DOES GEOGRAPHY AFFECT HEALTH?

ISPOR US 2023 Social Determinants of Health Workshop

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May 9, 2023

AGENDA

1. Meet the Panel
2. Overview of Social Determinants of Health (SDoH)
3. Data Availability
4. Methodological Considerations
5. Panel Discussion

Meet the Panel

1

Many countries are working towards greater health equity, yet they often face an absence of data to guide policy

National

"Longer, healthy lives more likely in countries with strong health inclusivity"

-Health Inclusivity Index by *The Economist* (2022)

Community

"Health does not begin in a hospital or clinic. It begins in our homes and communities, with the food we eat and the water we drink, the air we breathe, in our schools and our workplaces"

-Dr Tedros Adhanom Ghebreyesus, WHO Director General

Individual

Inclusive health cannot be created by focusing on healthcare alone. What is known about the **social determinants of health** such as a patient's education, income level and environment matters in patient care

Panel

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AXTRIA
INGENIOUS INSIGHTS

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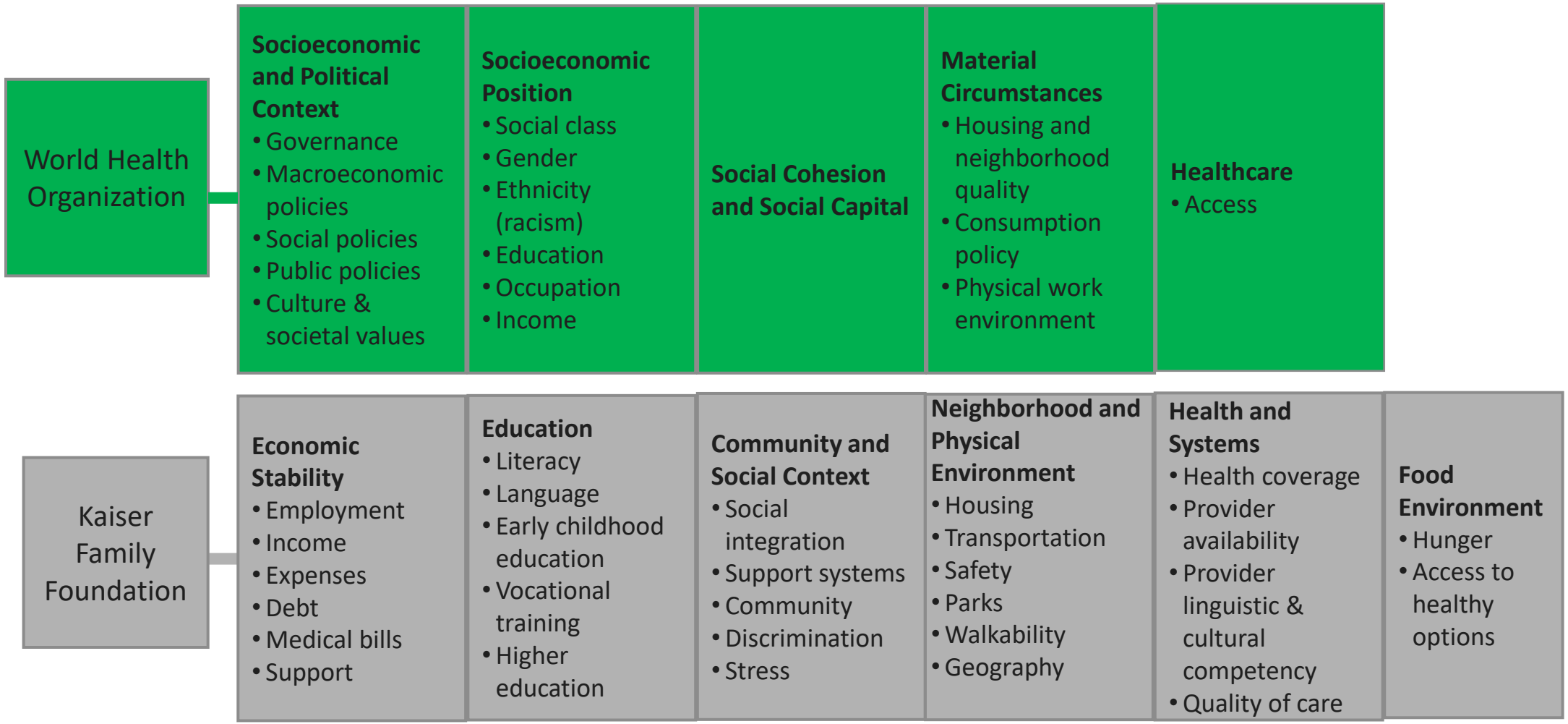
INGENIOUS INSIGHTS

Overview of Social Determinants of Health (SDoH)

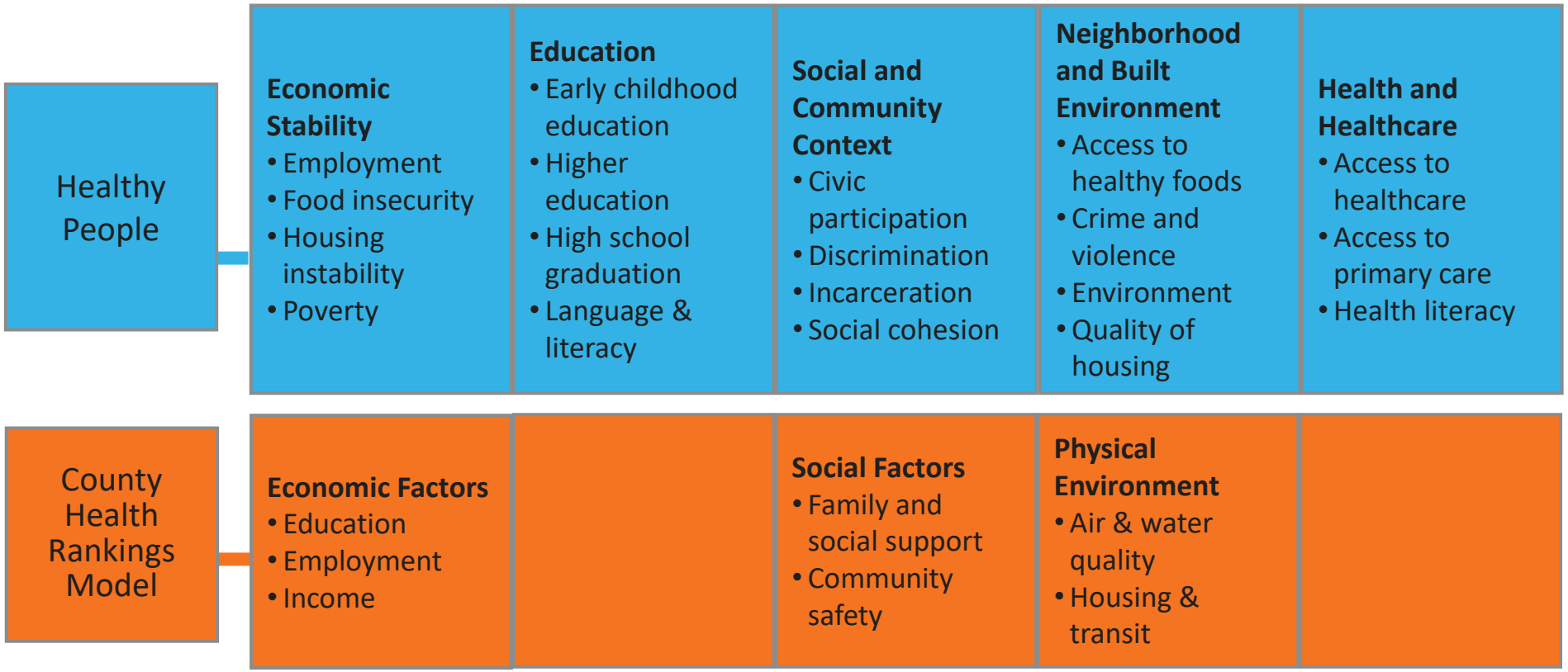
2

Social determinants of health (SDoH) are the non-medical factors that influence health outcomes



https://doi.org/10.2337/dci20-0053

Definitions of SDoH differ between organizations, but the main concepts remain similar



https://doi.org/10.2337/dci20-0053

Healthy people 2030 aims to create social, physical, and economic environments that promote attaining the full potential for health and well-being for all

Education Access and Quality
- Early Childhood Development and Education
- Enrollment in Higher Education
- High School Graduation
- Language and Literacy

Health and Healthcare
- Access to Health Services
- Access to Primary Care
- Health Literacy

Economic Stability
- Employment
- Food Insecurity
- Housing Instability
- Poverty

Neighborhood and Built Environment
- Access to Healthy Foods
- Crime and Violence
- Environmental Conditions
- Quality of Housing

Social and Community Context
- Civic Participation
- Discrimination
- Incarceration
- Social Cohesion

1

CDC's six pillar framework to address SDoH:

2

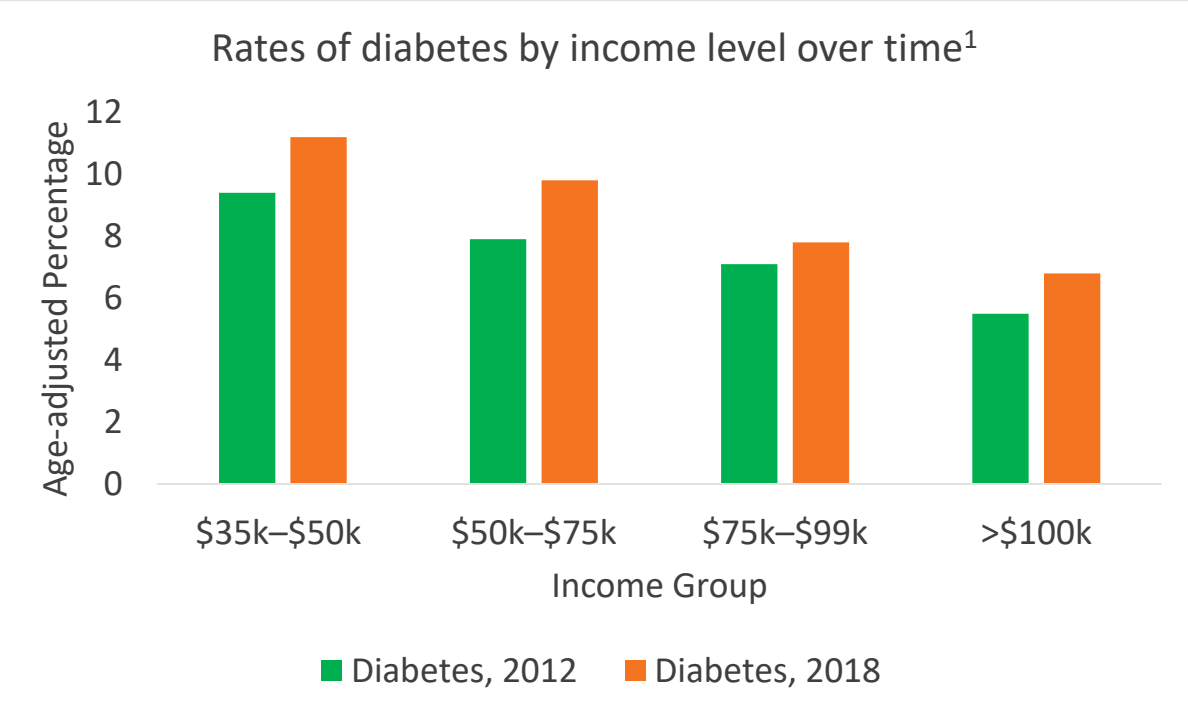
Our aim is to highlight how disparities in SDoH can be addressed through leveraging data to generate evidence supporting health equity research

