# STATISTICAL MODELS FOR HEALTH CARE QUALITY SURVEILLANCE AND PUBLIC REPORTING

**Sharon-Lise T. Normand**
Harvard Medical School & Harvard School of Public Health

Yale University: Harlan Krumholz (PI), Deron Galusha, Jennifer Mattera, Amy Rich, Yongfei Wang, and Yun Wang.

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## OVERALL GOAL

**PROVIDE RECOMMENDATIONS ON THE USE OF RISK-ADJUSTED MODELS FOR NATIONAL, STATE, AND HOSPITAL-LEVEL REPORTING**

***Results constitute recommendations to CMS**

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## HEALTHCARE RESEARCH AND QUALITY ACT:
### NATIONAL HEALTHCARE QUALITY REPORT

1. Inform Congress, providers, and consumers of health care about the state of health care quality.
2. Track progress in quality measurement over time.
3. Identify conditions requiring improvement in quality of care.
4. Provide national benchmarks.

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## SPECIFIC GOALS

1. Develop administrative claims-based risk-adjusted model for AMI.
2. Determine its suitability for public reporting.

Administrative Data = demographic, procedural, & diagnostic data derived from provider insurance claims.

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Sharon-Lise T. Normand
(sharon@hcp.med.harvard.edu)

## QUESTIONS

1. How we would answer the question in an ideal world, e.g., if we could collect any data or design any study?
2. How do we determine if models are suitable for public reporting?

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## BASIC IDEA

- Develop state-specific estimates using administrative data risk-factors, **Z**.
- Develop state-specific estimates using medical record data risk factors, **X**.
- Determine if statistical models are **acceptable**. If so, then determine whether the administrative data is a **surrogate** for the chart-based data.

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## WHY ASSESS SURROGACY?

In absence of randomization:

- Medical record data assumed to provide best method for risk-adjusting for differences in patient mix but $$$.
- Administrative data cheaper, relatively easy to obtain, but not detailed.

**Can we assess improvements in quality on the basis of the administrative data?**

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## COHORT & DATA SOURCES: AMI

Cohort: FFS Medicare beneficiaries (≥ 65 yrs) discharged with AMI in 1998.

Data Sources:

1. Administrative Data: Part A data (inpatient and outpatient); Part B; Medicare enrollment file.
2. Medical Record Data: detailed demographic and clinical information abstracted by 2 clinical data abstraction centers (Jencks et al, 2000; 2003).

Outcome: All-cause 30-day mortality.

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| DATA USED | |
|---|---|
| **DATA SOURCE** | **USE** |
| 1998 Administrative Data | Derivation and Validation of Administrative Data-Based Model |
| 1995 – 1997, 1999 Administrative Data | Validation of Administrative Data-Based Model |
| 1998 Medical Chart Data | Development of “Gold Standard” |

**All 50 states, District of Columbia, and Puerto Rico**

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## WHAT ARE THE STATISTICAL CONSIDERATIONS?

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## STATISTICAL CONSIDERATIONS

1. Observational Study: confounding, comorbidity vs. complication.
2. Focus of Inference: state vs. patient.
3. Appropriate Estimand: rate, ratio,etc.
4. Surrogacy of Administrative Data.

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## OBSERVATIONAL STUDY

Adjust for patient's condition at hospital arrival (Normand, Morris et al 1995):

- Demographic variables (age, male).
- Severity of Disease (e.g., location of MI).
- Comorbidity (eliminate potential complications, e.g., pneumonia).
- Parsimonious: variable reduction procedures.

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## OBSERVATIONAL STUDY

- Capitalize on previous work:
  - Hierarchical Condition Codes – 189 clinically coherent groupings of ICD-9-CM codes developed for CMS (Ash et al 2000).
  - Use literature to identify HCC's related to AMI (Lee et al 1995; Normand et al. 1996; Krumholz et al 1999)
- Fit model on developmental sample and assess performance on validation samples.

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## OBSERVATIONAL STUDY

Model Performance (Harrell, 2002)

- Discrimination: Area under the ROC curve.
- Predictive Strength: explained variation (Generalized $R^2$).
- Calibration: observed and predicted outcomes.
- Fit: residuals & over-fitting indices.

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## INFERENCE FOR STATE

- Separate sampling variability from between-state variation.
- Account for correlation among observations within a state.
- Hierarchical logistic regression model (Normand et al., 1997)

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## INFERENCE FOR STATE

Outcome: $Y_{ij}$ = 1 if $j^{th}$ patient in $i^{th}$ state died at 30-days; 0 otherwise

Within-State (sampling variability):

$\text{logit}(P(Y_{ij} = 1)) = \beta_{0i} + \beta(\text{Adjustors})_{ij}$

Between-State: $\beta_{0i} \sim N(\mu, \delta^2)$

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Sharon-Lise T. Normand
(sharon@hcp.med.harvard.edu)

# ESTIMATE

Predicted (state-specific):

$$\sum_j \text{logit}^{-1}(\beta_{0i} + \beta(\text{Adjustors})_{ij})/n_i$$

Expected (national):

$$\sum_j \text{logit}^{-1}(\mu + \beta(\text{Adjustors})_{ij})/n_i$$

**Standardized Mortality Rate (SMR):**

**(Predicted/Expected)** $\times$ **Mean**

**where Mean = national unadjusted rate.**

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# SURROGACY OF ADMINISTRATIVE DATA

Multiple Informant Literature

- Statistical approaches in presence of multiple assessment data (e.g., chart and admin).
- Developed primarily in psychiatric literature (e.g., parent report, teacher report).
- Old strategies: pooling or separate analyses using each source.
- New strategies: simultaneous multiple regression models (Horton, Laird, Murphy, et al. 2001).

