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

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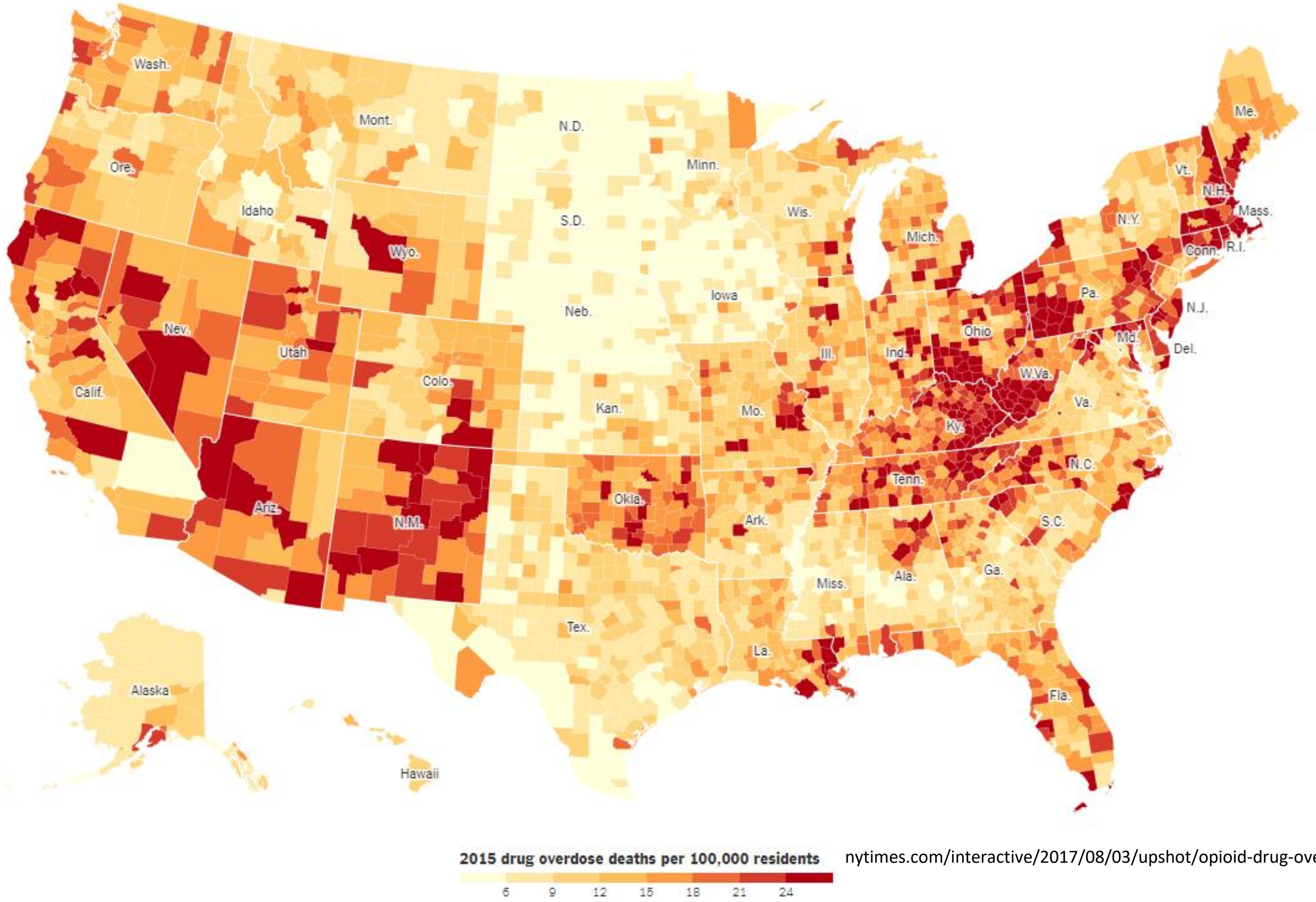
Opioid overdose deaths vary geographically



