Association between Patient Behaviors and Clinical Significance in the ED

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1 Introduction

1.1 Background

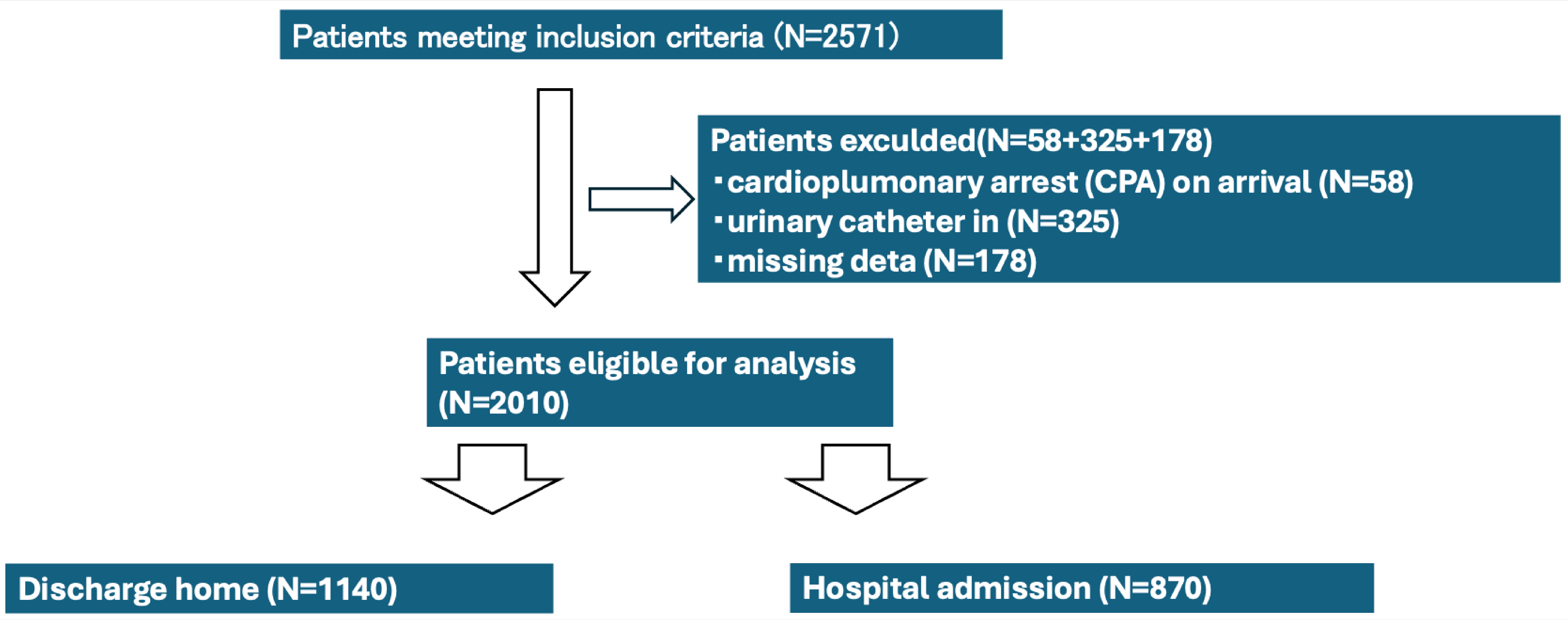
- Emergency departments (ED) face increasing patient numbers and overcrowding.
- Traditional triage systems are based on chief complaints, medical history, and vital signs, but they cannot fully capture subtle patient behaviors.
- Few studies have examined prognosis prediction based on patient's spontaneous behaviors in the ED, and one overlooked example is the '**request to urinate**.'
- We investigated how the probability of **hospital admission** changes according to the time from arrival at the ED to the patient's **request to urinate**.

1.2 Methods

- From January 29 to July 31, we collected data on ambulance-transported patients to the ED, including sex, age, ED arrival time, time of **request to urinate**, presence of a urinary catheter, and outcomes (discharge, outpatient, **admission** to general ward/CCU/SCU/ICU[1], transfer, or death).
- Patients with missing data, those who had a urinary catheter in place, and patients with caudiopulmonary arrest on arrival were excluded from the analysis.
- **Hierarchical Bayesian modeling** was performed with PyMC 5.25.1.

1. CCU:Cardiac Care Unit, SCU:Stroke Care Unit, ICU:Intensive Care Unit

1.3 Patient Flow



1.4 Table 1

	Discharged Home ($n = 1140$)	**Hospital Admission** ($n = 870$)
Age	62 (35.8-80.0)	77 (62.0-84.0)
Female	525 (46.1%)	389 (44.7%)
Time	49 (23-88)	89.5 (45-141)

1.5 Table 2: Comorbidity（併発症）

	Discharged Home ($n = 1140$)	**Hospital Admission** ($n = 870$)
None	102 (40.8%)	49 (26.3%)
Hypertention	56 (22.4%)	64 (34.4%)
Diabetes	30 (12.0%)	31 (16.7%)
Malignancy	22 (8.8%)	26 (14.0%)
Neuroligic Dis.	22 (8.8%)	22 (11.8%)
Cerebrovascular Dis.	19 (7.6%)	25 (13.4%)
Arriythmia	25 (10.0%)	19 (10.2%)
Dyslipidemia	16 (6.4%)	22 (11.8%)
Heart Failure	14 (5.6%)	17 (9.1%)
Chronic Lung Dis.	11 (4.4%)	13 (5.7%)
Renal Failure	9 (3.6%)	15 (8.1%)

1.6 Table 3: Diagnosis（診断）

	Discharged Home ($n = 1140$)	Hospital Admission ($n = 870$)
Orthopedics	81 (32.4%)	36 (19.3%)
Gastroenterology	40 (16.0%)	43 (23.1%)
Neurology	44 (17.6%)	16 (8.6%)
Infection	13 (5.2%)	34 (18.3%)
Cardiology	21 (8.4%)	20 (10.8%)
Urology	21 (8.4%)	7 (3.8%)
Cerebrovascular	1 (9.6%)	26 (14.0%)
Respiratory	10 (13.2%)	11 (5.9%)
Nephrology	5 (9.6%)	13 (7.0%)
Dermatology	9 (9.6%)	7 (3.8%)
Other	5 (2.0%)	11 (5.9%)

2 Analysis

2.1 Variables

- Observations: $i = 1, \cdots, n$.
- Binary outcome

$$y_i = 0\text{: Discharge Home / Outpatient}, \;\; y_i = 1\text{: } \textbf{Admission} \text{ / Death.}$$

- Elapsed Time from ED Arrival to **Request to Void**

$$t_i^{\mathrm{raw}} \geq 0 \qquad \text{(minutes).}$$

- Indicator $m_i \in \{0, 1\}$

$$m_i = 0\text{: No Request}, \quad m_i = 1\text{: Request Present.}$$

- Right-censoring was applied at 300

$$t_i := \min(t_i^{\mathrm{raw}}, 300).$$

2.2 Bayesian Hierarchical Logistic Regression

$$y_i \sim \mathrm{Bernoulli}(p_i), \qquad i = 1, \cdots, n,$$

$$\mathrm{logit}(p_i) = (1 - m_i)\left(\mathrm{logit}(\rho_0) + x_i^\top \beta\right) + m_i \left(\mathrm{logit}(\rho_1) + \Delta_i + x_i^\top \beta\right).$$

with Δ_i (next slide) and the linear part given by:

$$x_i^\top \beta = \beta_{\text{age}} a_i + \beta_{\text{age-mis}} a_i^{\text{mis}} + \beta_{\text{sex}} s_i + \beta_{\text{sex-mis}} s_i^{\text{mis}}.$$