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## MULTIPLE SOURCE RISK FACTORS

Chart: $\text{logit}(E(Y_j|X_j)) = \beta_0^{(x)} + \beta_1^{(x)}\mathbf{X}_j$

Admin: $\text{logit}(E(Y_j|Z_j)) = \beta_0^{(z)} + \beta_1^{(z)}\mathbf{Z}_j$

Usually want to assess if:

$$E(Y_j|X_j) = E(Y_j|Z_j)$$

Estimation via GEE

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## MULTIPLE INFORMANT LITERATURE

1. GEE uses independence working correlation matrix: $cor(Y|X, Y|Z) = 0$.
2. Association parameters needed for specific (geographic) units. Conditional independence assumptions.
3. Surrogacy: one source is the preferred source.

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## SURROGACY OF ADMINISTRATIVE DATA

1. $\text{logit}(E(Y_{ij}|X_{ij}, \beta_{0i}^{(x)})) = \beta_{0i}^{(x)} + \beta_1^{(x)}\mathbf{X}_{ij}$
2. $\text{logit}(E(Y_{ij}|Z_{ij}, \beta_{0i}^{(z)})) = \beta_{0i}^{(z)} + \beta_1^{(z)}\mathbf{Z}_{ij}$
3. $\beta_{0i}^{(k)} \sim N(\mu^{(k)}, \delta^{2(k)})$
4. $\theta(\mathbf{X})_i = \text{Mean}(Y) \times \sum_j E(Y_{ij}|X_{ij}, \beta_{0i}^{(x)}) \div \sum_j E(Y_{ij}|X_{ij}, \mu^{(x)}, \delta^{2(x)})$

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## SURROGACY OF ADMINISTRATIVE DATA

Surrogacy (Daniels and Hughes, 1997):

- Admin data is surrogate for chart data if admin data are <u>prognostic</u> of quality & <u>predictive</u> of outcome based on chart data.
- Let $\theta^*(\mathbf{X})_i$= estimated SMR from chart data.
- Let $\gamma^*(\mathbf{Z})_i$ = estimated SMR from admin data.

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## SURROGACY OF ADMINISTRATIVE DATA

Within-state: $(\theta^*(X)_i, \gamma^*(Z)_i) \sim N_2((\theta_i, \gamma_i), \mathbf{V})$

Between-state: $\theta_i | \gamma_i \sim N(\alpha_0 + \alpha_1 \gamma_i, \sigma^2)$

- $\alpha_1$ measures relationship of SMRs between chart-based & admin-based data.
- If $\alpha_1 \neq \mathbf{0}$, having $\sigma^2 = \mathbf{0}$ implies we could predict the chart-based rates perfectly given the admin-based rates.

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## SURROGACY OF ADMINISTRATIVE DATA

Estimation of Parameters:

- Non-parametric bootstrap for **V**: $\mathrm{Var}(\theta^*_i)$, $\mathrm{Var}(\gamma^*_i)$, and $\mathrm{Corr}(\theta^*_i, \gamma^*_i)$.
- Non-informative priors for $\alpha_0$, $\alpha_1$, $\{\gamma_i\}$, and $\sigma^2$.
- Estimate unknown parameters using MCMC methods.

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## RESULTS: ADMINISTRATIVE MODEL (27 Variables)

| | |
|---|---|
| Demographics | Age, Male |
| Cardiovascular History (HCC Codes) | PTCA, CABG, HF, MI, Angina, Atherosclerosis, Cardiopulmonary-Resp Failure, Hypertensive Heart Disease, Valvular Disease, Location of MI |
| Comorbidity (HCC Codes) *Taken from non-index admission | HTN, Stroke, CVD, COPD, Renal Failure, Diabetes, Pneumonia*, Malnutrition, Dementia, Functional Disability, PVD, Metastatic Cancer, Major Psychiatric Disorders, Trauma, Liver Disease |

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## RESULTS: CHART-BASED MODEL (32 Variables)

| | |
|---|---|
| Demographics | Age, Male |
| Severity | Duration of Chest Pain, ST-Elevation, Systolic Blood Pressure, Left (Right) Bundle Branch Block, Shock on Arrival, HF on Arrival, 2nd or 3rd Degree Heart Block |
| Labs | Creatinine, Blood Urea Nitrogen, White Blood Cell Count |
| Cardiovascular History | HF, CABG, PTCA, Location of MI |
| Comorbidity | HTN and COPD |