nytimes.com/interactive/2017/08/03/upshot/opioid-drug-overdose-epidemic.html

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

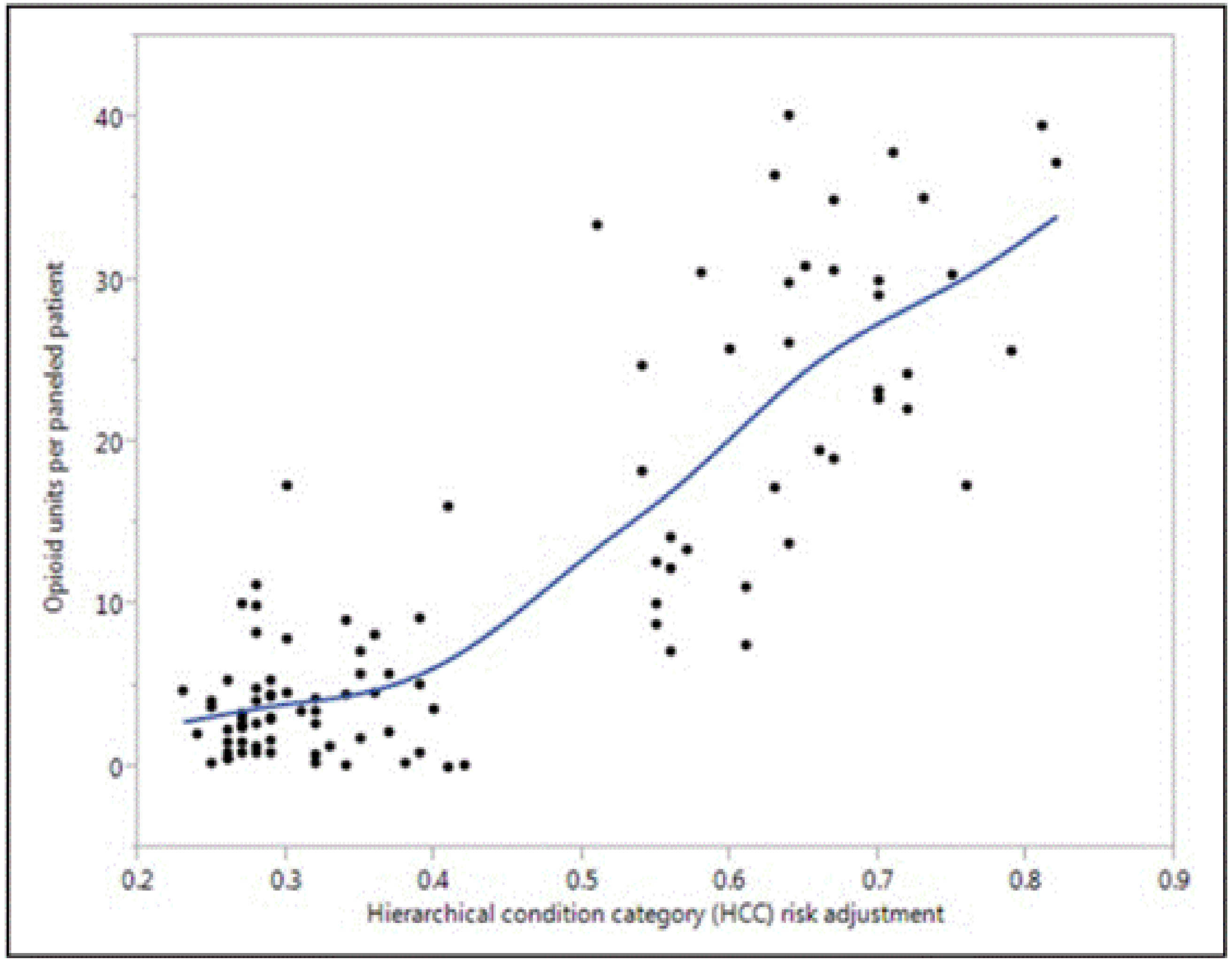
Mayo Clinic physicians in Rochester, MN

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

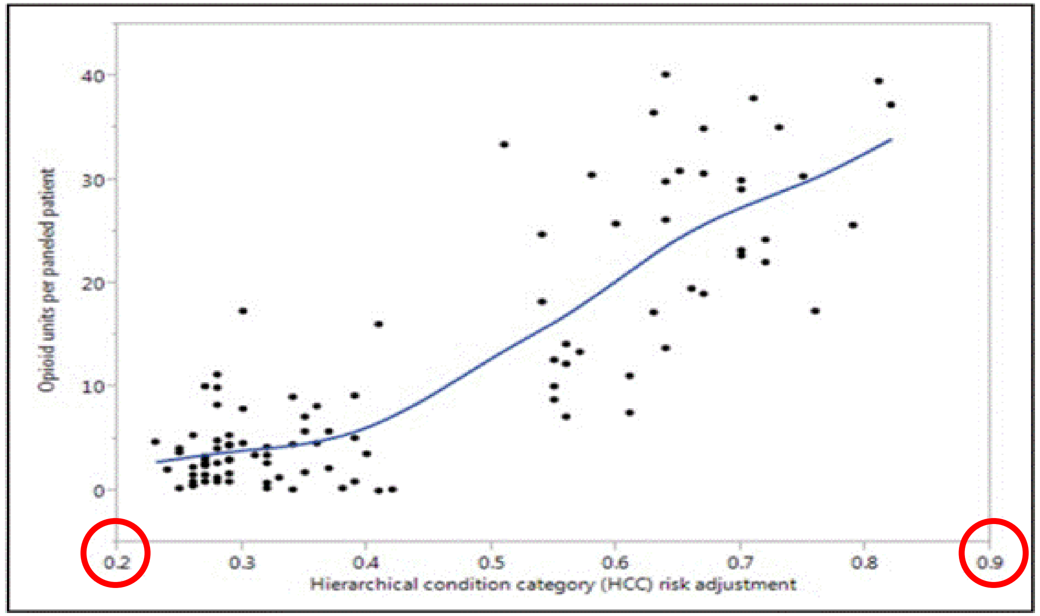
