Louisiana Office of Public Health STD/HIV/Hepatitis Program

Jurisdiction-Level Vulnerability Assessment

Cooperative Agreement for Emergency Response: Public Health Crisis Response 2018 Opioid Overdose Crisis Cooperative Agreement

Final Report

November 2019

Submitted by:
The Policy & Research Group
www.policyandresearch.com

8434 Oak St.
New Orleans, LA 70118

1400 4th Ave., Suite 1000
Seattle, WA 98101

TABLE OF CONTENTS

List of Abbreviations and Acronyms

ACS	American Community Survey
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CBOs	Community-Based Organizations
CDC	Centers for Disease Control and Prevention
CMS	Center for Medicare and Medicaid Services
ECHO	Extension for Community Healthcare Outcomes
FORHP	Federal Office of Rural Health Policy
FQHCs	Federally Qualified Health Centers
GLM	Generalized Linear Model
HBV	Hepatitis B Virus
HCV	Hepatitis C Virus
HHS	U.S. Department of Health and Human Services
HRSA	Health Resources & Services Administration
IDU	Injection Drug Use
LASSO	Least Absolute Shrinkage and Selection Operator
LDH	Louisiana Department of Health
LODSS	Louisiana Opioid Data and Surveillance System
MAT	Medication-Assisted Treatment
MME	Morphine Milligram Equivalent
NPIN	National Prevention Information Network
NPPES	National Provider Identification
OPH SHP	Louisiana Department of Health's Office of Public Health STD, HIV, and Hepatitis Program
PCA	Principal Components Analysis
PMP	Prescription Monitoring Program
PrEP	Pre-Exposure Prophylaxis
PRG	The Policy & Research Group
PWID	Persons Who Inject Drugs
SAMHSA	Substance Abuse and Mental Health Services Administration
SBIRT	Screening, Brief Intervention, and Referral to Treatment
UCR	Uniform Crime Reporting
ZCTA	ZIP Code Tabulation Area

INTRODUCTION

This report presents findings from the Louisiana Jurisdiction-Level Vulnerability Assessment. In 2018, the Louisiana Department of Health's Office of Public Health STD, HIV, and Hepatitis (OPH SHP) program received a multi-component cooperative agreement from the *Centers for Disease Control and Prevention* (CDC) and *U.S. Department of Health and Human Services* (HHS) to combat the opioid epidemic in Louisiana. One of the planned projects under this cooperative agreement was to conduct a statewide vulnerability assessment at a sub-state geographic level to identify jurisdictions particularly vulnerable to the rapid spread of injection drug-related HIV, hepatitis C virus (HCV), or overdose deaths. The CDC's "step-wise" approach for the assessment included 1) identifying and prioritizing indicators, 2) compiling data and calculating indicators, 3) developing the vulnerability assessment, and 4) identifying gaps in services in vulnerable areas. OPH SHP contracted with The Policy & Research Group (PRG) in February 2019 to conduct this assessment.

In this report, we first provide a brief epidemiologic profile of Louisiana as it relates to the opioid epidemic, HIV, and HCV. We then describe the methods used to conduct the assessment and present the results of our analytic approach. We highlight key findings and discuss how they can be used to inform the development of plans that strategically allocate prevention and intervention services to areas most in need. A detailed discussion of methods and results of additional analyses can be found in report Appendices.

BACKGROUND

In late 2014, an HIV outbreak in Scott County, Indiana – where 92% of the 181 new HIV cases diagnosed were coinfected with HCV – highlighted the potential for injection drug-related prescription opioid use to drive dual HIV and HCV epidemics.[1] This underscored the intersection of HIV, HCV, and injection drug use (IDU) and the need for public health departments to identify areas particularly vulnerable to the rapid spread of bloodborne infections due to IDU.