- a_i: standardized age, a_i^{mis}: missing indicator for age
- s_i: sex (0: male, 1: female), s_i^{mis}: missing indicator for sex

2.3 Effective Log-likelihood Δ_i

$$\Delta_i := (1 - c_i) \log \frac{f_1(t_i)}{f_0(t_i)} + c_i \log \left(\overline{\Phi} \left(\frac{C - \mu_1}{\sigma_1} \right) / \overline{\Phi} \left(\frac{C - \mu_0}{\sigma_0} \right) \right),$$

where $\overline{\Phi} = 1 - \Phi$ is the Gaussian survival function, and Gaussian densities

$$f_0(t) = \phi(t|\mu_0, \sigma_0^2), \quad f_1(t) = \phi(t|\mu_1, \sigma_1^2),$$

with

$$\mu_1 \geq \mu_0.$$

2.4 Prior Specification

$$\operatorname{logit}(\rho_0), \operatorname{logit}(\rho_1) \sim \mathrm{N}(0,1)$$

$$\log \sigma_k \sim \mathrm{N}(\log \mathrm{scale}, 1) \quad (k = 0, 1)$$

$$\mu_0 \sim \mathrm{TruncatedNormal}(t_{\mathrm{mean}}, 2 \cdot \mathrm{scale}, 0, 300)$$

$$\mu_1 = \min(\mu_0 + \delta_\mu, 300), \qquad \delta_\mu \sim \mathrm{HalfNormal}(\mathrm{scale})$$

$$\beta \overset{\text{i.i.d.}}{\sim} \mathrm{N}(0,1)$$

2.5 Inference and Diagnosis

No-U-Turn Sampler(NUTS) with 4chains:

- Baseline: 3,000 warm-up + 3,000 posterior draws
- Covariate: 1,500 warm-up + 1,500 posterior draws
- Settings: target_accept = 0.90, max_treedepth = 12
- JAX-Numpyro acceleration when available; otherwise PyMC, Convergence assessed via hat R, ESS, MCSE, and visual diagnosis (trace, rank, energy).

3 Evaluation

3.1 Evaluation Metrics

3.1.1 Population-level fit

For cumulative admissions,

- Observed $C_{\mathrm{obs}}(t)/N$ vs posterior mean $\mathrm{E}[\widehat{C}(t)]/N$ and 95% credible bands.
- Time-integrated scalars: ABC, IAE, ISE, RMSE, KS, CvM, empirical coverage_95, avg_band_width

3.1.2 Individual-level metrics

At landmark times, $T = 60, 120, 180, 240, 300$, we check

- AUC(t)
- Brier(t)

3.2 Study Population

- Ambulance-transported patients (Feb-Aug2025)
- Exclusions: CPA at arrival, existing urinary catheter, missing time infomation.
- Final sample size: $n = 2571$

3.3 MCMC Convergence

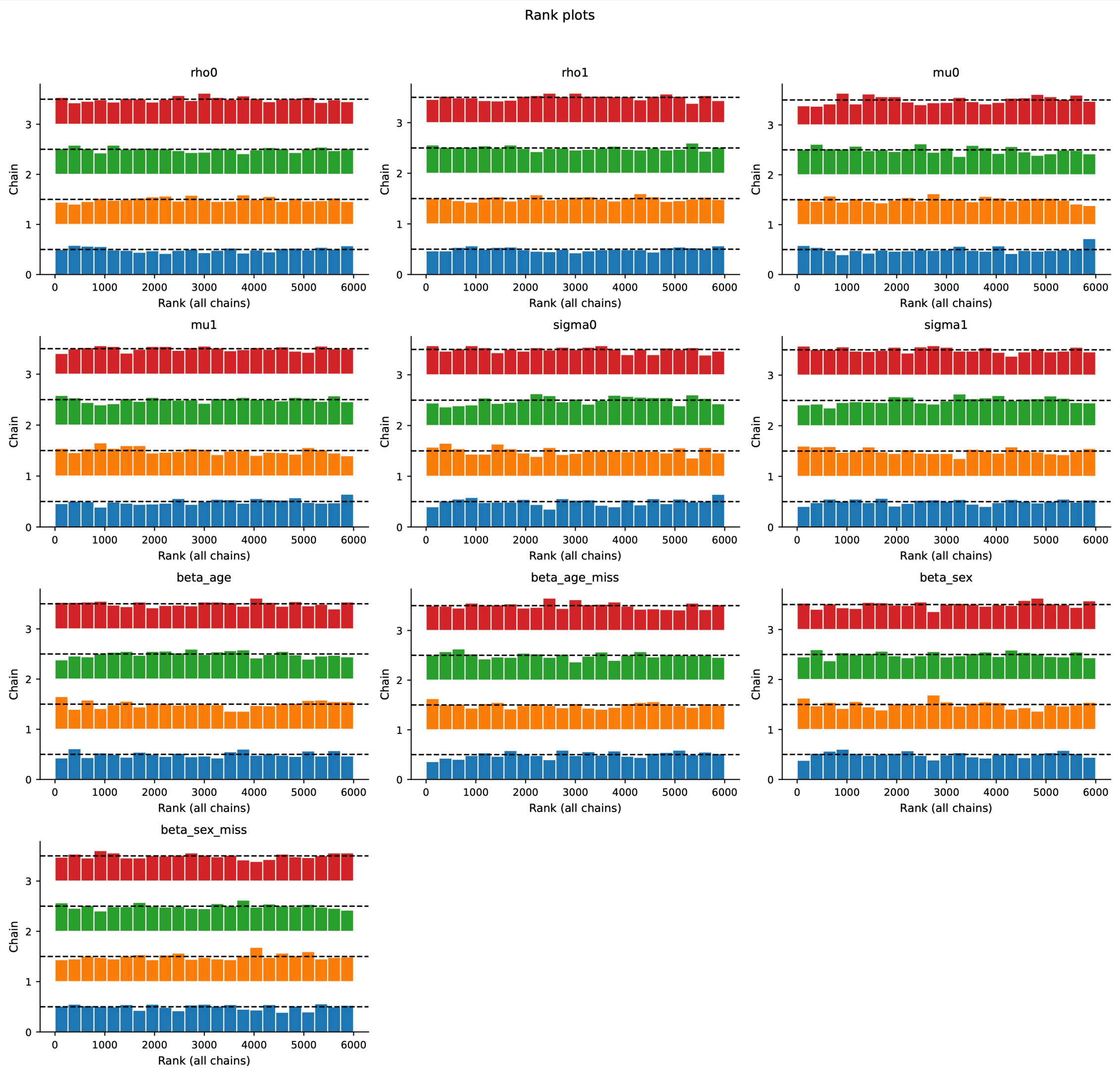
Sampling diagnostics showed stable mixing without pathological divergences on representative patameters:

