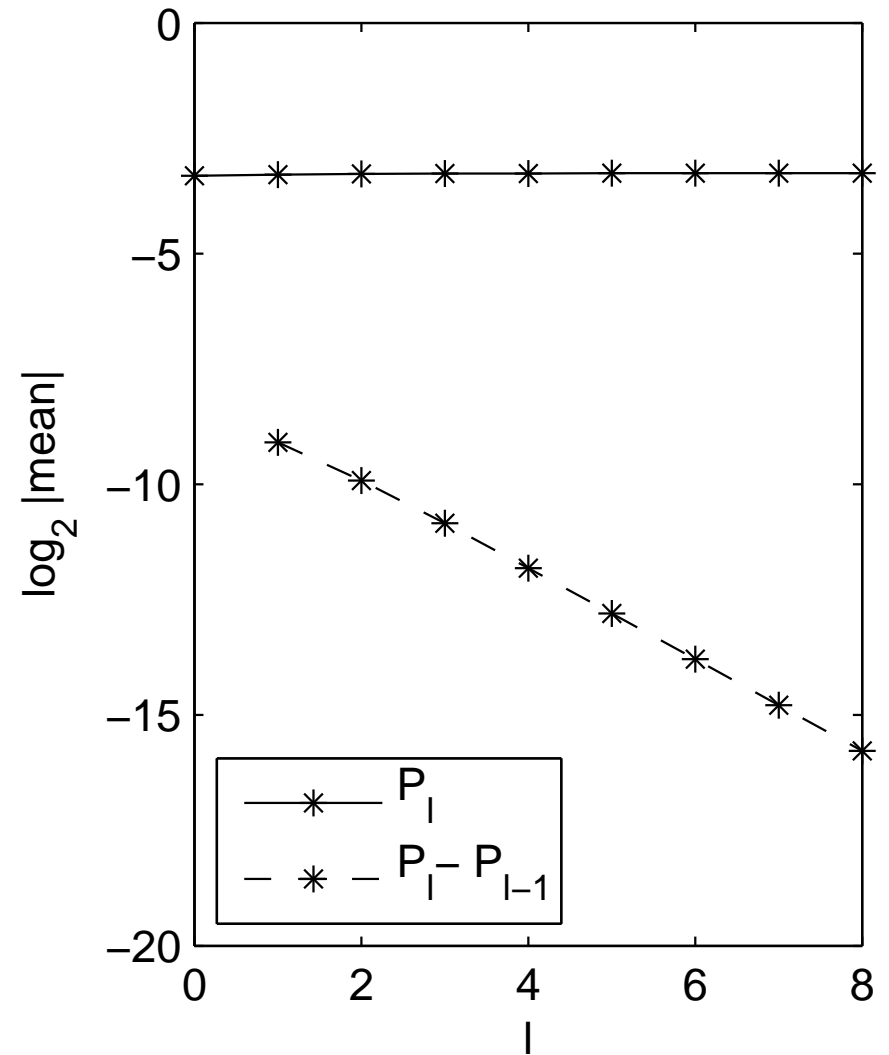
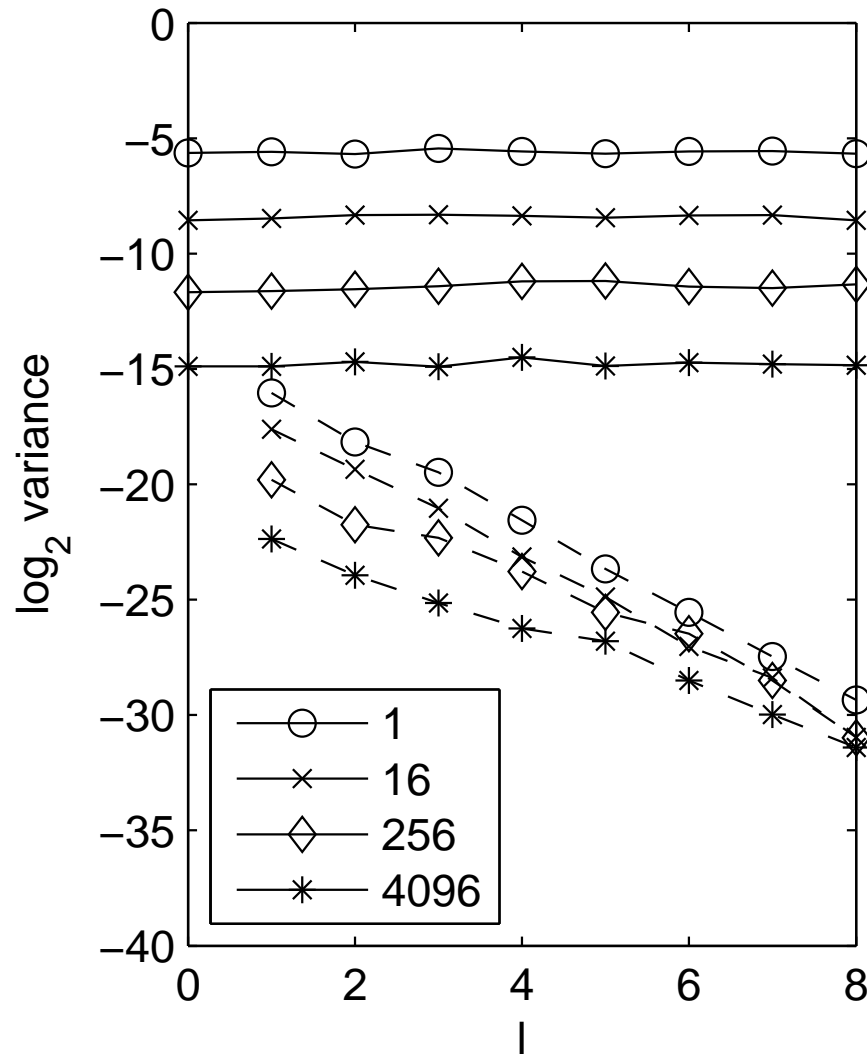
- $x_1 \longrightarrow W(T)$
- $x_2 \longrightarrow W(T/2)$
- $x_3, x_4 \longrightarrow W(T/4), W(3T/4)$
- ... and so on by recursive bisection

