

Quantum Amplitude Estimation for Financial Risk: A Rigorous Benchmark Against Classical Monte Carlo

iQuHACK 2026 – State Street × Classiq

TEAM WHAT THE DUCK?!

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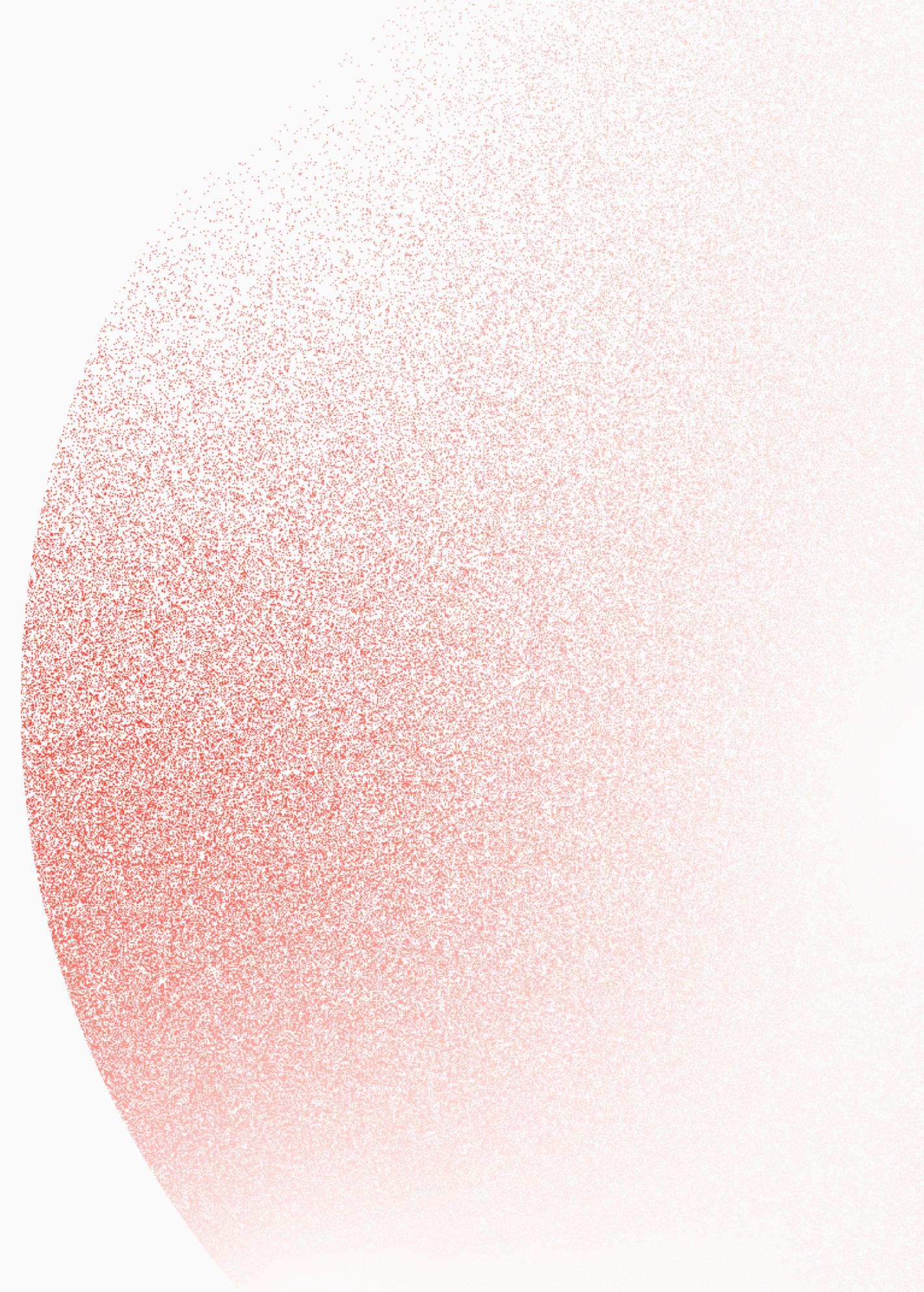


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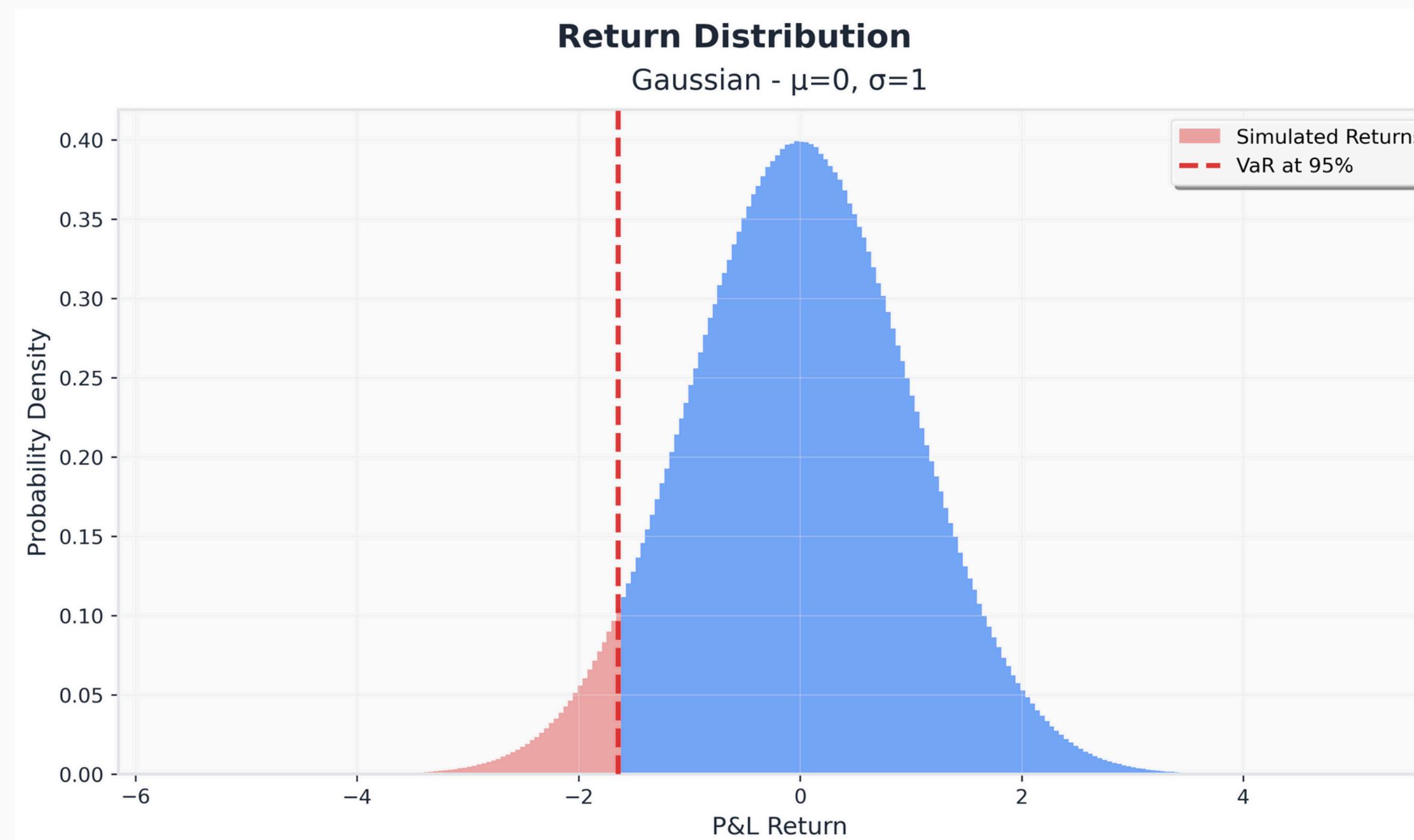
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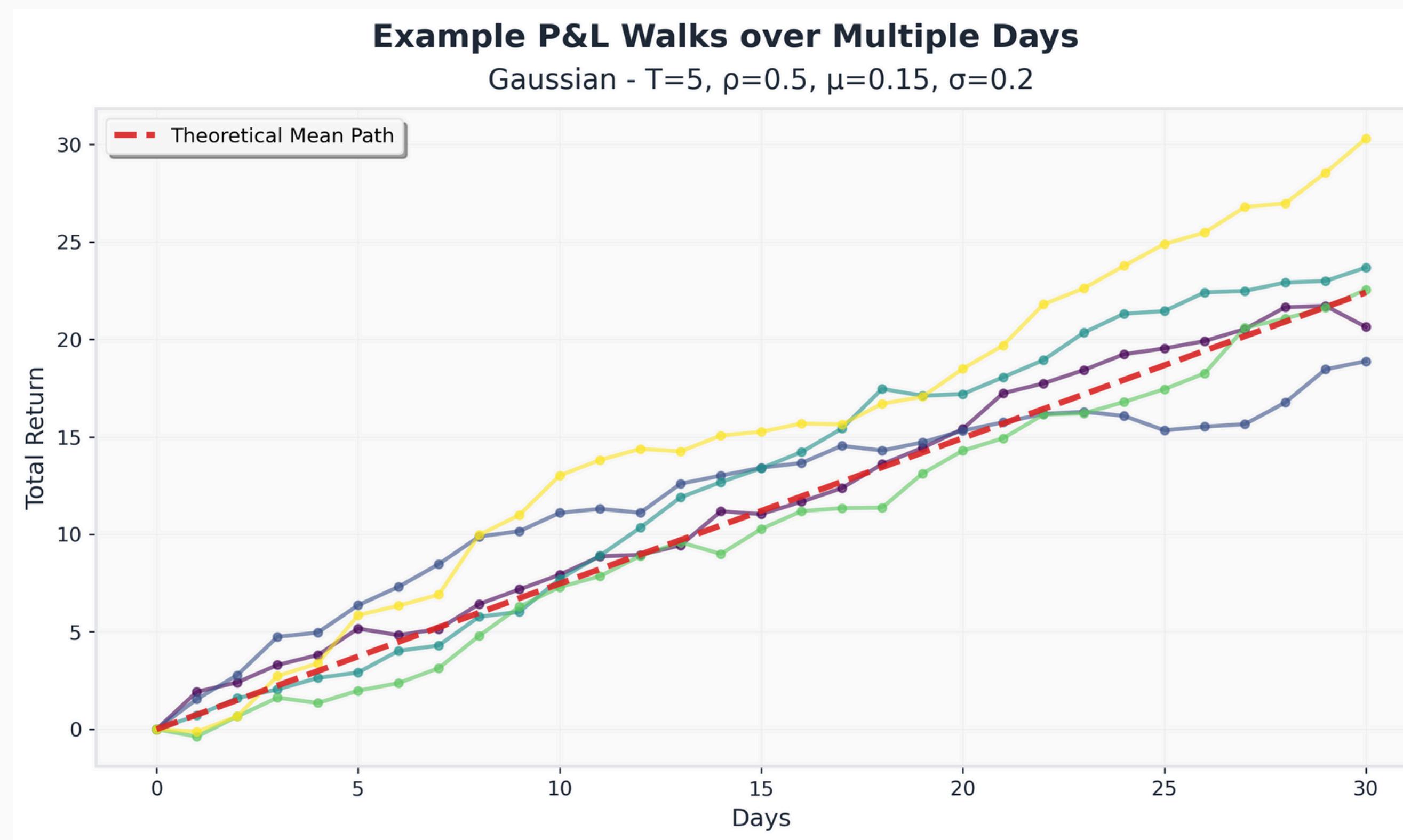
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Value at Risk as a Tail-Probability Constraint

