The Role of the Hospital Characteristics in Setting Appropriate Yardsticks for Hospital Profiling

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Overview

- **Recap: statistical model**
- **Illustration: Pneumonia mortality rate**
  Inpatient Quality Indicator #20
- **Look ahead: the role of hospital characteristics**
  - **Risk adjustment**
  - **Stabilization**

Risk Adjustment

Patient-level model

Patient i, event Y_i, attributes X_i

$$Y_i | p_i \sim \text{Bernoulli}(p_i), \ \text{logit}(p_i) = X_i' \beta$$

Hospital-level rates

Hospital h, patients A_h, volume n_h

Observed rate, $O_h = \frac{1}{n_h} \sum_{i \in A_h} Y_i$

Expected rate, $E_h = \frac{1}{n_h} \sum_{i \in A_h} \hat{Y}_i$

Risk-adjusted rate

$$RAR_h = \frac{O_h}{E_h} \cdot \overline{Y}, \text{ where } \overline{Y} = \frac{\sum_i Y_i}{N}$$

Smoothing

Signal extraction framework

$$\begin{aligned} RAR_h &= \theta_h + \epsilon_h \\ &= \text{signal} + \text{noise} \end{aligned}$$

$$\text{where} \quad \begin{aligned} &E(\theta_h) = \mu,\ \ Var(\theta_h) = \tau^2 \\ &E(\epsilon_h) = 0,\ \ Var(\epsilon_h) = \sigma_h^2 \end{aligned}$$

Smoothing

Reliability weighting

$$\theta_h = \underbrace{\mu + \lambda_h \cdot (RAR_h - \mu)}_{\text{Smoothed rate}} + \omega_h$$

$$\text{where} \quad E(\omega_h) = 0, Var(\omega_h) < \infty$$

OLS

$$\lambda_h = \frac{Cov(\theta_h, RAR_h)}{Var(RAR_h)} = \frac{Var(\theta_h)}{Var(\theta_h) + Var(\epsilon_h)} = \frac{\tau^2}{\tau^2 + \sigma_h^2}$$

