Challenge 1: Opioids Track
Understanding the Association between Social Determinants of Health (SDoH) and Health Service Resources with Heroin Overdose

Iris Sheu, Ali Zadmehr, Jenny Wang, MS, MBA
Evolent Health

Introduction

Opioid use has increasingly become a major health issue, affecting approximately 2.1 million people in 2016 and 91 deaths per day nationally, according to the Centers for Disease Control and Prevention (CDC) [1, 2]. In October 2017, HHS declared the opioid epidemic a public health crisis and the government passed an omnibus bill in March 2018 that added $3.3b in resources to opioid and mental health efforts [2, 3].

Ohio had the fifth highest rate of drug overdose deaths in 2016, despite establishing an Opiate Action Team in 2011 that focused on responsible opioid use, reducing supply, and overdose prevention and harm reduction through naloxone expansion [4]. These efforts did show promising progress in reducing opioid prescriptions by 28.4% from 2012 to 2017 [4, 5], but broad studies indicate more policy efforts are needed to address the limited resources in medication-assisted treatment which proves to be the most clinically and cost-effective method to reduce opioid dependency, abuse and overdose deaths [6, 7].

Using a multivariate logistic regression approach, our aim was to examine the correlation between Social Determinants of Health (SDoH), social infrastructure factors and health service resources with high incidences of heroin overdose responses in the urban area of Cincinnati, Ohio. It serves as a case study to explore potential levers for intervention and guide public policy on where to best allocate resources, which can be applicable to other areas of the United States. In this study, we hoped to answer the following questions: What are sociodemographic and geographic factors correlated with high incidence areas of heroin overdose? And how can current policies be changed to appropriately address and prevent further exacerbation of the opioid crisis in these areas?

Data Source

The outcome data was extracted from the Cincinnati Fire Incidents EMS response data, which was filtered on “HEROIN OVERDOSE” response type group. Dates of responses were restricted to include incidents spanning from January 1, 2017 to April 29, 2018. The latitude, longitude coordinates were mapped to corresponding census tracts using the Federal Communications Commission (FCC)’s census block API (Table 1).

Data used to explore social determinants health and health service resources were obtained from publicly available sources as summarized in Table 2 below. There were three main data themes of focus: social determinants of health from census and other public available data, prescribing patterns from 2015 Medicare Part D data, and substance treatment resources from the Substance Abuse and Mental Health Services Administration (SAMHSA). When needed, the addresses from the data were mapped to their corresponding census tract using the US Census Bureau's geocoder. Addresses without a match were removed (~20% of data).

Table 1: APIs for geocoding

API Source	**Description**
Federal Communications Commission (FCC)[a]	Latitude/Longitude to census tract
United States Census Bureau[b]	Address to census tract

[a] https://geo.fcc.gov/api/census/
[b] https://geocoding.geo.census.gov/geocoder/

Table 2: External data sources

Data Domain	**Source**
Social Determinants of Health	Center for Disease Control (CDC) Social Vulnerability Index 2014 (SVI)[c]
	US Department of Agriculture Food Access Research Atlas[d]
	US Census American Community Survey (ACS) 2016[e]
	US Department of Housing and Urban Development[f]
Prescription Pattern	CMS Part D Prescriber Data 2015[g]
Treatment Resource	Substance Abuse and Mental Health Services Administration (SAMHSA)[h]
Outcome – EMS responses to heroin overdose	City of Cincinnati EMS data

[c] https://svi.cdc.gov/
[d] http://www.ers.usda.gov/data-products/food-access-research-atlas/
[e] http://www.census.gov/data/developers/data-sets/planning-database.2016.html
[f] https://egis-hud.opendata.arcgis.com/datasets/
[g] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/PartD2015.html
[h] https://findtreatment.samhsa.gov/
[i] https://insights.cincinnati-oh.gov/stories/s/Heroin/dm3s-ep3u/

