“On the One Hand…”—Econometrics for Anesthesiologists

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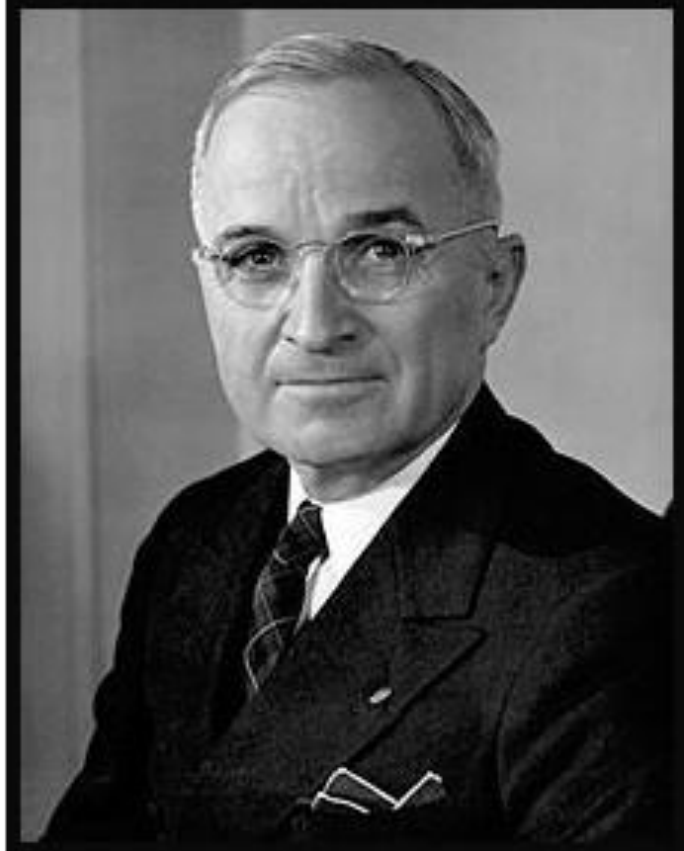
Disclaimer

- The work I am discussing precedes my appointment to the staff of the Council of Economic Advisers
- I am speaking in my capacity as an assistant professor at Stanford University
- Nothing in this talk should be construed as representing the views of the Federal Government

Disclosures

- No conflicts of interest to report
- I receive funding from the National Institute on Drug Abuse (K08DA042314)