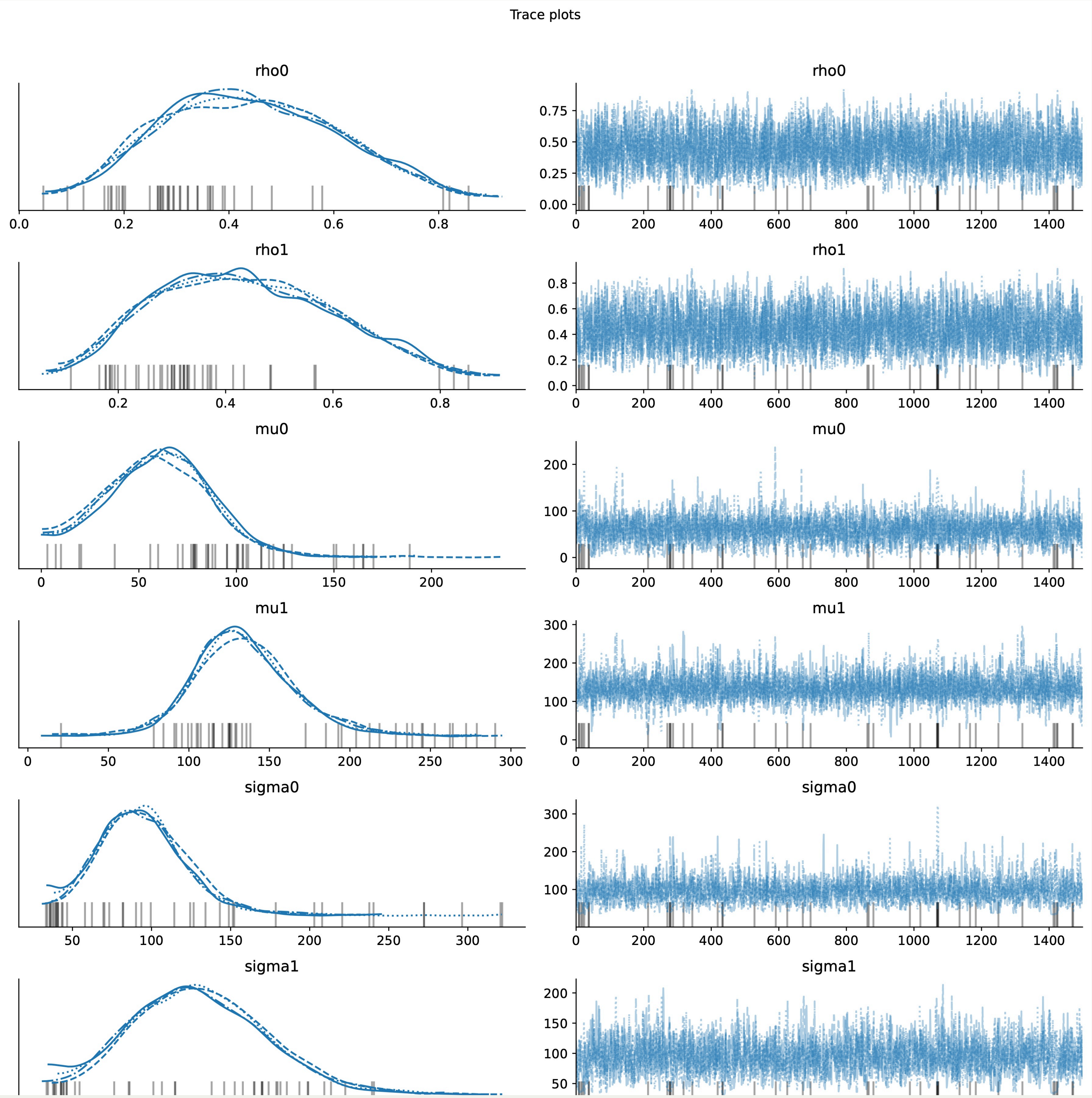
$$\rho_0,\ \rho_1,\ \mu_0,\ \mu_1,\ \sigma_0,\ \sigma_1,\ \beta.$$

Trace, rank, and energy plots were visually acceptable in the combined diagnostic bundle.

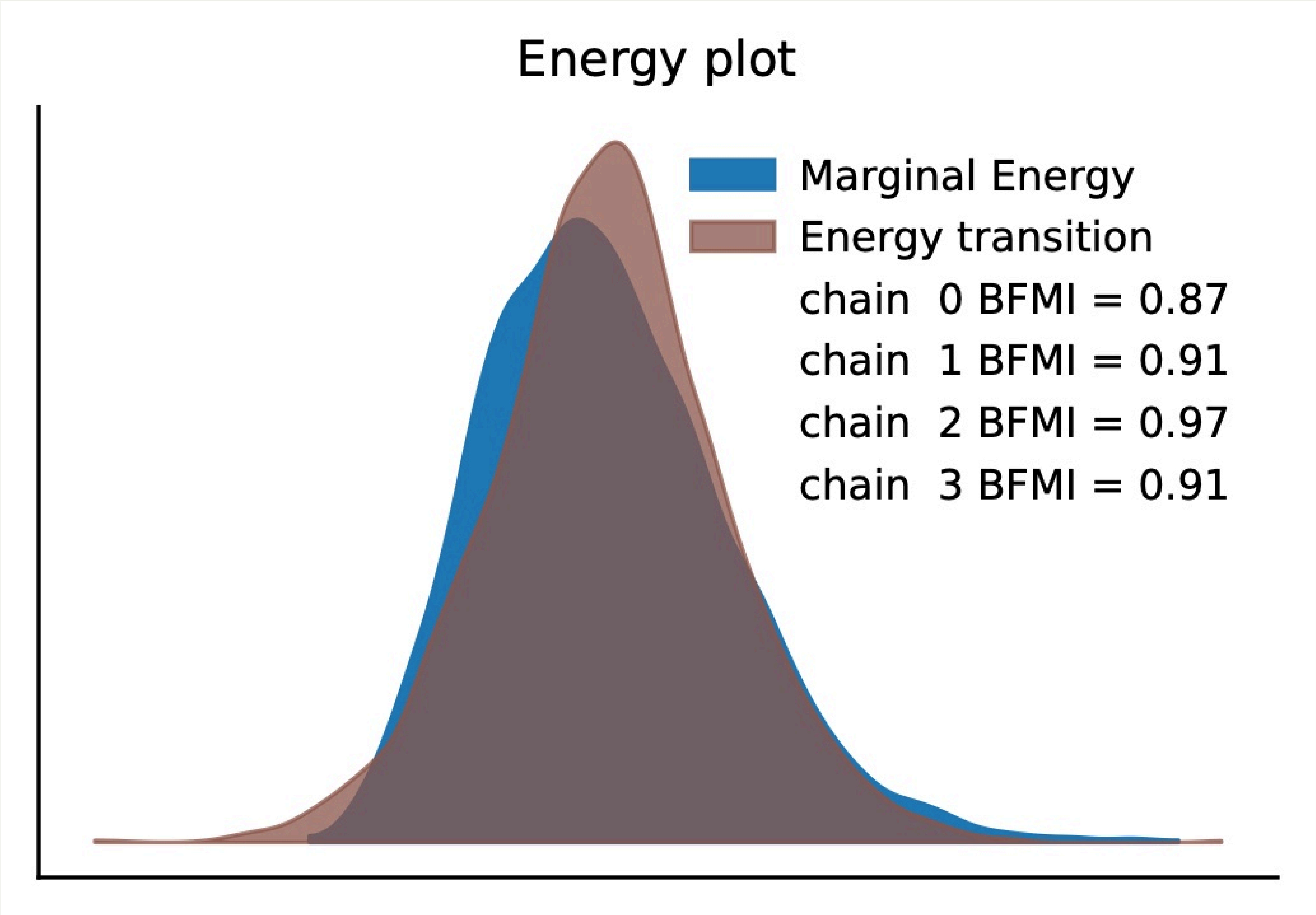
$\widehat{R}^2$ was almost 1.0 for all parameters.