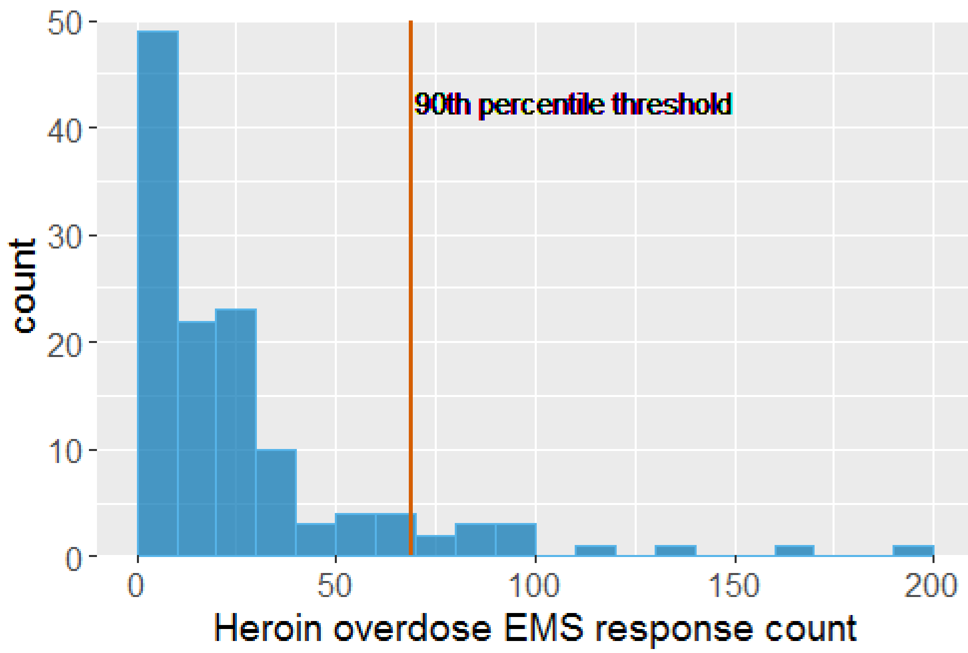
Methods

Multivariate logistic regression was used to analyze the associations between a set of social determinants of health and health services variables and opioid overdose incidents.

Both the EMS response data and data fields of interest from other public sources were processed and aggregated to create features on the census tract level, and then subsequently merged by census tract ID. In total, 127 census tracts in the Cincinnati region were identified with an EMS response.

The outcome variable, heroin overdose EMS response count, has a highly skewed distribution, with a small number of locations having very high volume of responses (Figure 1). We converted overdose responses per census tract to a binary outcome by setting a threshold at the 90th percentile of the incidents count, with 1 indicating the census tract with response volume ranked in the top 10th percentile.

Figure 1: Heroin overdose count per census tract histogram.



Feature selection started with literature review on factors associated with overdose. Public data from sources like the American Community Survey represented the sociodemographic characteristics of the tracts in which overdoses occurred, including factors such as education, financial stability, housing, and transportation accessibility etc. Medicare Part D data was used as a proxy for physician prescription patterns. We aggregated and averaged prescription counts and costs by relevant drug categories such as opioids and antipsychotics for physicians within each tract. We also utilized SAMHSA data on the locations of Buprenorphine treatment facilities and physicians who are licensed to prescribe Buprenorphine to understand the availability of medication-assisted addiction treatment within a census tract. Altogether, a total of 47 variables were created across the three main data focus areas.

Feature elimination and selection was further accomplished through the following methods. First, we analyzed the correlation of features and removed ones that were colinear. Next, we employed LASSO regression and recursive feature elimination (RFE) using the scikit-learn package in Python to identify significant features to include in the final dataset. Social determinants like the % minority in the census tract population and the estimated per capita income were found to be significant features from this analysis. In this way, we reduced the dataset to 12 features which were used to train a logistic regression model with Python's statsmodel package. Univariate statistics of the 12 features are summarized in Table 3, and model results are presented in Table 4.