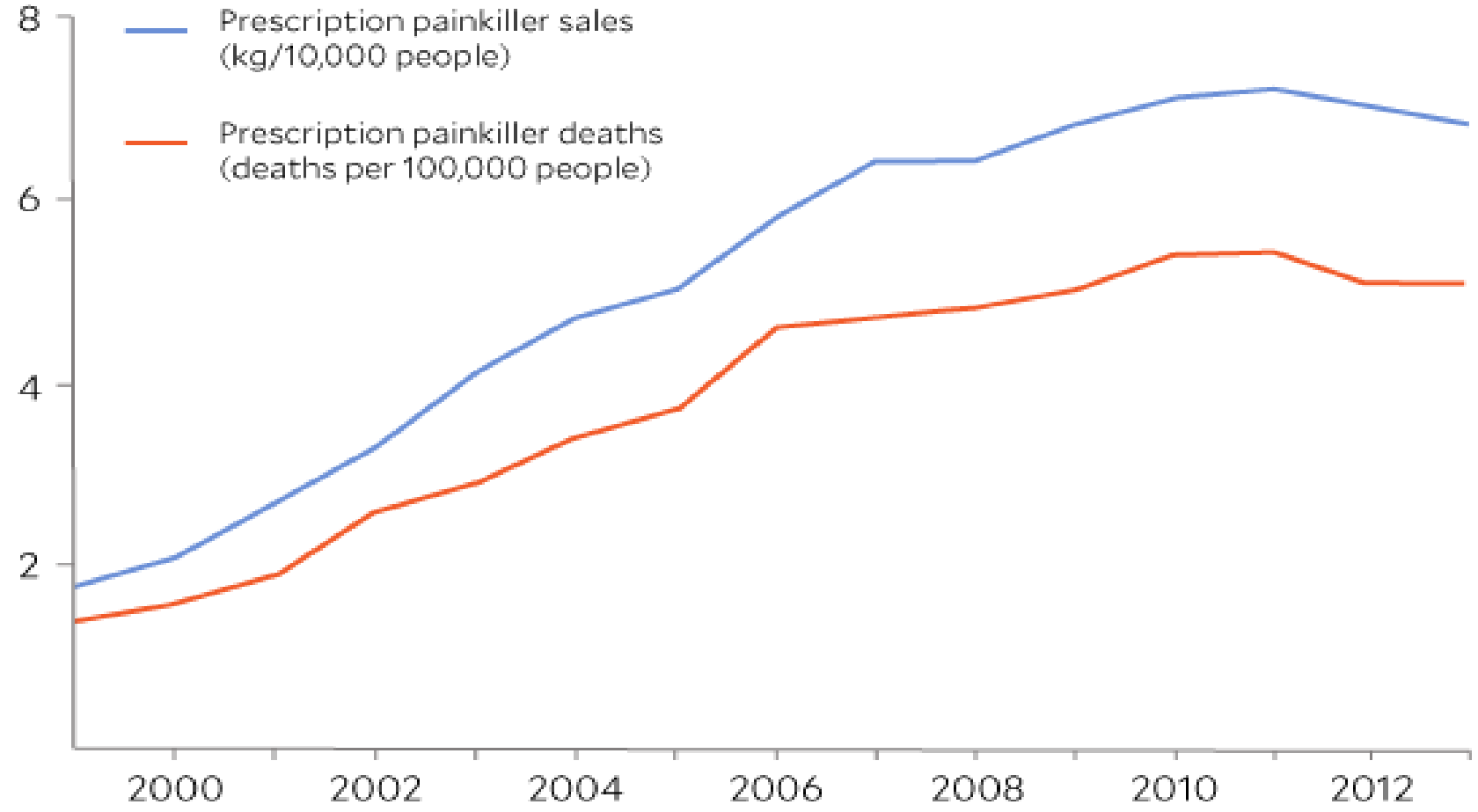


Give me a one-handed economist! All my economists say, On the one hand on the other.

(Harry S. Truman)

izquotes.com

Prescription Opioid Sales and Deaths, 1999-2013



Sources: National Vital Statistics System, Drug Enforcement Administration

MotherJones

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

$$Opioid\ Use\ (2001) = N_c^{2001}\mu_c^{2001} + N_L^{2001}\mu_L^{2001}$$

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

minus

$$Opioid\ Use\ (2001) = N_c^{2001}\mu_c^{2001} + N_L^{2001}\mu_L^{2001}$$

$$\Delta Opioid\ Use =$$

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

minus

$$Opioid\ Use\ (2001) = N_c^{2001}\mu_c^{2001} + N_L^{2001}\mu_L^{2001}$$

$$\Delta Opioid\ Use = N_c^{2013}(\mu_c^{2013} - \mu_c^{2001}) + N_L^{2013}(\mu_L^{2013} - \mu_L^{2001}) + \mu_c^{2013}\left(N_C^{2013} - N_c^{2001}\right) + \mu_L^{2013}(N_L^{2013} - N_L^{2001})$$

Growth in use (chronic)

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

minus

$$Opioid\ Use\ (2001) = N_c^{2001}\mu_c^{2001} + N_L^{2001}\mu_L^{2001}$$

$$\Delta Opioid\ Use = N_c^{2013}(\mu_c^{2013} - \mu_c^{2001}) + N_L^{2013}(\mu_L^{2013} - \mu_L^{2001}) + \mu_c^{2013}\left(N_C^{2013} - N_c^{2001}\right) + \mu_L^{2013}(N_L^{2013} - N_L^{2001})$$

Growth in use (chronic)

Growth in use (low)

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

minus

$$Opioid\ Use\ (2001) = N_c^{2001}\mu_c^{2001} + N_L^{2001}\mu_L^{2001}$$

$$\Delta Opioid\ Use = N_c^{2013}(\mu_c^{2013} - \mu_c^{2001}) + N_L^{2013}(\mu_L^{2013} - \mu_L^{2001}) + \mu_c^{2013}\left(N_C^{2013} - N_c^{2001}\right) + \mu_L^{2013}(N_L^{2013} - N_L^{2001})$$

Growth in use (chronic)

Growth in use (low)