Smoothing

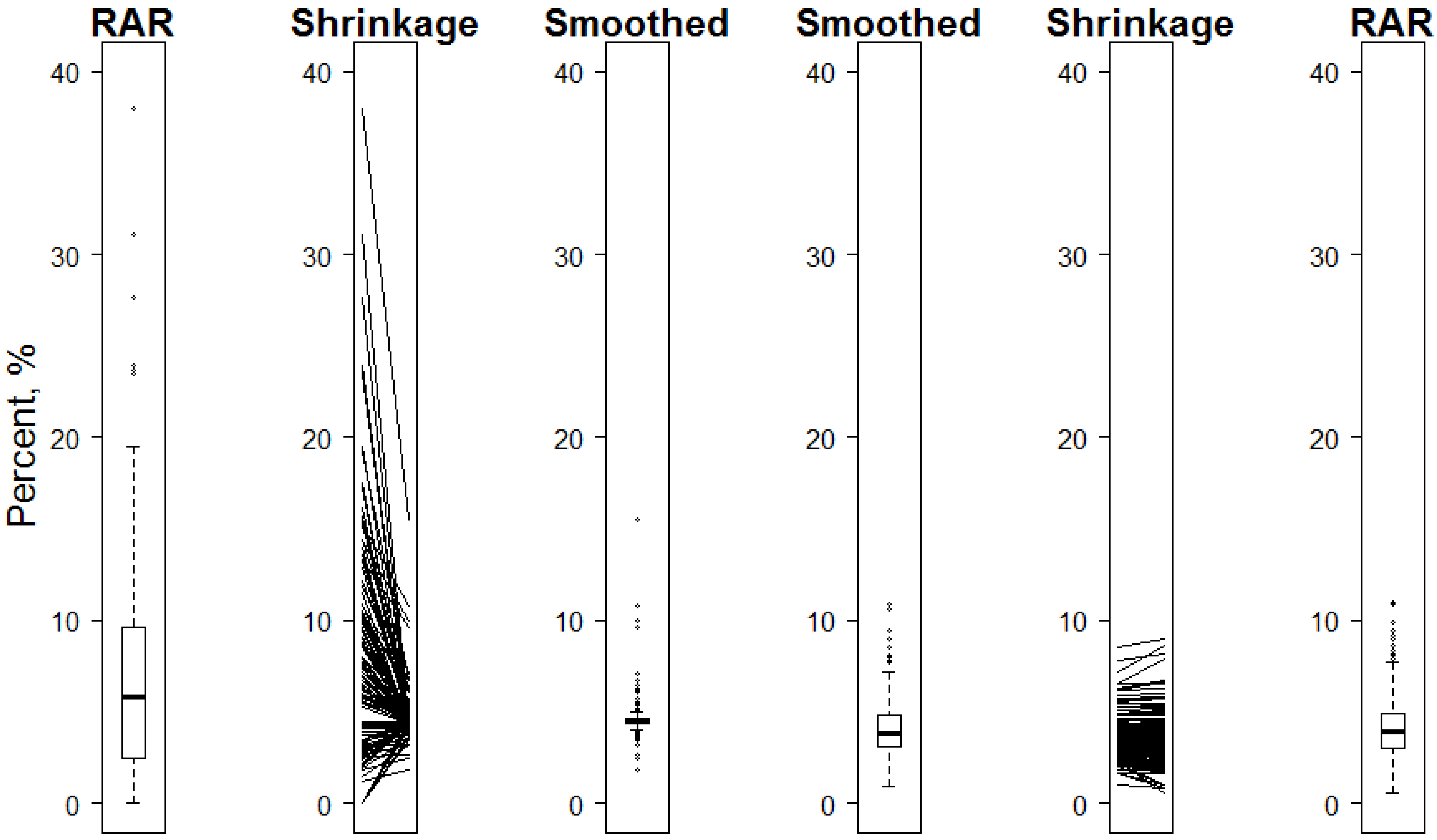
Noise variance

$$
\begin{aligned}
Var(\epsilon_h) &\approx Var\left(RAR_h | \theta_h\right) \\
&= Var\left(\overline{Y} \cdot \frac{O_h}{E_h}\right) \\
\Rightarrow \hat{\sigma}_h^2 &= \left(\frac{\overline{Y}}{n_h \cdot E_h}\right)^2 \sum_{i \in A_h} \hat{Y}_i \left(1 - \hat{Y}_i\right)
\end{aligned}
$$

Signal variance

$$
\begin{aligned}
Var(\theta_h) &= Var(RAR_h) - Var(\epsilon_h) \\
\Rightarrow \hat{\tau}^2 &= \frac{1}{H-1} \sum_h \left\{ \left(RAR_h - \overline{RAR}\right)^2 - \hat{\sigma}_h^2 \right\}
\end{aligned}
$$

Pneumonia Mortality Rate



1-3 cases/month

20+ cases/month

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Statistical Context

- **Risk adjustment**
  - **Remove variation due to patient case mix**
  - **Recalibrate expectation of quality**
- **Stabilization**
  - **Smoothing unstable estimates might mask true variation**
  - **Prior assumptions play a big role**
    - Bigger in low-information settings
    - Statistical challenge: what is the prior?

Policy Context

- **Risk adjustment**
  - **Level the playing field**
  - **Certain hospital types may take on unobserved risk**
- **Stabilization**
  - **Small hospitals present unstable estimates**
  - **Variation in quality may depend on hospital type**
  - **Prior assumptions set different expectations**
    - Empirically testable
    - Policy challenge: what is the message?

Hospital Characteristics in Risk Adjustment

Patient-level model

Patient i, event Y_i, attributes X_i, hospital characteristics Z_h

$$Y_i | p_i \sim \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = X_i' \beta + Z_{h[i]}' \gamma$$

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Hospital Characteristics in Stabilization

Signal extraction framework

$$RAR_h \quad = \quad \theta_h^* \quad + \quad \epsilon_h$$

where $\theta_h^* = \theta_h + Z_h'\gamma$

$$E(\theta_h^*) = \mu + Z_h'\gamma, \ Var(\theta_h) = \tau^2$$

$$E(\epsilon_h) = 0, \ Var(\epsilon_h) = \sigma_h^2$$

Potential Enhancements

- Empirical Bayes framework
  - Elucidate assumptions about prior distribution
  - Achieve credible posterior inferences
- Unified modeling
  - Perform risk adjustment and stabilization in one fell swoop
  - Computationally feasible