Multilevel QMC

- rank-1 lattice rule developed by Sloan, Kuo & Waterhouse at UNSW
- 32 randomly-shifted sets of QMC points
- number of points in each set increased as needed to achieved desired accuracy, based on confidence interval estimate
- results show QMC to be particularly effective on lowest levels with low dimensionality

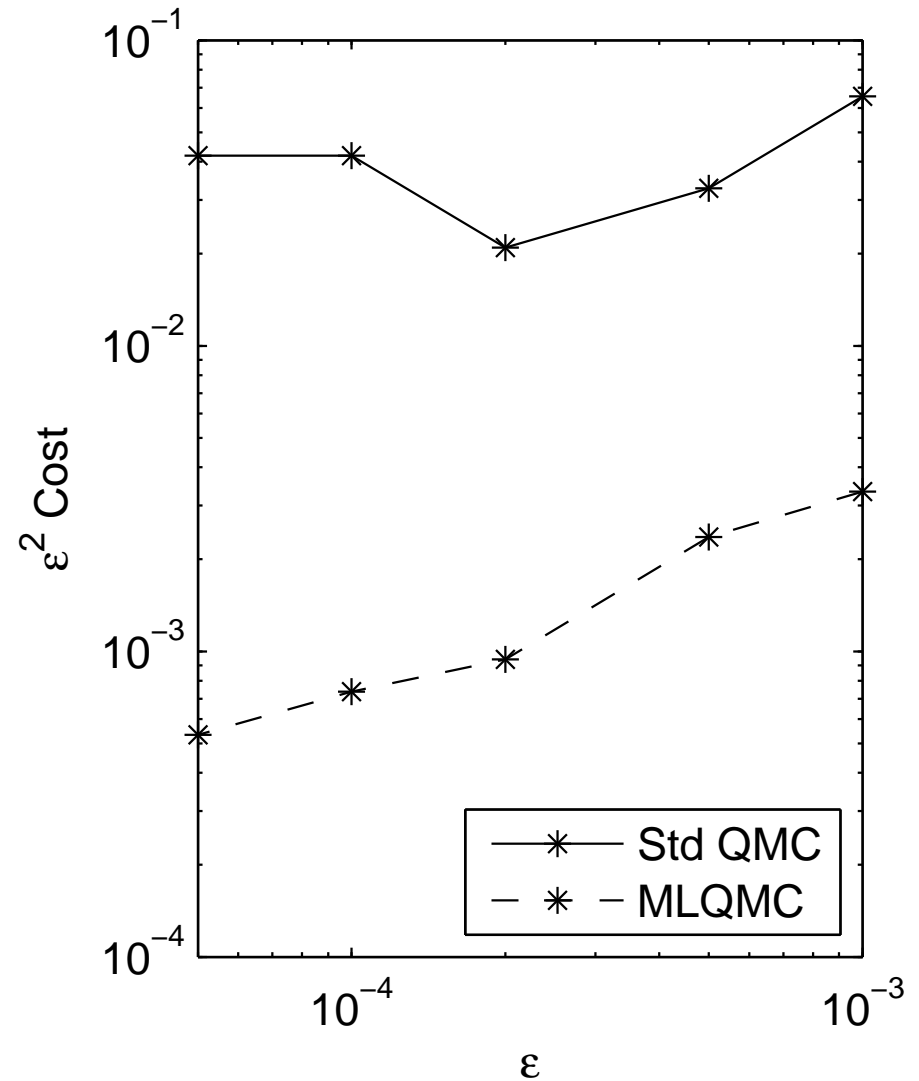
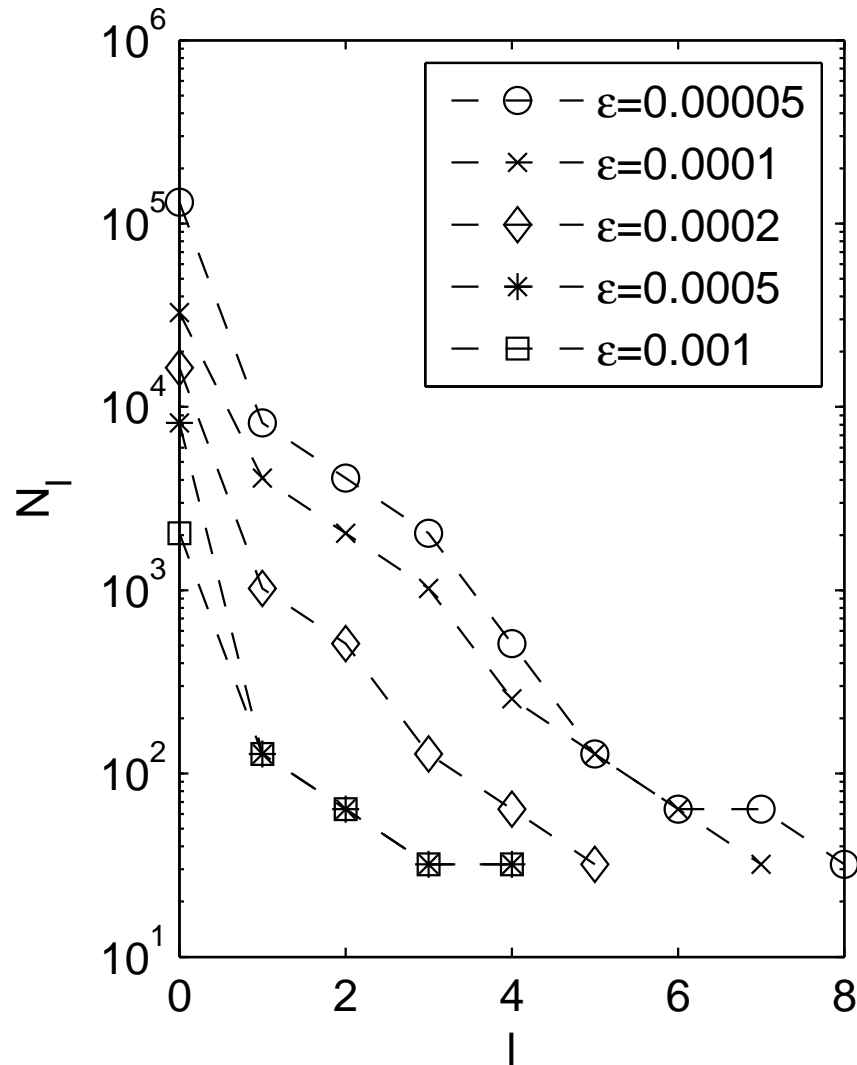
MLQMC Results