3.4 Rank Plot and Trace Plot





3.5 Energy Diagnosis



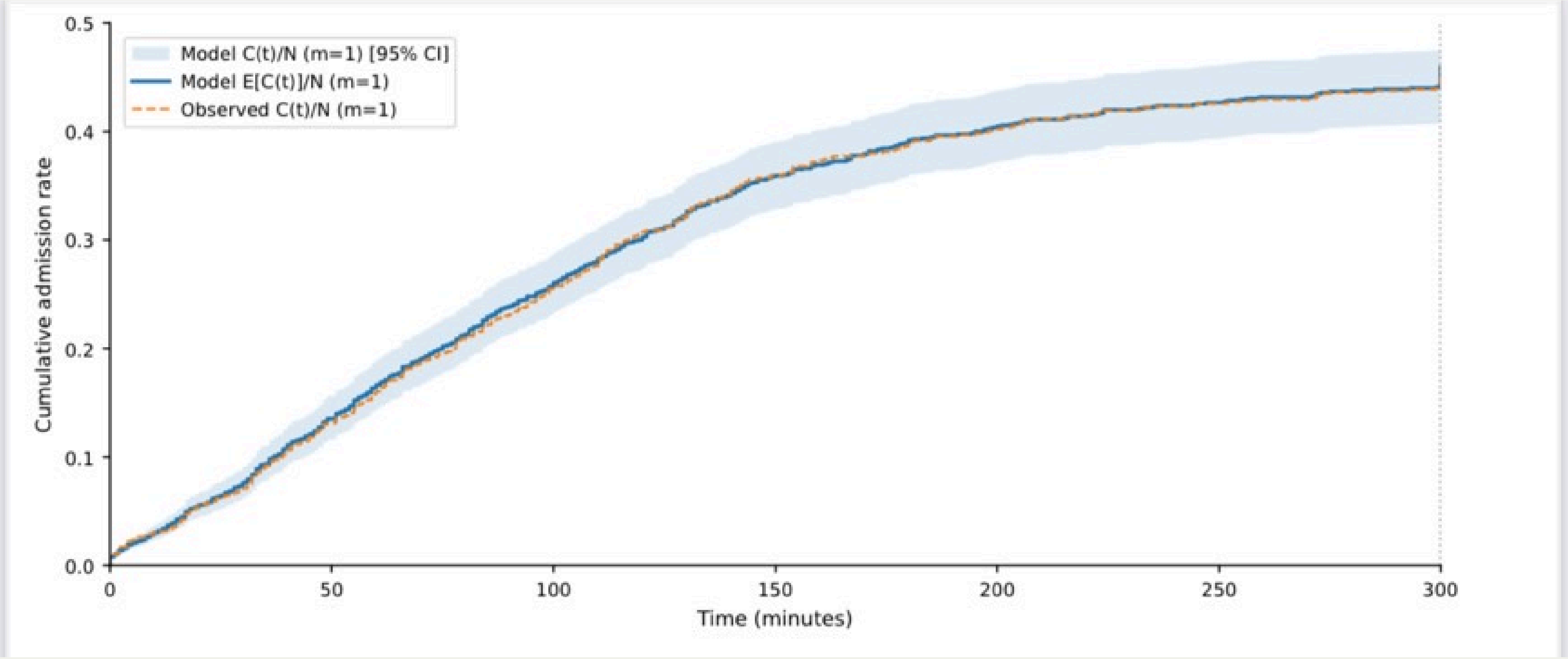
Energy Plots

3.6 Population-level Fit (1/2)

- Observed cumulative admission curve (0-300 min) well reproduced

Baseline (time-only)

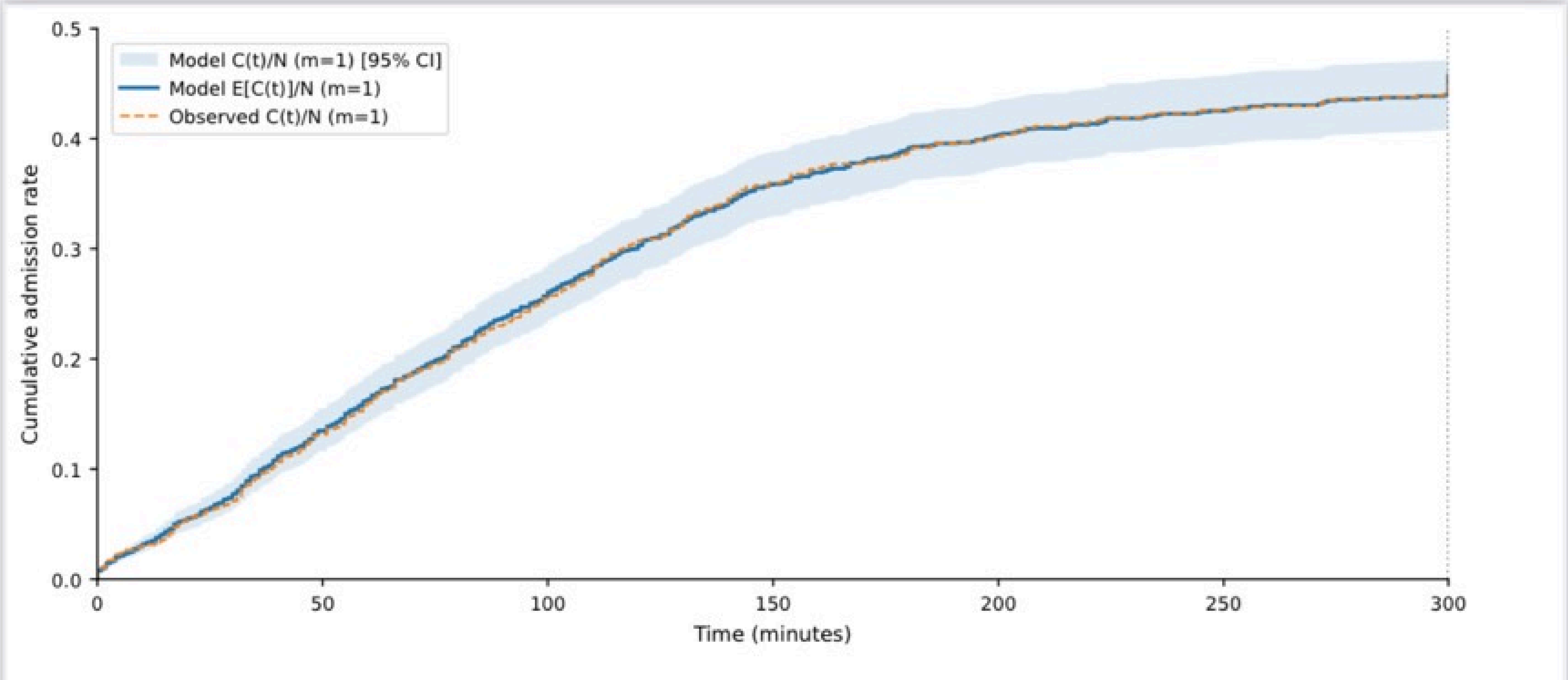
- Posterior mean closely followed empirical trajectory
- Narrow 95% credible band encompassed observed curve



3.7 Population-level Fit (2/2)

Covariate (time + age + sex)

- Covariate model maintained fit while improving individual-level accuracy.