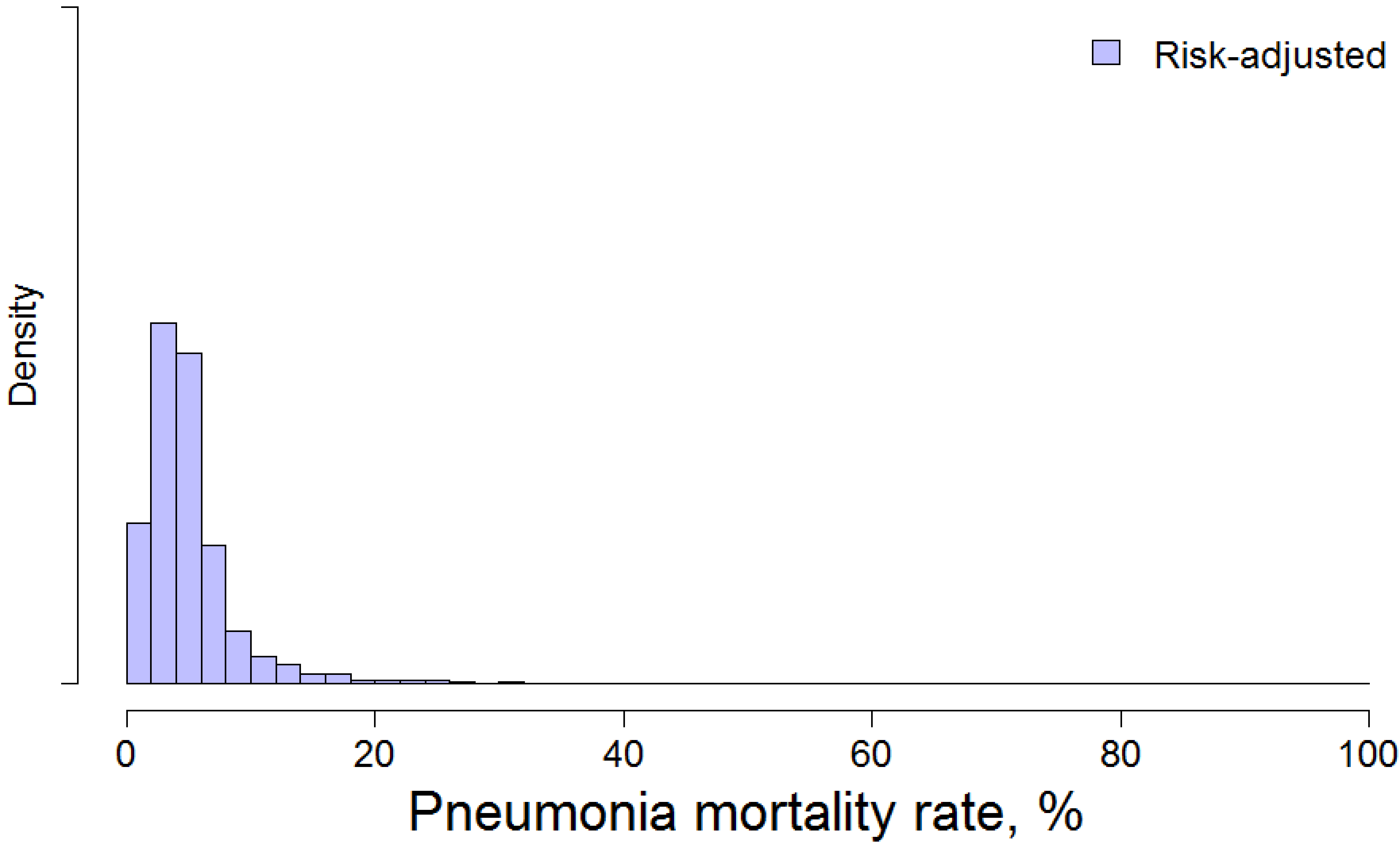
Empirical Bayes in Hospital Profiling

- **Decomposition of signal and noise**

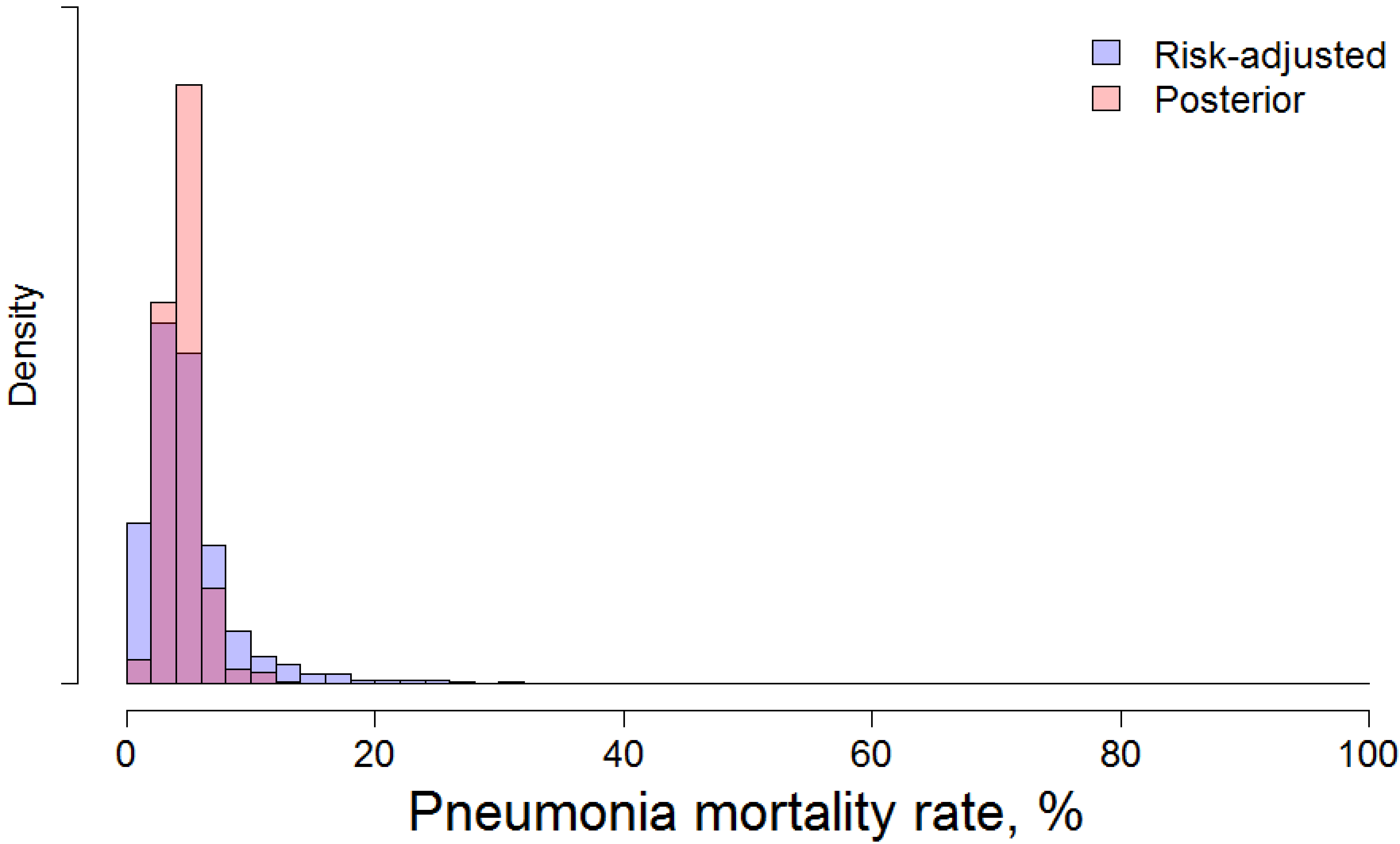
$$RAR_h = \theta_h + \varepsilon_h$$

True rate	$\theta_h \sim \text{Prior}$
Error	$\varepsilon_h \sim N(0, \sigma_h^2)$
Data	$RAR_h \mid \theta_h$
Posterior	$\theta_h \mid RAR_h$