Table 3: Univariate Statistics for Model Features Example predictors for EMS overdose response

Data Domain	Feature	Mean	Median	95% CI
SDoH	Percentage of population who speak English "less than well"	1.06	0.5	[0.743 - 1.38]
SDoH	Population estimate	3052.54	2675	[2780 - 3325]
SDoH	Percentage of occupied housing units with more people than rooms estimate	2.15	1.1	[1.67 - 2.63]
SDoH	Percentage of population living in mobile homes	0.23	0	[0.14 - 0.33]
SDoH	Percentage uninsured in the total civilian noninstitutionalized population estimate	14.14	13.9	[13.07 - 15.21]
SDoH	Percentage of population institutionalized	3.58	0.7	[2.11 - 5.05]
SDoH	Median income estimate per capita	25595	21789	[22917 - 2873.34]
SDoH	Percentage of census tract population in ethnic minority	47.46	46.1	[42.43 - 52.5]
SDoH	Percentage with low vehicle access	0.49	0	[0.4 - 0.58]
SDoH	Count of public housing units in census tract	6.24	2	[2.08 - 10.39]
Prescribing Patterns	Sum of anti-psychotics claims count (Medicare Part D)	165	0	[69.6 - 260.2]
Prescribing Patterns	Sum of opioids claims count (Medicare Part D)	1048	0	[427 - 1668]
Treatment Resources	Count of Buprenorphine facilities in census tract	0.18	0	[0.07 - 0.3]

Results

Using logistic regression, the estimated total census tract population, % of population that is a minority, % of population that is institutionalized (residents of institutional group quarters such as adult correctional facilities, skilled-nursing facilities, psychiatric hospitals, etc.), and the total sum of antipsychotics scripts prescribed by physicians in a census tract were found to have statistically significant correlations with high rates of heroin overdose incidents. The coefficients indicate that an increase in population estimate and % minority decreased the likelihood of high overdose incidents in a census tract. One possible explanation for the effect of population size is that overdoses tend to happen in less dense areas, ones that are out of the public eye. The negative association of the percentage of the population that is ethnically in the minority with heroin overdoses is supported by data that heroin addiction has in recent years been a problem increasingly for white populations [8]. On the other hand, the percentage of the population institutionalized and the total sum of antipsychotics claims prescribed by physicians within a census tract increased the likelihood of high overdose incidents. Our results show that an increase in the institutionalized population by 1% was associated with an 6% increase in odds for a census tract to be an area of high overdose incidents. An increase of 10 antipsychotic claims per census tract was associated with a 2% increase in odds of being a tract of high overdose incidents. This confirms the prior epidemiological and clinical studies around the co-occurrence of substance disorder and psychiatric disorder [7,9]. Addressing mental health conditions is paramount to treating substance abuse issues.

Table 4: Likelihood of high overdose incidents regression model coefficients

Feature	Coefficient	SE	Z ratio	P > |z| [95% CI]	OR [95% CI]
% Minority	-0.0463	0.018	-2.504	0.012* [-0.082 - -0.010]	0.955 [0.921 - 0.990]
Population Estimate	-0.0008	0	-2.381	0.017* [-0.001 - 0.000]	0.999 [0.999 - 1.000]
% Institutionalized	0.0625	0.029	2.129	0.033* [0.005 - 0.120]	1.064 [1.005 - 1.127]
Sum of Antipsychotics Claims	0.0016	0.001	1.997	0.046* [0.000 - 0.003]	1.002 [1.000 - 1.003]
Low rate vehicle access	1.6231	0.883	1.838	0.066 [-0.108 - 3.354]	5.069 [0.898 - 28.623]
% of Population who speak English “less than well”	0.4228	0.241	1.753	0.080 [-0.050 - 0.896]	1.526 [0.951 - 2.449]
Per Capita Income Estimate	-6.11E-05	3.52E-05	-1.734	0.083 [0.000 - 0.000]	1.000 [1.000 - 1.000]
% Uninsured & non-institutionalized	0.1121	0.067	1.681	0.093 [-0.019 - 0.243]	1.119 [0.982 - 1.275]
% Mobile Homes	-1.6994	1.139	-1.492	0.136 [-3.932 - 0.534]	0.183 [0.020 - 1.705]