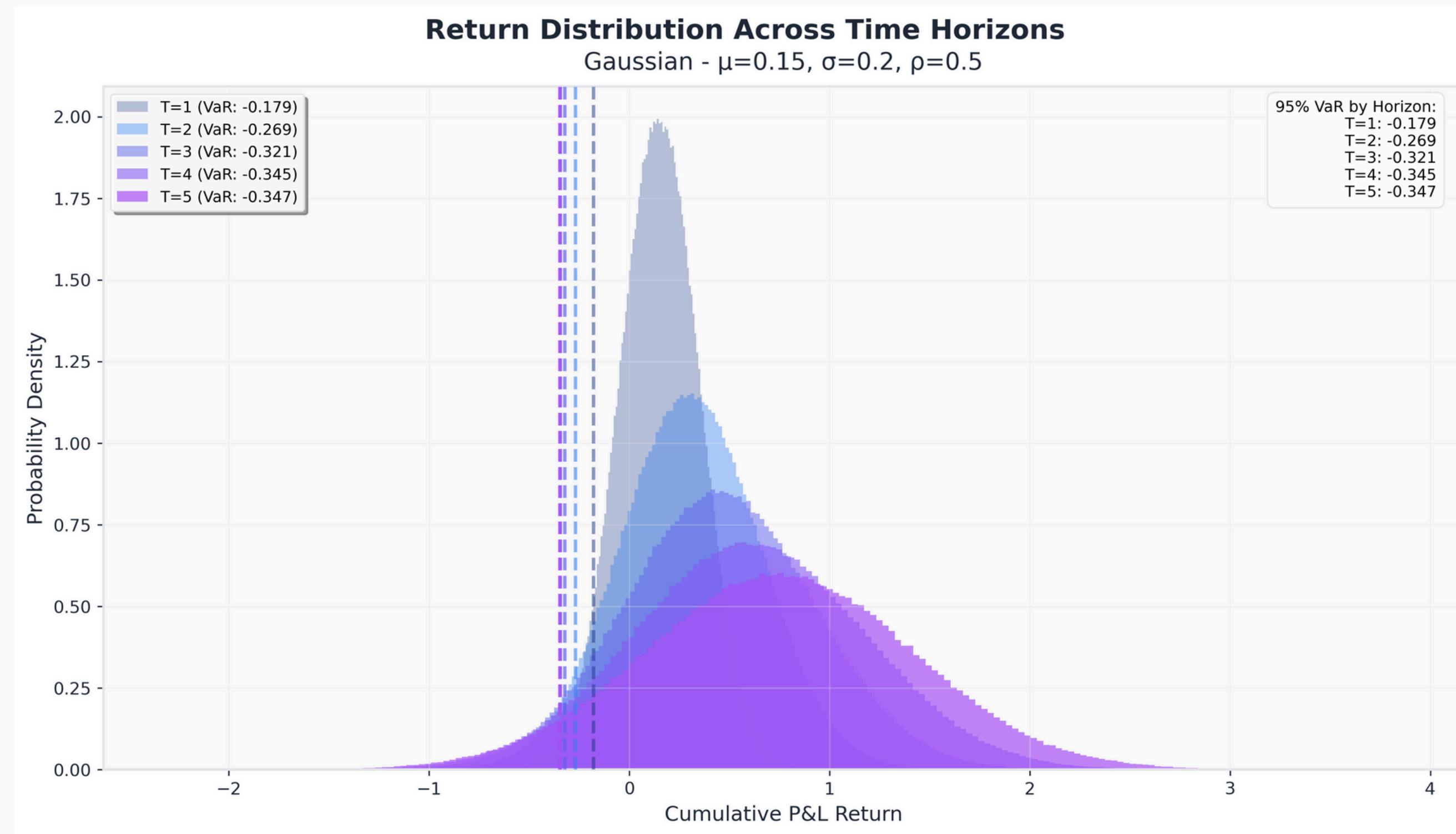
$\text{VaR}(\alpha)$ = the value v such that $P(X \leq v) = \alpha$



Random Walk



Daily Correlated Distributions



Classical vs Quantum VaR

Both methods compute VaR by solving the same bisection problem at a fixed tail probability α .
The search procedure, stopping rule, and target confidence level are identical.