1. https://health.gov/healthypeople; **2.** https://www.cdc.gov/about/sdoh/cdc-doing-sdoh.html

However, chronic conditions show disparity across different income levels

https://frac.org/blog/whats-state-childhood-obesity

To address disparities in diabetes, the American Diabetes Association has proposed a Health Equity Bill of Rights



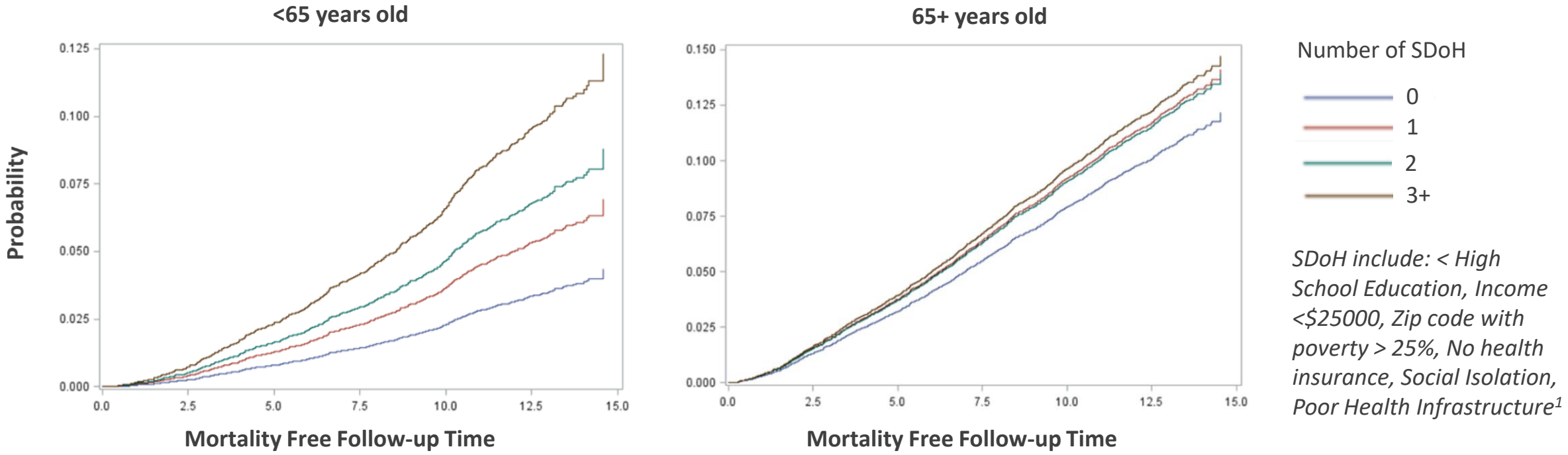
The American Diabetes Association published a **Health Equity Bill of Rights**[2] in 2020 which focuses on creating a future without unjust health disparities.

Some of these rights include:

- The right to access insulin & other drugs affordably
- The right to insurance that covers diabetes management and future cures
- The right not to face stigma or discrimination
- The right to the latest medical advances

1. https://www.cdc.gov/nchs/nhis/shs/tables.htm; 2. https://diabetes.org/healthequitynow

The American Cancer Society also seeks to reduce disparities in cancer care through health equity initiatives



- The **American Cancer Society (ACS)** has been undertaking various initiatives to promote health equity and reduce disparities in cancer care
- Some of the initiatives include the CHANGE[2] program and partnerships with organizations like NAACP[3] and NHMA[4]
- These initiatives facilitate greater outreach and enable effective interventions for underserved populations

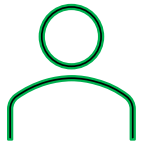
1. https://doi.org/10.1002/cncr.33894; 2. CHANGE: Community Health Advocates Implementing Nationwide Grants for Empowerment and Equity; 3. NAACP: National Association for the Advancement of Colored People; 4. NHMA: National Hispanic Medical Association

To promote health equity, the FDA has issued guidance to sponsors for trial recruitment of underrepresented racial/ethnic groups

FDA guidance outlines how to collect and present **race and ethnicity** data and recommends that sponsors develop a plan to address the inclusion of clinically relevant populations. This guidance focuses on racial and ethnic demographic characteristics of study populations to identify issues like health disparities and differential access to healthcare[1]

NIH National Institute on Minority Health and Health Disparities

The PhenX Social Determinants of Health Assessment Collection - toolkit for data protocols to help measure individual / structural factors that shape behaviors & health outcomes[2]



Individual-level

- Access to health services
- Discrimination in healthcare
- Family history of incarceration
- Housing instability
- Internet access

Community-level

- Minimum wage
- Neighborhood biking and walking environment
- Water access and sanitation
- Race/ethnic residential segregation
- Residential concentrations of income

1. https://www.fda.gov/media/157635/download ; 2.https://www.nimhd.nih.gov/resources/phenx/

Payers' increasing focus on SDoH has prompted the pharmaceutical industry to incorporate health equity in their research and business objectives

Payers are focusing on differences in **clinical and economic** outcomes between patients with different insurance coverage types (Medicare Advantage vs. fee-for-service, dual eligible, etc.).[1]

In response to payer recommendations, the healthcare industry has begun to recognize that focusing on medical care alone is not an effective way to manage population health. Pairing medical care with SDoH, could significantly **improve care, lower costs, and improve quality of life** for millions.[2]

1. Jiang S, et al. (2022). *Journal of managed care & specialty pharmacy*, *28*(11), 1321–1330. https://doi.org/10.18553/jmcp.2022.28.11.1321; **2.** https://www.ehidc.org/sites/default/files/resources/files/Importance%20of%20SDOH%20Data%20March%202019.pdf

However, there are several barriers related to improving delivery of care through SDoH

Cross-agency collaboration

Between **45%** and **57%** of SDoH stem from outside of the healthcare system and 80 percent of what influences health comes from beyond one's physician visits.[1] Only **one-third** of stakeholders reported partnering with community–based support groups to address social needs.[2]

Care gap

To properly **care** for a patient, treatments must positively impact their knowledge, attitudes, and motivations, as well as their physical health in a cost-effective manner. Without full understanding of a patient's social determinants of health, treatment is limited.[3]

1. https://www.ncqa.org/wp-content/uploads/2021/06/20210622_NCQA_Health_Equity_Social_Determinants_of_Health_in_HEDIS.pdf; 2. Heidari E, et al. (2022). *Journal of managed care & specialty pharmacy*, *28*(5), 538–543; 3. https://certintell.com/blog/the-sdoh-care-gap/

There are also several data-related gaps in current practice for SDoH research

Substantial Costs

The costs of acquiring and/or analyzing **"omic"** data linked to other sources of RWD can be substantial (i.e., tens of millions of dollars per year to license specialty datasets, or billions of dollars to acquire RWD providers), and the return on investment is difficult to determine. [1]

Poor Data Collection

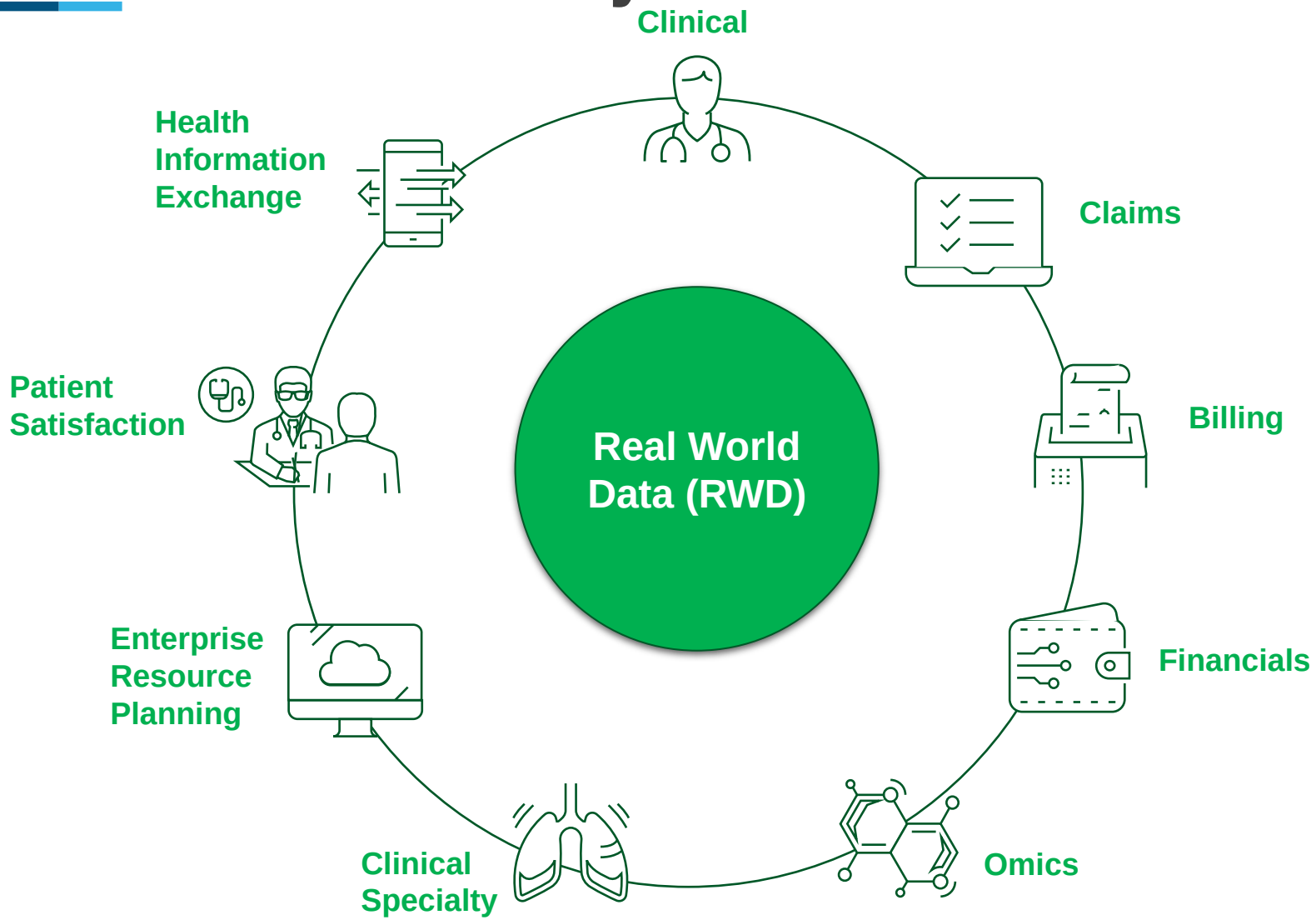
There is a lack of comprehensive data for both health and social outcomes; lack of large sample sizes, particularly for subgroup analyses; and differences in unmeasured characteristics between those who participate in health-related social needs (**HRSN**) interventions and those who do not.[2]