Public housing count	-0.1617	0.111	-1.461	0.144 [-0.379 - 0.055]	0.851 [0.685 - 1.057]
Licensed buprenorphine treatment facility count	-0.6021	0.734	-0.82	0.412 [-2.041 - 0.837]	0.548 [0.130 - 2.309]
% Occupied Housing	0.1338	0.17	0.786	0.432 [-0.200 - 0.467]	1.143 [0.819 - 1.596]

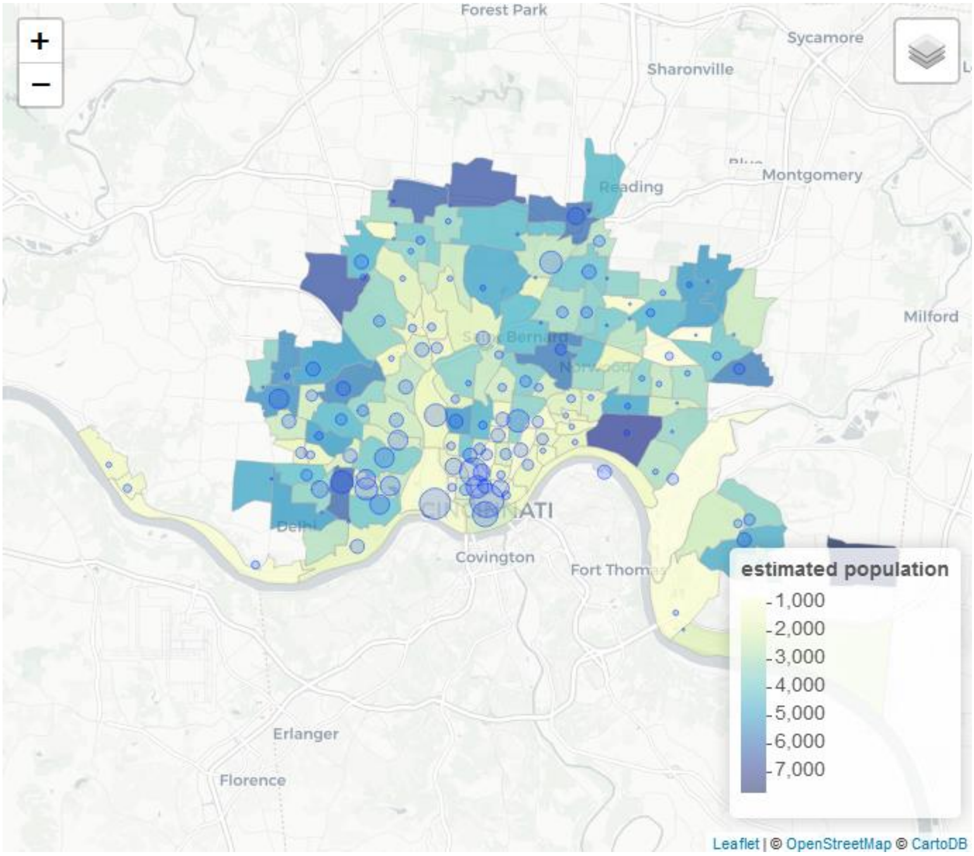
* $p < 0.05$

Other social determinants variables such as low transportation, per capita income and % uninsured and non-institutionalized are also strongly correlated with the heroin overdose but not statistically significant at the 0.05 level. The count of buprenorphine treatment facilities also did not show statistical significance. Fourteen census tracts have at least one buprenorphine treatment facility in the Cincinnati region, and the smaller proximity of urban areas may allow people to more easily travel to facilities.

Discussion

Through this study, we can gain an understanding of characteristics of areas with higher likelihood of heroin overdose events and dedicate appropriate resources to those areas. Efforts to combat the opioid epidemic that require distribution of resources or physical locations, such as increasing access to naloxone or setting up safe injection sites, can be guided by this data-driven approach. By utilizing sociodemographic statistics and historical anti-psychotic prescription data of physicians, public officials can use a combination of these factors (e.g. - lower populations, higher prescriptions) to prioritize areas in which to set up resources and enable the greatest impact. We also created a heat map of population size against heroin overdose responses in Figure 2 below to illustrate how geographic visualizations like this serve as actionable tools to aid in policy planning.