THE ONLY DIFFERENCE IS HOW THE TAIL PROBABILITY IS ESTIMATED

NAIVE MONTE-CARLO

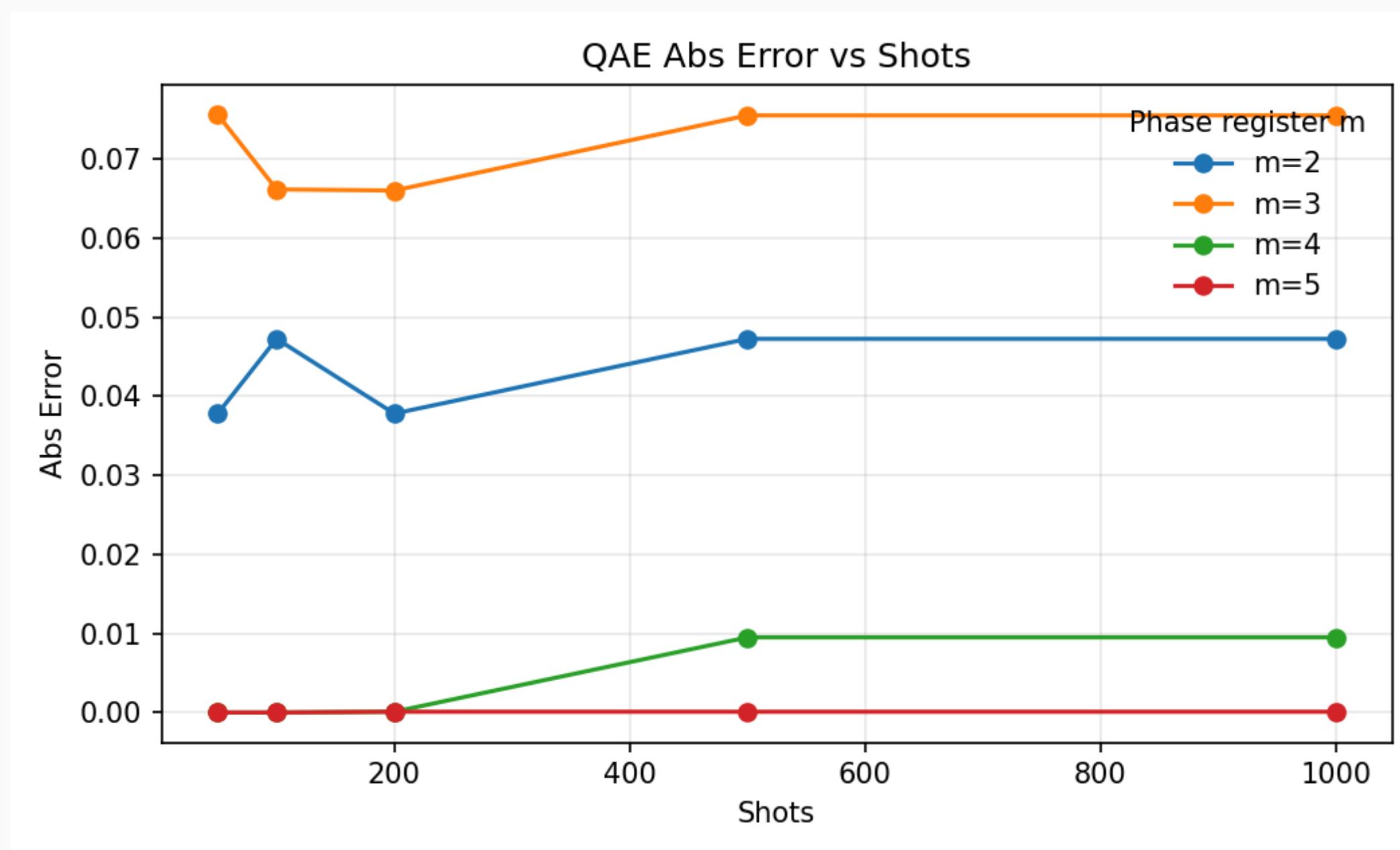
1. Set tail probability $\alpha = 0.07$
2. **VaR** = unknown threshold v such that
 $P(X \leq v) = \alpha$
3. **Monte Carlo** estimates $\alpha^*(v)$
$$\alpha^*(v) = (1 / N) \cdot \sum_{i=1}^N \mathbb{1}[X_i \leq v]$$
4. Bisection updates v
5. **Stop when** $\alpha^*(v) \approx \alpha$

HYBRID QUANTUM-CLASSICAL ALGORITHM USING IQAE

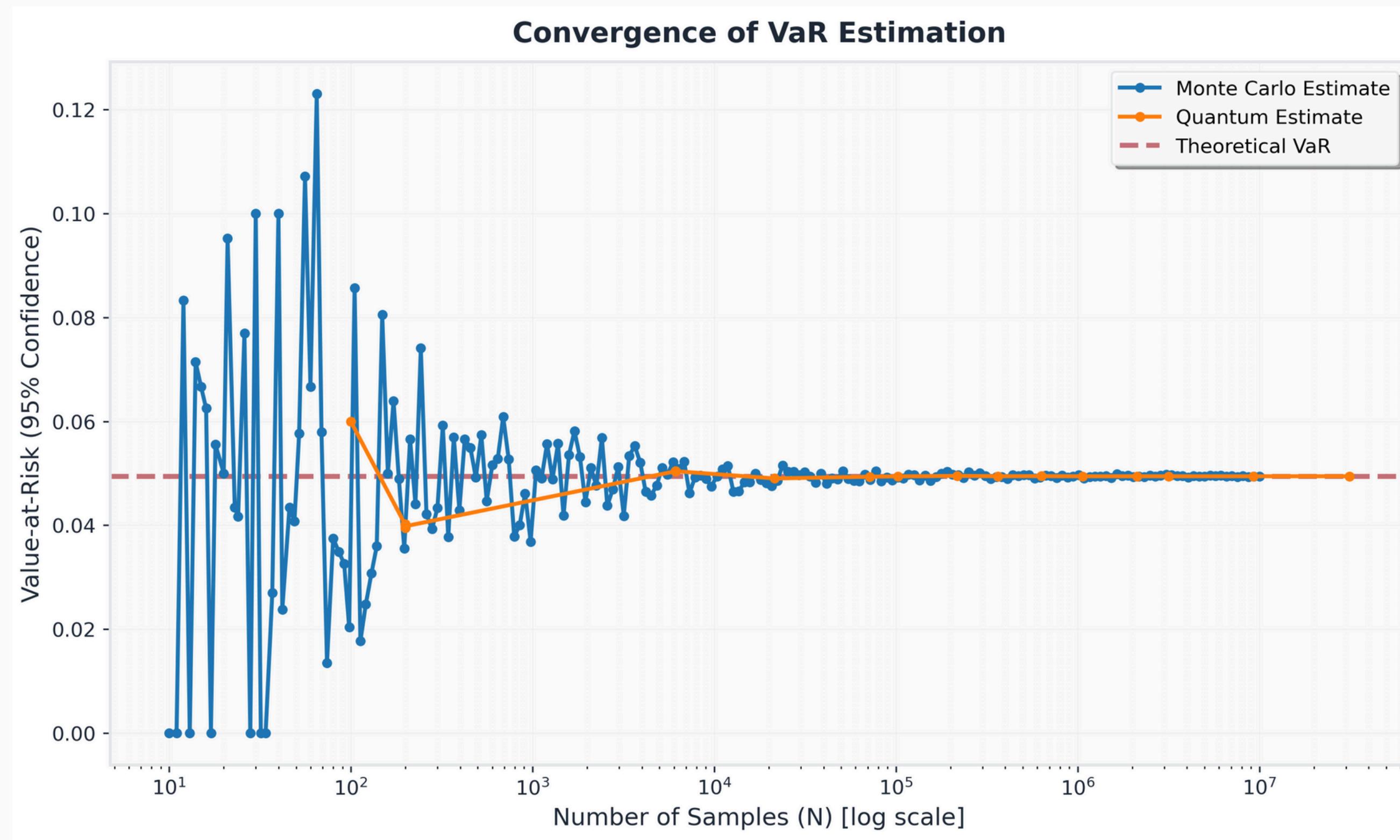
1. Set tail probability $\alpha = 0.07$
2. **VaR** = unknown threshold v such that $P(X \leq v) = \alpha$
3. **IQAE** estimates $\alpha^*(v)$
4. Bisection updates v
5. **Stop when** $\alpha^*(v) \approx \alpha$

QAE

- More phase depth correlates with less error
- Shots does not have a significant or consistent correlation
- Verrrrry slow, especially as phase depth increases



