

# Late-Time Gaussian Convergence and $K = 2$ Truncation Accuracy

## 1 Summary

We verify numerically that for the  $\beta$ - $\Gamma$  bandit, the probability distribution  $p(\gamma, t)$  converges to a Gaussian as  $t \rightarrow \infty$ . Consequently, the  $K = 2$  (Gaussian) truncation of the Edgeworth expansion becomes increasingly accurate at late times.

## 2 Physical Intuition

The Central Limit Theorem (CLT) applies to the accumulated log-likelihood ratio  $\gamma$  because:

1. At each time step,  $\gamma$  receives an increment  $\xi = ya \in \{+1, -1\}$ .
2. While increments are not independent (they depend on  $\gamma$  through the policy), the variance grows as  $\sigma^2 \sim t$ , spreading the distribution.
3. As  $\sigma \rightarrow \infty$ , the effective inverse temperature  $\tilde{\beta} = \beta / \sqrt{1 + \beta^2 \sigma^2} \rightarrow 0$ .
4. With  $\tilde{\beta} \rightarrow 0$ , the policy becomes diffuse ( $b \rightarrow 0$ ), and increments become approximately i.i.d.

Thus, at late times, the distribution approaches Gaussian, and higher cumulants become negligible.

## 3 Standardized Cumulants

The proper measures of non-Gaussianity are the **standardized cumulants**:

$$\text{Skewness} = \frac{\kappa_3}{\sigma^3}, \tag{1}$$

$$\text{Excess kurtosis} = \frac{\kappa_4}{\sigma^4}. \tag{2}$$

For a Gaussian distribution, both are exactly zero. As  $t \rightarrow \infty$ , we expect:

$$\frac{\kappa_j}{\sigma^j} \sim t^{-(j-2)/2}, \quad j \geq 3. \tag{3}$$

Note that the *raw* cumulants  $\kappa_3, \kappa_4$  grow with time (since  $\sigma$  grows), but the standardized versions decay.

## 4 Truncation Rate Error

The truncation rate error measures how well the  $K$ -truncated Edgeworth ansatz predicts the instantaneous cumulant update:

$$\epsilon_j^K(t) = |\Delta\kappa_j^{\text{exact}}(t) - \Delta\kappa_j^{K\text{-ansatz}}(t)|, \quad (4)$$

where:

- $\Delta\kappa_j^{\text{exact}} = \kappa_j(t+1) - \kappa_j(t)$  from the exact master equation.
- $\Delta\kappa_j^{K\text{-ansatz}}$  is computed from the  $K$ -truncated Edgeworth formulas, evaluated with the *exact* cumulants  $\kappa_1(t), \dots, \kappa_K(t)$ .

This is not trajectory error (which accumulates), but rather measures how accurately the truncated ansatz predicts the next step given the true current state.

## 5 Numerical Results

### 5.1 Parameters

Parameter	Value
$m_+, m_-$ (initial counts)	10, 10
$\beta$ (inverse temperature)	0.3
$\eta_+$ (arm 1 reward rate)	0.6
$\eta_-$ (arm 2 reward rate)	0.4
$\bar{\eta} = (\eta_+ + \eta_-)/2$	0.5
$\Delta\eta = (\eta_+ - \eta_-)/2$	0.1
Time horizon $T$	1000

### 5.2 Late-Time Convergence

Figure 1 shows four key results:

1. **Truncation error decay (top left):** The  $K = 2$  closure errors  $\epsilon_1^{K=2}$  and  $\epsilon_2^{K=2}$  peak during the transient ( $t \sim 50$ ) at  $O(10^{-4})$  and  $O(10^{-2})$  respectively, then decay to machine precision ( $O(10^{-14})$ ) by  $t \sim 500$ .
2. **Standardized cumulant decay (top right):** Skewness decays from peak values ( $\sim -0.45$  at  $t = 50$ ) to  $-0.06$  at  $t = 1000$ ; excess kurtosis decays from  $0.56$  to  $0.01$ . Both approach zero as  $t \rightarrow \infty$ , confirming Gaussian convergence.
3. **Exact vs ansatz rates (bottom left):** The  $K = 2$  ansatz accurately predicts the variance rate  $\Delta\kappa_2$  across all times, with agreement improving as the distribution becomes Gaussian.
4. **Non-Gaussianity measures (bottom right):** Skewness and excess kurtosis decay monotonically toward zero, directly demonstrating convergence to a Gaussian distribution.