Figure 2: Heat map for the Population Estimate of Cincinnati compared against counts of heroin overdose EMS responses in 2017 – April 2018



This analysis is limited by the size and scope of our data. We used the EMS heroin overdose response data as a proxy for overdose events related to opioid use, but there may be overdose events that don't receive an emergency response request, and areas where overdose events happen may be disproportionately reported in certain regions as compared to others. Similarly, Medicare Part D prescription data is only a subset of prescriptions, so this does not paint an accurate picture regarding prescription patterns of physicians in the area. We only have 127 census tracts in this model which may pose challenge to applying the exact findings to other regions. Future iterations could utilize individual level data to enhance this model, and expand the dataset to incorporate areas of the United States, including more rural areas, where treatment resources might be more limited and factors associated with higher overdose events may be different. More complete data would allow us to better understand levers beyond the clinical setting to address the opioid epidemic. Despite these limitations, the study presents an applicable framework in which to aggregate and leverage numerous sources of publicly available data to understand sociodemographic, prescription behavior, and treatment factors that allow for better allocation of resources to address the opioid epidemic.

Reference

[1] HHS Press Office (October 26,2017). HHS Acting Secretary Declared Public Health Emergency to Address National Opioid Crisis. U.S. Department of Health and Human Services. Retrieved May 1, 2018 from https://www.hhs.gov/about/news/2017/10/26/hhs-acting-secretary-declares-public-health-emergency-address-national-opioid-crisis.html

[2] Ahrnsbrak R., & Bose J.,& Hedde S. L., & Lipari R. N., & Park-Lee E. (September 2017). Substance Abuse and Mental Health Services Administration. Key Substance Use and Mental Health Indicators in the United States: Results from the 2016 National Survey on Drug Use and Health. Retrieved on April 15th from https://www.samhsa.gov/data/sites/default/files/NSDUH-FFR1-2016/NSDUH-FFR1-2016.pdf

[3] Lopez G. (March 22,2018). Congress's omnibus bill adds $3.3 billion to fight the opioid crisis. It's not enough. Retrieve on April 17th from https://www.vox.com/policy-and-politics/2018/3/22/17150294/congress-omnibus-bill-opioid-epidemic

[4] Penm J.,& MacKinnon N. J., & Boone J. M., & Ciaccia A., & McNamee C., & Winstanley E. L. (January 4, 2017). Strategies and policies to address the opioid epidemic: A case study of Ohio. Journal of the American Pharmacists Association 57 (2017) S148eS153

[5] Schierholt S. W. (2018). Ohio Automated Rx Reporting System 2017 Annual Report. Retrieve on May 1st from State of Ohio Board of Pharmacy website: https://www.ohiopmp.gov/documents/Annual%20Report%20(2017).pdf

[6] Center for Disease Control and Prevention. Opioid Prescribing (2017). Retrieve April 20th from https://www.cdc.gov/vitalsigns/opioids/

[7] Stoller K. B., &. Stephens M. C., & Schorr A. (2016). Integrated Service Delivery Models for Opioid Treatment Programs in an Era of Increasing Opioid Addiction, Health Reform, and Parity. White paper submitted to American Association for the Treatment of Opioid Dependence in partial fulfillment of contract #HHSP233201400268P. http://www.aatod.org/wp-content/uploads/2016/07/2nd-Whitepaper-.pdf

[8] Cicero TJ, Ellis MS, Surratt HL, & Kurtz SP. (2014). The Changing Face of Heroin Use in the United States A Retrospective Analysis of the Past 50 Years. JAMA Psychiatry. 2014;71(7):821–826. doi:10.1001/jamapsychiatry.2014.366

[9] Kessler, R. C., Chiu, W. T., Demler, O., & Walters, E. E. (2005). Prevalence, Severity, and Comorbidity of Twelve-month DSM-IV Disorders in the National Comorbidity Survey Replication (NCS-R). Archives of General Psychiatry, 62(6), 617–627. http://doi.org/10.1001/archpsyc.62.6.617