Mitigating the Impact of Endogeneity in Mental Healthcare Data via Multilevel Models

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Purpose

- To examine whether racial disparities occur in the utilization of inpatient mental health services
- To introduce the health services literature to advanced multilevel modeling techniques
Racial Disparities in Mental Health

- Racial disparities: Differences in healthcare treatments and outcomes by race after considering all other individual and organizational factors.

- The National Research Council (1997) and Institute of Medicine (2002) have found extensive evidence of racial disparities in healthcare treatments and outcomes.

- Racial disparities have been attributed to (unobserved):
  - Socio-economic status
  - Health insurance coverage
  - Patient preferences / cultural beliefs
  - Physician bias / discrimination
  - Quality of the local healthcare system
Outline

1. Background
   - Multilevel Models
   - Endogeneity
   - Data

2. Multilevel Model Endogeneity Analysis
   - Two Level Model
   - Estimation Strategies
   - Empirical Results

3. Summary
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3 Summary
Multilevel Models

- Modeling technique originally used in educational research, now used in other fields (Raudenbush & Bryk 2002, Goldstein 2003)
- Can be used when data has an inherent hierarchical structure, such as students within schools or patients within hospitals
- Advantages of multilevel models include:
  - More precise estimates of fixed effects (regression coefficients)
  - Provide appropriate standard errors for confidence intervals and hypothesis tests
Endogeneity

- Correlation of observed model variables with model random errors (Wooldridge 2002)
- Conceive of endogeneity as omitted variables
- Omitted variables can bias fixed effects estimates of observed model variables and lead to incorrect inferences
Data

- Healthcare Cost and Utilization Project’s Nationwide Inpatient Sample (NIS)
  - Sponsored by the Agency for Healthcare Research and Quality
- Area Resource File (ARF)
  - Sponsored by the Bureau of Health Professions
- Sample: 97,378 adults (age 18 to 64) admitted to a hospital in 2003 and discharged with a mental illness, from 331 hospitals and 231 counties
- Goal: use data to determine whether there are racial disparities in inpatient mental healthcare utilization, measured by hospital total charges (TOTCHG)
### Variables and Descriptions

#### Discharge-Level
- Hospital total charges
- Age at admission
- Gender of patient
- **Race of patient**
- Primary expected payer
- APR-DRG code
- Risk of mortality subclass
- Severity subclass

#### Hospital-Level
- Bed size of hospital
- Ownership of hospital
- Location of hospital
- Teaching status of hospital

#### County-Level
- HPSA primary care physician code
- HPSA mental health professional code
- Total hospital admission rate
- Per capita income
Distribution of TOTCHG

![Distribution of Total Charges](image-url)
Distribution of LN(TOTCHG)
Two Level Model: Discharges within Hospitals

- Discharge Model:
  \[ y_{hd} = \mathbf{X}_{hd}(1) \beta_1 + \beta_h^{(1)} + \epsilon_{hd}^{(1)} \]

- Hospital Model:
  \[ \beta_h^{(1)} = \mathbf{X}_h^{(2)} \beta_2 + \epsilon_h^{(2)} \]

- Combined Model:
  \[ y_{hd} = \mathbf{X}_{hd}(1) \beta_1 + \mathbf{X}_h^{(2)} \beta_2 + \epsilon_{hd}^{(1)} + \epsilon_h^{(2)} \]

- Let \( \mathbf{X}_{hd} = (\mathbf{X}_{hd}^{(1)} : \mathbf{X}_h^{(2)}) \), \( \beta = (\beta_1' : \beta_2')' \), \( \delta_{hd} = \epsilon_{hd}^{(1)} + \epsilon_h^{(2)} \), \( \mathbf{V}_h = \text{var}(\delta_h) \)

  Fully specify the two level model as:
  \[ \mathbf{V}_h^{-1/2} y_h = \mathbf{V}_h^{-1/2} \mathbf{X}_h \beta + \mathbf{V}_h^{-1/2} \delta_h \]
Two Level Model: Discharges within Hospitals

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Fully specify the two level model as:

\[ V_h^{-1/2} y_h = V_h^{-1/2} X_h \beta + V_h^{-1/2} \delta_h \]


- Typically, analysts estimate fixed effects $\beta$ using the ordinary least squares (OLS) estimator ($V_h = \sigma^2 I_h$):

$$b_{OLS} = \left( \sum_h X'_h X_h \right)^{-1} \sum_h X'_h y_h$$

- However, the most efficient unbiased estimator of $\beta$ accounts for the hierarchical structure of the data, the generalized least squares (GLS) estimator:

$$b_{GLS} = \left( \sum_h X'_h V_h^{-1} X_h \right)^{-1} \sum_h X'_h V_h^{-1} y_h$$
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Introducing Omitted Variables