1. Dagenais S, et al. (2022). *Clinical pharmacology and therapeutics*, *111*(1), 77–89. https://doi.org/10.1002/cpt.2480; **2.** SDOH-Evidence-Review.pdf (hhs.gov)

Data Availability

3

Real-world data (RWD) are related to patient health status and/or the delivery of healthcare routinely collected from a variety of sources



SDoH can be used to support diversity, equity, and inclusion (DE&I) in clinical trials

Identifies study population where inclusion/exclusion criteria are related to DE&I (e.g., certain race/ethnicity groups)

Improves DE&I in trials by targeting the sites with higher disparity rates

Evaluates the impact of SDoH factors on clinical outcomes of interest with post-hoc trial data analysis

SDoH data can bring additional insights to RWD studies

- Linkage of SDoH data at the patient or geographical level

- Evaluate the impact of targeted interventions in the real-world setting

- Identify unmet needs among populations with certain SDoH characteristics

- Identify additional SDoH-related risk factors and confounders to improve study design, analysis and the interpretation of outcomes

However, availability of SDoH data varies across RWD sources

Primary Surveys

- Owned by study sponsor
- Specific patient population; small sample sizes
- Depending on objective, can contain rich SDoH information

Patient Registries

- May be available for research purposes
- Specific patient population; sample sizes vary
- Tend to contain rich patient data, including SDoH

EHR Data

- A digital version of a patient's medical chart, generated during care delivery
- Can contain SDoH information

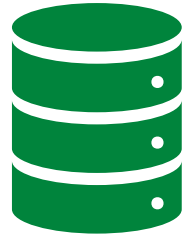
Administrative Claims

- Widely available for research purposes
- General population; medical, pharmacy, lab claims; large sample sizes
- SDoH usually very limited

There are multiple sources of SDoH data that can enhance insights derived from administrative claims

Z-codes for diagnostic documentation in administrative claims

Area-level SDoH from publicly available datasets

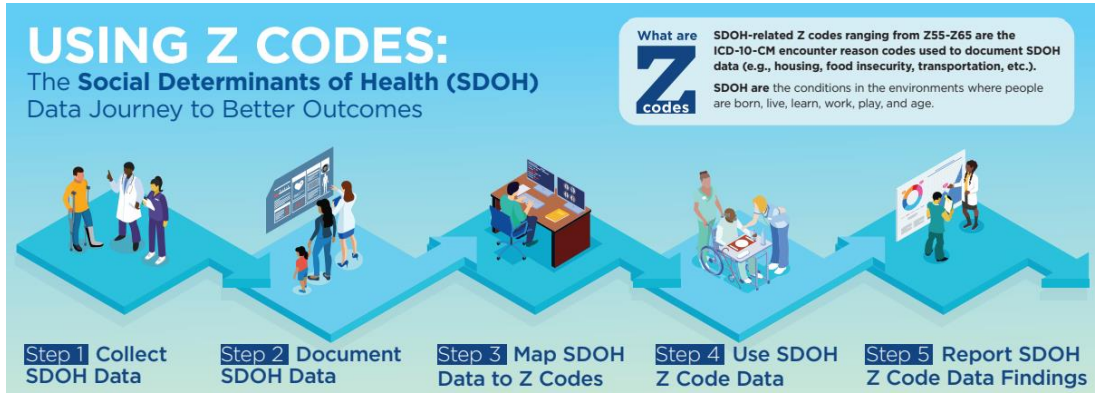


Direct linkage at patient level, such as consumer data or EMR

For the rest of this section, we will be focusing on these enhancements to administrative claims data, their characteristics, and their limitations

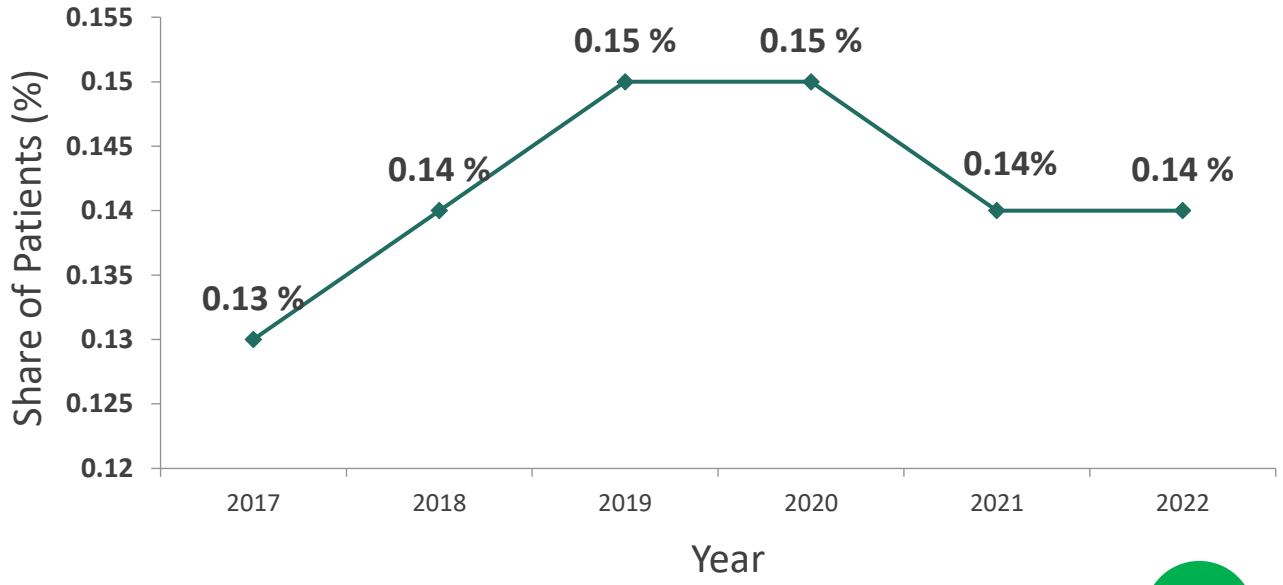
SDoH data can be captured in administrative claims through Z-codes but are extremely underutilized

- V-codes (ICD-9) and Z-codes (ICD-10) are allocated for diagnostic documentation in clinical data sources[1]



- Year-over-year proportion of Z-codes usage nationally remains low

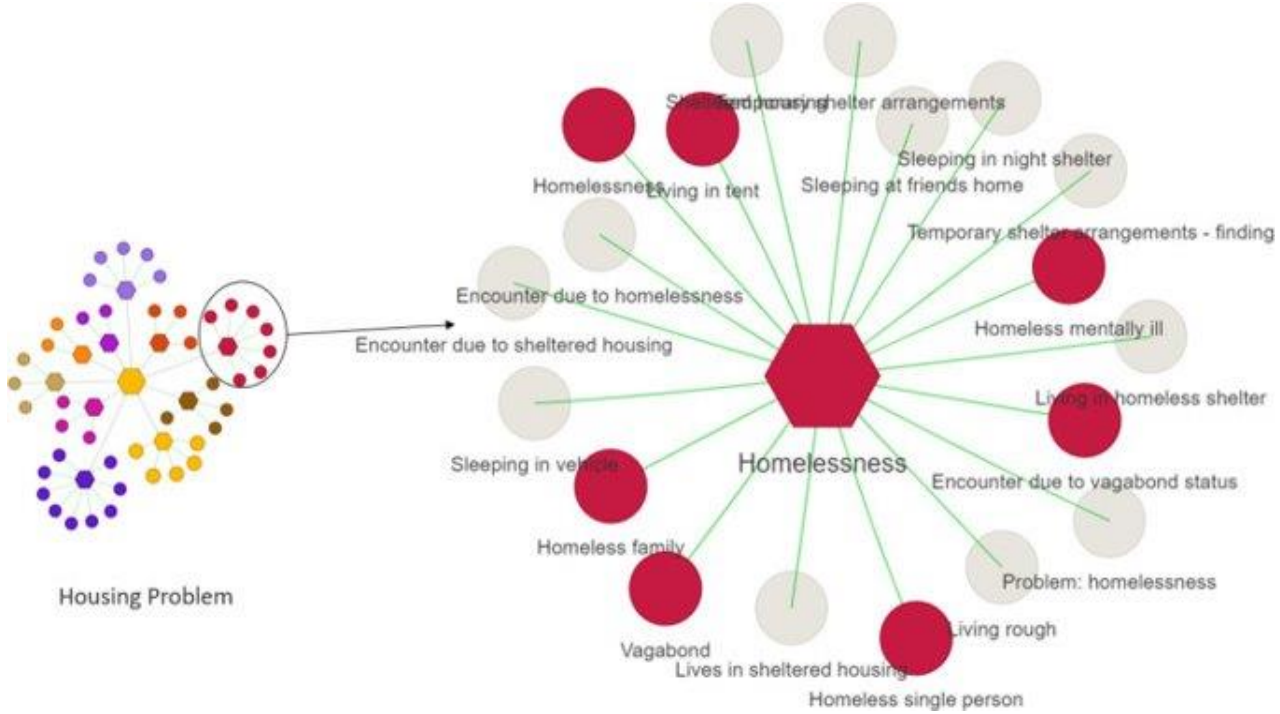
Annual Proportion of Patients with a Z-Code Billed to a Healthcare Claim (National) [2]



