

# Health disparities and fairness: discussion

Trang Quynh Nguyen  
trang.nguyen@jhu.edu

Departments of Mental Health and of Biostatistics  
Johns Hopkins Bloomberg School of Public Health

JSM session 220213  
2021.08.12

# Cheng talk. Establish disparity baseline for an intervention

Study goal: evaluate the effect of a preventive care program on dental health disparity between children on public health insurance and children on private health insurance

This component: establish baseline disparity as average difference in dental health b/w comparable groups matched on:

- ▶ individual-level vars: age, sex, race/ethnicity, urbanicity, distance from clinic, oral hygiene behavior, dental fear, caries risk level, phase of care
- ▶ clinic-level vars: urbanicity, number of patients, percent publicly insured, number of patient visits, dentist/hygienist-to-patient ratios
- ▶ community-level vars: median hh income, race/ethnicity composition, percent foreign born, percent below poverty line, employment rate, educ composition, percent kids w/o insurance, percent kids in married families, language

I'll comment on the defining of a disparity

## Defining a disparity – my early experience

match sexual minority/majority in a national survey to look at differences in health outcomes

– why did you adjust for education?

adjustment for covariates requires a lot more thought

## Defining a disparity – Jackson (2020)

“differences across socially privileged versus socially marginalized groups that society considers inequitable, avoidable, and unjust”

- ▶ health disparity: an avoidable, systematic difference in health between socially advantaged versus marginalized groups
- ▶ healthcare disparity: differences in healthcare services that are not due to differences in underlying health needs or preferences

# Defining a disparity – Jackson (2020)

“differences across socially privileged versus socially marginalized groups that society considers inequitable, avoidable, and unjust”

- ▶ health disparity: an avoidable, systematic difference in health between socially advantaged versus marginalized groups
- ▶ healthcare disparity: differences in healthcare services that are not due to differences in underlying health needs or preferences

Allowability – which sources of difference are fair and allowable?

- ▶ allowable: to adjust
- ▶ non-allowable: not to adjust

Allowability considerations

- ▶ modifiability/amenability to intervention: e.g., age, sex often allowed when considering racial health disparities
- ▶ social contract: e.g., distribution of goods based on fair criteria – when designing interventions
- ▶ purpose (societal vs. actor perspective): may allow differences that are outside of the actor’s control

## Defining a disparity – my early experience

from a societal perspective, education should be treated as a non-allowable

from the perspective of an NGO providing support for sexual minority adults, education might be an allowable

(but I was taking the societal perspective)

# Defining the baseline disparity for an intervention that aims to reduce disparity

the same considerations apply in guiding which covariates to adjust for and which not to adjust for

important: which components of disparity is the intervention intended to address?

- ▶ those should be treated as nonallowables and not adjusted away

note on matching on group membership

- ▶ corresponds to interest in disparity within groups only (should be intentional)

## Estimation of disparity defined based on allowables + nonallowables

Jackson (2020) provides formal definition of the disparity estimand based on allowables and nonallowables

and methods for estimation for a specific case

- ▶ requires appropriate piecing together of the joint distribution of allowables and nonallowables when removing contributions of allowables from the disparity measure

Also relevant is Nabi et al.'s (2019) method of projecting the observed data distribution onto the model where unfair/nonallowable pathways are zeroed out



# Katki talk. Impact of LC screening rec.s that incorporate risk/benefit prediction on disparities in screening eligibility

Previously, screening rec.s race/ethnicity blind (based on age, smoking history)

Disparity: African-Americans less eligible b/c smoke less, but have higher risk of cancer and earlier cancer

Screening rec.s that incorporate race-aware prediction models perform better on some fairness criteria

# The importance of good data

population:

- ▶ National Health Interview Survey (NIHS 2015)

build models to predict outcome in the absence of screening:

- ▶ Prostate, Lung, Colorectal, and Ovarian Cancer Screening Trial (PLCO)
- ▶ National Lung Screening Trial (NLST)
- ▶ National Health Interview Survey (NHIS 1997-2001)

inform assumption about benefit of screening:

- ▶ National Lung Screening Trial (NLST)

# What might be fair?

Thinking about fairness is hard, and maybe counter-intuitive

If knew each individual's  $Y_1, Y_0$  (POs under screening or not),  
might decide ( $D$ ) to recommend screening if:  $Y_0$  bad AND  $Y_1 - Y_0$  good  
– inspired by criteria used in the study

One way to think about fairness: want decision/eligibility that is equal across groups ( $G$ ) given  $(Y_0, Y_1 - Y_0)$  – *social contract* idea (Jackson 2020)

$$D \perp\!\!\!\perp G \mid (Y_0, Y_1 - Y_0)$$

– a generalized version of *equalized odds*

# What might be fair?

Thinking about fairness is hard, and maybe counter-intuitive

If knew each individual's  $Y_1, Y_0$  (POs under screening or not),  
might decide ( $D$ ) to recommend screening if:  $Y_0$  bad AND  $Y_1 - Y_0$  good  
– inspired by criteria used in the study

One way to think about fairness: want decision/eligibility that is equal across groups ( $G$ ) given  $(Y_0, Y_1 - Y_0)$  – *social contract* idea (Jackson 2020)

$$D \perp\!\!\!\perp G \mid (Y_0, Y_1 - Y_0)$$

– a generalized version of *equalized odds*

Depending on *perspective*,

- ▶ might want this parity for the screening that results,  $S(D)$  (instead of  $D$ )
- ▶ or might define POs for eligible or not (instead of screening or not)