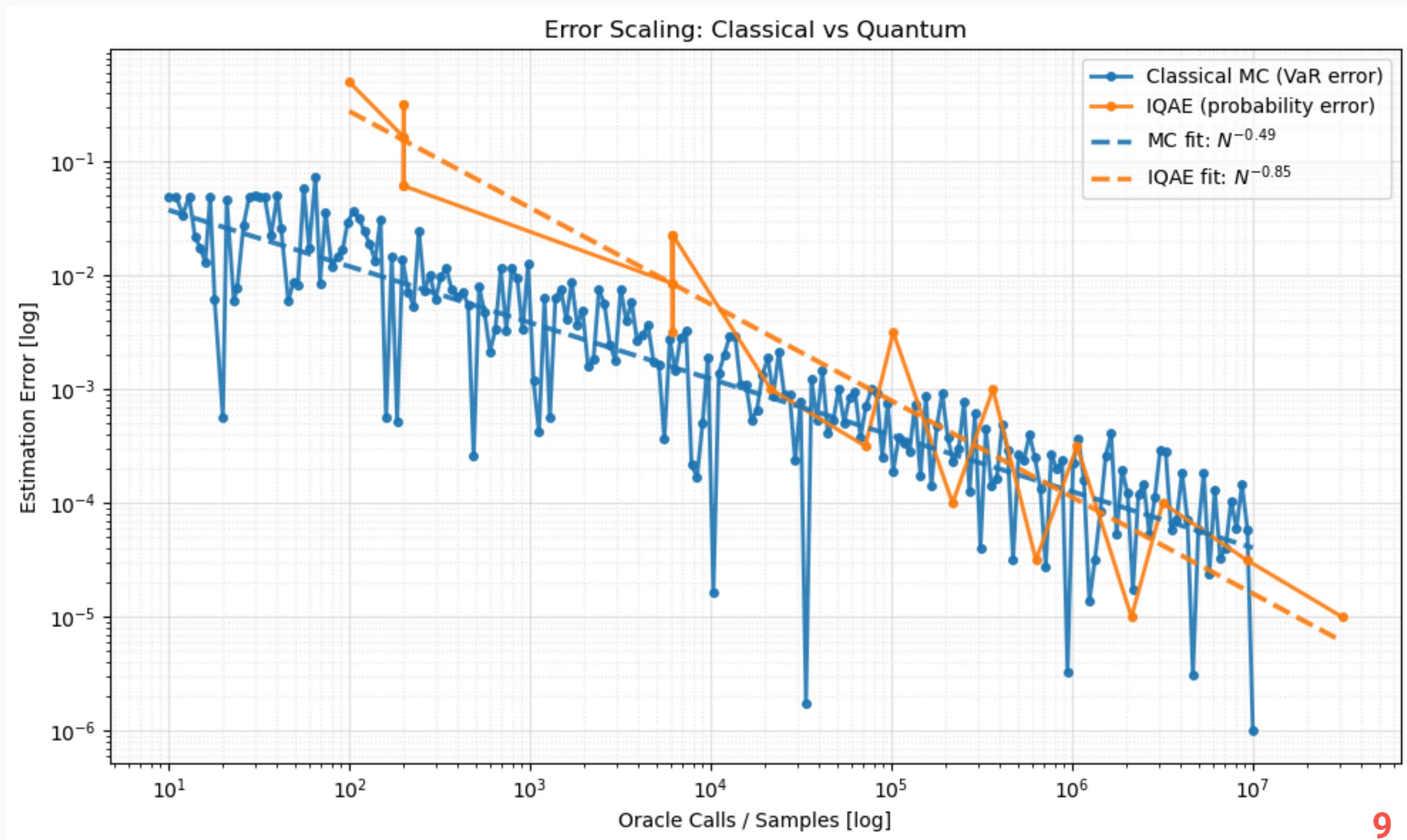
Estimation Convergence: Classical Monte Carlo vs Quantum IQAE



Estimation Error Scaling: Classical Monte Carlo vs Quantum IQAE

QUESTION

- Classical: Monte Carlo sampling
 - Cost scales as $O(1 / \varepsilon^2)$
- Quantum: Iterative Quantum Amplitude Estimation (IQAE)
 - Cost scales as $O(1 / \varepsilon)$



Error Sources in VaR Estimation

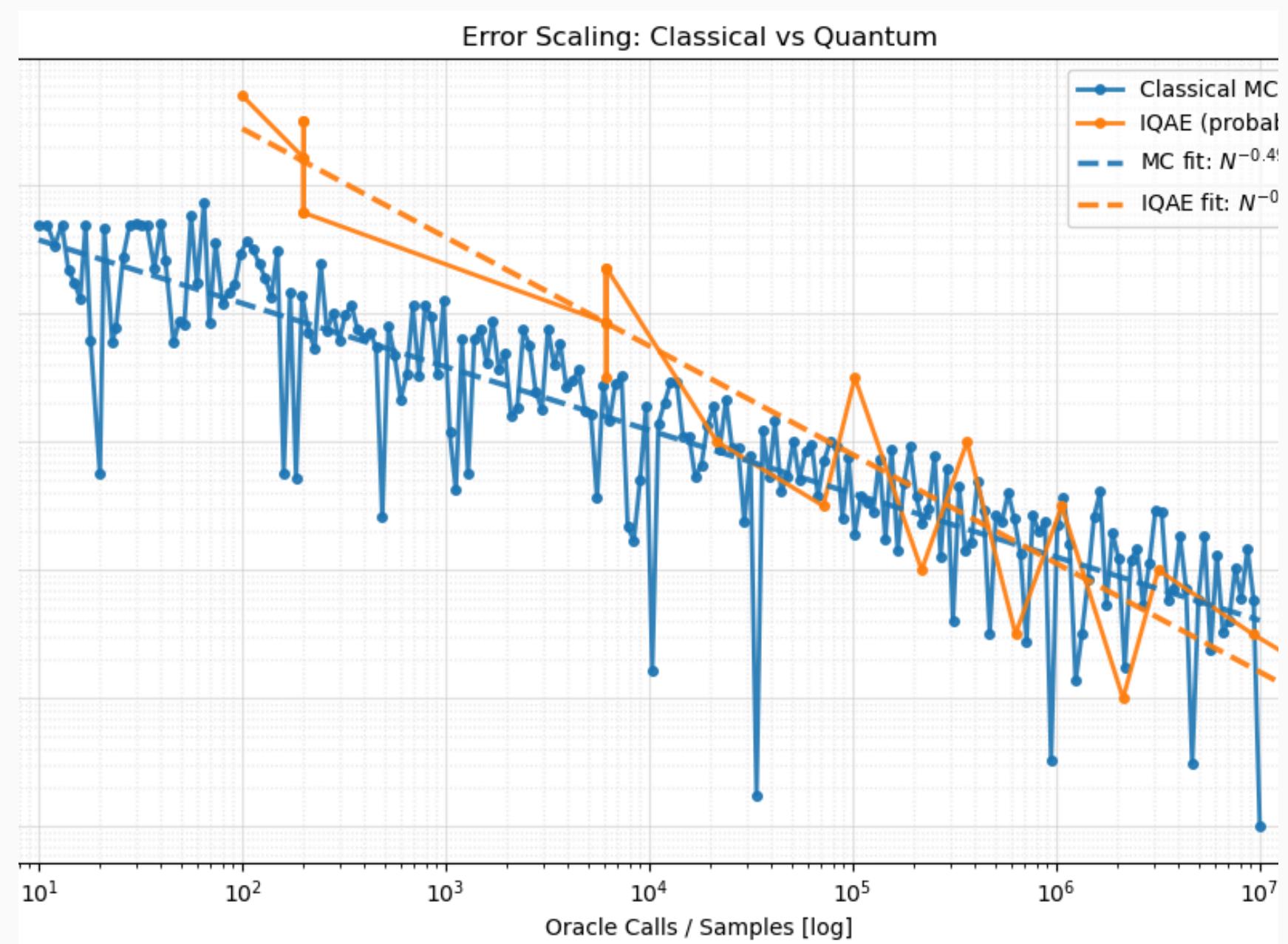
Total error = modeling error + estimation error