Growth in n (chronic)

$$Opioid\ Use\ (2013) = N_c^{2013}\mu_c^{2013} + N_L^{2013}\mu_L^{2013}$$

minus

$$Opioid\ Use\ (2001) = N_c^{2001}\mu_c^{2001} + N_L^{2001}\mu_L^{2001}$$

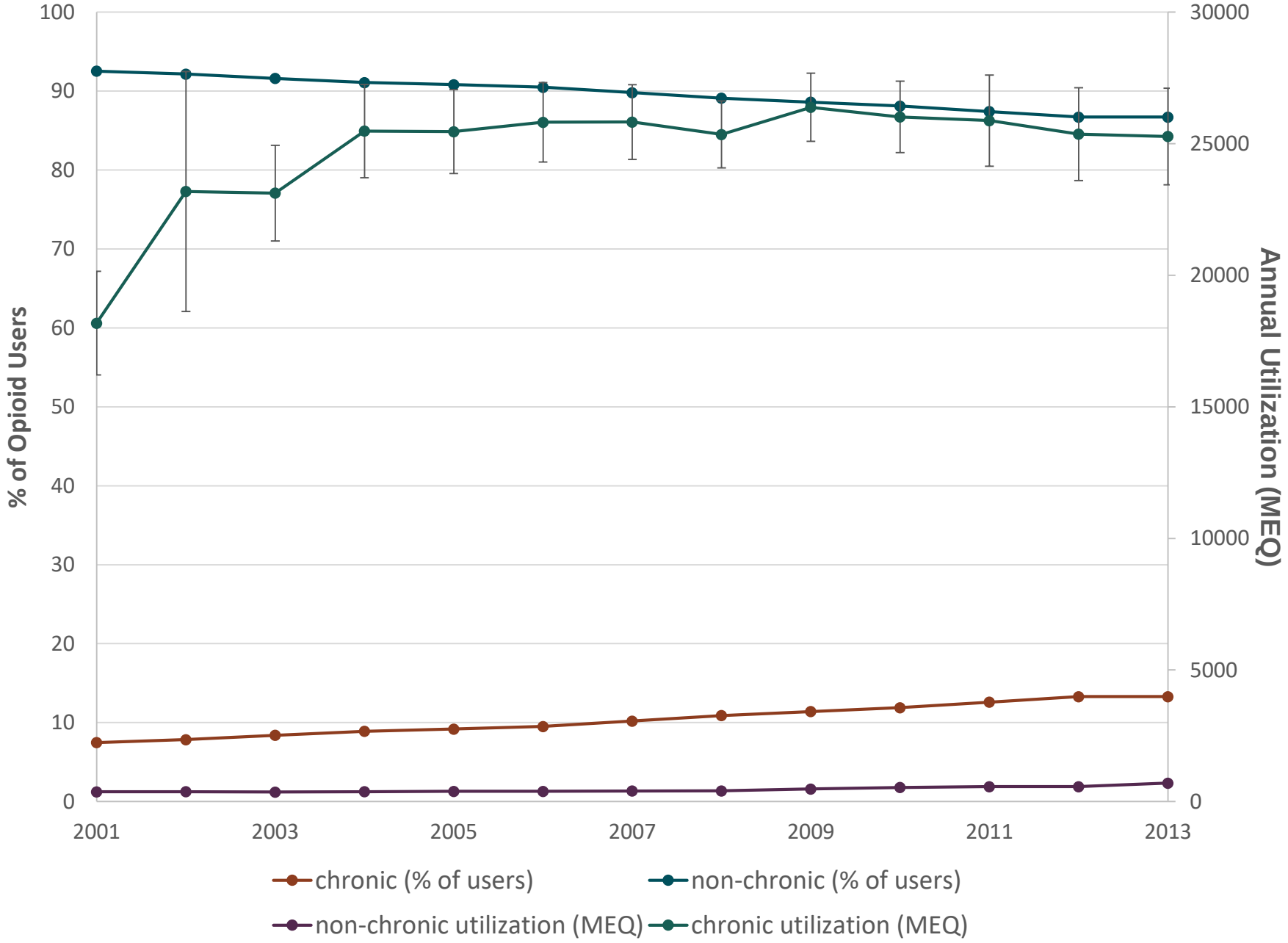
$$\Delta Opioid\ Use = N_c^{2013}(\mu_c^{2013} - \mu_c^{2001}) + N_L^{2013}(\mu_L^{2013} - \mu_L^{2001}) + \mu_c^{2013}\left(N_C^{2013} - N_c^{2001}\right) + \mu_L^{2013}(N_L^{2013} - N_L^{2001})$$

