Association Between Opioid Prescription Propensity and Medicare Patient Panels’ Mean HCC Risk Scores

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Opioid overdose deaths vary geographically
Possible impact of physician prescriptions

Patients covered by Medicare are six times more likely to suffer from opioid addiction, compared to those covered by commercial health insurance (Lembke & Chen, 2016)

Barnett et al. (2017) discovered that patients who were prescribed high-intensity opioids, without previous opioid treatment, were more likely to use opioids in the long term

North et al. (2017)

• studied case complexity, a cost-based proxy for a patient’s health condition
• found a positive association between physicians’ average patient case complexities and propensities to prescribe opioids
• provided preliminary results using a convenience sample from one MN hospital
North et al.’s approach

**Population**
Mayo Clinic physicians in Rochester, MN

**Sample size**
100

**Physician specialties studied**
family practice & internal medicine
Thesis Goals

Explore the association between average case complexity and physician propensity over a wider range of average complexities.

Explore variation in the association across specialties.

Investigate possible geographic variation
  • Develop a new methodology for flagging geographic outliers.
2016 Medicare Part D physician-level data

Captures over 1M physicians’ prescriptions spanning from Jan. 1, 2016 to June 30, 2017

Includes the main variables of interest:

- X = Mean HCC risk score (average patient case complexity)
  - comes from patients’ individual HCC scores
    - higher scores = higher medical spending = higher case complexity
- Y = SLOB = #days’ supply of all opioid prescriptions / #opioid beneficiaries
- secondary explanatory variables: physician specialty and U.S. state
North et al. vs. Medicare Data: Association among family practitioners & internists

\[ 0.2 < \overline{HCC} < 0.9 \]
Positive, linear association

\[ 0 < \overline{HCC} < 4.0 \]
Positive, linear, but then becomes nonlinear when \( \overline{HCC} > 1.0 \)
Methodology must consider two sources of variation

Across specialties

Across states within specialties
(Below: nurse practitioners’ top states)
Transforming SLOB uncovers bimodality issues that future research must address.
Moving from exploratory analyses to methodology

**Findings from exploratory analyses**
- nonlinear association
- variation across specialties
- variation across states within specialties
- skewness in SLOB distribution

**Methodology**
- specify quadratic linear model
- fit separate model for each specialty
- specify hierarchical models with state random effects
- let $Y = \ln(\text{SLOB})$
Baseline statistical model

For each physician $i$ and state $j$,

$$ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})HCC_{ij} + (\beta_2 + u_{2j})HCC^2_{ij} + \epsilon_{ij}$$

where

$$u_{0j} \sim N(0, \sigma^2_0), u_{1j} \sim N(0, \sigma^2_1), u_{2j} \sim N(0, \sigma^2_2) \text{ and } \epsilon_{ij} \sim N(0, \sigma^2)$$
Selecting each specialty’s best model: a hypothesis-testing approach

<table>
<thead>
<tr>
<th>Models compared</th>
<th>Null hypothesis</th>
<th>Test statistic</th>
<th>Decision rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1], [2]</td>
<td>( \text{Var}(u_{2j}) = 0 )</td>
<td>( 2(\ln L_{[1]} - \ln L_{[2]}) \sim \chi_1^2 )</td>
<td>Pick [1] if ( p &lt; .05 ); else continue</td>
</tr>
<tr>
<td>[2], [3]</td>
<td>( \beta_2 = 0 )</td>
<td>( 2(\ln L_{[2]} - \ln L_{[3]}) \sim \chi_1^2 )</td>
<td>Pick [2] if ( p &lt; .05 ); else continue</td>
</tr>
<tr>
<td>[3], [4]</td>
<td>( \text{Var}(u_{1j}) = 0 )</td>
<td>( 2(\ln L_{[3]} - \ln L_{[4]}) \sim \chi_1^2 )</td>
<td>Pick [3] if ( p &lt; .05 ); else continue</td>
</tr>
<tr>
<td>[4], [5]</td>
<td>( \text{Var}(u_{0j}) = 0 )</td>
<td>( 2(\ln L_{[4]} - \ln L_{[5]}) \sim \chi_1^2 )</td>
<td>Pick [4] if ( p &lt; .05 ); else continue</td>
</tr>
<tr>
<td>[5], [6]</td>
<td>( \beta_1 = 0 )</td>
<td>( 2(\ln L_{[5]} - \ln L_{[6]}) \sim \chi_1^2 )</td>
<td>Pick [5] if ( p &lt; .05 ); else pick [6]</td>
</tr>
</tbody>
</table>