1. https://www.cms.gov/files/document/zcodes-infographic.pdf; **2.** https://www.trillianthealth.com/insights/the-compass/provider-documentation-of-social-determinants-of-health-continues-to-stall

Patient-level linkage of SDoH from text in EHR / consumer data can generate rich insights

- Electronic Health Records (EHR)
  - structured and unstructured components
  - Physician's notes may contain comments about SDoH, which can be extracted using Natural Language Processing (NLP)
- Consumer data
  - May contain person or household level SDoH data
- Linking EHR/consumer data requires tokenization, is labor and cost expensive



1. Park Y, et al. AMIA Annu Symp Proc. 2022 Feb 21;2021:940-949.

Publicly available data sources contain rich information about SDoH

[1]

Social vulnerability index

- Indicates the relative vulnerability of every U.S. Census tract
- 16 social factors, including unemployment, racial and ethnic minority status, and disability

[2]

Contains population characteristics reported across geographies on:

- Education, housing, business, economy, race, ethnicity, income, poverty, employment

[3]

Contains geographical information about:

- Health care professions, health facilities, economics, hospital utilization, hospital expenditures at the county, state, and national levels

*Other public sources covering issues such as behavioral risk, health, and nutrition include **BRFSS, NHANES,** and **NCIPC**.*

BRFSS - Behavioral Risk Factor Surveillance System | NHANES – National Health and Nutrition Examination Survey | NCIPC - National Center for Injury Prevention and Control

INGENIOUS INSIGHTS

1. https://data.cms.gov/

2. https://data.census.gov/

3. https://data.hrsa.gov/

Examples of area-level SDoH data in US Census data

United States™ Census Bureau

Population and People
Total Population
331,449,281

Business and Economy
Total Employer Establishments
8,000,178

Race and Ethnicity
Hispanic or Latino
62,080,044

Education
Bachelor's Degree or Higher
35%

Health
Without Healthcare Coverage
8.6%

Income and Poverty
Median Household Income
69,717

Housing
Total Housing Units
140,498,736

Family and Living Arrangements
Total Households
127,544,730

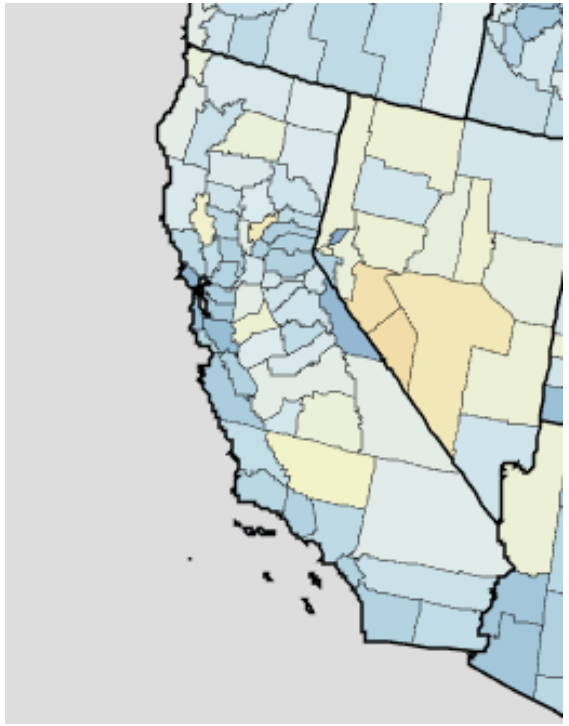
Employment
Employment Rate
58.6%

Data available at the national, state, census tract, metropolitan area, zip-code, etc.

AXTRIA INGENIOUS INSIGHTS

Source: https://data.census.gov/

Geographic-level disparity of health outcomes: cardiovascular disease-related deaths



California

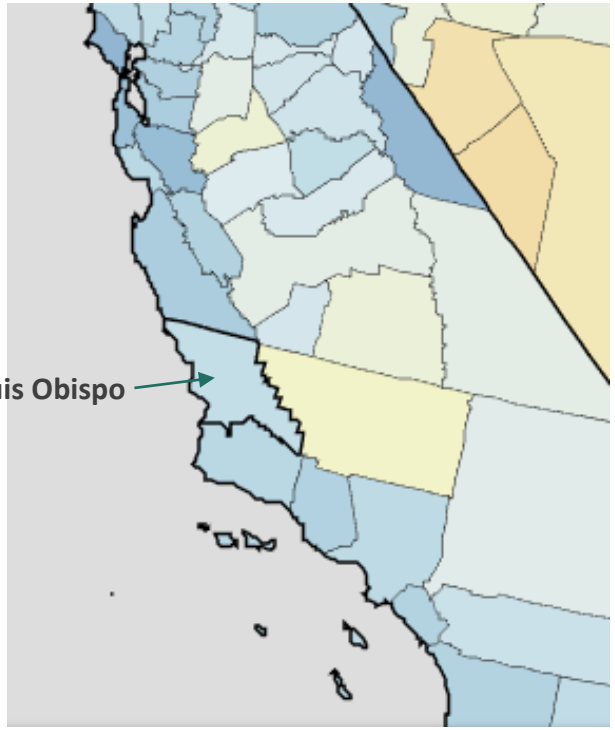
CVD Deaths per 100k population: **221.94**

Physicians per 100k population: **387.95**

Kern County, CA

CVD Deaths per 100k population: **311.74**

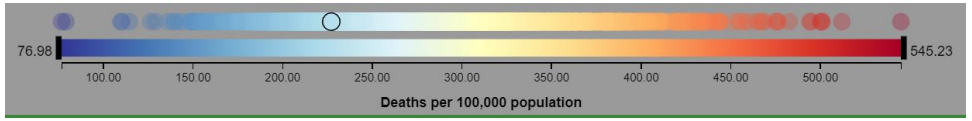
Physicians per 100k population: **159.97**



San Luis Obispo County, CA

CVD Deaths per 100k population: **227.44**

Physicians per 100k population: **408.25**



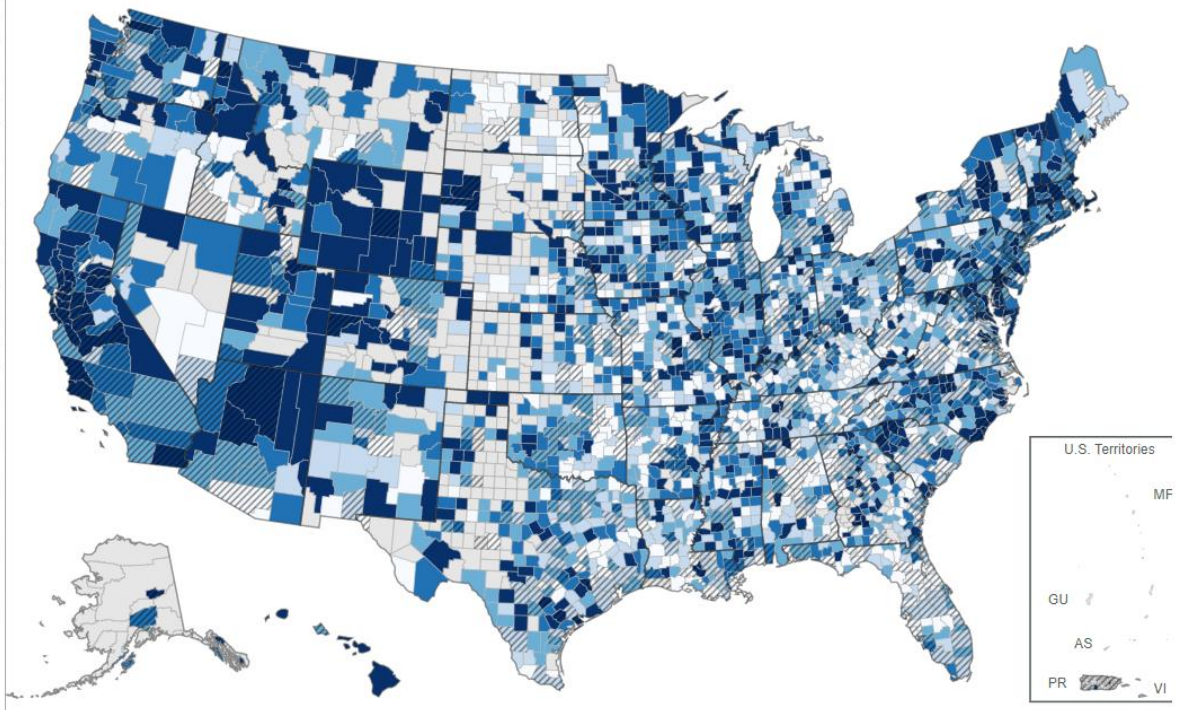
https://www.cdc.gov/dhdsp/maps/atlas/index.htm

Geographic-level disparity of health outcomes: acute myocardial infarction among Medicare beneficiaries

Year	2021
Geography	County
Measure	Average princip
Adjustment	Unsmoothed ac
Analysis	Base measure
Domain	Primary chronic
Condition/Service	Acute myocardi
Sex	All
Age	All
Race and Ethnicity	All
Dual Eligible	Dual & non-dua
Medicare Eligibility	All
Comparison Sex	All
Comparison Age	All
Comparison Race and Ethnicity	All
Comparison Dual Eligible	Dual & non-dua
Comparison Medicare Eligibility	All

Download Data | Download Map

Download Geographic Profile Data



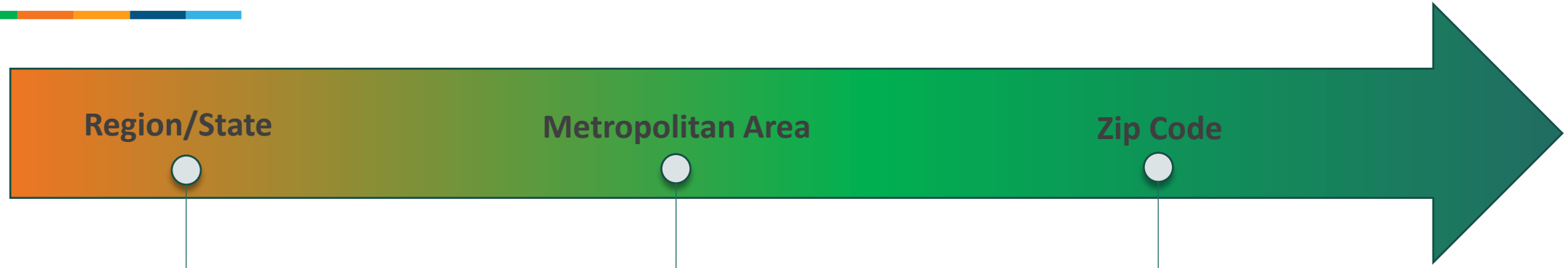
Disparities can be explored by:

- Visualizing health outcomes measures at a region, state, or county level, or by age group, sex, and race
- Exploring outcomes disparity using comparison stratified by geographical location, age group, sex, or race

One caveat of public data is enrollees of government insurance programs may be lower income, older, or have disability status, factors which may not necessarily represent patients enrolled in commercial plans

https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Chronic-Conditions/CCDashboard

Administrative claims can be enhanced by leveraging the wealth of public SDoH data available at geographic levels



Optum[1]

Administrative claims and provider data at the regional- / state-level

United Healthcare administrative claims data

IBM MarketScan[2]

Administrative claims data at the Metropolitan Statistical Area-level

Claims data from employers, health plans, and state Medicaid agencies

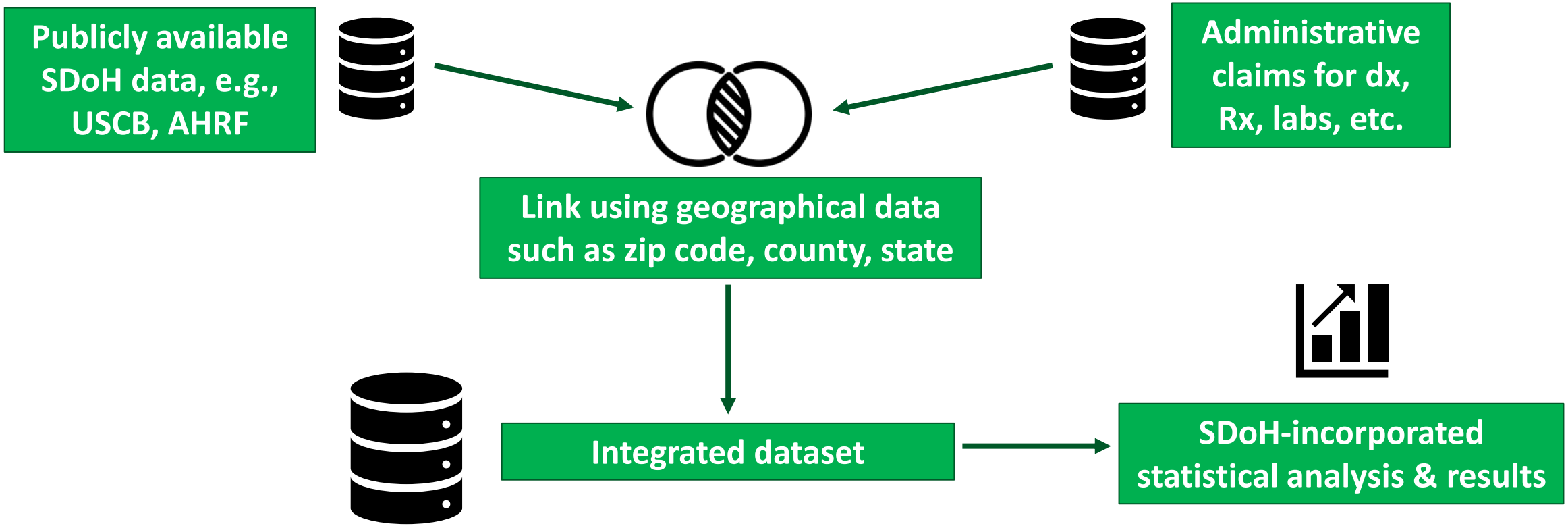
APLD[3]

Provider data at the zip-code level and patient data at the 3-digit zip code-level

Electronic medical records, physician surveys, inpatient billing, pharmacy / medical claims

1. https://www.optum.com/business/life-sciences/real-world-data/claims-data.html; **2.** https://www.ibm.com/downloads/cas/0NKLE57Y; **3.** https://www.iqvia.com/solutions/real-world-evidence/real-world-data-and-insights

Linking patient claims to publicly available SDoH data offers valuable insights



Methodological Considerations

4

DISCLAIMER: analysis is for illustrative purposes only, not intended to make any conclusions regarding patient outcomes

This analysis aims to compare 4 methods for integrating geography-based SDoH with patient-level health data

Method 1	RWD patient-level analysis; qualitative comparison of SDoH at the county-level
Method 2	Aggregate patient-level health data to the county-level and analyze along with SDoH data at the county-level
Method 3	RWD patient-level analysis where county-level SDoH are attributed to each patient based on the county they live in
Method 4	Mixed effect modeling of method 3, where county is the random effect

Data sources	Simulated patient data from CMS county-level prevalent comorbidities; SDoH data from USCB, ACS, and USBLS; access to care data from AHRF

CMS – Centers for Medicare and Medicaid Services | USCB – United States Census Bureau | ACS – American Community Survey USBLS – US Bureau of Labor Statistics | AHRF – Area Health Resource Files

Significant clinical and SDoH predictors of health outcomes among a cohort of simulated patients will be identified

Outcome	Chronic Kidney Disease (stages 1-5; patient-level = yes/no, county-level = prevalence rate)	CMS
Clinical & demographic predictors	Atrial Fibrillation, Diabetes, Heart Failure, Hyperlipidemia, Hypertension, Ischemic Heart Disease, Stroke, Age, Sex	CMS
	Race	USCB
Social determinants of health	Employment	USBLS
	Poverty Status*§	USCB
	Education**, Insurance Status	ACS
	Number of Physicians / 100K People	AHRF

Patient-level clinical conditions, age, and sex were simulated based on CMS data stratified by age (<65, ≥65) at the county-level and by sex (male, female) at the state-level. All other variables were used directly from the source, reported at the county-level.

CMS – Centers for Medicare and Medicaid Services | USCB – United States Census Bureau | USBLS – US Bureau of Labor Statistics | ACS American Community Survey | AHRF – Area Health Resource Files

*Note: chronic conditions prevalence percentages are from 2018. SDoH data, hence, is from 2018 with a few exceptions. *Data from 2020. **Aggregate of data from 2017-2021.*
§USCB official definition: pre-tax cash income against a threshold that is set at three times the cost of a minimum food diet, adjusted for family size.

Analysis will focus on patient- and county-level data from Texas

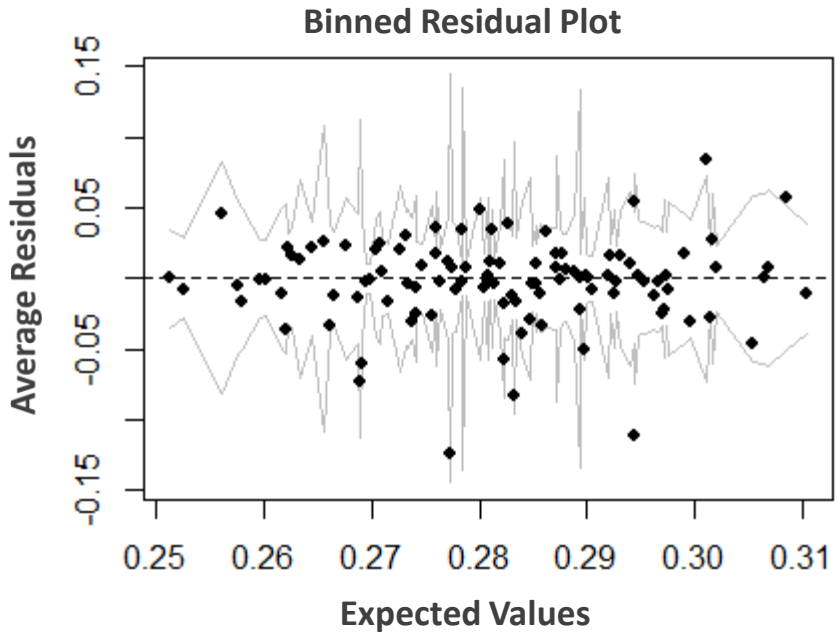
- 8 out of top 10 high-risk counties based on prevalence of selected chronic conditions were in Texas
- Texas has counties with a wide range of diversity; 2.8% - 90.3% population being Non-Hispanic White[1]
- The range of median household income varies from 31k - 106k USD (vs national average of 70k USD)[1]

1. https://www.countyhealthrankings.org/explore-health-rankings/data-beyond-the-rankings

Method 1: RWD patient-level analysis identifies significant demographic and clinical predictors of CKD

Logistic regression using simulated patient-level health data

Chronic Kidney Disease (y/n) ~ Age ≥65 + Sex + Atrial Fibrillation + Stroke + Hypertension + Diabetes + Hyperlipidemia + Heart Failure + Ischemic Heart Disease



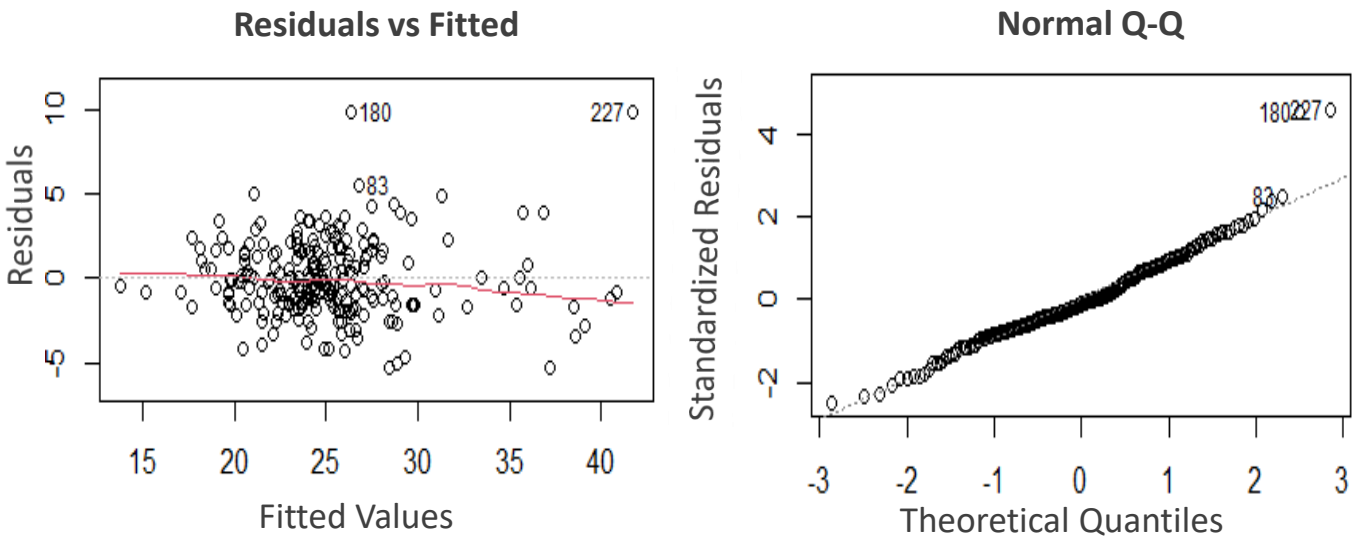
	B	OR	Lower CI	Upper CI	P-value
Age ≥65	-0.09	0.91	0.88	0.94	<0.001
Diabetes	0.05	1.06	1.03	1.09	<0.001
Hyperlipidemia	0.06	1.06	1.03	1.09	<0.001
Hypertension	0.04	1.05	1.02	1.07	0.002
Ischemic Heart Disease	0.03	1.03	1.00	1.07	0.05

Good overall model fit with some outliers. The high number and magnitude of negative outliers suggests overprediction for higher expected values of CKD.