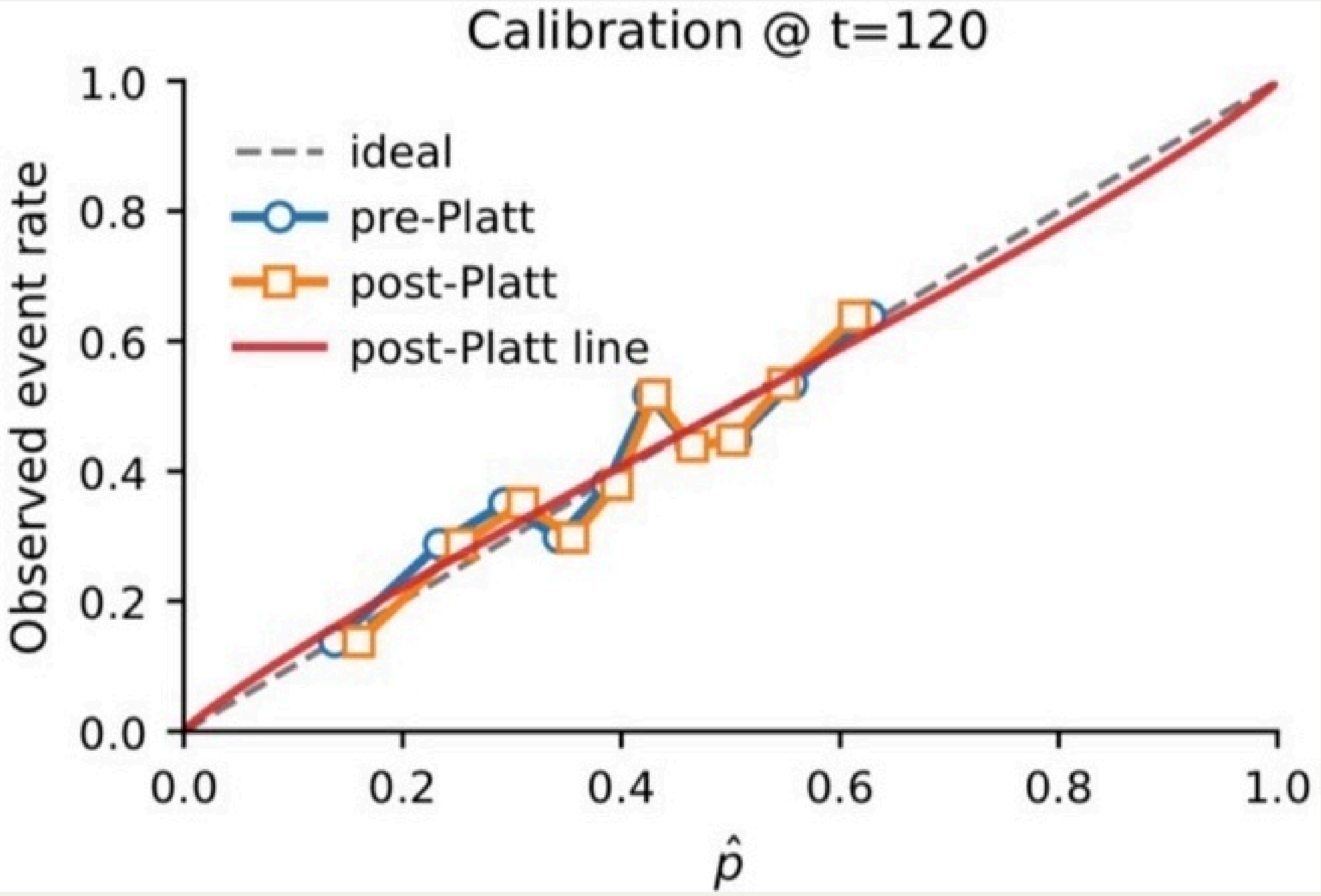


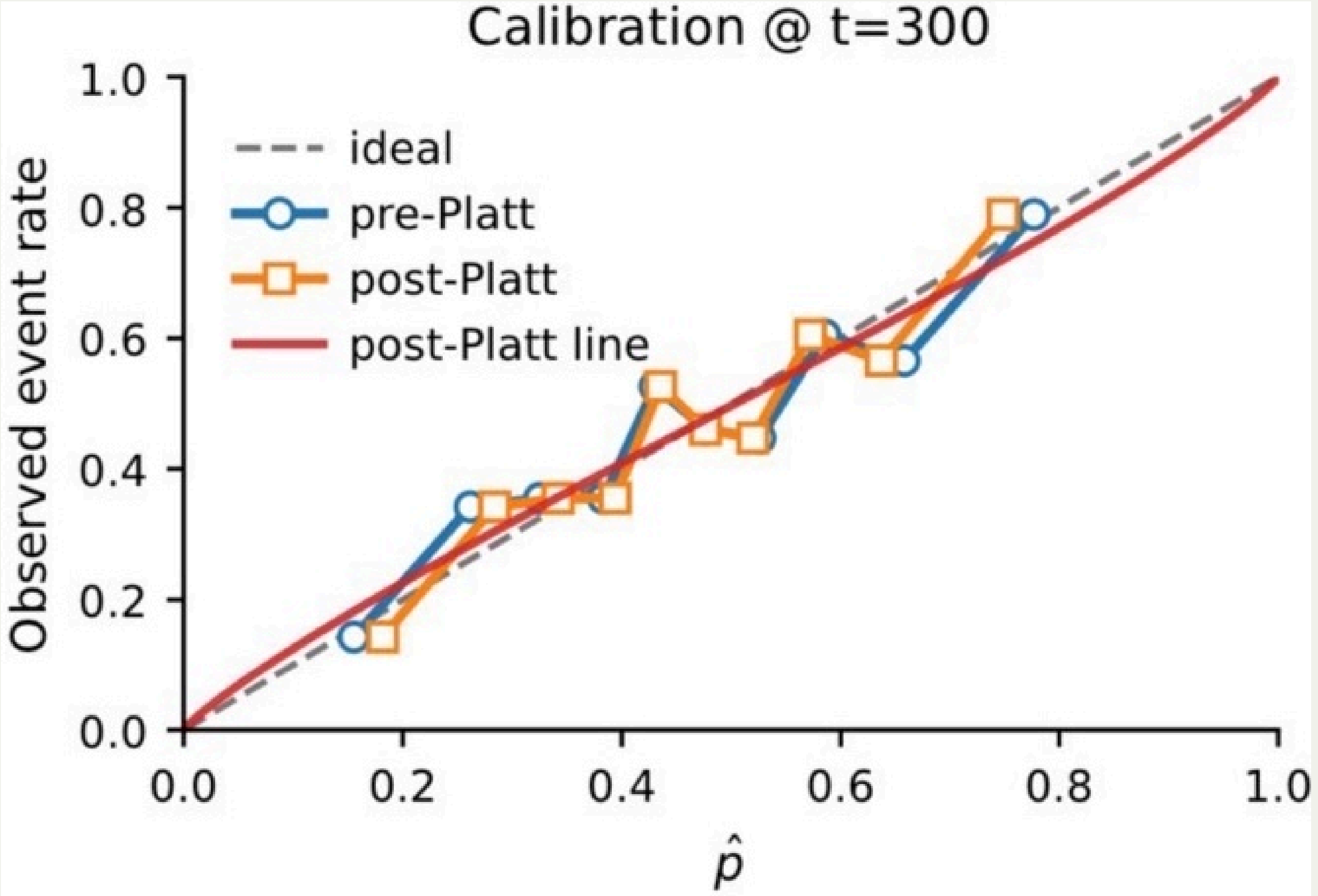
3.8 Calibration

- Recalibration improved alignment with 45° line at $t = 120$:

$$\operatorname{logit}(\mathrm{P}[Y = 1|\hat{p}]) = \gamma_1 + \gamma_2 \operatorname{logit}\hat{p}.$$

- $\mathrm{AUC}(t)$ remained stable; only 2~3% patients crossed threshold.



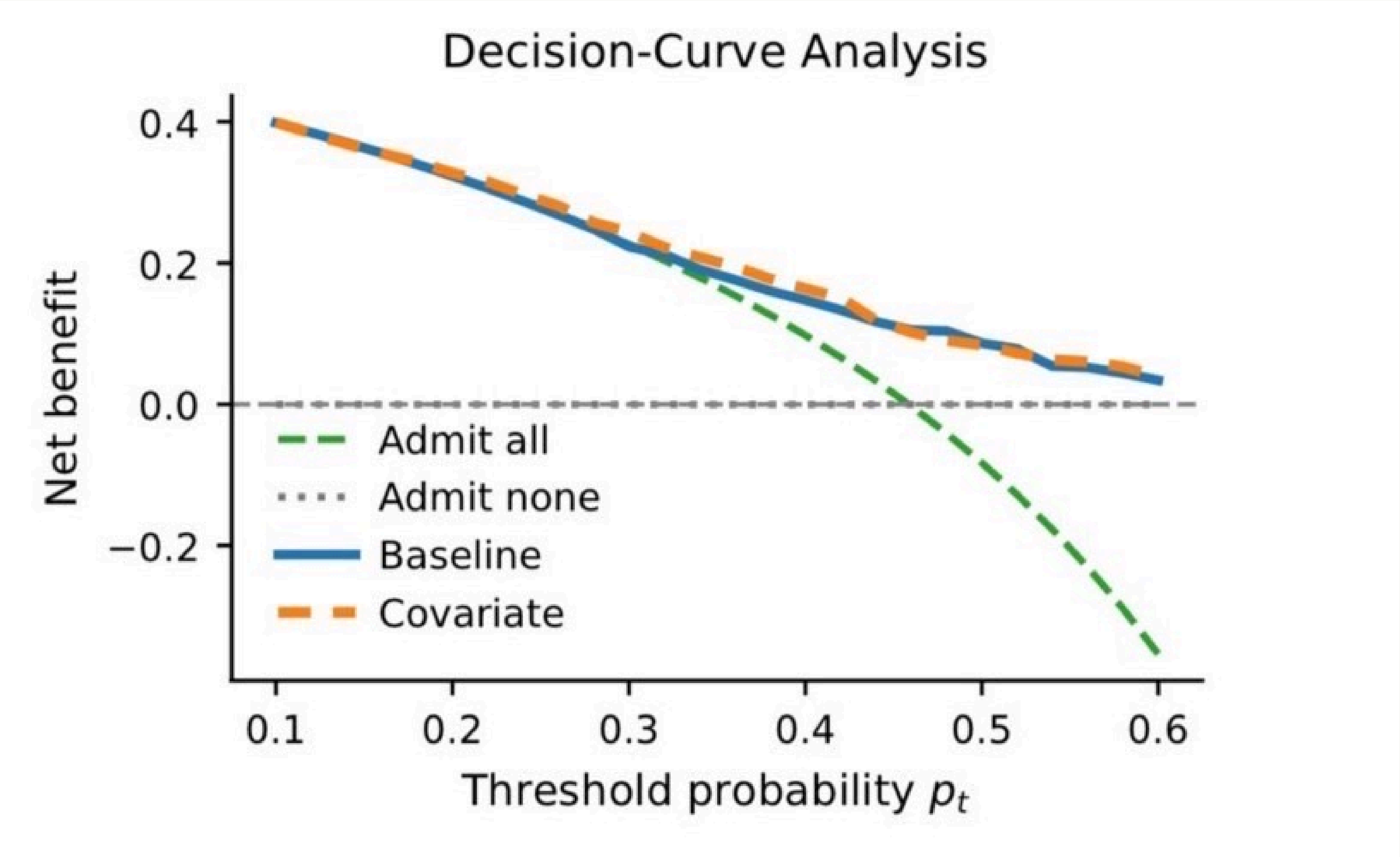


3.9 Decision Curve Analysis

- Covariate > Baseline for

$$p_t \in [0.1, 0, 6]$$

- Covariate shows small, directionally favorite net benefit vs Baseline at $p_t \in [0.2, 0.4]$, but CIs include zero. Evidence of advantage is modest.



$$\text{NB}(p_t) = \frac{\text{TP}}{N} - \frac{\text{FP}}{N}\frac{p_t}{1-p_t}$$

- TP: True Positive, FP: False Positive
- NB: Net Benefit

3.10 Robustness to TTU Measurement Error

- Add jitter to t_i^{raw}:

$$\tilde{t}_i = t_i^{\mathrm{raw}} + \epsilon_i, \qquad \epsilon \overset{\text{i.i.d.}}{\sim} \mathrm{Unif}(-\delta, \delta).$$

- Changes in AUC and Brier score were negligible.