Captures over 1M physicians' prescriptions spanning from Jan. 1, 2016 to June 30, 2017

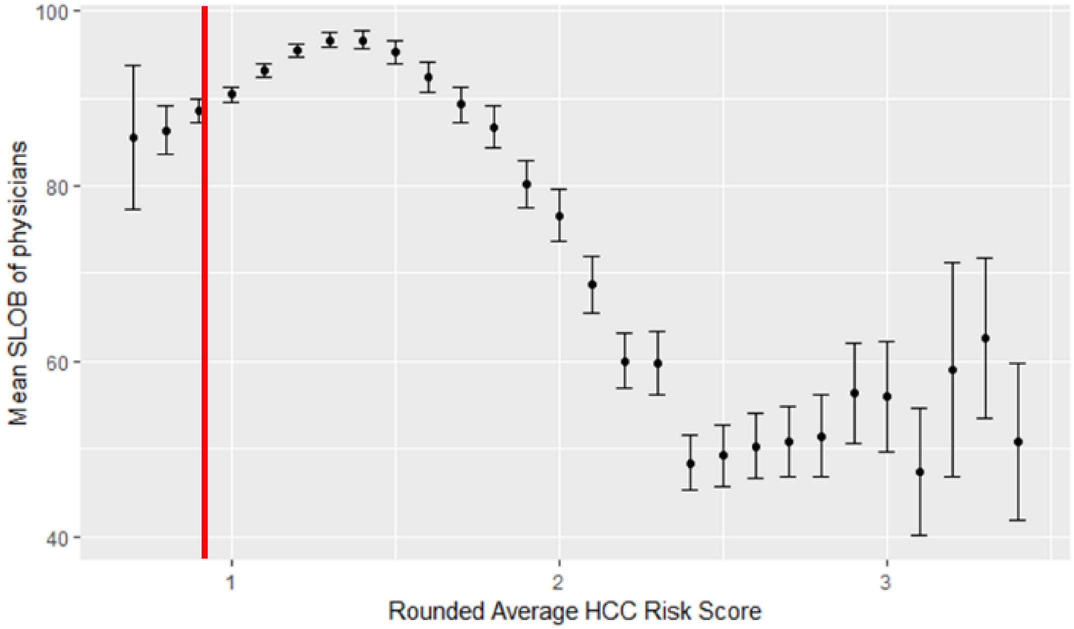
Includes the main variables of interest:

- 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

Medicare Part D: boomerbenefits.com/medicare-part-d-plans/what-is-part-d/

North et al. vs. Medicare Data: Association among family practitioners & internists