The burden of both HIV and opioid addiction/misuse in Louisiana is high, relative to other states. In 2017, it ranked 4th highest in the nation for HIV case rates and 3rd highest for AIDS case rates; roughly 5% of new HIV cases and 7% of new AIDS cases were attributable to IDU.[2] Furthermore, the 2017 age-adjusted rate of drug overdose deaths in Louisiana was 24.5 per 100,000, compared to the U.S. national rate of 21.7. The 2017 prescription opioid rate in the state was also among the highest in the nation (Louisiana had a rate of 89.5 opioid prescriptions per 100 persons, compared to the U.S. average of 58.7 prescriptions).[3] With regard to HCV, there are an estimated 500 people each year in Louisiana who are newly infected. However, many of these infections are asymptomatic and, subsequently, neither diagnosed nor reported. Data indicate that younger age groups are particularly at risk of new infection, especially those between the ages of 24 and 34 who have witnessed a rapid increase in HCV incidence since 2000; by contrast, cases identified in the older age groups, particularly individuals between 50 and

---

[1] Van Handel, M. M., Rose, C. E., Hallisey, E. J., Kolling, J. L., Zibbell, et al. (2016). County-level Vulnerability Assessment for Rapid Dissemination of HIV or HCV infections among Persons who Inject Drugs, United States. Journal of Acquired Immune Deficiency Syndromes, 73(3), 323-331; National Public Radio (2018). Mapping How the Opioid Epidemic Sparked an HIV Outbreak. Retrieved September 3, 2019 from https://www.npr.org/sections/health-shots/2018/01/14/577713525/mapping-how-the-opioid-epidemic-sparked-an-hiv-outbreak.

[2] Louisiana Department of Health Office of Public Health STD/HIV Program (2018). Louisiana HIV, AIDS, and Early Syphilis Surveillance Quarterly Report. December 31, 2019. Retrieved September 3, 2019 from http://ldh.la.gov/assets/oph/HIVSTD/HIV_Syphilis_Quarterly_Reports/2018Reports/Fourth_Quarter_2018_HIV_Syphilis_Report.pdf.

[3] National Institute on Drug Abuse (2019). Drug Overdose Deaths. Retrieved September 3, 2019 from https://www.drugabuse.gov/opioid-summaries-by-state/louisiana-opioid-summary.

70 years old, tend to represent undiagnosed cases that are only just now being identified due to increased screening efforts coupled with their entrance into medical care.[4] Given the opioid, HIV, and HCV epidemiologic profile of Louisiana, there is a recognized need to identify geographic areas in the state that may be at risk for a syndemic of injection-related opioid overdose, HIV, and HCV.

METHODS

STUDY DESIGN

The CDC recommended three vulnerability assessment approaches for this project: qualitative hotspot mapping, statistical modeling, and geospatial analysis. Informed by the work of Van Handel et al. (2016) and Rickels et al. (2017), we used an ecologic study design that employed statistical modeling of vulnerability at the ZIP Code Tabulation Area (ZCTA) level in Louisiana.[5,6] Louisiana's 510 ZCTAs with residential populations comprise the study sample. Data were gathered from several sources, including (but not limited to): the OPH SHP*; Louisiana Department of Health* (LDH), *Louisiana Opioid Data and Surveillance System* (LODSS); *Louisiana Board of Pharmacy, Prescription Monitoring Program* (PMP); *Center for Medicare and Medicaid Services* (CMS), *National Provider Identification* (NPPES); *National Prevention Information Network* (NPIN) *Organizations Database; County Health Rankings and Roadmaps;* and the *American Community Survey* (ACS). (See Appendix B for details on measures and data sources). To be considered for inclusion, data must have been reported at the ZIP Code, ZCTA, or parish (county) level, and had to be recent – collected for 2016, 2017, or period measures that include these time points (e.g., ACS 5-year population estimates released in 2017).[7] All analyses and maps presented in this report were produced using Stata 15.

PRIMARY OUTCOME MEASURE

While both Van Handel et al. (2016) and Rickels et al. (2017) used *acute HCV* as the outcome measure of interest in their studies, after talking with our project partner (OPH SHP) and experts on opioid use and addiction, the opioid epidemic, and infectious disease in Louisiana , we determined chronic HCV in persons under 40 years old to be the best proxy for risky injection-drug use in Louisiana.[8] The rationale is that the incidence of acute HCV is very low across Louisiana. According to those with whom we spoke, most individuals do not develop symptoms related to HCV or seek care until at least 6-months after infection. Due to this, most newly diagnosed cases of HCV in Louisiana are reported as chronic, not acute, HCV. We focused on persons under the age of 40, because this is the group at highest risk of new infection. While incidence is highest in persons over 50, experts explained that these cases typically

---

[4] Louisiana Office of Public Health Infectious Disease Epidemiology Section. (2017). Hepatitis C Annual Report. Retrieved September 3, 2019 from http://ldh.la.gov/assets/oph/Center-PHCH/Center-CH/infectious-epi/Annuals/HepC_LaIDAnnual.pdf.