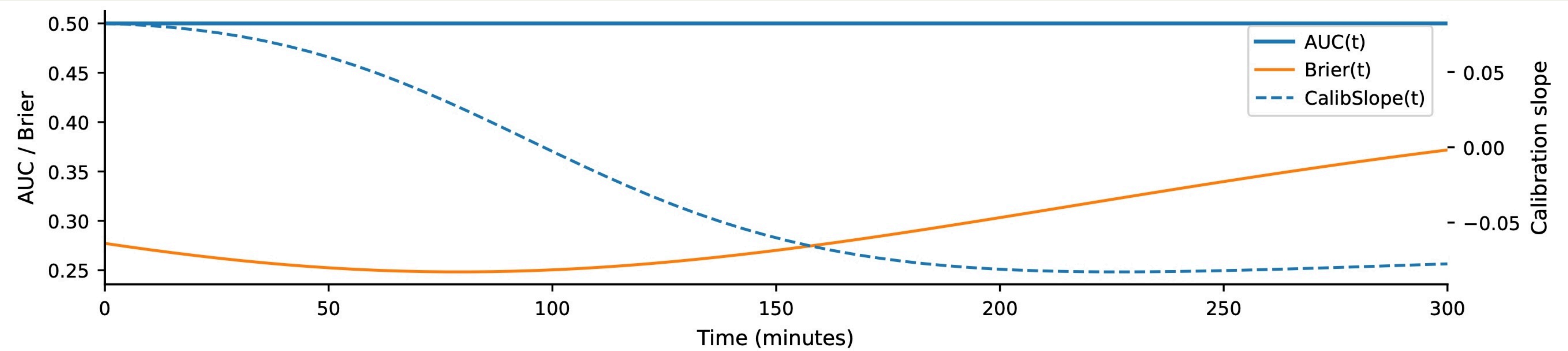
Jitter (±min)	AUC					Brier					Cal. Intercept		Cal. Slope	
	60	120	180	240	300	60	120	180	240	300	120	300	120	300
0.0	0.642	0.655	0.651	0.662	0.681	0.211	0.223	0.228	0.228	0.223	-0.010	-0.010	0.899	0.884
5.0	0.642	0.650	0.648	0.660	0.680	0.212	0.224	0.229	0.228	0.223	-0.036	-0.011	0.861	0.876
10.0	0.642	0.650	0.651	0.662	0.682	0.210	0.224	0.228	0.227	0.222	-0.045	-0.009	0.870	0.891

3.11 Individual-level Performance (1/2)

Baseline model (time-only)

- Discrimination: $\mathrm{AUC}(t) \approx 0.50 \rightarrow$ close to random prediction
- Overall accuracy: $\mathrm{Brier}(t) \approx 0.40$ increased with time $\rightarrow$ worsening accuracy

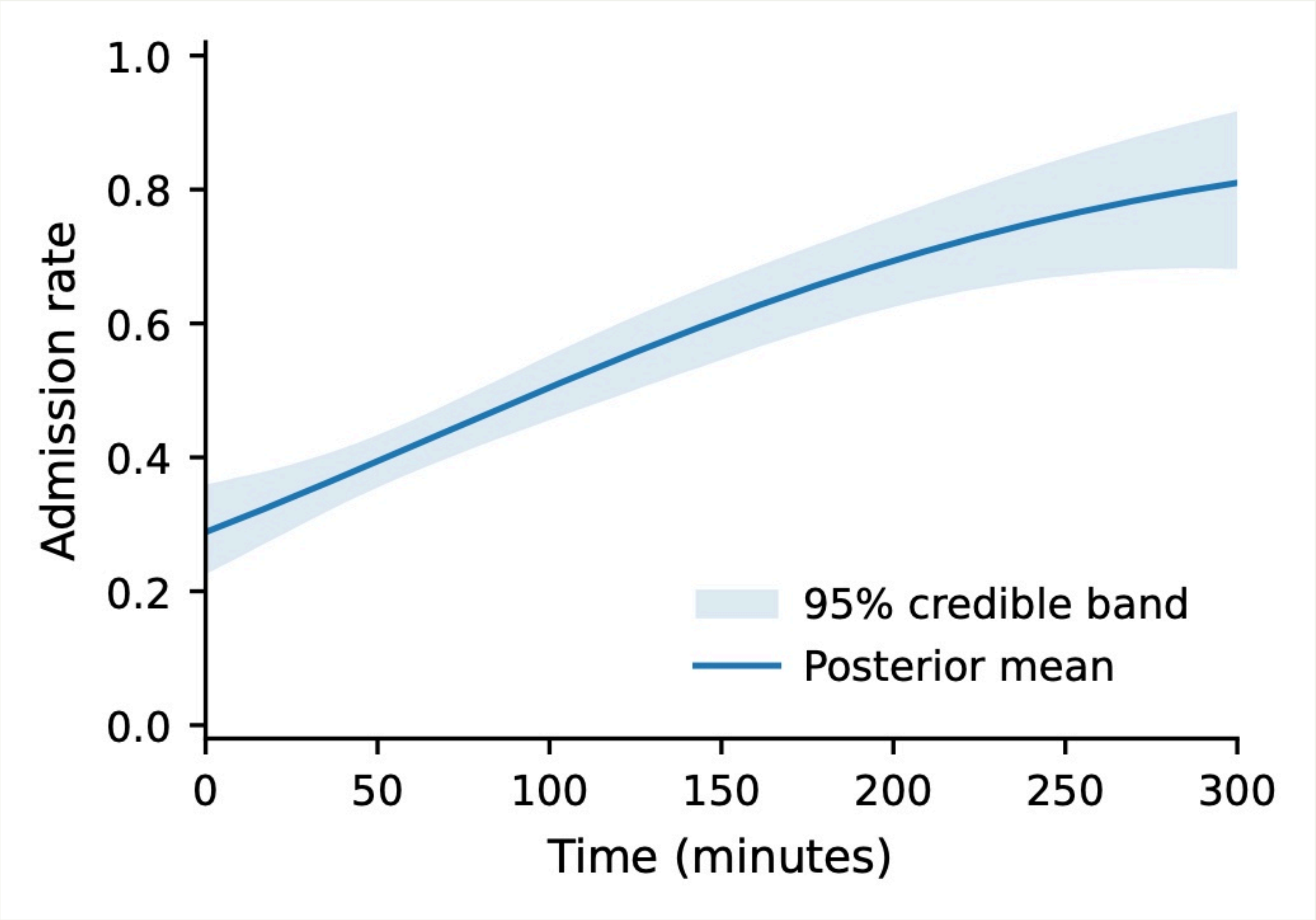
$$\mathrm{Brier}(t) = \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - y_i)^2.$$