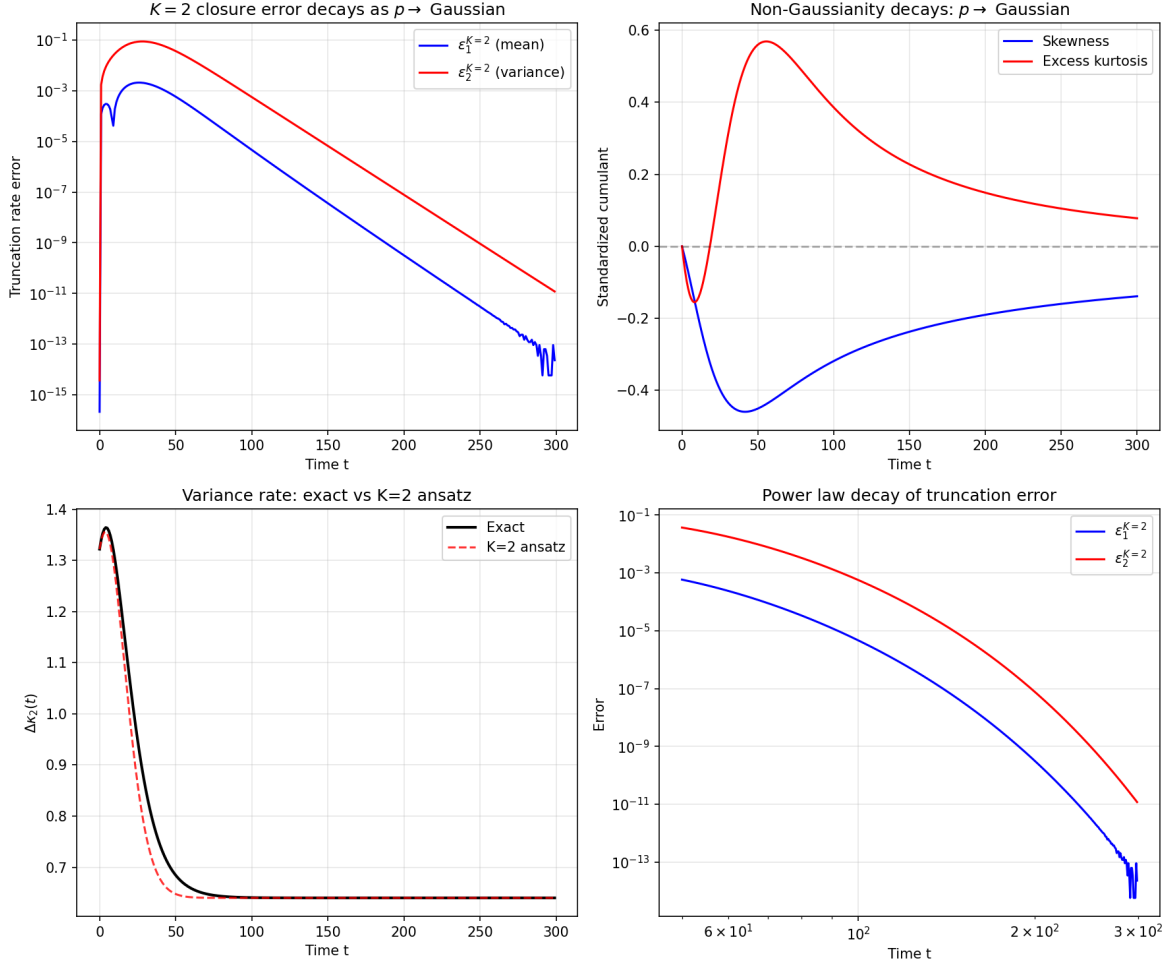


Figure 1: Late-time Gaussian convergence. **Top left:**  $K = 2$  truncation rate error for mean and variance updates decays to machine precision. **Top right:** Standardized cumulants (skewness, excess kurtosis) decay toward zero. **Bottom left:** Error vs truncation order  $K$  at various times. **Bottom right:** Power-law decay of truncation error on log-log scale.