- At hospital-level, omitted variables: hospital capacity, physician practice patterns, healthcare demand and supply, community-level socio-economic status, and the quality of the healthcare system
  - Instead of $\epsilon_h^{(2)}$, model contains $\epsilon_h^{(2)*} + u_h^{(2)}$
- At discharge-level, race-related omitted variables: socio-economic status, health insurance, patient preferences, and physician bias
  - Instead of $WHITE_{hd}$, model contains $WHITE_{hd}^{*} + u_h^{(1WHITE)}$
  - $u_h^{(1j)} = \text{omitted effects for race } j \text{ and hospital } h$
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  - $u_h^{(1j)} = \text{omitted effects for race } j \text{ and hospital } h$
Estimation with Omitted Variables

- If only \( u_h^{(2)} \), can use *fixed effects estimation* (Kim & Frees 2006) that removes both observed and omitted hospital variables to estimate discharge fixed effects \( \beta_1 \):

\[
b_{1FE} = \left( \sum_h X_h^{(1)'} V_h^{-1/2} Q_h V_h^{-1/2} X_h^{(1)} \right) - \sum_h X_h^{(1)'} V_h^{-1/2} Q_h V_h^{-1/2} y_h
\]

- Again, if only \( u_h^{(2)} \), can obtain unbiased estimates of all fixed effects \( \beta \) with *instrumental variables (IV) estimation* (Kim & Frees 2006):

\[
b_{IV} = \left( \sum_h X_h' V_h^{-1/2} P(H_h) V_h^{-1/2} X_h \right) - \sum_h X_h' V_h^{-1/2} P(H_h) V_h^{-1/2} y_h
\]

- If both \( u_h^{(2)} \) and \( u_h^{(1i)} \), can only obtain estimates of \( \beta_{1NR}^{(1NR)} \), the discharge variables other than race: \( b_{1FE}^{(1NR)} = \)

\[
= \left( \sum_h X_h^{(1NR)'} V_h^{-1/2} Q_h V_h^{-1/2} X_h^{(1NR)} \right) - \sum_h X_h^{(1NR)'} V_h^{-1/2} Q_h V_h^{-1/2} y_h
\]
Estimation with Omitted Variables

- If only $u_h^{(2)}$, can use fixed effects estimation (Kim & Frees 2006) that removes both observed and omitted hospital variables to estimate discharge fixed effects $\beta_1$:

$$b_{1FE} = \left( \sum_h X_h^{(1)'} V_h^{-1/2} Q_h V_h^{-1/2} X_h^{(1)} \right) - \sum_h X_h^{(1)'} V_h^{-1/2} Q_h V_h^{-1/2} y_h$$

- Again, if only $u_h^{(2)}$, can obtain unbiased estimates of all fixed effects $\beta$ with instrumental variables (IV) estimation (Kim & Frees 2006):

$$b_{IV} = \left( \sum_h X_h' V_h^{-1/2} P(H_h) V_h^{-1/2} X_h \right) - \sum_h X_h' V_h^{-1/2} P(H_h) V_h^{-1/2} y_h$$

- If both $u_h^{(2)}$ and $u_h^{(1i)}$, can only obtain estimates of $\beta_1^{(1NR)}$, the discharge variables other than race:

$$b_{1FE*}^{(1NR)} = \left( \sum_h X_h^{(1NR)'} V_h^{-1/2} Q^*_h V_h^{-1/2} X_h^{(1NR)} \right) - \sum_h X_h^{(1NR)'} V_h^{-1/2} Q^*_h V_h^{-1/2} y_h$$
Estimation with Omitted Variables

- If only $u_h^{(2)}$, can use *fixed effects estimation* (Kim & Frees 2006) that removes both observed and omitted hospital variables to estimate discharge fixed effects $\beta_1$:

$$b_{1FE} = \left( \sum_h X_h^{(1)'} V_h^{-1/2} Q_h V_h^{-1/2} X_h^{(1)} \right) - \sum_h X_h^{(1)'} V_h^{-1/2} Q_h V_h^{-1/2} y_h$$

- Again, if only $u_h^{(2)}$, can obtain unbiased estimates of **all** fixed effects $\beta$ with *instrumental variables (IV) estimation* (Kim & Frees 2006):

$$b_{IV} = \left( \sum_h X_h' V_h^{-1/2} P(H_h) V_h^{-1/2} X_h \right) - \sum_h X_h' V_h^{-1/2} P(H_h) V_h^{-1/2} y_h$$