Method 2: Analysis of county-level health and SDoH data identify geography-based predictors of CKD prevalence

Simple linear regression using county-level health and SDoH data

Prevalence of Chronic Kidney Disease ~ Percent Age ≥65 + Percent Male + Atrial Fibrillation (%) + Stroke (%) + Hypertension (%) + Diabetes (%) + Hyperlipidemia (%) + Heart Failure (%) + Ischemic Heart Disease (%) + Percent below Poverty Threshold + Uninsurance Rate + Unemployment Rate + Percent Population with Bachelor's Degree + Percent White Non-Hispanic + Physician Rate



	B	Lower CI	Upper CI	p-value
Atrial Fibrillation (%)	0.40	0.10	0.70	0.010
Diabetes (%)	0.46	0.32	0.60	<0.001
Hyperlipidemia (%)	0.24	0.17	0.31	<0.001
Percent below Poverty Threshold	0.17	0.06	0.27	0.002
Percent Uninsured	-0.10	-0.20	0.01	0.066
Percent Non-Hispanic White	-0.03	-0.06	0.00	0.072

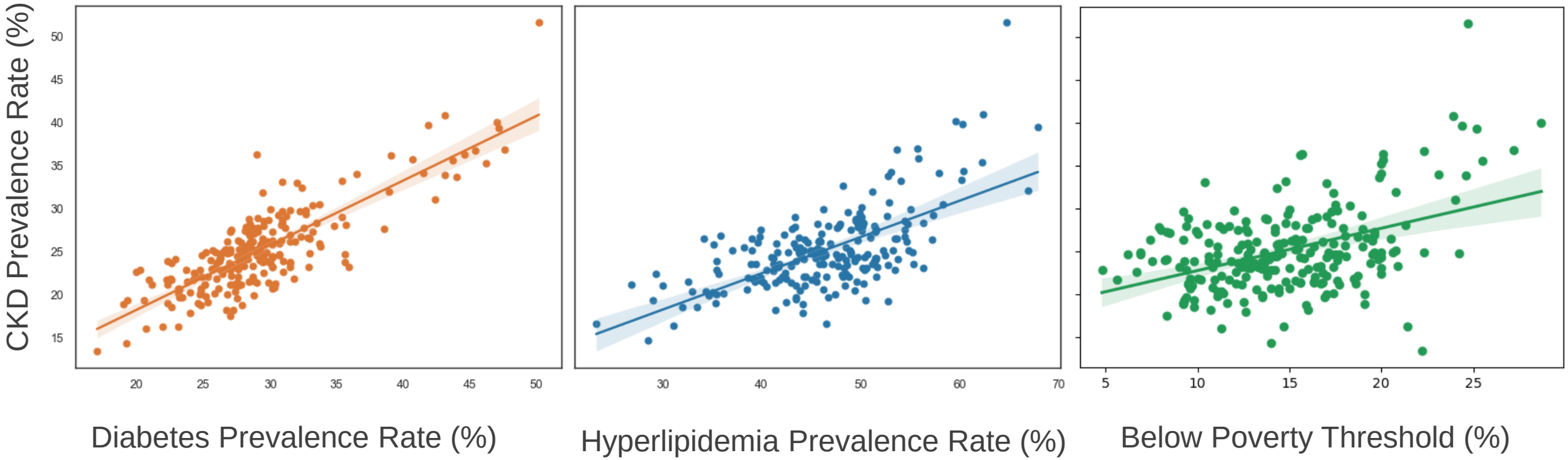
Good linear model fit with a few counties as outliers

Unadjusted county-level rates of CKD correlate to prevalence of significant predictors in method 2 analysis

p-value<0.001
Estimate: 0.45

p-value<0.001
Estimate: 0.25

p-value=0.002
Estimate: 0.17



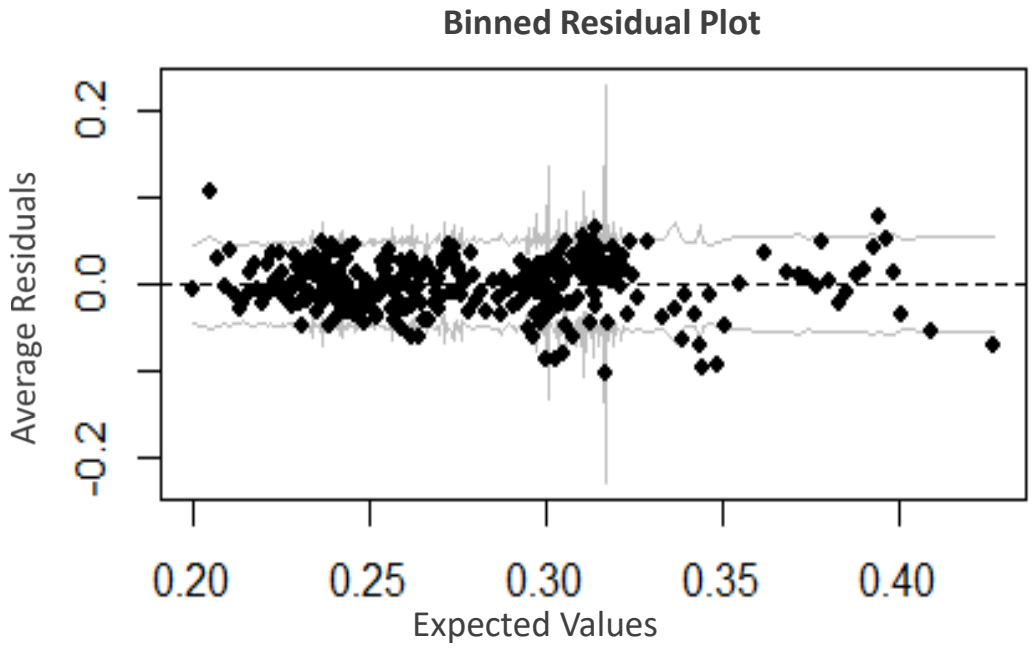
Findings from method 1 can inform clinical decision making, while method 2 may guide public health and policy interventions

Method 1	Method 2
• Patient-level health data	• County-level health and SDoH data
• Logistic regression with patient-level CKD (yes/no) as the outcome	• Linear regression with county-level CKD prevalence rate as the outcome
• Age, diabetes, hyperlipidemia, hypertension, and ischemic heart disease as significant predictors	• Atrial fibrillation, diabetes, hyperlipidemia, percent below poverty threshold, percent uninsured, and percent non-Hispanic white as significant predictors
• Can be used as a reference for establishing relationships between patient clinical profiles and health outcomes	• Introduces SDoH data into clinical analysis and does not depend on simulated data if patient-level data is not available

Method 3: Integrating county-level SDoH with patient-level health data provides insight on how community factors may influence individual outcomes

Logistic regression using simulated patient-level health and county-level SDoH data

Chronic Kidney Disease (y/n) ~ Age ≥65 + Sex + Atrial Fibrillation + Stroke + Hypertension + Diabetes + Hyperlipidemia + Heart Failure + Ischemic Heart Disease + Percent below Poverty Threshold + Uninsurance Rate + Unemployment Rate + Percent Population with Bachelor's Degree + Percent White Non-Hispanic + Physician Rate



Good overall fit having a few outliers, with a bit of overprediction for CKD in counties falling in the higher range of expected values

	B	OR	Lower CI	Upper CI	p-value
Age ≥65	-0.06	0.94	0.91	0.98	0.002
Hypertension	0.03	1.03	1.00	1.06	0.065
Percent below Poverty Threshold	-0.01	0.99	0.99	1.00	0.031
Percent Uninsured	0.01	1.01	1.01	1.02	<0.001
Unemployment Rate	0.02	1.02	1.01	1.04	0.001
Percent Non-Hispanic White	-0.01	0.99	0.99	0.99	<0.001

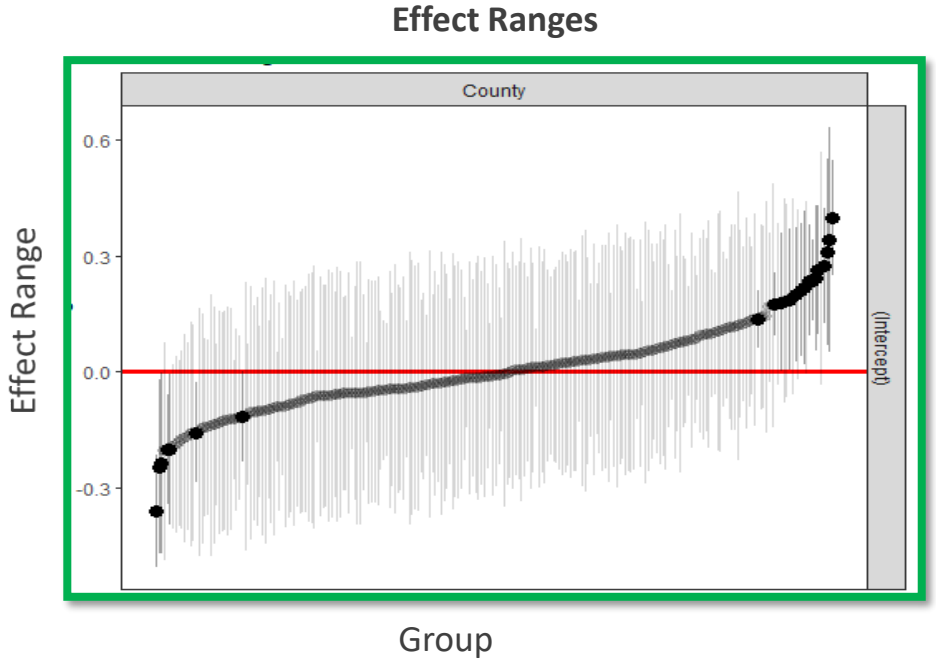
Findings from method 2 may guide public health and policy interventions while method 3 can inform clinical decision making through a health equity lens