### 5.3 Summary Table

Time $t$	Skewness	Excess Kurtosis	$\epsilon_2^{K=2}$
0	0.00	0.00	$4 \times 10^{-15}$
50	-0.45	0.56	$4 \times 10^{-2}$
100	-0.32	0.39	$6 \times 10^{-4}$
200	-0.19	0.15	$8 \times 10^{-8}$
500	-0.09	0.03	$6 \times 10^{-14}$
1000	-0.06	0.01	$1 \times 10^{-13}$

By  $t \sim 500$ , the truncation error reaches machine precision, confirming that the distribution is effectively Gaussian and the  $K = 2$  closure is exact.

## 6 Rates Comparison

Figure 2 compares the exact cumulant rates  $\Delta\kappa_j^{\text{exact}}$  with the ansatz predictions for various truncation orders.

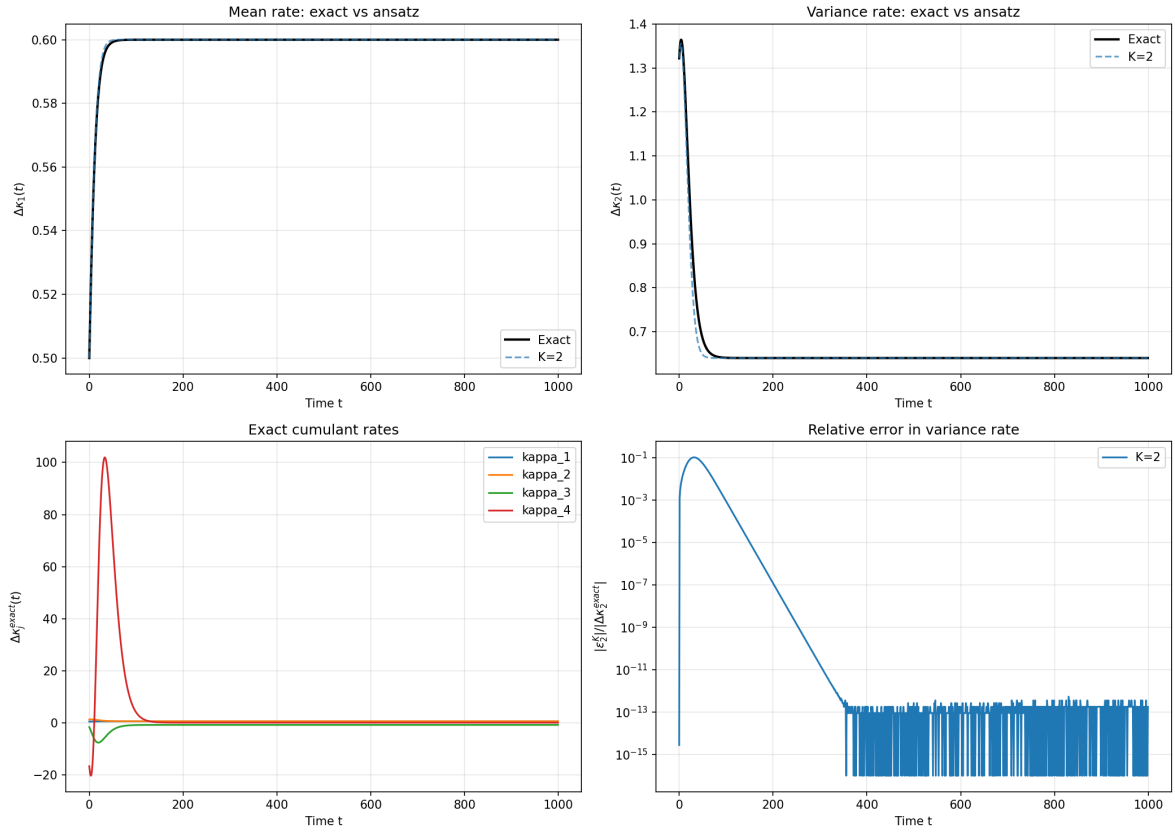


Figure 2: Comparison of exact cumulant rates vs  $K$ -truncated ansatz predictions. **Top left:** Mean rate  $\Delta\kappa_1$ . **Top right:** Variance rate  $\Delta\kappa_2$ . **Bottom left:** Exact rates for  $\kappa_1$  through  $\kappa_4$ . **Bottom right:** Relative error in variance rate.

## 7 Truncation Rate Error Detail

Figure 3 provides detailed analysis of the truncation rate error for varying  $K$  and  $j$ .