Setting the Yardstick



Yardstick from a Gamma Prior



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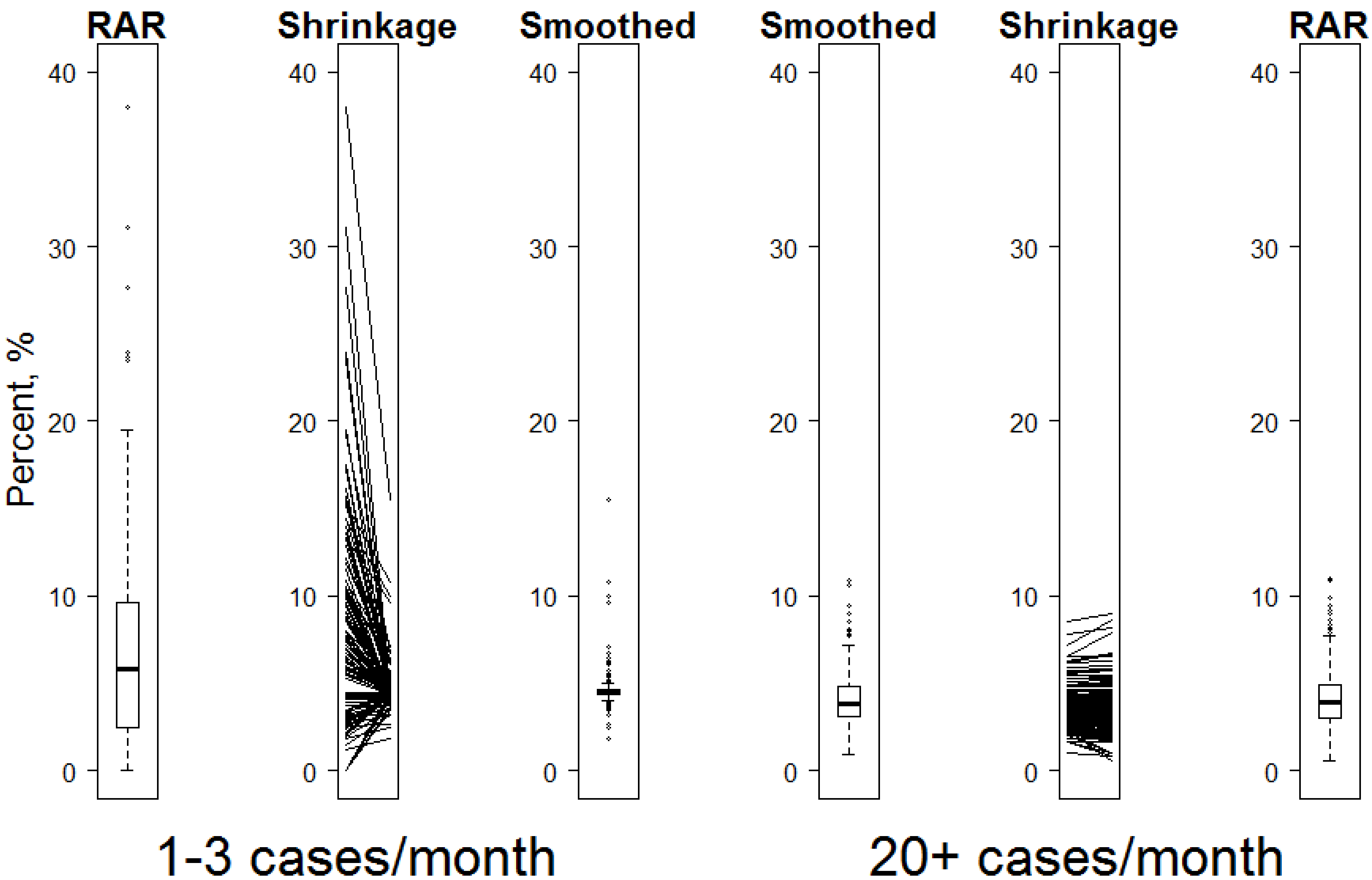
Addressing Overshrinkage

Does smoothing mask variation in true rate?

- **Restrictive prior distributions can hide possible outliers**