$0.2 < \overline{HCC} < 0.9$

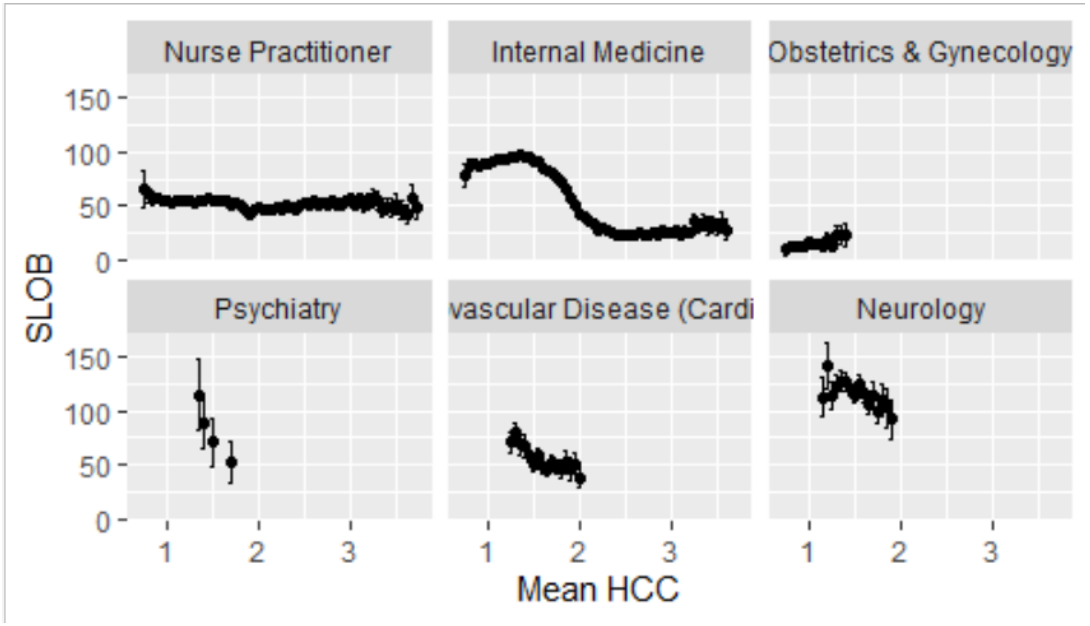
Positive, linear association

$0 < \overline{HCC} < 4.0$

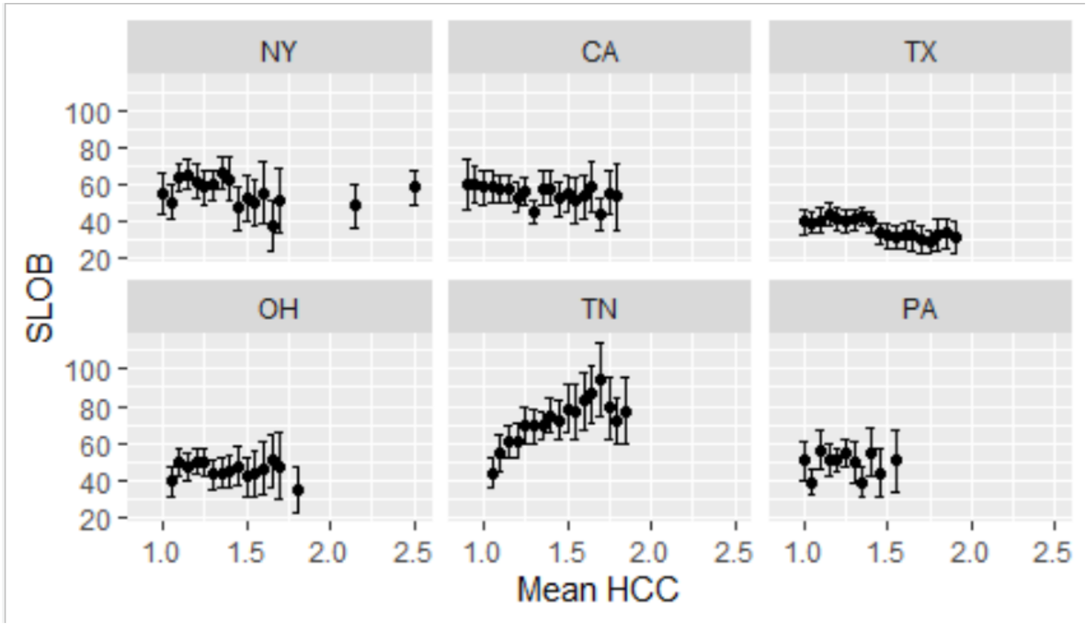
Positive, linear, but <u>then</u> becomes nonlinear when $\overline{HCC} > 1.0$