Modeling / Discretization Error

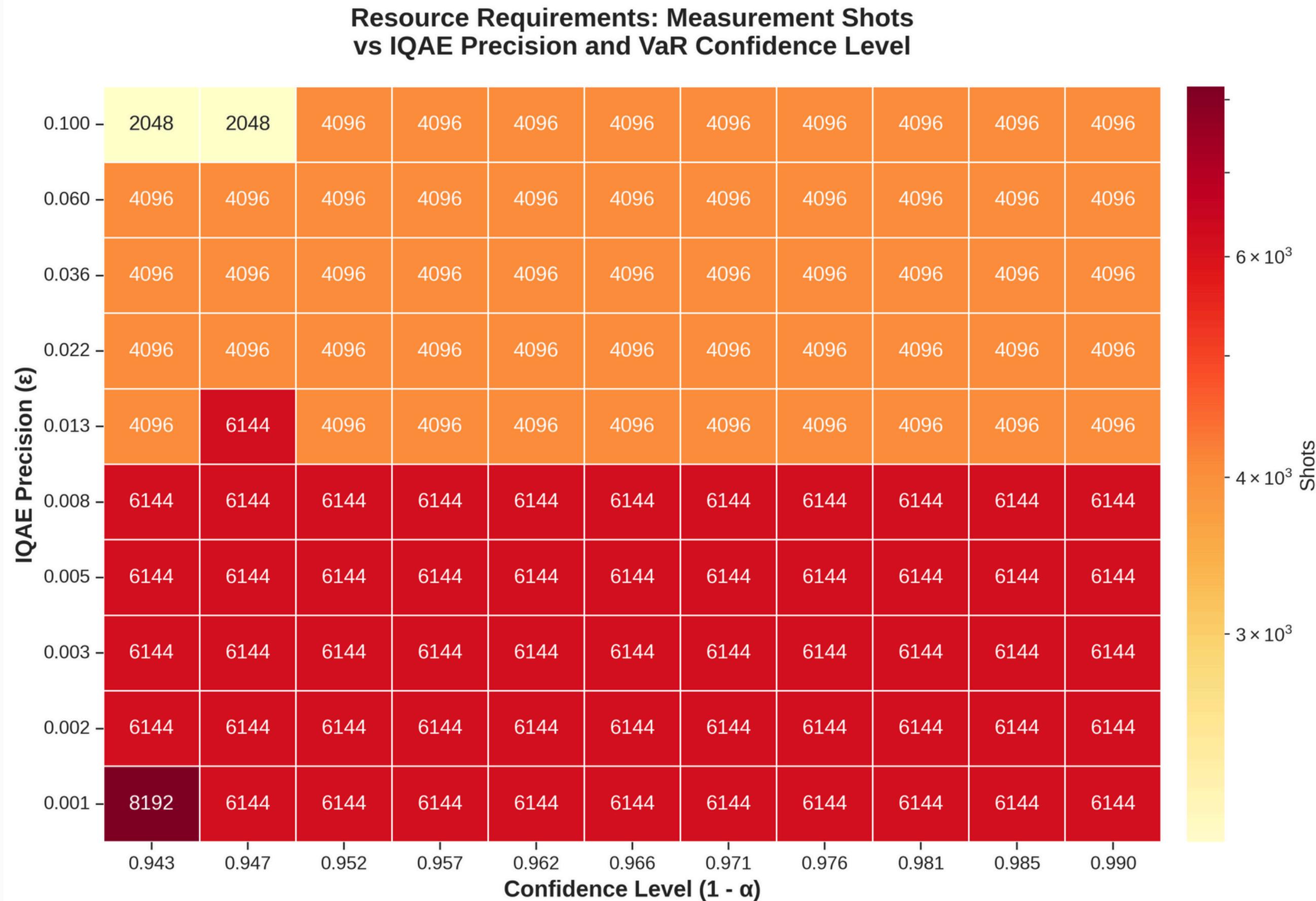
- Can only sample bins
- Defines a fixed lower bound on accuracy

Probability Estimation Error

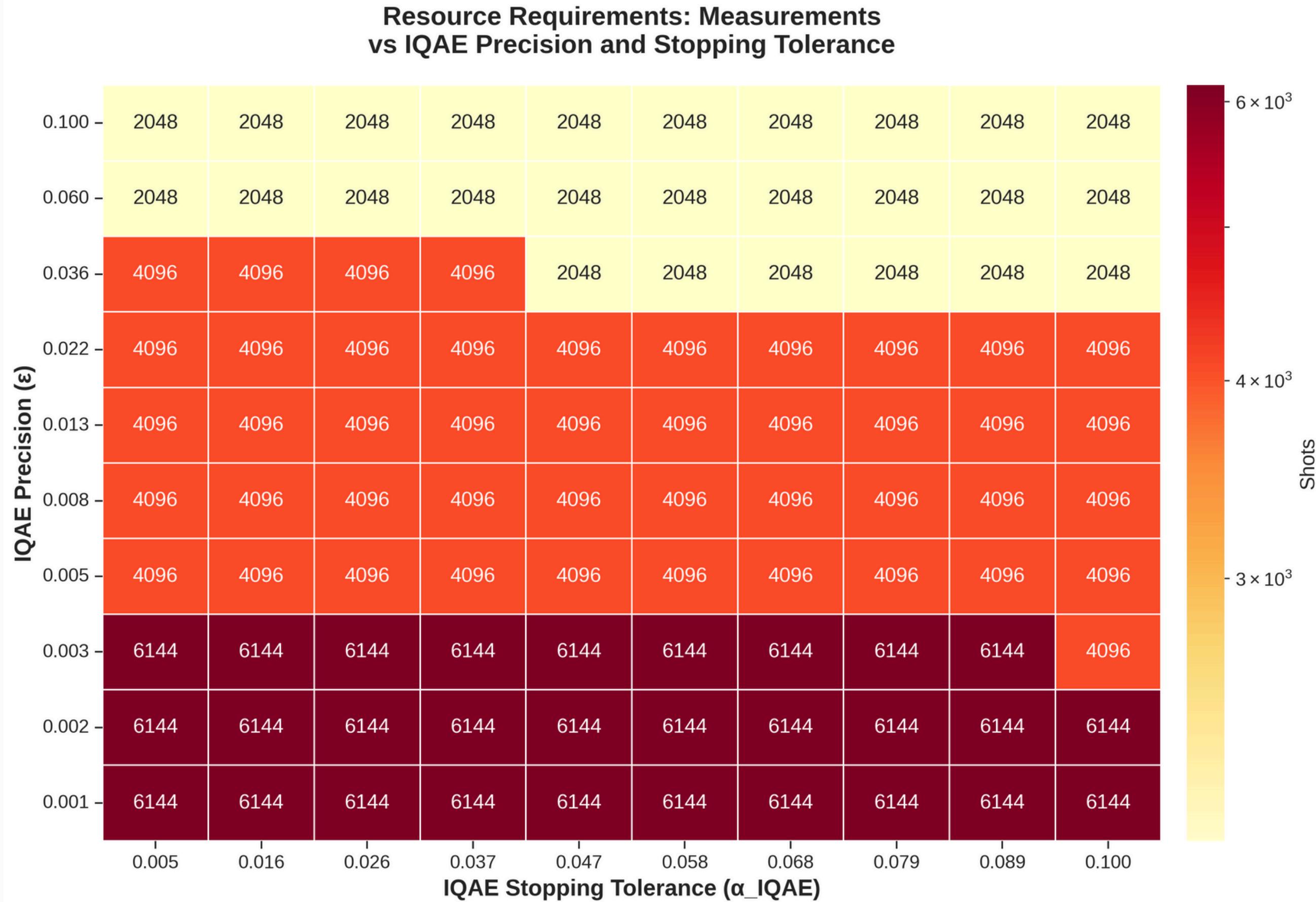
- Quantum speedup
- Scaling:
 - Classical MC: $O(1/\sqrt{N})$
 - Quantum IQAE: $O(1/N)$