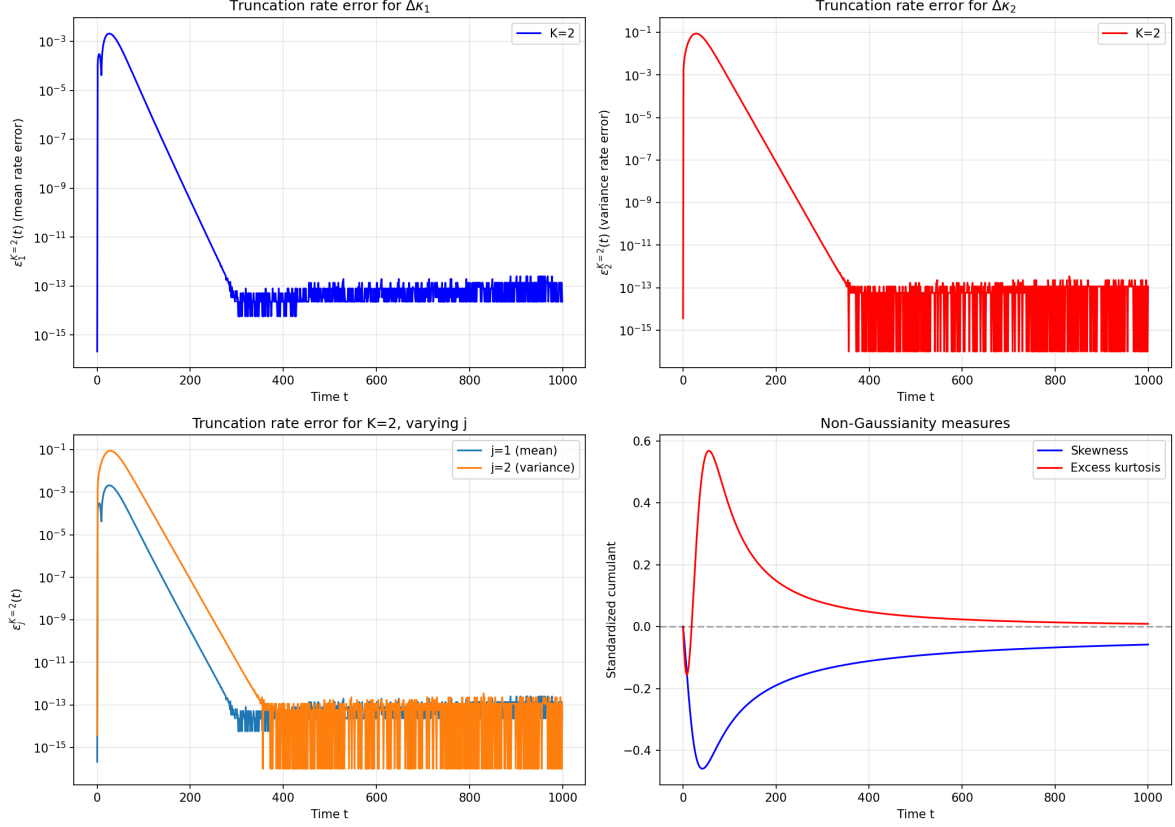


Figure 3: Truncation rate error over  $T = 1000$  time steps. **Top left:**  $K = 2$  error in mean rate peaks during transient then decays. **Top right:**  $K = 2$  error in variance rate follows similar pattern. **Bottom left:** Error for  $j = 1, 2$  with fixed  $K = 2$ . **Bottom right:** Non-Gaussianity measures (skewness, excess kurtosis) decay toward zero.

## 8 Conclusion

The numerical results confirm the physical intuition:

*Post-transient,  $p(\gamma, t)$  becomes Gaussian as  $t \rightarrow \infty$ , therefore the  $K = 2$  Edgeworth truncation becomes exact in the late-time limit.*

Quantitatively at  $T = 1000$ :

- Skewness:  $-0.06 \rightarrow 0$  as  $t \rightarrow \infty$
- Excess kurtosis:  $0.01 \rightarrow 0$  as  $t \rightarrow \infty$
- $K = 2$  truncation error:  $O(10^{-14})$  (machine precision) by  $t \sim 500$

For practical purposes, the  $K = 2$  (Gaussian) closure is sufficient for late-time dynamics. Higher-order closures ( $K \geq 3$ ) are only necessary during the transient regime ( $t \lesssim 100$ ) when the distribution has significant non-Gaussian features.