\[1\] \( \ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})HCC_{ij} + (\beta_2 + u_{2j})HCC^2_{ij} + \varepsilon_{ij} \)

\[2\] \( \ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})HCC_{ij} + \beta_2 HCC^2_{ij} + \varepsilon_{ij} \)

\[3\] \( \ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})HCC_{ij} + \varepsilon_{ij} \)

\[4\] \( \ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + \beta_1 HCC_{ij} + \varepsilon_{ij} \)

\[5\] \( \ln(SLOB_{ij}) = \beta_0 + \beta_1 HCC_{ij} + \varepsilon_{ij} \)

\[6\] \( \ln(SLOB_{ij}) = \beta_0 + \varepsilon_{ij} \)
Baseline ([1]) is the most common best model

<table>
<thead>
<tr>
<th>Specialty</th>
<th>Best model</th>
<th>Outlier states</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nurse Practitioner</td>
<td>1</td>
<td>AZ, NJ, TN</td>
</tr>
<tr>
<td>Internal Medicine</td>
<td>1</td>
<td>CT, NJ, NY</td>
</tr>
<tr>
<td>Dentist</td>
<td>1</td>
<td>AL, CA, GA, IL</td>
</tr>
<tr>
<td>Family Practice</td>
<td>1</td>
<td>SC</td>
</tr>
<tr>
<td>Physician Assistant</td>
<td>1</td>
<td>IA, WV</td>
</tr>
<tr>
<td>Student</td>
<td>1</td>
<td>WV</td>
</tr>
<tr>
<td>Emergency Medicine</td>
<td>1</td>
<td>AL, AZ</td>
</tr>
<tr>
<td>Obstetrics &amp; Gynecology</td>
<td>3</td>
<td>AL, MA, MN, SC</td>
</tr>
<tr>
<td>Optometry</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Psychiatry</td>
<td>2</td>
<td>AR, GA, IL, KS, LA</td>
</tr>
<tr>
<td>General Surgery</td>
<td>1</td>
<td>CT, MI, WI</td>
</tr>
<tr>
<td>Orthopedic Surgery</td>
<td>1</td>
<td>LA, SC</td>
</tr>
<tr>
<td>Cardiovascular Disease</td>
<td>1</td>
<td>NY, TX</td>
</tr>
<tr>
<td>Ophthalmology</td>
<td>1</td>
<td>CA, MI, SC, TN</td>
</tr>
<tr>
<td>Podiatry</td>
<td>2</td>
<td>MN, PA, IN, WV</td>
</tr>
<tr>
<td>Psychiatry &amp; Neurology</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Neurology</td>
<td>1</td>
<td>AL, LA, PA, UT</td>
</tr>
<tr>
<td>Gastroenterology</td>
<td>2</td>
<td>AL, FL, GA, MA</td>
</tr>
<tr>
<td>Dermatology</td>
<td>1</td>
<td>AZ, CA, UT</td>
</tr>
<tr>
<td>Pediatric Medicine</td>
<td>2</td>
<td>AZ, CO, FL, GA</td>
</tr>
<tr>
<td>Urology</td>
<td>2</td>
<td>KY, MD</td>
</tr>
</tbody>
</table>

Model [1]: \( \ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})HCC_{ij} + (\beta_2 + u_{2j})HCC_{ij}^2 + \epsilon_{ij} \)
Outlier states fall outside of 95% confidence ellipses

Best nurse practitioner model

Best psychiatry model
Outlier states do not form a clear geographic pattern
Conclusions

Using richer Medicare Part D data, the relationship between mean HCC and SLOB often
• increases within the North et al. (2017) range of mean HCC scores, but then
• decreases and levels off among higher mean HCCs that North et al. do not observe

The relationship varies widely across specialties

Outlier states vary geographically and rarely include Rust Belt states (WV, MI, PA, WI)

The baseline statistical model best fits the Medicare data for most top specialties

Future work should build upon the methodology by
• addressing bimodality in certain specialties’ log(SLOB) distributions
• using a more granular geographic level than states
References


Thank you!