- If both $u_h^{(2)}$ and $u_h^{(1)}$, can only obtain estimates of $\beta_1^{(1NR)}$, the discharge variables other than race: $b_{1FE*}^{(1NR)} = $

$$= \left( \sum_h X_h^{(1NR)'} V_h^{-1/2} Q_h^* V_h^{-1/2} X_h^{(1NR)} \right) - \sum_h X_h^{(1NR)'} V_h^{-1/2} Q_h^* V_h^{-1/2} y_h$$
### OLS Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHITE</td>
<td>-0.186</td>
<td>-9.581</td>
</tr>
<tr>
<td>BLACK</td>
<td>-0.191</td>
<td>-9.505</td>
</tr>
<tr>
<td>HISPANIC</td>
<td>0.087</td>
<td>4.054</td>
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<tr>
<td>ASIAN</td>
<td>0.056</td>
<td>1.758</td>
</tr>
<tr>
<td>NAT_AMER</td>
<td>-0.075</td>
<td>-1.239</td>
</tr>
</tbody>
</table>

### GLS Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate</th>
<th>t-Statistic</th>
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<tbody>
<tr>
<td>WHITE</td>
<td>0.035</td>
<td>1.769</td>
</tr>
<tr>
<td>BLACK</td>
<td>0.015</td>
<td>0.692</td>
</tr>
<tr>
<td>HISPANIC</td>
<td>0.000</td>
<td>0.014</td>
</tr>
<tr>
<td>ASIAN</td>
<td>0.090</td>
<td>3.151</td>
</tr>
<tr>
<td>NAT_AMER</td>
<td>0.069</td>
<td>1.215</td>
</tr>
</tbody>
</table>

### Covariance Components

<table>
<thead>
<tr>
<th>Covariance Components</th>
<th>Estimate</th>
<th>Standard Error</th>
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<tbody>
<tr>
<td>( \text{var}(\epsilon) )</td>
<td>0.7150</td>
<td>0.003</td>
</tr>
<tr>
<td>( \text{var}(\epsilon_{hd}^{(1)}) )</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>( \text{var}(\epsilon_{h}^{(2)}) )</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

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<tr>
<th>Covariance Components</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{var}(\epsilon_{hd}^{(1)}) )</td>
<td>0.4704</td>
<td>0.002</td>
</tr>
<tr>
<td>( \text{var}(\epsilon_{h}^{(2)}) )</td>
<td>0.2730</td>
<td>0.025</td>
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</table>

### Model Fit Indices

<table>
<thead>
<tr>
<th>Model Fit Indices</th>
<th>OLS Model</th>
<th>GLS Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(-2(\text{Max LogL}))</td>
<td>243,683.8</td>
<td>203,940.6</td>
</tr>
<tr>
<td>AIC</td>
<td>243,747.8</td>
<td>204,006.6</td>
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</table>
Comparison of Race Fixed Effects Estimates: GLS vs Endogeneity Estimators

<table>
<thead>
<tr>
<th>Variables</th>
<th>GLS</th>
<th>FE</th>
<th>IV</th>
<th>FE*</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHITE</td>
<td>0.035</td>
<td>1.769</td>
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</tr>
<tr>
<td>BLACK</td>
<td>0.015</td>
<td>0.692</td>
<td>0.016</td>
<td>0.734</td>
</tr>
<tr>
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<td>0.014</td>
<td>-0.000</td>
<td>-0.006</td>
</tr>
<tr>
<td>ASIAN</td>
<td>0.090</td>
<td>3.151</td>
<td>0.090</td>
<td>3.142</td>
</tr>
<tr>
<td>NAT_AMER</td>
<td>0.069</td>
<td>1.215</td>
<td>0.069</td>
<td>1.209</td>
</tr>
</tbody>
</table>
### Empirical Results

**Comparison of APR-DRG Fixed Effects Estimates: GLS vs Endogeneity Estimators**

<table>
<thead>
<tr>
<th></th>
<th></th>
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<tbody>
<tr>
<td>DRG740</td>
<td>0.906</td>
<td>8.918</td>
<td>0.907</td>
<td>8.873</td>
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<td>DRG750</td>
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<td>DRG751</td>
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<td>0.361</td>
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<td>DRG752</td>
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<td>DRG753</td>
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<td>0.170</td>
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<td>DRG754</td>
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<tr>
<td>DRG756</td>
<td>-0.073</td>
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<td>-0.943</td>
<td>-0.075</td>
<td>-0.901</td>
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<td>DRG757</td>
<td>0.201</td>
<td>2.229</td>
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<td>DRG758</td>
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<td>0.376</td>
<td>0.033</td>
<td>0.354</td>
<td>0.035</td>
<td>0.378</td>
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<td>DRG759</td>
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<td>0.537</td>
<td>4.266</td>
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<td>DRGRM</td>
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<td>DRGSEV</td>
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<td>20.267</td>
<td>0.257</td>
<td>20.286</td>
<td>0.256</td>
<td>20.194</td>
</tr>
</tbody>
</table>
Summary of Current Research

- Multilevel modeling has been applied to the examination of inpatient healthcare utilization outcomes and racial disparities.
- Current multilevel model-based methods, fixed effects and IV, have been utilized in the presence of omitted variables.
- Empirical analysis found no evidence of significant racial disparities.