Sensitivity to confidence level and ϵ



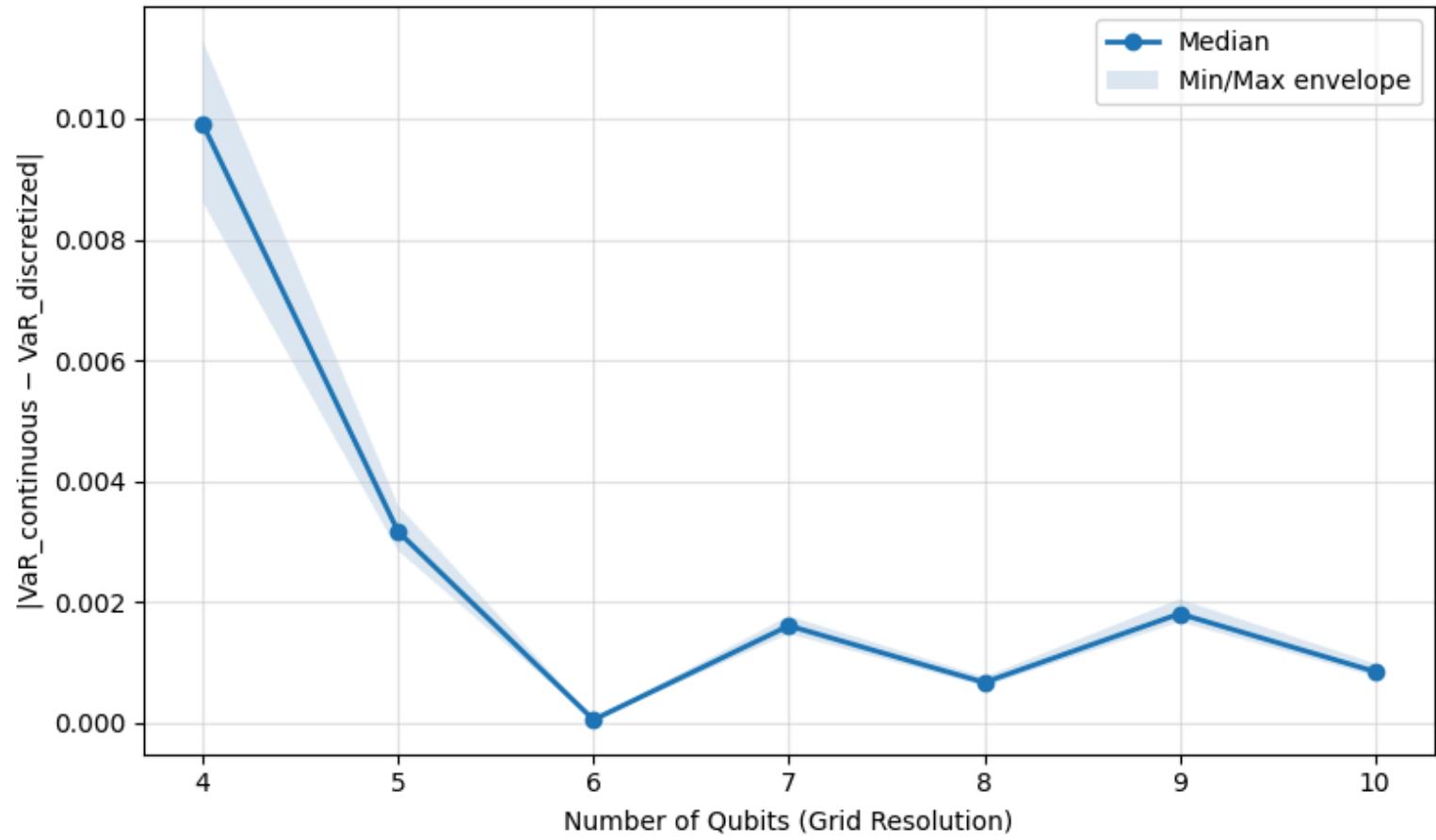
Sensitivity to stopping threshold and ϵ



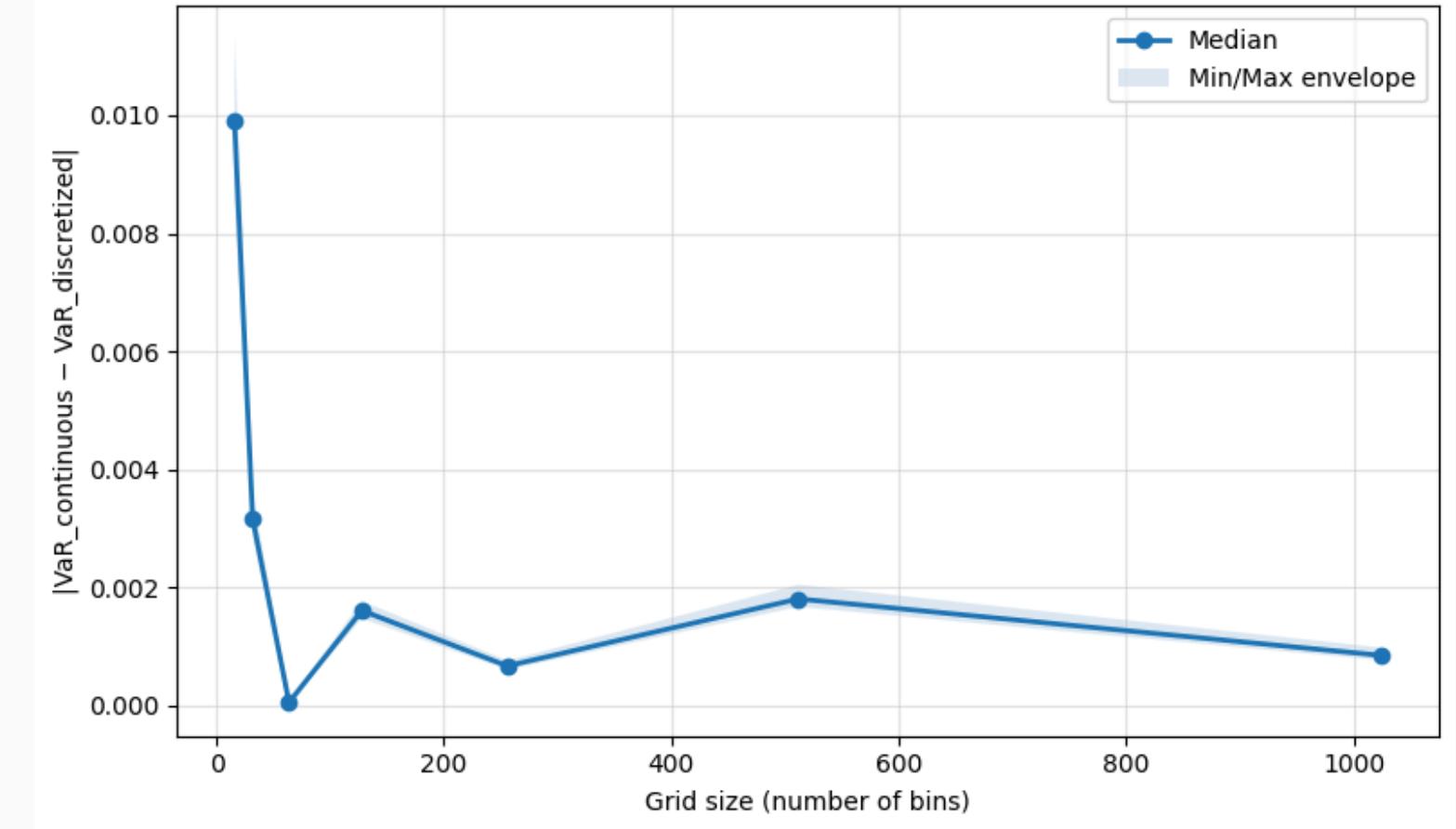
Sensitivity to discretization resolution

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Discretization Error vs Grid Resolution



Discretization Error vs Grid Resolution



Increasing the number of qubits or bins reduces discretization error.

GPU-Accelerated Optimization: Hyperparameter Tuning

Error = Queries + Distributions x Iterations + Step Error

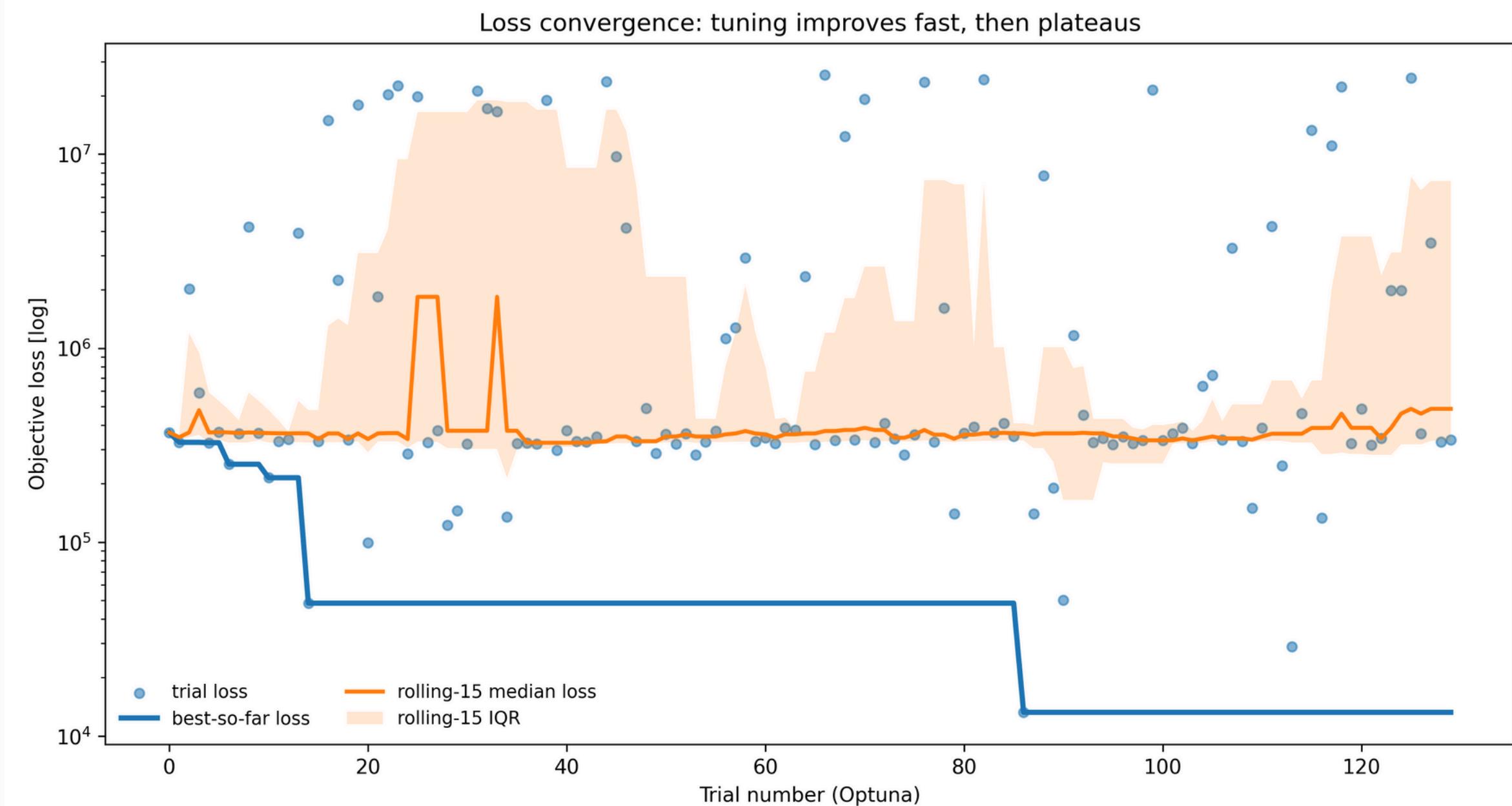
Classical Parameters:

- Stratification Buckets
- Heuristic Params
- Confidence
- Tilt Tau

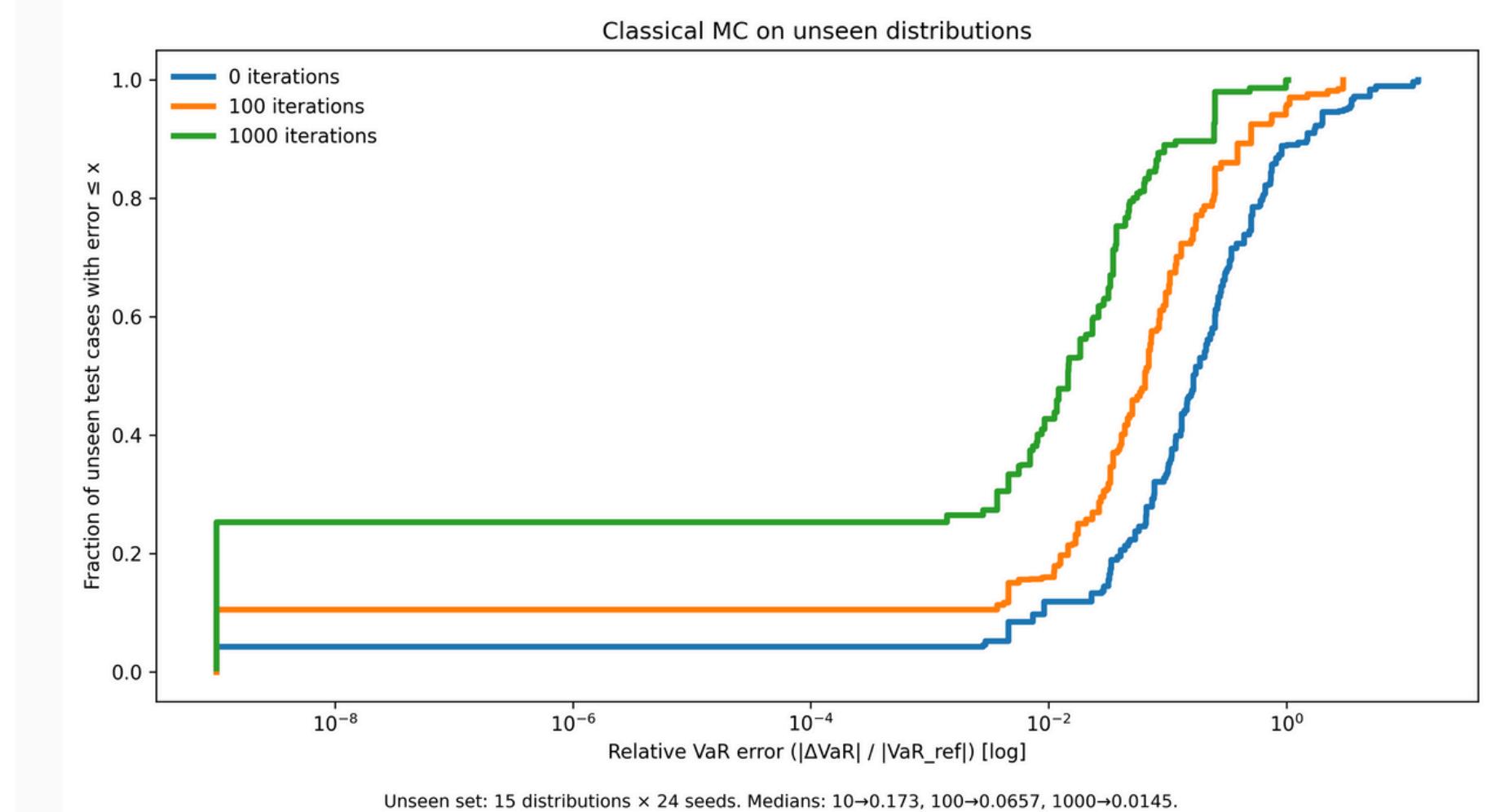
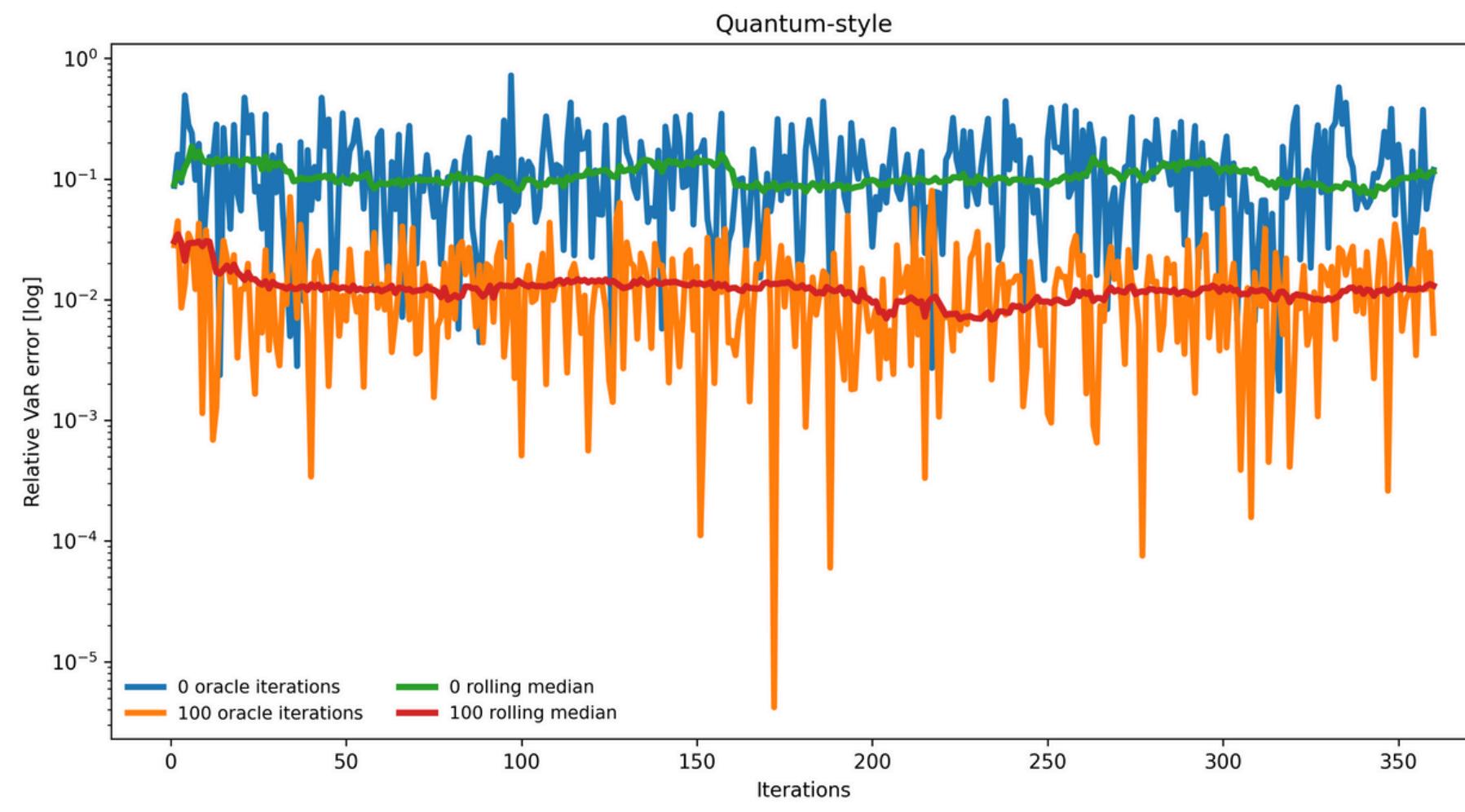
Quantum Parameters:

- Circuit width/depth
- Probability Tolerance
- Search Space

Minimize Weighted Error!