Growth in use (chronic)

Growth in use (low)

Growth in n (chronic)

Growth in n (low)


100
90
80
70
60
50
40
30
20
10
0
% of Opioid Users
30000
25000
20000
15000
10000
5000
0
Annual Utilization (MEQ)
2001
2003
2005
2007
2009
2011
2013
chronic (% of users)
non-chronic (% of users)
non-chronic utilization (MEQ)
chronic utilization (MEQ)

- Results
  - 47% of growth due to increase in number of chronic users
  - 42% of growth due to increase in use among chronic users

Annals of Internal Medicine®

LETTERS | 7 NOVEMBER 2017

Distribution of Prescription Opioid Use Among Privately Insured Adults Without Cancer: United States, 2001 to 2013

Eric C. Sun, MD, PhD; Anupam B. Jena, MD, PhD

Article, Author, and Disclosure Information

Background: Deaths from prescription opioids have sharply increased in the United States. In response, the Centers for Disease Control and Prevention recently issued recommendations for opioid prescribing for chronic pain (1). In light of this and other public health efforts, an integral piece of epidemiologic information about opioid misuse remains unknown: the distribution of use across the population. This fact has important policy implications. Concentration of opioid use among a few patients would argue for focused efforts aimed at reducing use among these persons.

Outline of Talk

- Why do we care about retrospective studies?
- Overview of Econometric Methods

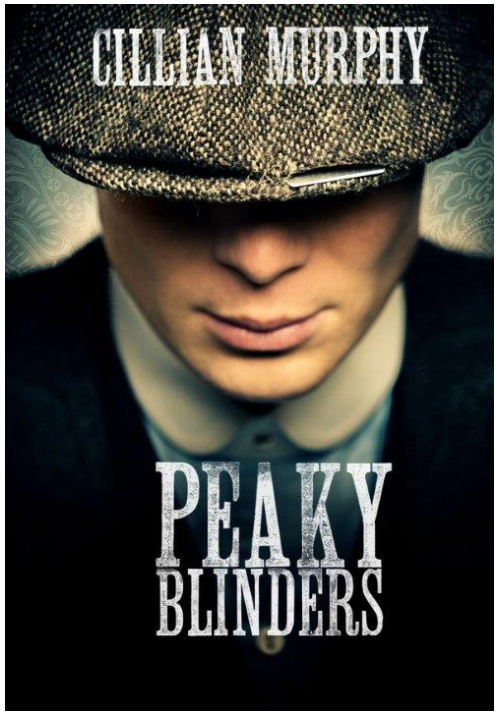
Outline of Talk

- **Why do we care about retrospective studies?**
- Overview of Econometric Methods

Limitations of Clinical Trials

- Key Benefit: Internal Validity
  - Randomization ensures that (on average), treatment and control populations are similar
- Key Drawback: External Validity
  - Homogenous population
  - Do not address “real world” concerns such as costs, health care system
  - “Machinery” of trials ensure that population likely different from “real world” population
  - Philipson et al. 2011; Rothwell 2006; Patsopoulos, 2011

Limitations of Clinical Trials



Limitations of Clinical Trial

- Studio Test Audience Differs from General Viewing Public in Two Significant Ways
  - Found out about screening
    - Often have industry connections/motivated
  - Interested enough to attend
    - Attending a screening is more costly than watching TV at home (commuting, interviews, etc)
- Bottom Line: More likely to “like” TV more than the average viewer
  - Note that this difference is *not* simply differences in observable characteristics

Limitations of Clinical Trials

- Similarly, trial patients likely to be different from “real world” patients
  - Key is (a) found out about trial and (b) willing to enroll
    - More motivated
    - More open to the therapy
- Trial protocols tend to exacerbate these differences
  - “run in” periods
  - “helpful reminders”
- May affect external validity if compliance/adherence are important

Limitations of Clinical Trials

- Clinical trials measure *efficacy*
- Policymakers interested in *effectiveness*
  - How does treatment work in the context of costs, adherence, etc.
- Secondary data possible better able to address effectiveness
  - Rooted in real world
  - Must address bias

Outline of Talk

- Why do we care about retrospective studies?
- **Overview of Econometric Methods**
  - Primer on bias
  - How can we deal with bias?

