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

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Opioid overdose deaths have risen (1999-2016)
Opioid addiction has crippled the US

Opioids are pain-relievers, whether they come from
• doctors’ prescriptions (oxycodone, hydrocodone, synthetic opioids) or
• black markets (heroin, synthetic opioids)

Opioid overdose deaths persist: 46,802 in 2018; 50,042 in 2019

Purdue Pharma reached an $8B settlement w. the Dept. of Justice for
• paying doctors to promote and increase prescriptions of its drugs
• failing to prevent prescriptions from entering black markets
Physician prescriptions might contribute

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)
• found a positive association between average patient case complexity and physician propensity to prescribe opioids
• provided preliminary results using a convenient sample
North et al.’s approach is narrow

Their population: physicians at the Mayo Clinic in Rochester, MN

Their sample size: 100

Their physician specialties studied: family practice & internal medicine
North et al. motivate using richer data


This dataset has ~1.13M rows (i.e. physicians) and 84 columns.

Variables include:

• physician demographics (state, specialty, gender)
• claim types (opioids, antibiotics, antipsychotics)
• aggregate patient panel demographics (age, gender, race)
Key terms and variables

Part D: optional prescription drug coverage for Medicare patients

Patient panel: a physician’s entire group of patients (beneficiaries) seen

SLOB: a physician’s total supply length (in days) of all opioid prescriptions per opioid beneficiary
Key terms and variables

Hierarchical Condition Category (HCC) risk score
- compares a patient’s estimated medical expenditures to the Medicare population’s average medical spending
- higher scores = higher medical spending = higher case complexity

Mean HCC risk score: a patient panel’s average case complexity
North et al. motivate the following approach

I model the relationship between mean HCC score and SLOB

SLOB must be log-transformed
North et al. motivate the following approach

The distribution of log SLOB varies by physician specialty

I first study two specialties with roughly normal distributions
Simple linear regressions are insufficient

\[
\ln SLOB = \beta_0 + \beta_1 \overline{HCC} + \epsilon
\]
\[
\epsilon \sim N(0, \sigma^2)
\]

RMSE: 0.527

RMSE: 0.582
Splines can better fit nonlinearity

\[ y = S(x) \]

where

\[
S(x) = \begin{cases} 
S_0(x) = \sum_{i=0}^{k} \beta_{0i} x^i, & t_0 \leq x \leq t_1 \\
\vdots \\
S_{n-1}(x) = \sum_{i=0}^{k} \beta_{(n-1)i} x^i, & t_{n-1} \leq x \leq t_n 
\end{cases}
\]

for \( n \) knots \( t_1, \ldots, t_n \)

See Cosma Shalizi’s “Advanced Data Analysis from an Elementary Point of View” for more background
Cubic B-splines (w. 0 internal knots) fit better

RMSE: 0.521

RMSE: 0.575
Geographic variation motivates hierarchical modelling
A simple hierarchical model

For each physician \( i \), and state \( j \),

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

where

\[
u_{0j} \sim N(0, \sigma_0^2), u_{1j} \sim N(0, \sigma_1^2), \varepsilon_{ij} \sim N(0, \sigma^2)
\]

\( \hat{u}_{0j} \) is state \( j \)’s deviation from the average random intercept (0)

\( \hat{u}_{1j} \) is state \( j \)’s deviation from the average random slope (0)
Hierarchical Model Results

General Surgery

Random effects:

<table>
<thead>
<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
<th>Corr</th>
</tr>
</thead>
<tbody>
<tr>
<td>nppes_provider_state</td>
<td>(Intercept)</td>
<td>0.611680</td>
<td>0.78298</td>
<td>-0.33</td>
</tr>
<tr>
<td></td>
<td>mean_hcc</td>
<td>0.0002285</td>
<td>0.01515</td>
<td>-0.33</td>
</tr>
<tr>
<td>Residual</td>
<td></td>
<td>0.2862741</td>
<td>0.53506</td>
<td></td>
</tr>
</tbody>
</table>

Number of obs: 7772, groups: nppes_provider_state, 52

Fixed effects:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.923980</td>
<td>0.020988</td>
<td>91.472</td>
</tr>
<tr>
<td>0.075971</td>
<td>0.007824</td>
<td>9.698</td>
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</tbody>
</table>

Correlation of Fixed Effects:

| (Intr) | mean_hcc | -0.614 |

Orthopedic Surgery

Random effects:

<table>
<thead>
<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
<th>Corr</th>
</tr>
</thead>
<tbody>
<tr>
<td>nppes_provider_state</td>
<td>(Intercept)</td>
<td>0.04402</td>
<td>0.2098</td>
<td>-0.74</td>
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<tr>
<td></td>
<td>mean_hcc</td>
<td>0.03265</td>
<td>0.1807</td>
<td>-0.74</td>
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<tr>
<td>Residual</td>
<td></td>
<td>0.32159</td>
<td>0.5670</td>
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</table>

Number of obs: 9503, groups: nppes_provider_state, 52

Fixed effects:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.31322</td>
<td>0.043385</td>
<td>53.75</td>
</tr>
<tr>
<td>0.46702</td>
<td>0.03816</td>
<td>12.24</td>
</tr>
</tbody>
</table>

Correlation of Fixed Effects:

| (Intr) | mean_hcc | -0.868 |
States’ Predicted Random Effects
Key Interpretations

Both specialties’ fixed slopes alone suggest a positive relationship

A 95% CI for the general surgeons’ state slopes: [0.069, 0.083]

A 95% CI for the orthopedic surgeons’ state slopes: [0.199, 0.695]

No clear patterns emerge wrt states (so far . . . )
Next Steps

Improving the general and orthopedic surgeons’ models
  • *e.g.* using splines of mean HCC, more random effects

Moving to the specialties with trickier log SLOB distributions
  • *e.g.* family practice, internal medicine


Thank you!