[5] Rickels, M., Rebeiro, P. F., Sizemore, L., Juarez, P., Mutter, M., Wester, C., & McPheeters, M. (2017). Tennessee's In-state Vulnerability Assessment for a "Rapid Dissemination of Human Immunodeficiency Virus or Hepatitis C Virus Infection" Event Utilizing Data About the Opioid Epidemic. *Clinical Infectious Diseases, 66*(11), 1722-1732.

[6] For information on CDC project recommendations, see Van Handel, M. (2018). Jurisdiction Vulnerability Assessment Technical Assistance Kick-off [PowerPoint slides).

[7] We chose 2016 and 2017 as these were the time points for which most data were available.

[8] The CDC provided a list of recommended core indicators to consider, including: drug related overdose deaths; acute HCV diagnoses or HCV diagnoses among young adults; opioid prescription rates; drug-related crimes; or an economic indicator. Though we ultimately settled on *chronic HCV in people under 40 years old* as the preferred outcome of interest, we considered alternative health outcomes as indicators of vulnerability including persons living with HIV where the mode of transmission was related injection drug use and opioid-related deaths. Where data are available, we present information on health outcomes that could serve as alternative indicators of risk for the most vulnerable ZCTAs, in Appendix C.

represent older undiagnosed cases; therefore, this age group has been excluded from analysis to focus our study on recent cases.[9]

PREDICTOR VARIABLES

IDENTIFYING PLAUSIBLE PREDICTOR VARIABLES

We began by compiling a list of variables that local experts agreed could be predictive of high-risk injection drug use in Louisiana; specifically, we sought indicators associated with opioid overdose and injection drug-related bloodborne infections. We asked a group of experts on opioid use and addiction, the opioid epidemic, and/or infectious disease in Louisiana to review the list of 78 variables identified in Rickels et al. (2017) and discuss whether or not any were ill-suited as predictors for Louisiana and whether or not there were any potential indicators missing from the list. From this process, no indicators were removed; however, several plausible predictors were added to our list.[10]

Once we compiled the data, we operationalized each of the predictors for which we could obtain data into a single measure for analysis.[11] In all, 73 variables were constructed (including the outcome of interest). Variables are broadly categorized into the following eight domains: demographic characteristics, social characteristics, economic characteristics, housing characteristics, health outcomes, opioid and medication-assisted treatment (MAT) prescriptions, access to health care, and high-impact prevention and intervention services.[12] See Appendix B for details on all variables considered for analysis.

VARIABLE SELECTION

Following the work of both Van Handel et al. (2016) and Rickels et al. (2017), after compiling our list of plausible predictors, we employed a multi-step approach to identify the most parsimonious set of indicators with the strongest predictive association with our proxy measure for risky IDU (*chronic HCV in people under 40 years old*). We provide a brief overview of this process below; a detailed discussion of variable selection methods can be found in Appendix A.

Our first step was a comprehensive review of the list of measures we had compiled. For this, we reviewed and categorized variables in terms of when they were reported, what they measure, variability, and missingness. During this step, we removed 16 variables from consideration because data were not recent enough, too recent, exhibited too little variation, or exceeded allowed missingness. Next, to ensure each of the 510 ZCTAs in Louisiana were retained in analysis, we imputed missing predictor data where necessary. Following imputation, we conducted a data reduction process using a

[9] For more information on the HCV profile of Louisiana, see: Louisiana Office of Public Health Infectious Disease Epidemiology Section. (2017). Hepatitis C Annual Report. Retrieved September 3, 2019 from http://ldh.la.gov/assets/oph/Center-PHCH/Center-CH/infectious-epi/Annuals/HepC_LaIDAnnual.pdf.

[10] Additional predictors include: number of people within flood zones, calls to suicide hotline, acute HBV, chronic HBV, percentage of blue-collar workers, education desert, chronic HCV in persons under 40, extent of homelessness in an area; access to HIV treatment/care; access to HCV treatment/care; access to HIV and HCV testing; access to substance use disorder provider; access to Pre-exposure prophylaxis (PrEP); access to syringe services.

[11] We attempted to obtain data for the full list of identified predictors; however, we were unable to obtain data for 9 of the 78 variables identified by Rickels et al. (2017) and 1 additional predictor identified by experts. In addition, in several cases, Rickels et al. (2017) considered both counts and rates of some predictors, and they considered logged and unlogged versions of predictors. In these instances, we did not operationalize the count or log variables.