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Sharon-Lise T. Normand
(sharon@hcp.med.harvard.edu)

| DATA SOURCE [N; 30-Day Mortality] | $R^2$ | OBSERVED MORTALITY (%) [lowest, highest]* | ROC AREA |
|---|---|---|---|
| 1998 Derivation [134,661; 18%] | 0.12 | [4.0, 40.0] | 0.71 |
| 1998 [134,440; 18.1] | 0.12 | [4.2, 40.1] | 0.70 |
| 1995 [274,404; 19.0] | 0.11 | [4.7, 39.7] | 0.69 |
| 1996 [275,792; 18.5] | 0.11 | [4.5, 39.6] | 0.69 |
| 1997 [271,902;18.1] | 0.11 | [4.3, 39.4] | 0.70 |
| 1999 [268,819; 18.6] | 0.12 | [4.0, 43.4] | 0.70 |
| Administrative: 1998 Linked [26,085; 17.4] | 0.10 | [4.6, 37.0] | 0.69 |
| Chart Based: 1998 Linked [26,085; 17.4] | 0.25 | [2.4, 55.2] | 0.78 |

*Predicted Deciles of Risk

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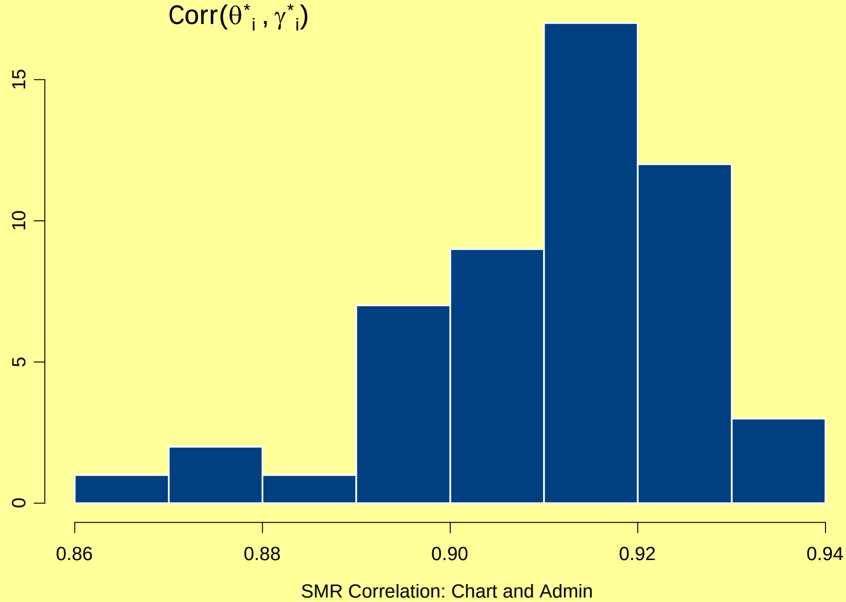
## Within-State Correlation: SMR Chart & Admin

$\text{Corr}(\theta^*_i, \gamma^*_i)$

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# SURROGACY ESTIMATES

$$\theta_i | \gamma_i \sim N(\alpha_0 + \alpha_1 \gamma_i, \sigma^2)$$

| Parameter | Estimate | 95% Credible Interval |
|---|---|---|
| $\alpha_0$ | 0.045 | [0.019, 0.090] |
| $\alpha_1$ | **0.742** | **[0.485, 0.890]** |
| $\sigma^2$ | $(0.087)^2$ | $[(0.079)^2, 0.097)^2]$ |

Estimated in BUGS, 2000 burn-in, 2000 iterates

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| | SUMMARY | ADMIN | CHART |
|---|---|---|---|
| Patient-Level | Generalized $R^2$ | 0.12 | 0.25 |
| Patient-Level | Observed Mortality (%):<br>Lowest Decile<br>Highest Decile | <br>4.0<br>40.0 | <br>2.4<br>55.2 |
| Patient-Level | ROC Area | 0.71 | 0.78 |
| State-Level | Maximum \|Difference\|:<br>SMR (%): Admin – Chart | 1.5 (Overall SMR = 17.4) | |
| State-Level | **Surrogacy**:<br>$\alpha_1$ [95% Credible Interval]<br>$\sigma^2$ [95% Credible Interval] | <br>0.74 [0.49, 0.89]<br>$(0.087)^2$ $[(0.079)^2, 0.097)^2]$ | |

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## SUMMARY

- Administrative model compares favourably with chart model, both at state and patient level.
- Admin-Based estimated SMRs meet criteria for surrogacy
  - **Implies we can assess improvements in quality on the basis of the administrative data.**
- Assumption throughout is chart-based model is the gold-standard.

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## SUMMARY

- Usefulness of administrative data depends on ultimate use.
  - Public domain summaries
  - Penalizing hospitals
- Hospital-Specific Models:
  - 4,322 hospitals with at least one discharge in 1998.
  - 25% of hospitals have < 11 discharges.
  - 50% of hospitals have > 25 discharges.

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