Outline of Talk

- Why do we care about retrospective studies?
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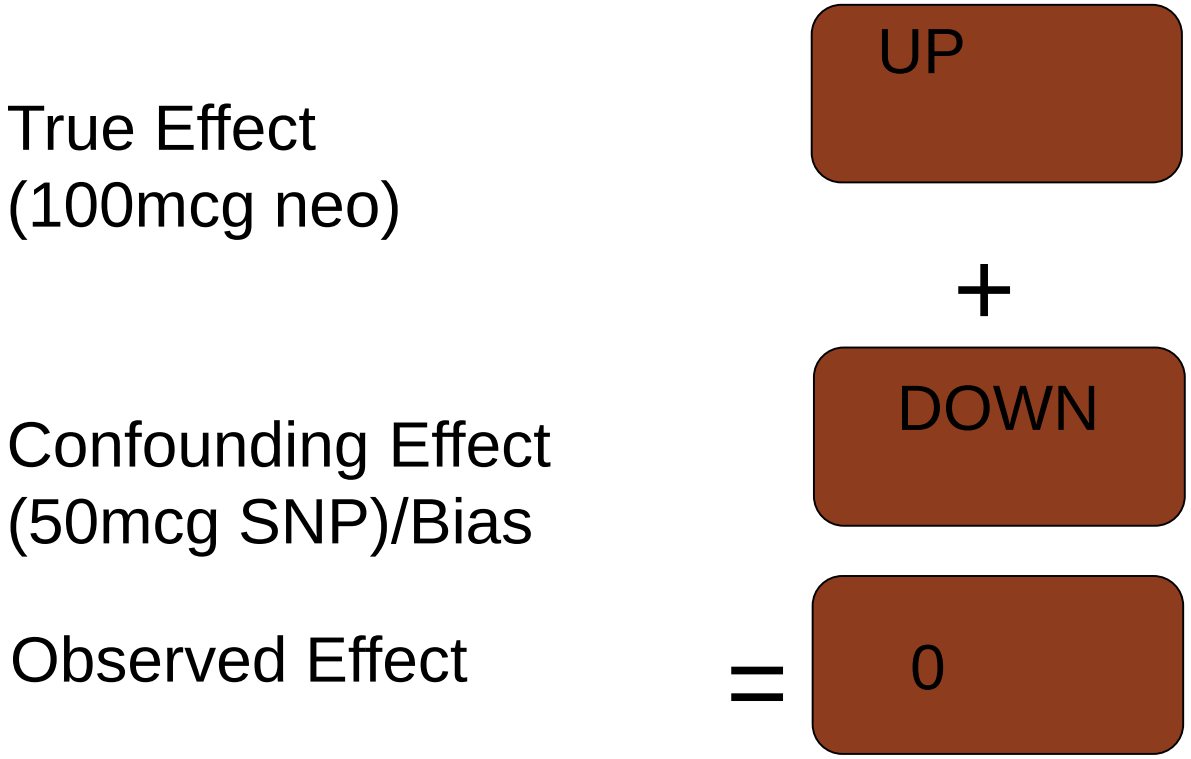
  - **Primer on bias**
  - How can we deal with bias?

Quick Primer on Bias

- Consider the following scenario
  - Resident see a low MAP, pushes 100mcg phenylephrine
    - Doesn‘t notice that his attending (med student?) also pushed 50mcg SNP

Quick Primer on Bias



Thinking about bias

True Effect
(100mcg neo)

UP

+

Confounding Effect
(200mcg neo)

UP

Observed Effect

=

UP!!!

Quick Primer on Bias

- For bias to be important:
  - Confounder is unobserved
  - Confounder is correlated with treatment
  - Potential effect of confounder helps sign bias
    - SNP: downward biased (observed effect less than true effect)
    - Neo: upward biased (observed effect more than true effect)

Outline of Talk

- Why do we care about retrospective studies?
- **Overview of Econometric Methods**
  - Primer on bias
  - **How can we deal with bias?**

Quick Primer on Bias

- How to Address Bias
  - Control for bias (e.g., watch what attending is doing)
  - Eliminate bias (e.g., IM succinylcholine)
    - Quasi-randomization, natural experiments

Controlling for bias

- Basic idea: identify possible confounders and “net out” their potential effect
- Comes with potential cost: decreased effective sample size