GBM: European call



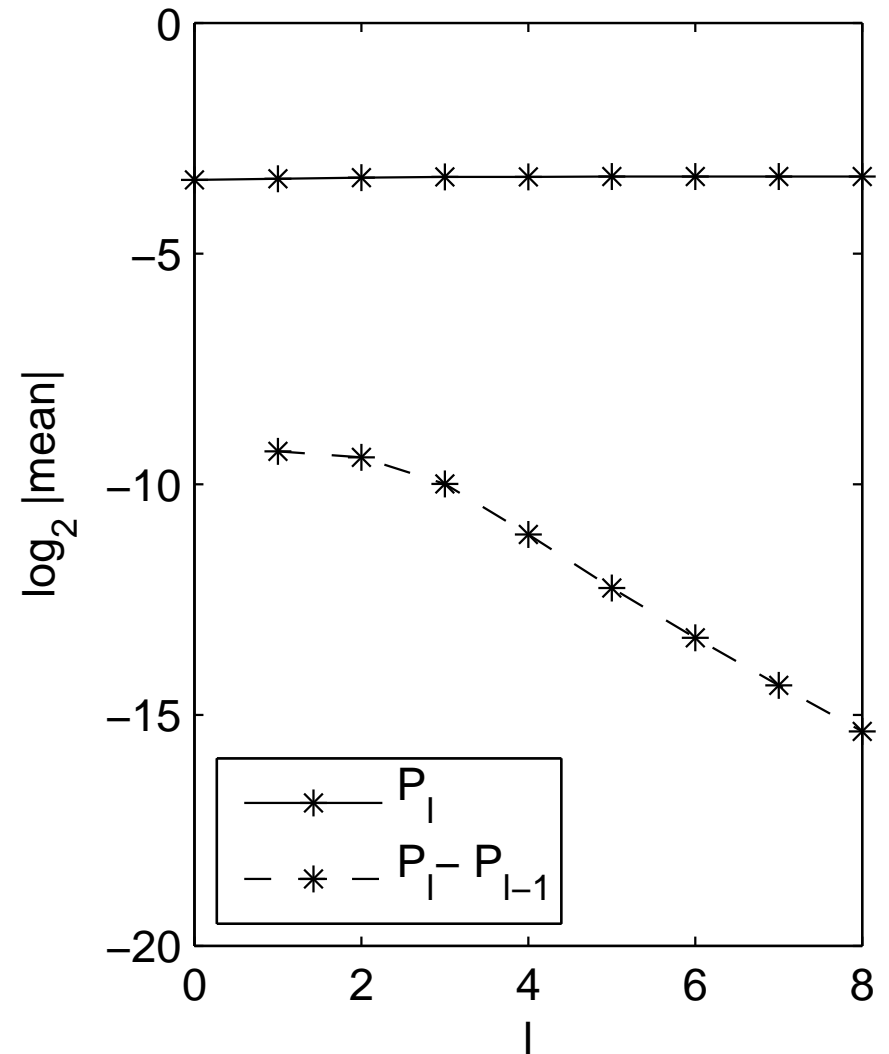
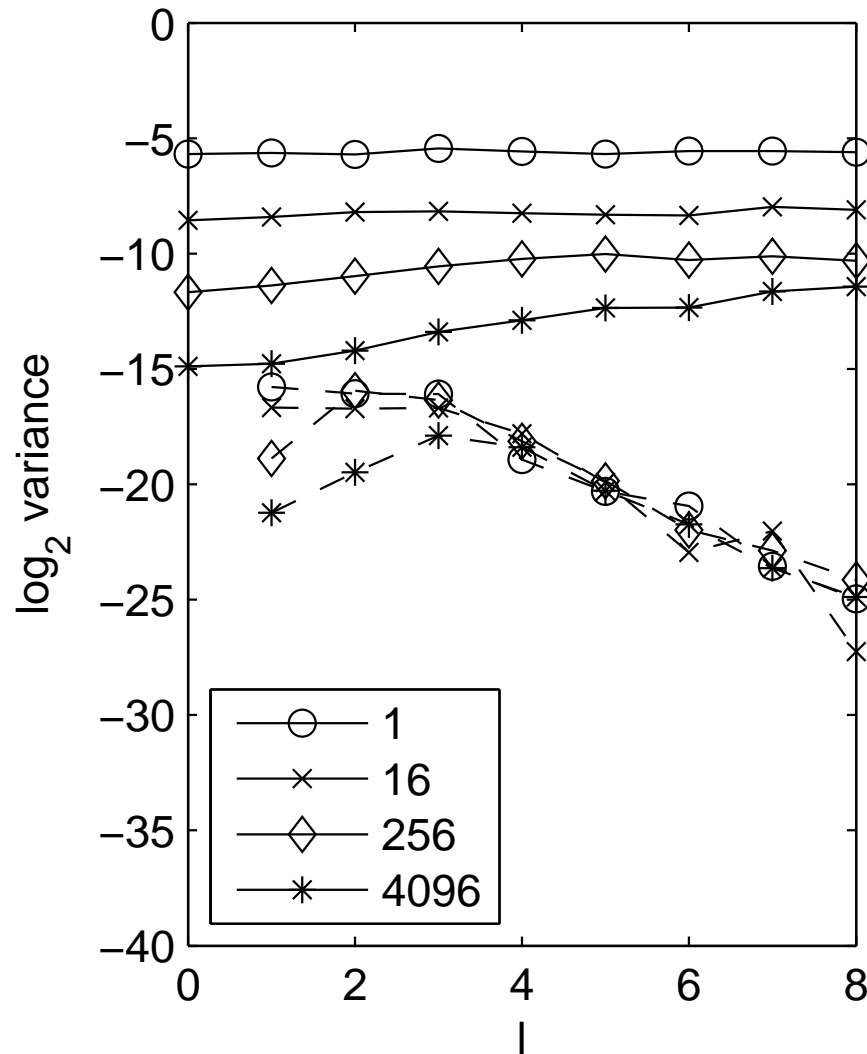
MLQMC Results