Method 2	Method 3
• County-level health and SDoH data	• Patient-level health and county-level SDoH data
• Linear regression with county-level CKD prevalence rate as the outcome	• Logistic regression with patient-level CKD (yes/no) as the outcome
• Atrial fibrillation, diabetes, hyperlipidemia, percent below poverty threshold, percent uninsured, and percent non-Hispanic white as significant predictors	• Age, hypertension, percent below poverty threshold, percent uninsured, unemployment rate, percent with Bachelor's degree or higher, and percent non-Hispanic white as significant predictors
• Smaller sample; prone to high residual estimates if a high-risk county acts as an outlier; possible overfitting if many variables used	• Larger sample sizes; leverages all patient-level data along with county-level SDoH in the same statistical model

Method 4: Mixed effect modeling with county as the random effect accounts for non-independence of patients within geographies

Logistic regression using simulated patient-level health and county-level SDoH data

Chronic Kidney Disease (y/n) ~ Age ≥65 + Sex + Atrial Fibrillation + Diabetes + Stroke + Hypertension + Hyperlipidemia + Ischemic Heart Disease + Percent below Poverty Threshold + Uninsurance Rate + Unemployment Rate + Percent Population with Bachelor's Degree + Percent White Non-Hispanic + Physician Rate + (1|County)



	B	OR	Lower CI	Upper CI	p-value
Age ≥65	-0.07	0.93	0.89	0.97	<0.001
Unemployment Rate	0.03	1.04	1.01	1.06	0.001
Percent with Bachelor's Degree or Higher	0.01	1.01	1.00	1.01	0.028
Percent Non-Hispanic White	-0.01	0.992	0.990	0.993	<0.001

Grey vertical bars represent individual counties. The red horizonal line denotes an effect of 0. The mixed-effect model is well-fitting as majority of counties have an effect of zero.

Findings from methods 3 and 4 can inform clinical decision making through a health equity lens, while method 4 statistically accounts for hierarchical clustering at the county-level

Method 3	Method 4
• Patient-level health and county-level SDoH data	• Patient-level health and county-level SDoH data
• Logistic regression with patient-level CKD (yes/no) as the outcome	• Mixed effect model with patient-level CKD (yes/no) as the outcome and county as the random effect
• Age, hypertension, percent below poverty threshold, percent uninsured, unemployment rate, percent with Bachelor's degree or higher, and percent non-Hispanic white as significant predictors	• Age, unemployment rate, percent with Bachelor's degree or higher, and percent non-Hispanic white as significant predictors
• Likely biased standard errors due to non-independence of samples within counties; multicollinearity if county is used as a predictor	• Unbiased standard errors due to accounting for non-independence of samples within counties; lacks patient-level SDoH

CONSIDERATIONS

- Specific research objective
- Data availability
- Appropriate model fit

CONCLUSIONS

Health Equity

Disparities in healthcare impact many people and can include factors such as race, income level, gender, geography, sexual orientation, and gender identity

https://www.ispor.org/docs/default-source/ispor-good-practices-for-outcomes-research-index/ispor_top10-2022-2023_online.pdf?sfvrsn=61a9ec28_2

Panel Discussion

5

Questions

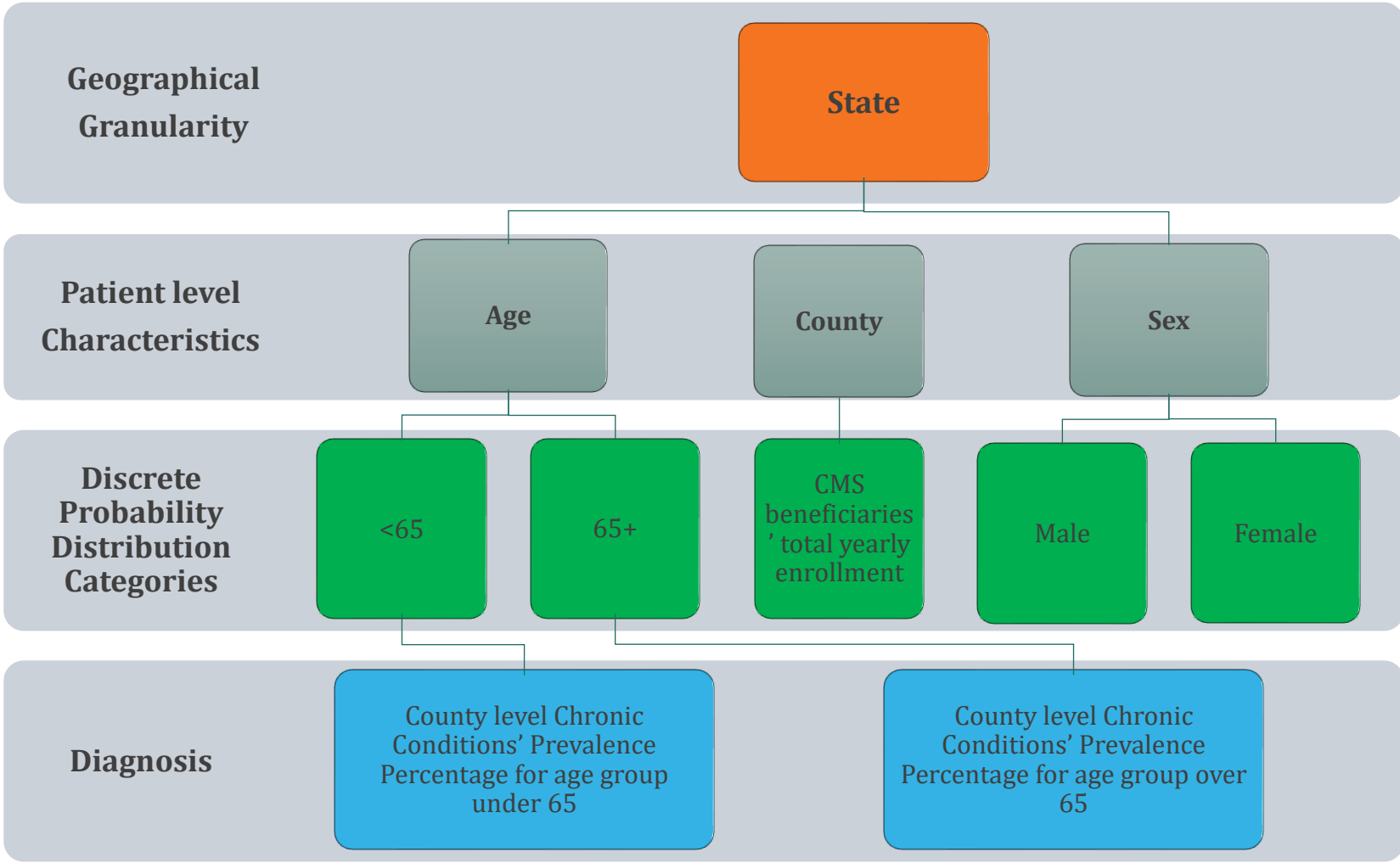
Future

Appendix

Panel questions

- In the future, can we envision including collection of SDoH data in clinical trials?
- Which therapeutic areas are having the greatest disparities and health inequities in terms of access to care?
- What incentive do payers have to promote and utilize Z-codes for reporting and tracking SDoH if these are not billable?
- What incentive do physicians / healthcare providers have to report and track SDoH through Z-codes? What prevents them from doing so?

Patient Level Data Simulation



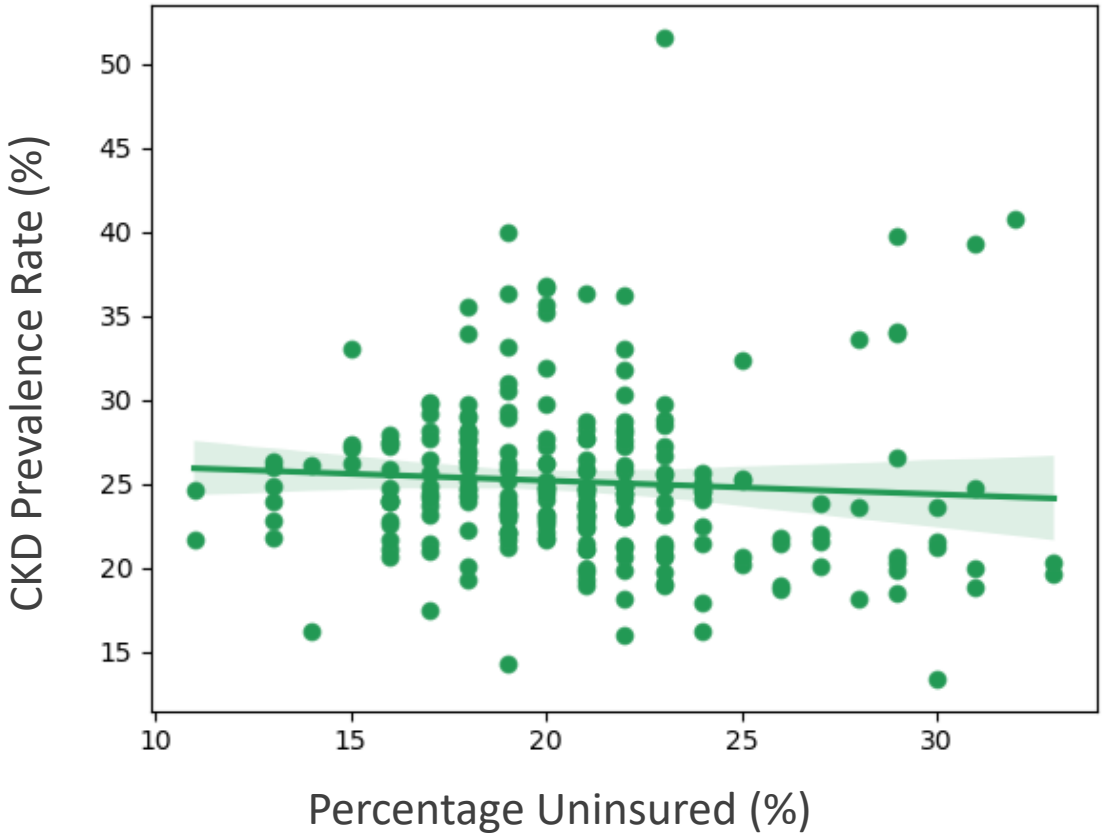
State level age and sex distributions are assumed for each of its counties.

The condition diagnosis is based on the prevalence percentage at a county level and compared with a random sample generated from a uniform distribution.