Methodology must consider two sources of variation

Across specialties

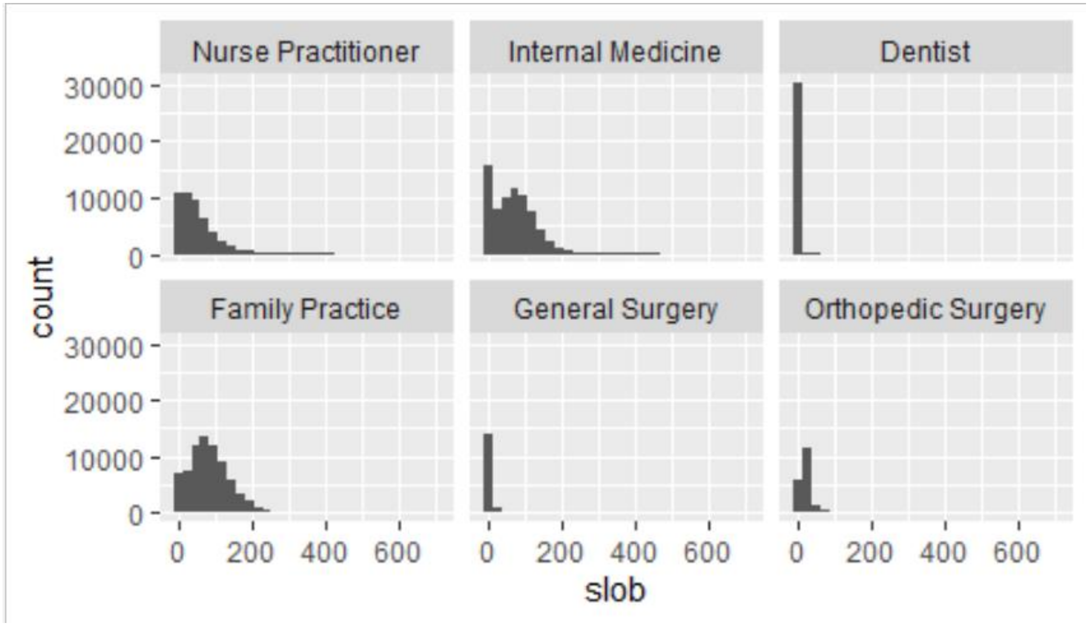


Across states within specialties (Below: nurse practitioners' top states)