- **Prior means of true rate may or may not depend on peer grouping**
- **In the policy context expectations matter**

The Effect of Stabilization



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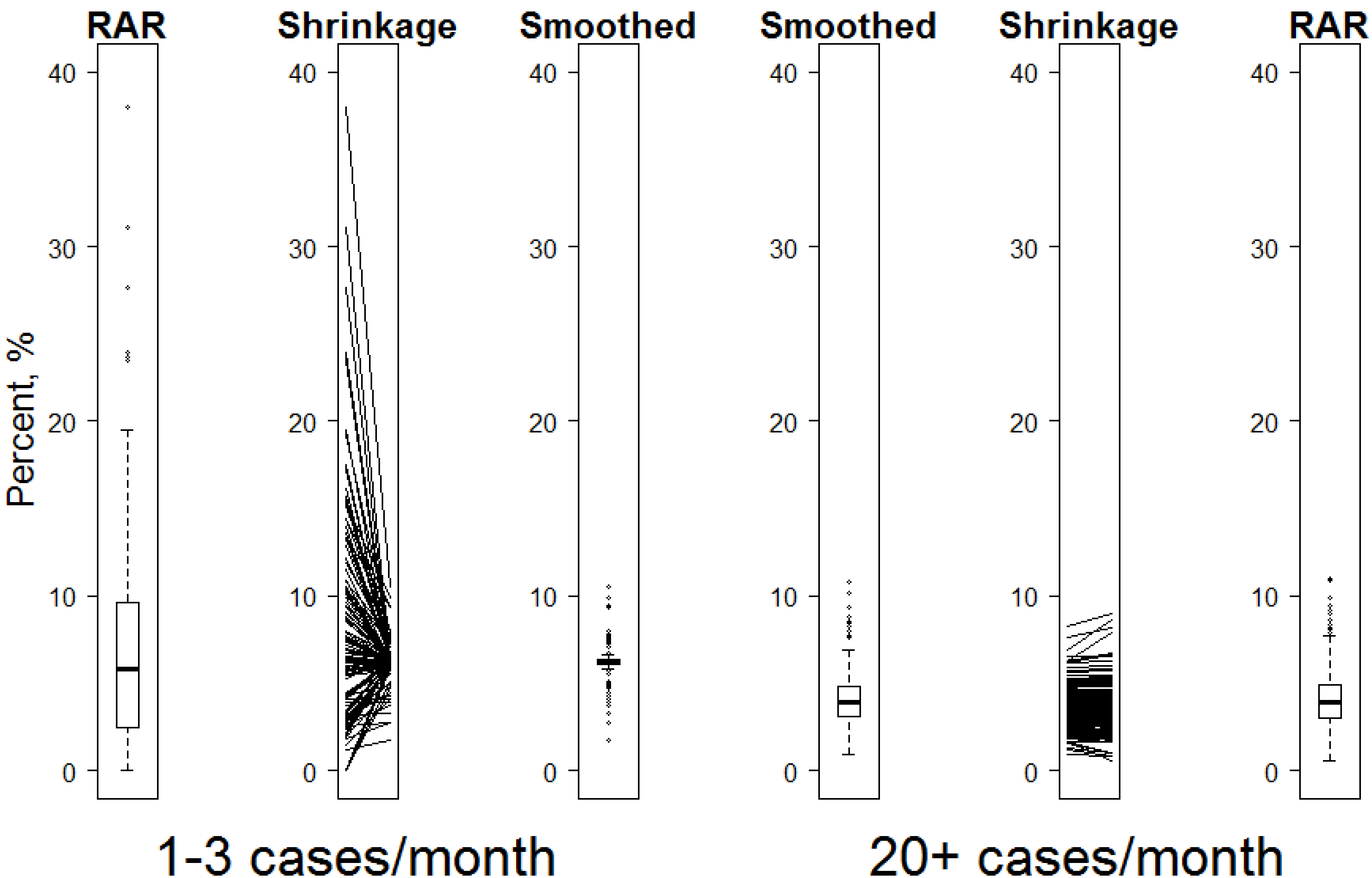
Mixture of Normals by Volume Quintile