GPU-Accelerated Optimization: Hyperparameter Tuning



GPU-Accelerated Optimization: Improved Monte Carlo Baseline

- CDF sampling on GPU
 - Tail check is just a compare + reduction
 - No sorting
 - One-time precompute on GPU
 - Massive batching
 - Cache and reuse across thresholds
 - Budget safe refinement
 - Multi-GPU scaling
 - Importance sampling on GPU
 - Minimal PCIe transfers



GPU Monte Carlo + IQAE

GPU Monte Carlo (MC): cheap, massively parallel coarse CDF estimates → quickly bracket VaR

QAE: spend quantum queries only where it matters → high-precision tail probability near the final threshold

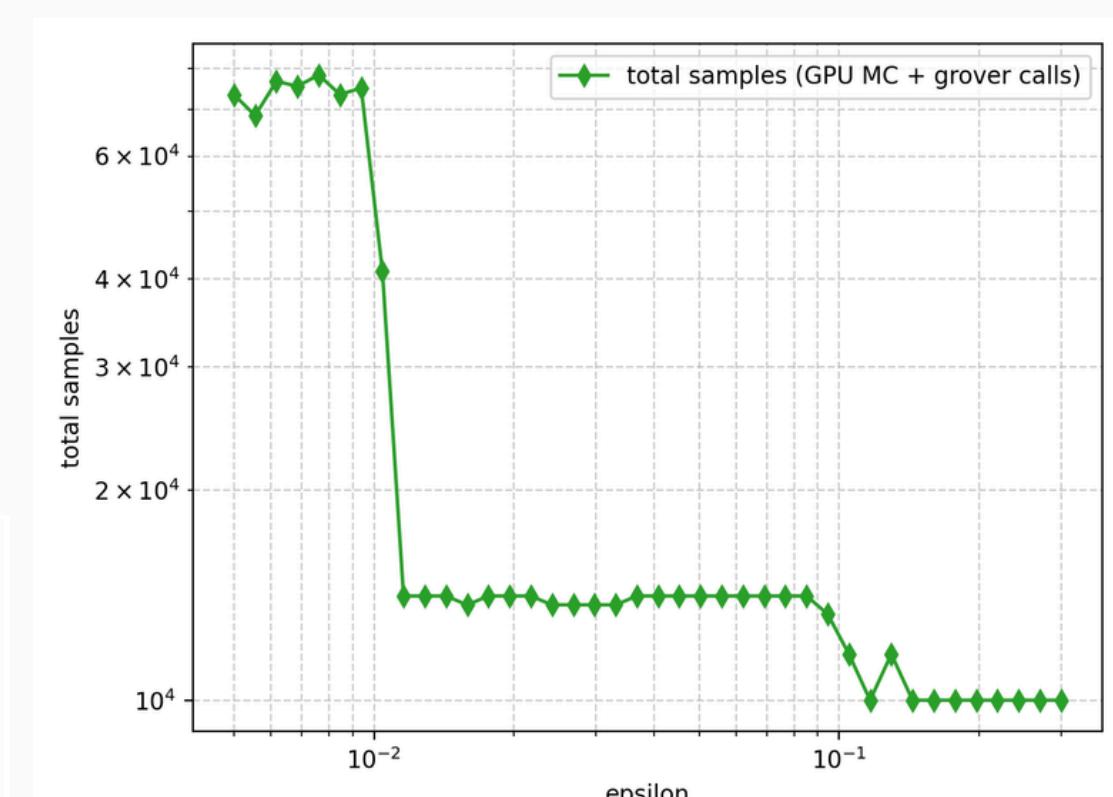
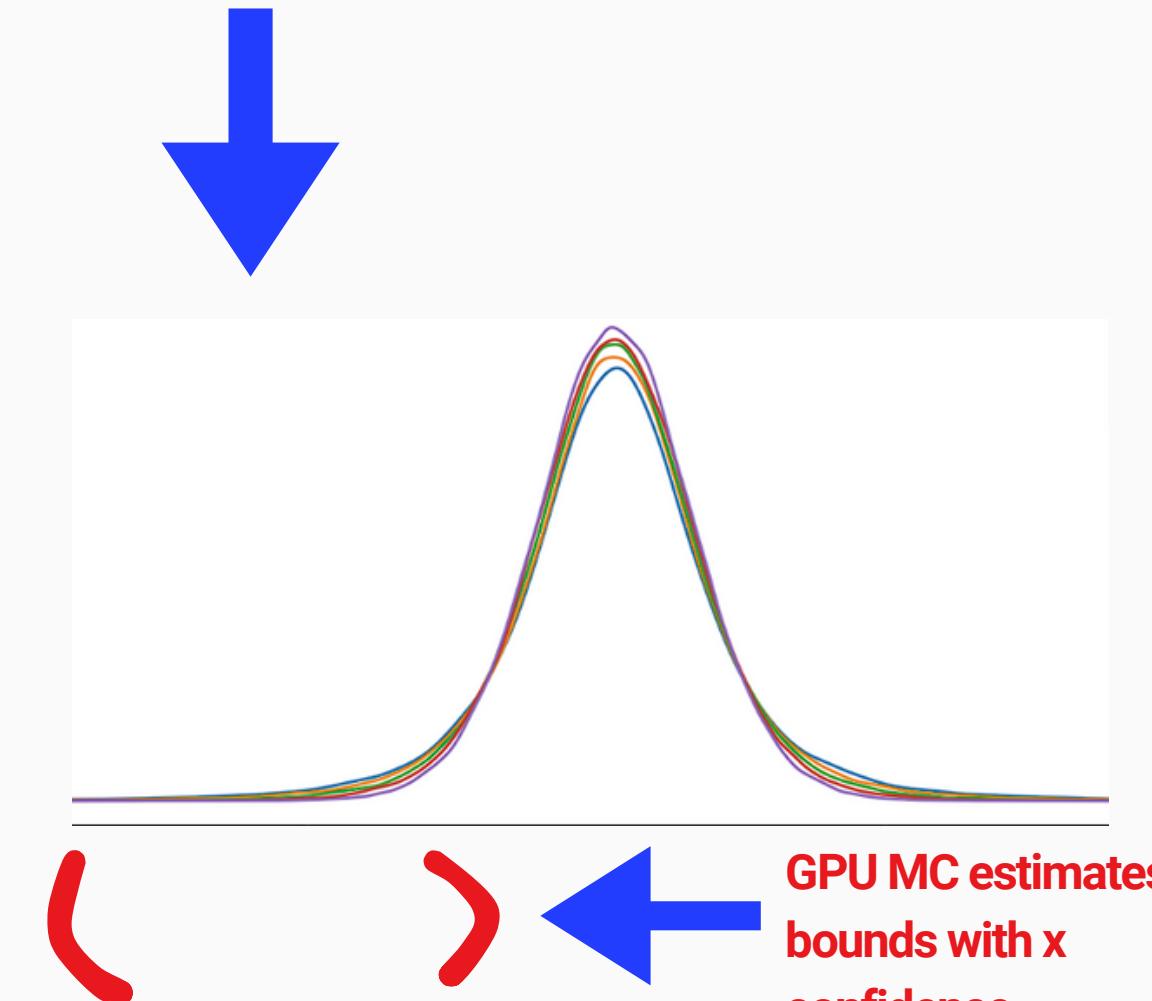
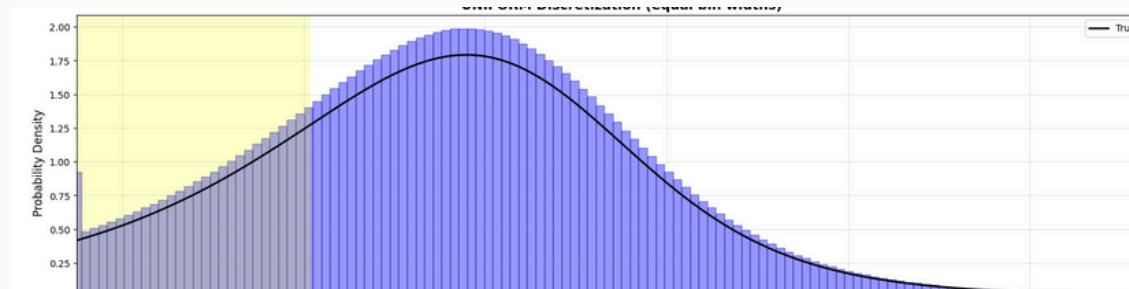
Outcome: Fewer IQAE calls + Higher precision

+ Efficient discretization

Tail prioritizing grid discretization



Uniform Discretization within the pipeline





The End

What The Duck!?

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MASSACHUSETTS

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