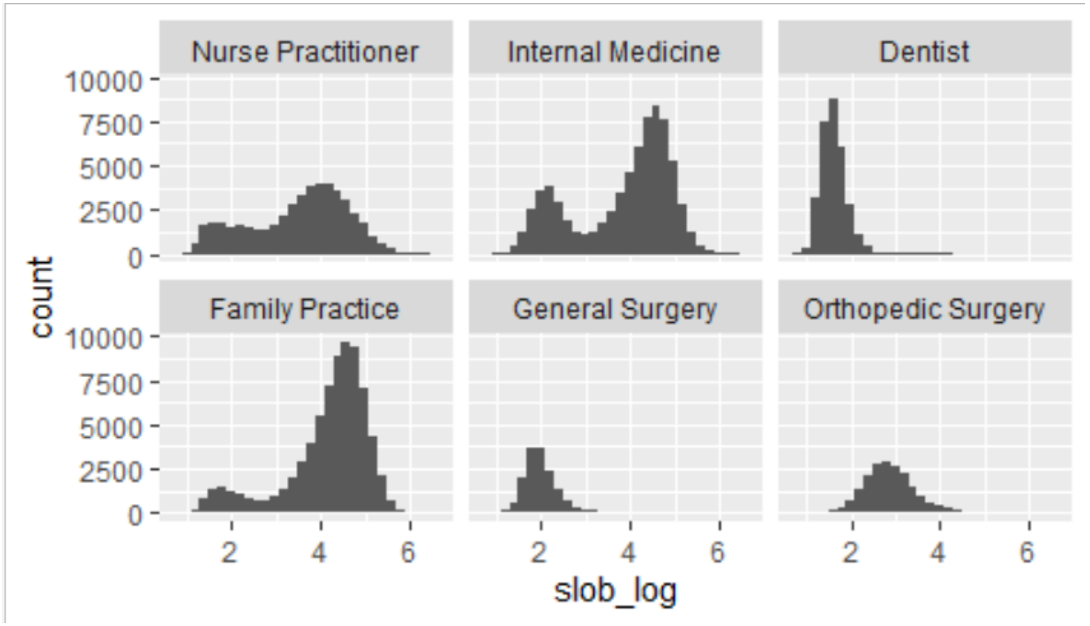


Transforming SLOB uncovers bimodality issues that future research must address

SLOB



log(SLOB)



Moving from exploratory analyses to methodology

Findings from exploratory analyses	**Methodology**
nonlinear association	specify quadratic linear model
variation across specialties	fit separate model for each specialty
variation across states within specialties	specify hierarchical models with state random effects
skewness in SLOB distribution	let Y = ln(SLOB)

Baseline statistical model

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

$$ln\left(SLOB_{ij}\right) = \left(\beta_0 + u_{0j}\right) + \left(\beta_1 + u_{1j}\right)\overline{HCC}_{ij} + \left(\beta_2 + u_{2j}\right)\overline{HCC}_{ij}^2 + \varepsilon_{ij}$$

where

$$u_{0j} \sim N(0, \sigma_0^2), u_{1j} \sim N(0, \sigma_1^2), u_{2j} \sim N(0, \sigma_2^2) \text{ and } \varepsilon_{ij} \sim N(0, \sigma^2)$$

Selecting each specialty's best model: a hypothesis-testing approach

Models compared	Null hypothesis	Test statistic	Decision rule
[1], [2]	Var(u_{2j}) = 0	$2(ln\,L_{[1]} - ln\,L_{[2]}) \sim \chi_1^2$	Pick **[1]** if p<.05; else continue
[2], [3]	β_2 = 0	$2(ln\,L_{[2]} - ln\,L_{[3]}) \sim \chi_1^2$	Pick **[2]** if p<.05; else continue
[3], [4]	Var(u_{1j}) = 0	$2(ln\,L_{[3]} - ln\,L_{[4]}) \sim \chi_1^2$	Pick **[3]** if p<.05; else continue
[4], [5]	Var(u_{0j}) = 0	$2(ln\,L_{[4]} - ln\,L_{[5]}) \sim \chi_1^2$	Pick **[4]** if p<.05; else continue
[5], [6]	β_1 = 0	$2(ln\,L_{[5]} - ln\,L_{[6]}) \sim \chi_1^2$	Pick **[5]** if p<.05; else pick **[6]**

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

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

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

[4] $ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + \beta_1\overline{HCC}_{ij} + \varepsilon_{ij}$