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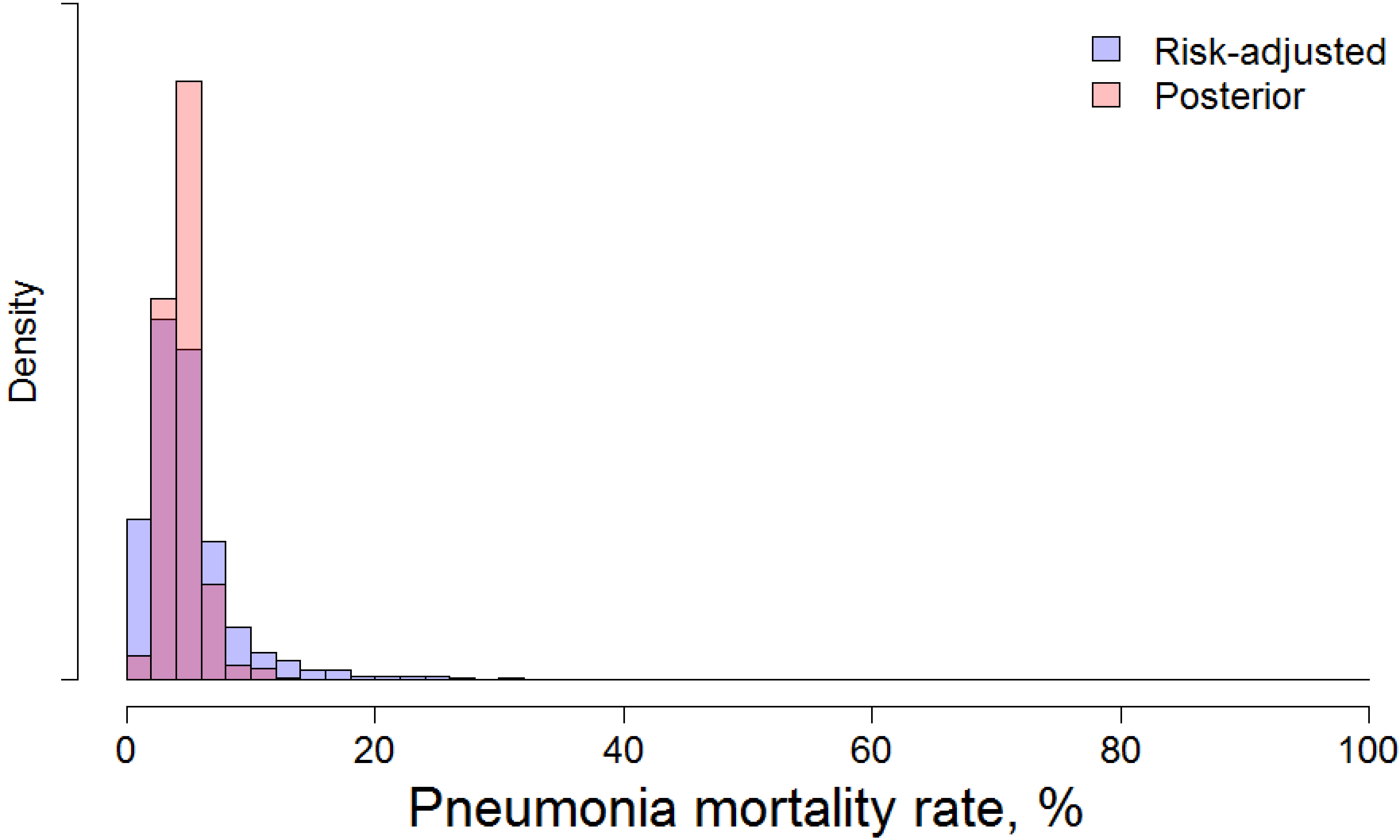
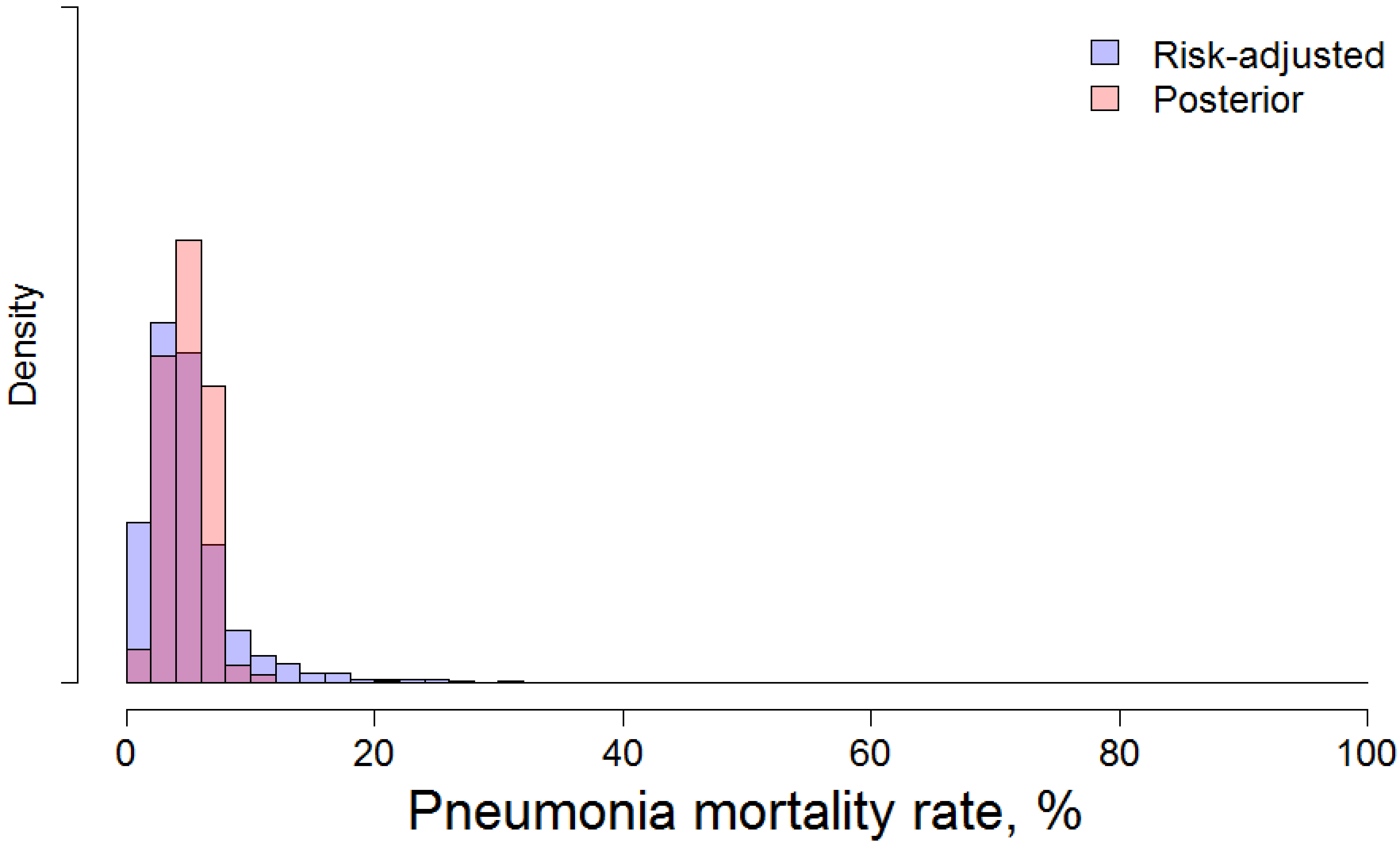
Yardstick from a Gamma Prior