To keep things simple, pretend  $D = S$ , or think of the PO subscript as for eligibility

# What might be fair?

So one ideal is equal treatment of equals

$$D \perp\!\!\!\perp G \mid (Y_1, Y_0) \quad \text{or} \quad D \perp\!\!\!\perp G \mid C$$

for some  $C = c(Y_1, Y_0)$  that we decide matters

Another desirable is equal outcome (under the decision) for equals

$$Y(D) \perp\!\!\!\perp G \mid (Y_1, Y_0) \quad \text{or} \quad Y(D) \perp\!\!\!\perp G \mid C$$

more complicated; relevant work Coston et al. (2020)

And there are other ways to think about fairness...

Things get complex when explicitly incorporating

- ▶ perspectives
- ▶ allowables/nonallowables (or unfair pathways)
- ▶ polar/nonpolar decisions (Paulus & Kent, 2020)

## Let's just consider equal treatment of equals

$$D \perp\!\!\!\perp G \mid C \text{ where } C = c(Y_1, Y_0)$$

but  $C$  is not observed

so use proxy  $\hat{C}$  – based on predictive covariates  $X$  and possibly  $G$

intuitive – equal treatment of equal risk/expected benefit

two natural questions

- ▶ when does  $D \perp\!\!\!\perp G \mid \hat{C}$  hold?
- ▶ when does it imply the ideal  $D \perp\!\!\!\perp G \mid C$ ?

## When does $D \perp\!\!\!\perp G \mid \hat{C}$ hold?

Interestingly,  $D \perp\!\!\!\perp G \mid \hat{C}$  holds if decision is based only on  $\hat{C}$ , i.e.,  $D = h(\hat{C})$ , because conditional on  $\hat{C}$ ,  $D$  is a constant

but not if decision is also based on some other variables, e.g.,  $D = h(\hat{C}, X)$ , due to  $D \leftarrow X \leftrightarrow G$

This suggests that if screening recommendation  $D$  is based purely on predicted risk and/or life-days gained ( $\hat{C}$ ), we should see no disparity conditional on  $\hat{C}$

but if screening rec. is based on  $\hat{C}$  combined with age, smoking history ( $X$ ), and  $X$  is differentially distributed across groups, we should generally see disparity in this metric

# Does $D \perp\!\!\!\perp G \mid \hat{C}$ imply $D \perp\!\!\!\perp G \mid C$ ?

Generally, no

$D = h(\hat{C})$  case:

$$P(D = d \mid G, C) = \sum_c P(D = d \mid \hat{C} = c)P(\hat{C} = c \mid G, C)$$

for this to not depend on  $G$ , we need  $\hat{C} \perp\!\!\!\perp G \mid C$ , but  $C$  is not a variable that breaks the  $G$ - $\hat{C}$  link

so what do we do? if  $P(\hat{C} \mid G, C)$  is identified, i.e.,  $C = Y_0$ ,

- ▶ estimate deviation from parity
- ▶ approximate parity by constrained regression (Zink & Rose, 2020) in fitting  $\hat{C}$ ?

$D = h(\hat{C}, X)$  case: similar result but conditioning on  $X$

note that conditioning on  $X$  means treating  $X$  as an allowable



## Zink talk. Fairness in insurance risk adjustment

Health care spending of certain groups are not predicted well by risk adjustment formula, resulting in under/overcompensation

which incentivizes insurers to favor/disfavor different groups

Identify under/overcompensated groups

Develop risk adjustment formulas that are more fair by incorporating fairness constraints

The result: improved fairness

# Constrained/penalized regression

with different constraints/penalizations based on different fairness metrics

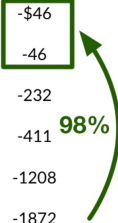
Which of the metrics does the insurer care about? Which (if fair) would remove the incentive to favor/disfavor groups?

to achieve fairness for the groups, we need fairness for the insurer

- ▶ group average constraint
- ▶ penalizing/constraining net compensation
- ▶ group-error covariance constraint
- ▶ penalizing difference in mean residual

## Large increases in fairness

Regression Method	R <sup>2</sup>	MHSUD Net Compensation
Average	12.4%	-\$46
Covariance	12.4	-46
Net Compensation	12.5	-232
Weighted Average	12.6	-411
Mean Residual Difference	12.8	-1208
Ordinary Least Squares	12.9	-1872



is net compensation the metric that matters?

unrelated: could the varying results be partly due to the difference b/w penalization and constant constraint?

# Purpose, polar/non-polar decisions, multiple actors

There is increased recognition that one size does not fit all

disparity/parity measures, prediction algorithms, etc. are best informed by *purpose*, e.g., whether decisions are *polar/non-polar* (Paulus & Kent 2020)

This work makes it clear that in perhaps many settings, there are more than one or two *perspectives*, and fairness (or not) results from the interacting actions of the multiple *actors*.

# History → decision → evolving actions

We aim to make fair decisions based on data (which reflects the past)

As such decisions change the incentive structure, the actions of different actors may change

A policy question is how to steer the chain of actions so that we converge to fairness and shorten the time to convergence

and a question for statisticians is how we can help with that

THANK YOU!