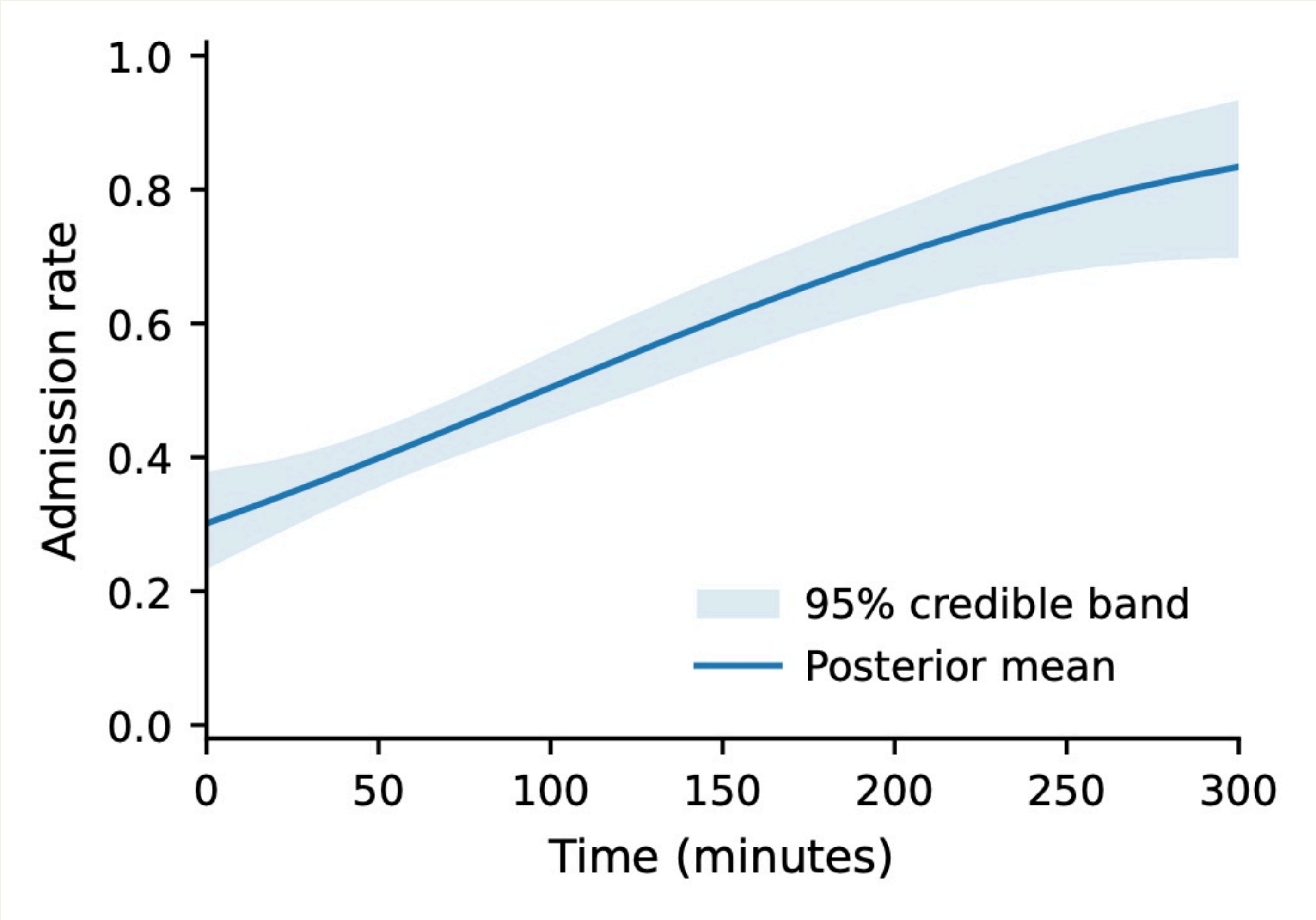
3.12 Individual-level Performance (2/2)

- Covariate Model (time + age + sex)
- Discrimination: $\mathrm{AUC}(t) \approx 0.70$ improve
- Overall accuracy: $\mathrm{Brier}(t) \approx 0.35$ consistently lower than baseline model.

3.13 Posterior Predictive Checks

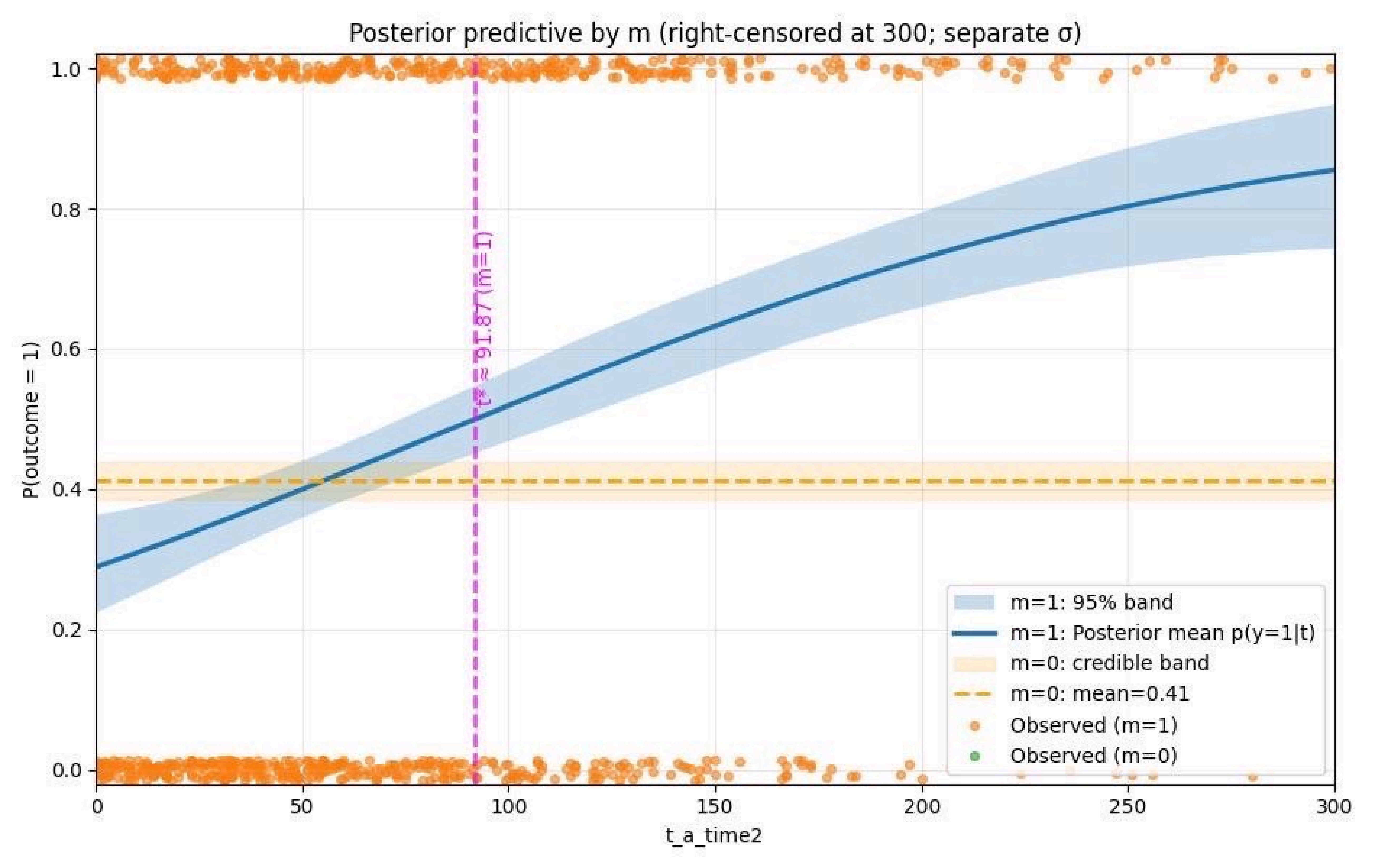


Baseline Model



Covariate Model

3.14 Posterior



Posterior Distribution of the Baseline Model

4 Summary

- Model predictions fit the observed data well.
- The hospitalization rate was below 50% among patients who requested urination within approximately 92 minutes after arrival at the ED.
- Hospitalizasion rate increased over time.
- Adding age and sex increased AUC to ≈ 0.68, lowered Brier score, and improved calibration.

Discussion and Feedback

- We developed an app. URL: accm.jp/urination
- Integrate patient behaviors and clinical data into the model to enable earlier prediction of hospitalization probability.
- We applied Bayesian regression in this study. What other approaches might be suitable for this problem?
- We did not record whether urinary catheter were inserted before RD arrival or the exact time of insertion in the ED. Catheter uses likely affecs the expression of voiding desire and should be considered in future research.