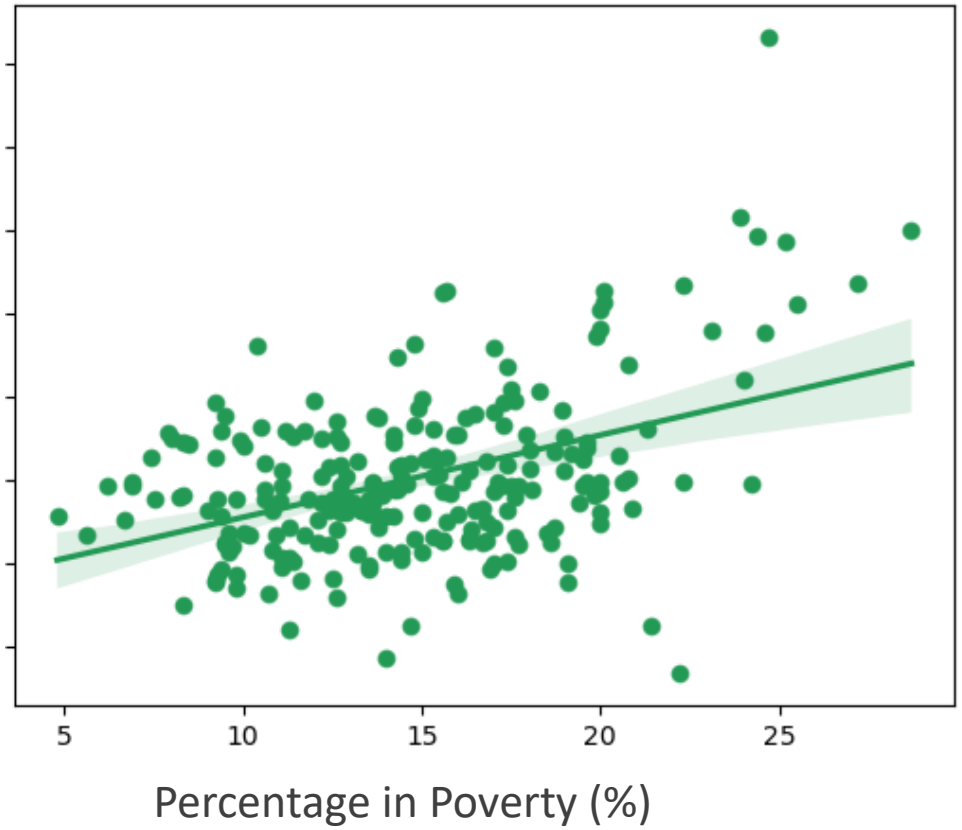
Uninsurance and poverty rate vs CKD for Method 2

County-level health & SDoH data

p-value = 0.06
Estimate: -0.1



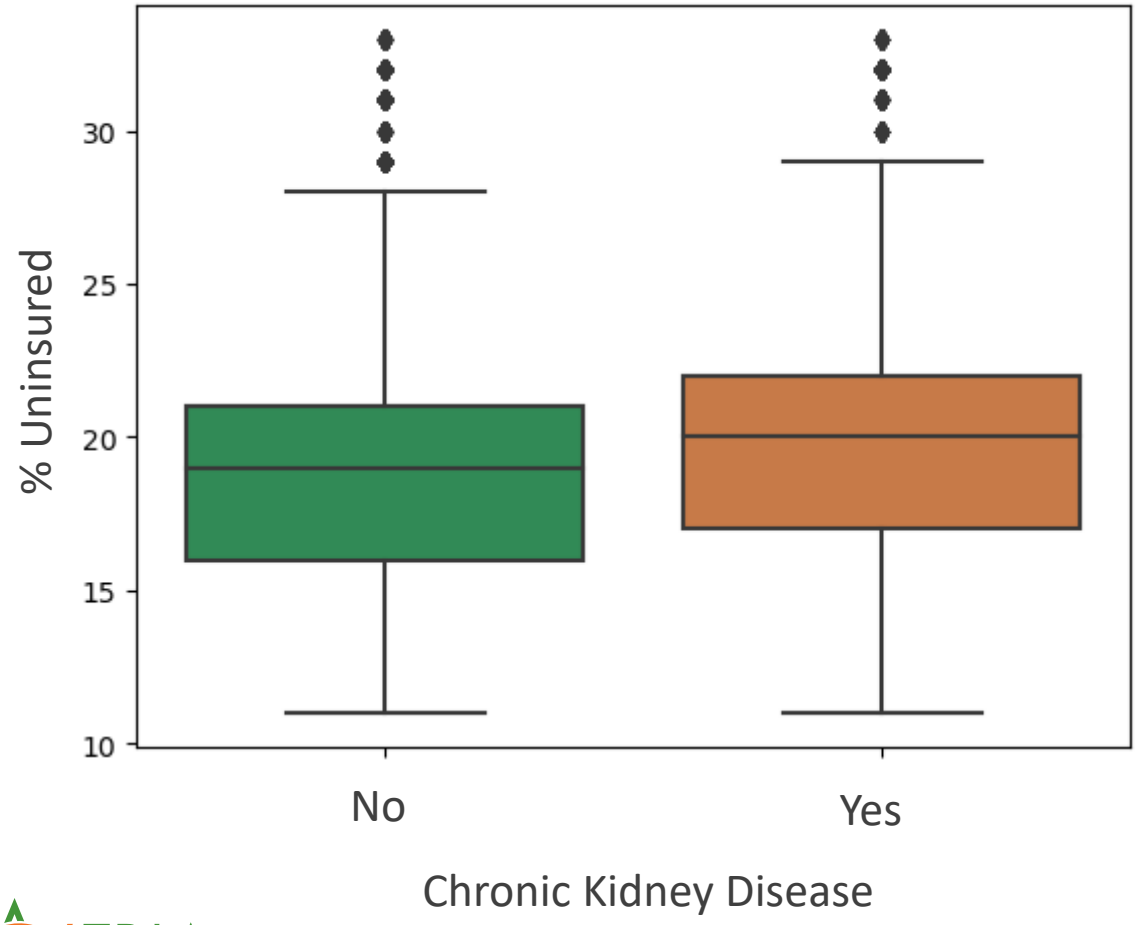
p-value = 0.002
Estimate: 0.17



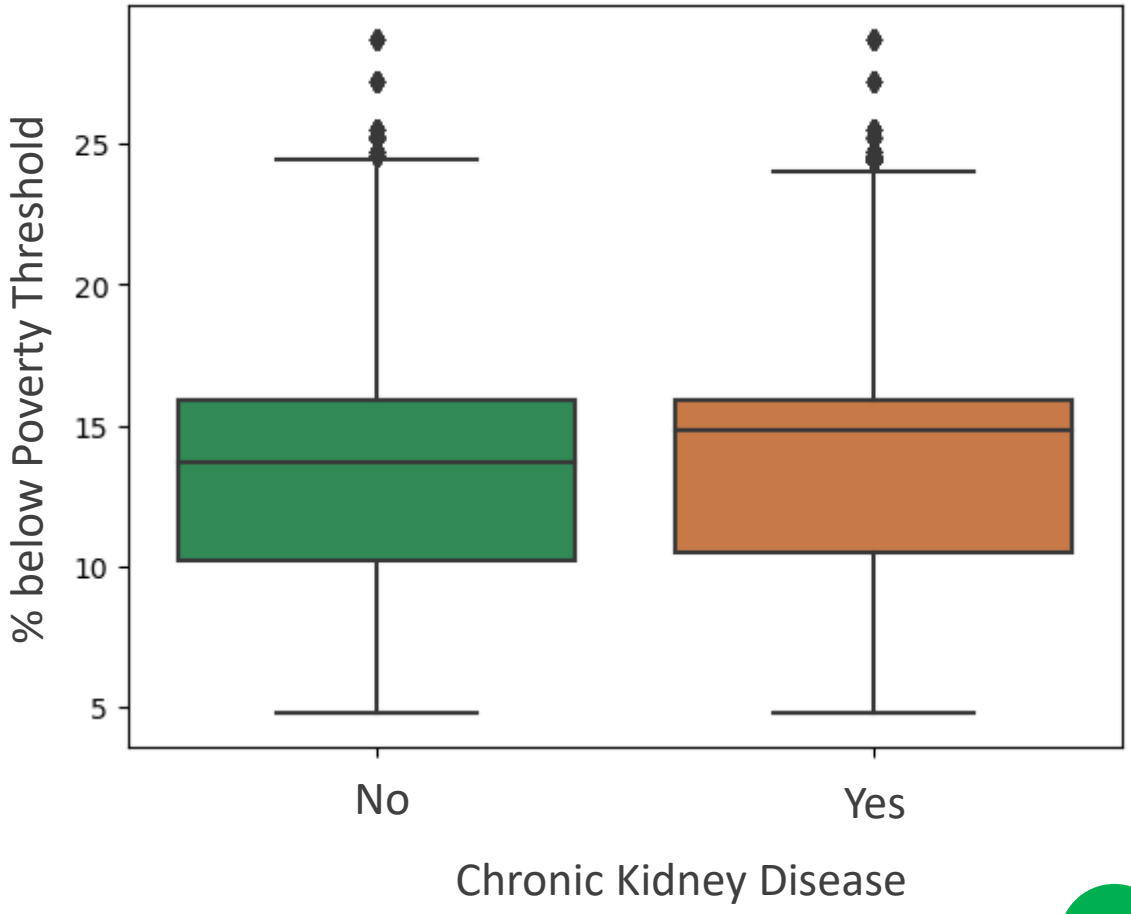
Uninsurance and poverty rate vs CKD for Method 3

Patient-level health & county-level SDoH data

p-value < 0.001
OR: 1.01



p-value = 0.03
OR: 0.99



Z-codes

https://www.cms.gov/files/document/z-codes-data-highlight.pdf

Key Findings:

Among the 33.1 million continuously enrolled Medicare FFS beneficiaries in 2019, **1.59%** had claims with Z codes, as compared to 1.31% in 2016.

The 5 most utilized Z codes were:

1) **Z59.0** Homelessness
2) **Z63.4** Disappearance and death of family member
3) **Z60.2** Problems related to living alone
4) **Z59.3** Problems related to living in a residential institution
5) **Z63.0** Problems in relationship with spouse or partner

Z55	Problems related to education and literacy
Z56	Problems related to employment and unemployment
Z57	Occupational exposure to risk factor
Z59	Problems related to housing and economic circumstances
Z60	Problems related to social environment
Z62	Problems related to upbringing
Z63	Other problems related to primary support group, including family circumstances
Z64	Problems related to certain psychosocial circumstances
Z65	Problems related to other psychosocial circumstances