GBM: European call



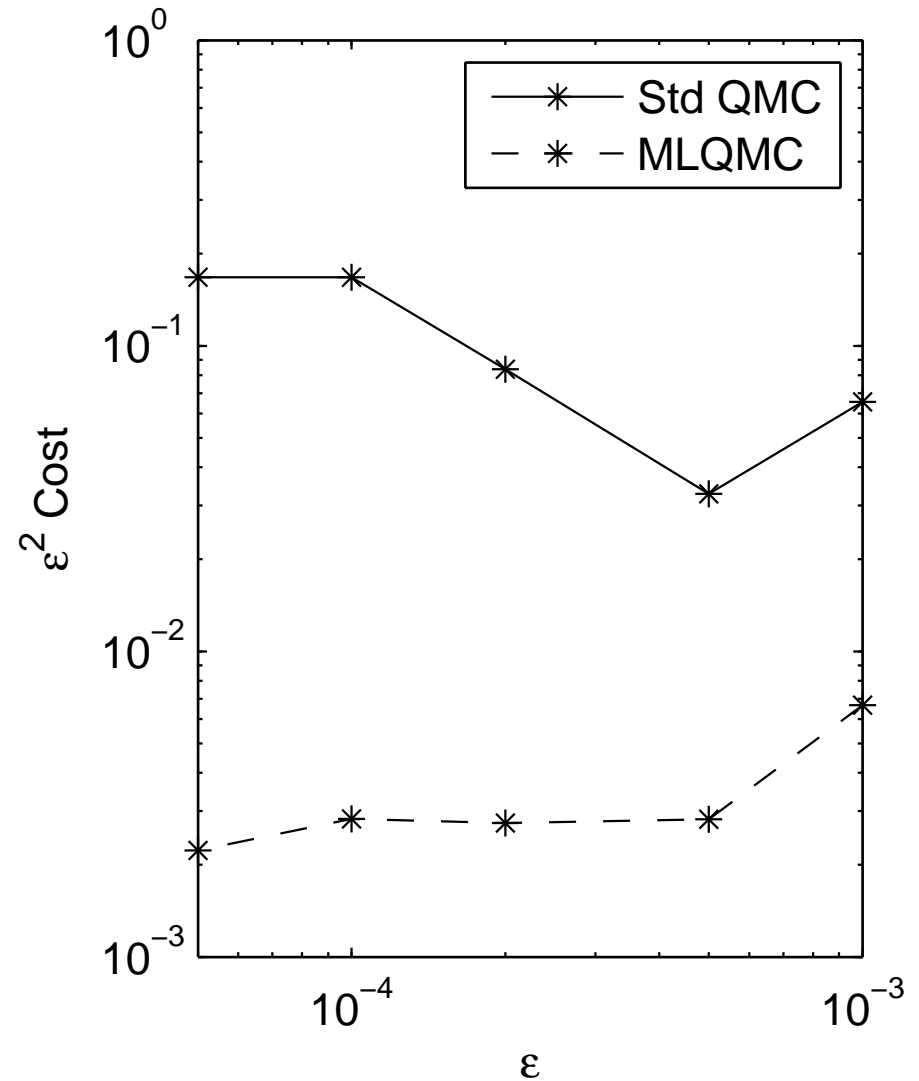
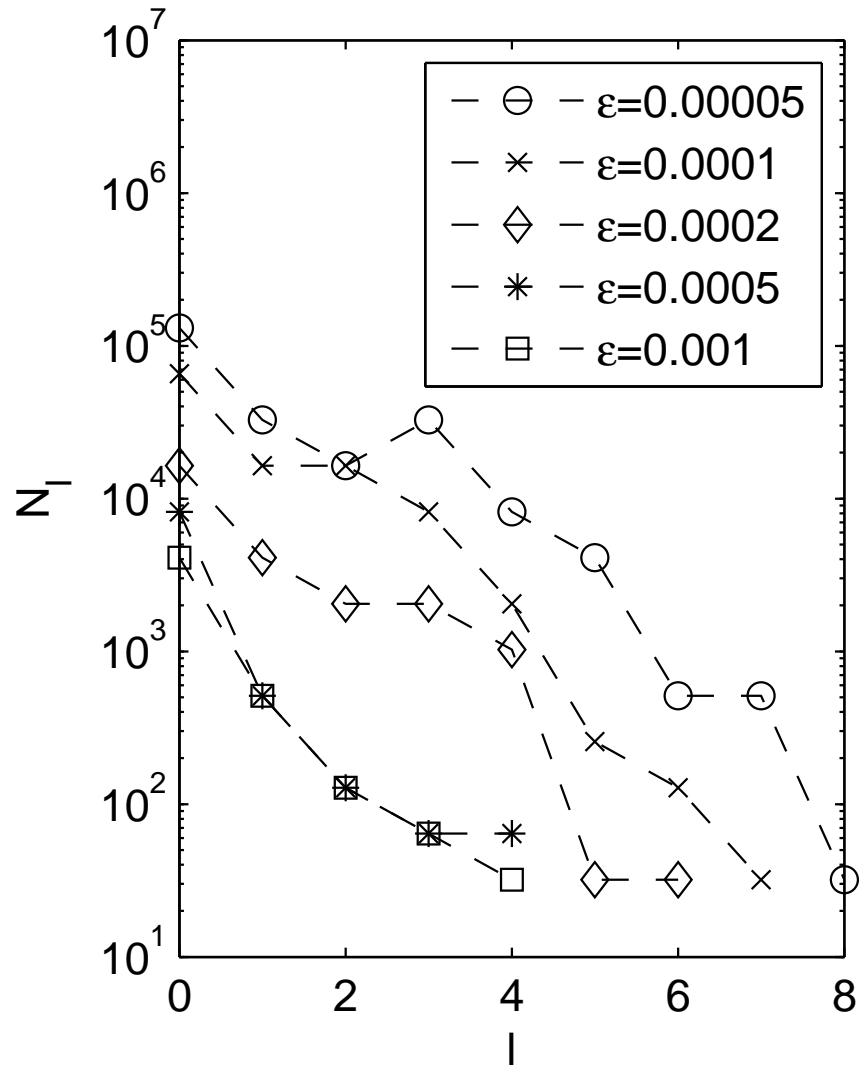
MLQMC Results

GBM: barrier option



MLQMC Results

GBM: barrier option



Conclusions

Results so far:

- much improved order of complexity
- fairly easy to implement
- significant benefits for model problems

However:

- lots of scope for further development
 - multi-dimensional SDEs needing Lévy areas
 - adjoint Greeks and “vibrato” Monte Carlo
 - numerical analysis of algorithms
 - execution on NVIDIA graphics cards (128 cores)
- need to test ideas on real finance applications

Papers

M.B. Giles, “Multilevel Monte Carlo path simulation”, to appear in *Operations Research*, 2007.

M.B. Giles, “Improved multilevel convergence using the Milstein scheme”, to appear in *MCQMC06* proceedings, Springer-Verlag, 2007.

M.B. Giles, “Multilevel quasi-Monte Carlo path simulation”, submitted to *Journal of Computational Finance*, 2007.

www.comlab.ox.ac.uk/mike.giles/finance.html

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