[5] $ln(SLOB_{ij}) = \beta_0 + \beta_1\overline{HCC}_{ij} + \varepsilon_{ij}$

[6] $ln(SLOB_{ij}) = \beta_0 + \varepsilon_{ij}$

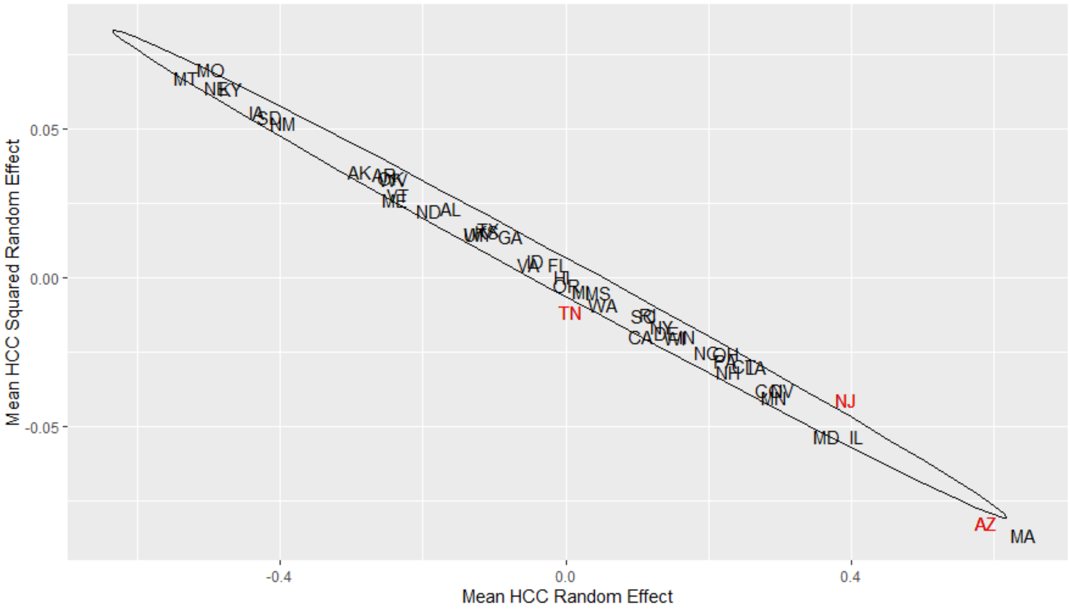
Baseline (**[1]**) is the most common best model

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

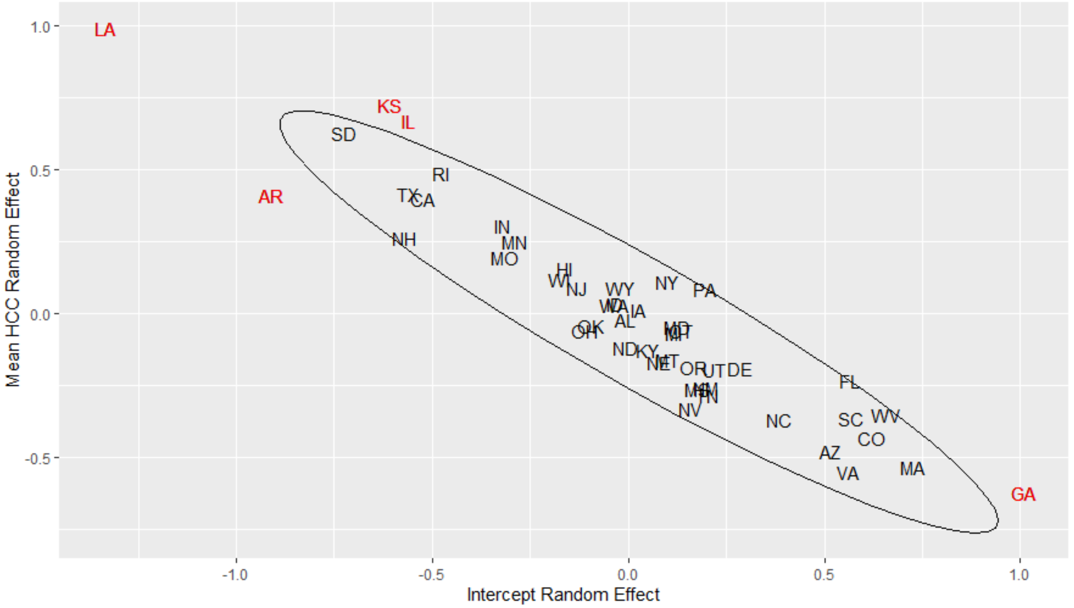
Model **[1]**: $ln(SLOB_{ij}) = (\beta_0 + u_{0j}) + (\beta_1 + u_{1j})\overline{HCC}_{ij} + (\beta_2 + u_{2j})\overline{HCC}_{ij}^2 + \varepsilon_{ij}$