A Primer on Bias – Costs of Dealing with Bias

Suppose I want to see if height affects survival

- Two heights: short and tall

Sample size =100,000

- 50,000 tall
- 50,000 short

A Primer on Bias – Costs of Dealing with Bias

- So, my study will compare survival among 50,000 tall people to 50,000 short people
- Good power
- Likely to find a significant effect

A Primer on Bias – Costs of Dealing with Bias

Now, suppose I need to control for race

Assume

- 2 races: White, Asian
- most Whites are tall and most Asians are short

A Primer on Bias – Costs of Dealing with Bias

Now comparing “tall” to “short” is not sufficient

- Because I’m also comparing “white” to “Asian”

“Controlling” requires that I compare survival among

- tall whites to short whites
- tall Asians to short Asians
- Take average of above

A Primer on Bias – Costs of Dealing with Bias

Controlling for race effectively makes my sample size smaller

- Sample size now driven by “exceptions to the rule”
  - Need lots of short whites and tall asians
- May no longer have statistical power

Controlling for Bias

"..as we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say there are some things we know we do not know. But there are also unknown unknowns—the ones we don't know we don't know"

-Donald Rumsfeld

Controlling for Bias

- Most studies typically control/adjust for observable characteristics
  - i.e., age, sex, observable indicators of health
  - “known knowns”
- But what about unobservable characteristics?
  - “known unknowns”
  - “unknown unknowns”

Controlling for Bias

- Richness of MPOG data allow investigators to control for unobservables
  - Physician fixed effects, hospital fixed effects, year fixed effects
  - Adjust for unobservable characteristics unique to the physician, hospital , year

Physician Fixed Effects

Original Investigation

FREE

February 26, 2019

Association of Overlapping Surgery With Perioperative Outcomes

Eric Sun, MD, PhD[1,2]; Michelle M. Mello, JD, PhD[2,3]; Chris A. Rishel, MD, PhD[1]; et al

» Author Affiliations | Article Information

JAMA. 2019;321(8):762-772. doi:10.1001/jama.2019.0711

Quasi-Randomization

- We know as physicians—much of what determines whether a patient gets treatment A or B is random
  - Attending (consultant) preference
  - Distance to nearest hospital with given preferences/characteristics
  - Arbitrary cutoffs
- Quasi-randomization attempts to use this randomness to isolate causal effects

Quasi-Randomization

- Instrumental Variables
  - Identify something (instrument) that affects whether you get treatment but which likely has no effect on outcomes
    - Distance to nearest hospital with regional anesthesia capabilities (Neumann, 2014)
    - Number of AAs/CRNAs available to do cases on a given day (Sun, 2018)
    - Instrument is used to randomize patients
- Regression Discontinuity
  - Exploit arbitrary cutoffs to examine treatment effects
    - no nerve blocks if plt<100k
- MPOG contains lots of data one could exploit
  - Date/Time of surgery (call)
  - Lab values

Instrumental Variables

FREE

Perioperative Medicine | October 2018

Anesthesia Care Team Composition and Surgical Outcomes

Eric C. Sun, M.D., Ph.D.; Thomas R. Miller, Ph.D., M.B.A.; Jasmin Moshfegh, M.A., M.Sc.; Laurence C. Baker, Ph.D.

+ Author Notes

Anesthesiology 10 2018, Vol.129, 700-709. doi:10.1097/ALN.0000000000002275

Instrumental Variables

- Anesthesia care can be provided by either a nurse anesthetist (NA), or anesthesiologist assistant (AA), or physician (MD)
- Is there a difference in outcomes when a NA or AA is supervised by a MD?
- Important policy implications
  - NAs can practice in all 50 states, AA in only 16 states+DC
- Key Issue: Cases performed by NAs may differ from those performed by AAs
  - Address this issue by exploiting random daily variation in the AA/NA case mix
  - Call, vacation, etc
    - Unlikely to be association with patient/case severity as these schedules are determined long in advance

Key Takeaways

- Retrospective/database studies add tremendous value--if you can deal with bias
- One way to deal with bias is to adjust for potential confounders
  - Richness of MPOG data allow for use of specific fixed effects to adjust for *unobservable confounders*
- Another way to deal with bias is to consider “real-life” randomizations
  - Again, richness of MPOG data provide ways to exploit this

Questions?