Yardstick from Volume Peer Groups



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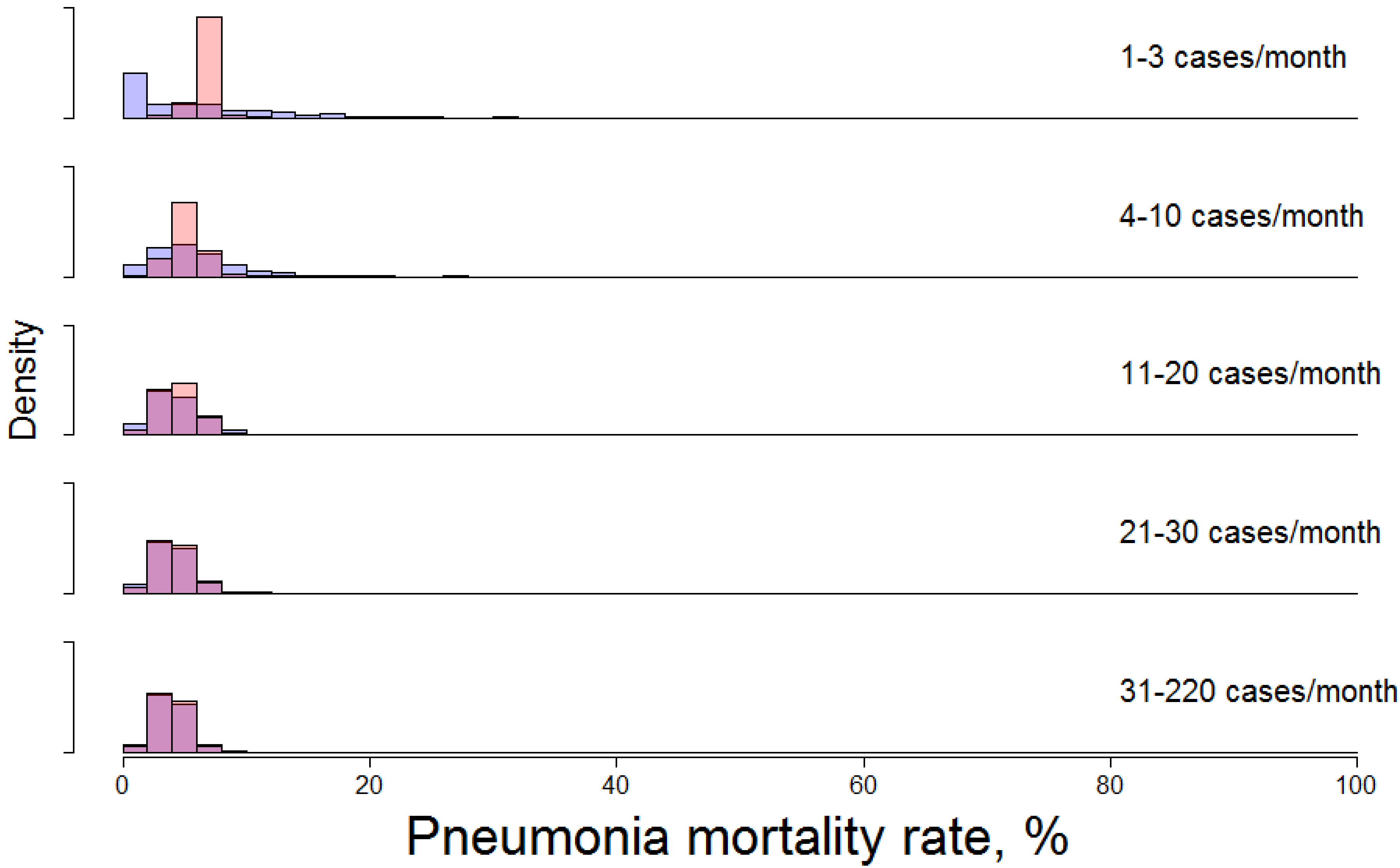
Peer Groups by Volume Quintiles



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Policy Implication

- It depends on the application
  - Self-monitoring
  - Public reporting
  - Pay for performance
- What is the message?
  - Leveling the playing field in risk adjustment is not a testable exercise
  - Setting expectations via the prior is empirically justifiable, “potentially resolvable”

Research Implications

- Standing by our prior, with or without peer grouping
- Empirical justification
  - Literature review
  - Exploratory data analysis
  - Hypothesis driven
  - Simulation based

For More Information

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