Outlier states fall outside of 95% confidence ellipses

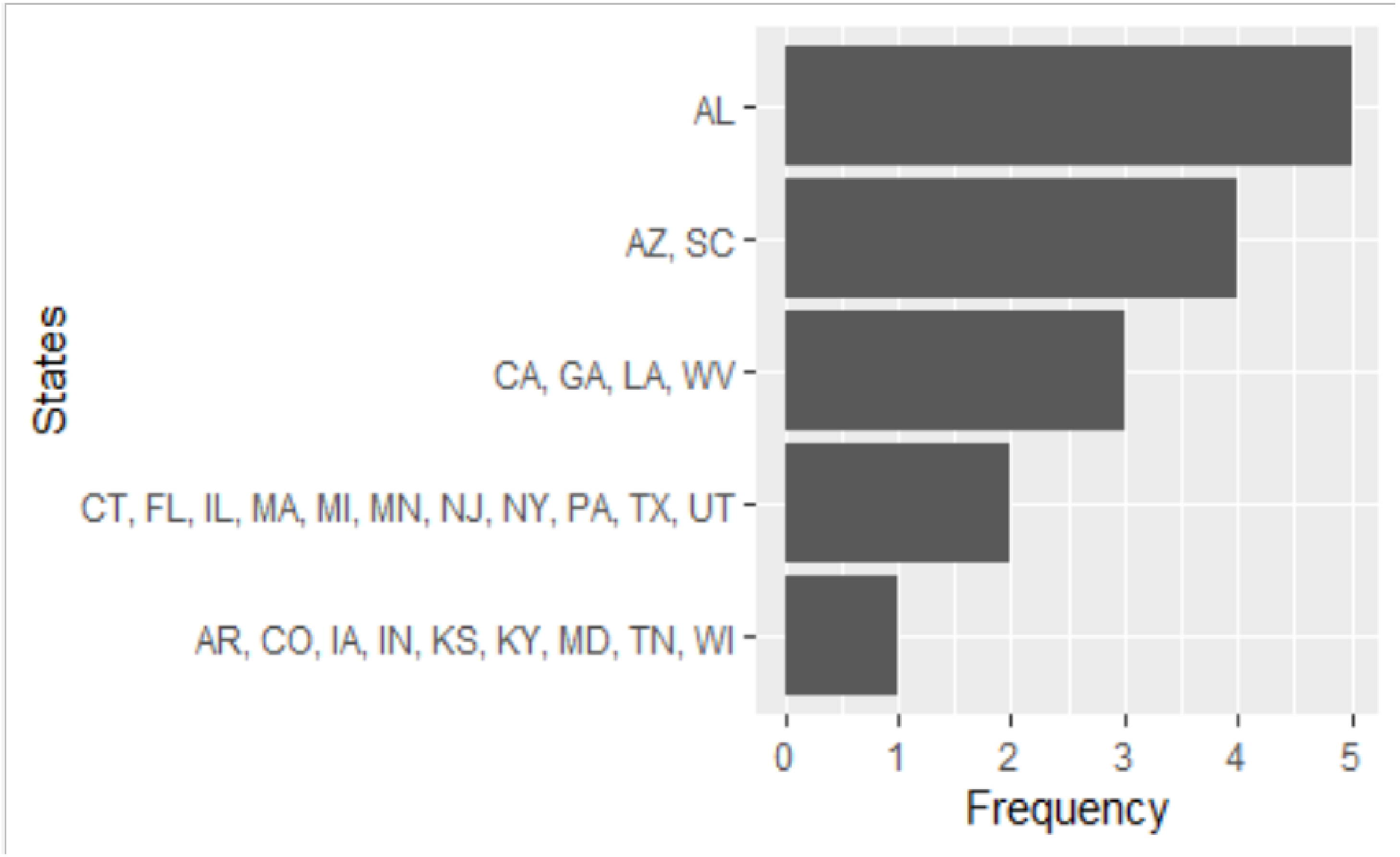
Best nurse practitioner model



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

Barnett, M. L., Olenski, A. R., & Jena, A. B. (2017). Opioid-Prescribing Patterns of Emergency Physicians and Risk of Long-Term Use. *The New England Journal of Medicine*, 376(7), 663-673.

Lembke, A., & Chen, J. H. (2016). Use of Opioid Agonist Therapy for Medicare Patients in 2013. *JAMA Psychiatry*, 73(9), 990-992.

North, F., Tulledge-Scheitel, S. M., & Crane, S. J. (2017). Association of provider opioid prescribing practices and the Centers for Medicare and Medicaid Services hierarchical condition category score: A retrospective examination of correlation between the volume of provider-prescribed opioid medications and provider panel complexity. *SAGE Open Medicine*, 5, 1-7.

Thank you!