[12] According to the CDC, "High-Impact Prevention (HIP) is a public health approach to disease prevention in which cost-effective, proven, and scalable interventions are targeted to specific populations based on disease burden." CDC reporting guidance for the Jurisdictional Vulnerability Assessment highlighted the following as HIP services: HIV testing and treatment, HCV testing and treatment, syringe services programs, MAT programs substance use disorder treatment (esp. opioids), and Naloxone distribution. For more information on high impact prevention services, see: https://www.cdc.gov/nchhstp/highimpactprevention/docs/HIP-at-a-glance-P.pdf.

combination of principal components analysis (PCA), factor analysis, simple regression, and correlation. Variables were retained if they were highly associated with a retained principal component or provided unique information. In all, 33 variables were removed from consideration during this process, and 24 were retained for the full model (including the outcome of interest and population size).

In order to construct an interpretable and parsimonious empirical model that is predictive *of chronic HCV in persons under 40* (our proxy variable), we conducted a final variable selection process that used a stepwise method to select the best set of linear predictors that minimizes information loss. This process was based on part of the selection algorithm proposed by Imbens and Rubin (2015); it is an iterative approach that considers additive combinations of candidate predictors to incrementally select into the set of predictors that maximizes model fit as defined by the log likelihood values and Akaike information criterion (AIC).[13] We retained the following 12 variables in our final model: *percentage of population never married*, *percentage with no high school diploma*, *percentage of population that is unemployed*, *violent crimes*, *percentage of housing units that are crowded*, *poor physical health days*, *rate of injury-related deaths*, *mean morphine milligram equivalent* (MME) *rate for opioid analgesics*, *MME rate for MAT drugs*, *rate of prescription opioid sales*, *mental health providers*, *primary care providers*. In addition to these 12 predictors, a variable *year*, which reflects the year of observation for time variant predictors was also retained; time indicates whether or not the data were collected for 2016 or 2017. See Appendix B for a full description of variables considered in analysis, including notes on variable selection and analysis.

STATISTICAL MODEL

We modeled the rate of new diagnoses of chronic HCV infection in persons under 40 using a multi-level negative binomial regression model. We employed a three-level model where time (two annual observations, 2016 and 2017) is nested in ZCTAs, and ZCTAs are nested in parish, with ZCTA population included in the model as an offset. [14] We assessed model fit using methods suggested by Hilbe (2014). In brief, we conducted tests of overdispersion and investigated with diagnostic assessment-of-fit statistics whether or not a different count model was more appropriate (e.g., Poisson). Results of the preferred model, including standardized coefficients (for interpreting relative strength of the predictors) are presented below. Although the coefficients in the model are interpretable, many indicate counter-intuitive relationships with the dependent variable. These estimated relationships, however curious, should not be taken at face value. Omitted variable bias is undoubtedly at play here; the model is simply attributing an association between missing variables and the outcome to the limited set of variables that are retained in the model. Remember that we have not set out to construct an explanatory model – one that represents the hypothesized means (causal or associational) by which an outcome (*chronic HCV in persons under 40*) can be empirically explained. Instead our objective was to identify an optimized (i.e., parsimonious) prediction model selected from a set of candidate variables based on goodness-of-fit criteria (AIC), according to a stepwise algorithm. There is simply no way that the retained variables explain – nor do their coefficients provide an estimate of – the "true" underlying system that produced the observed outcomes

[13] Imbens, G. W. and Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. New York: Cambridge University Press.

[14] According to Hilbe (2014, pg. 63), "Statisticians use an offset with a model to adjust for counts of events over time periods, areas, and volumes. The model is sometimes referred to as a proportional intensity model." Using an offset not only adjusts for potential correlations in observations, but it also allows the outcome of the model to be interpreted as a rate. See: Hilbe, J. M. (2014). *Modeling Count Data*. New York: Cambridge University Press; and Osgood, D., W. (2000). Poisson-Based Regression Analysis of Aggregate Crime Rates *Journal of Quantitative Criminology 16(1), 21-43.*

Table 1. Results of Preferred Analytic Model

	Coefficient	Standard Error	p-Value	Standardized Coefficient
Year	0.6081	0.0498	0.0000	0.3042
Percentage of population never married	0.0146	0.0043	0.0010	0.1873
Rate of injury-related deaths	0.0141	0.0048	0.0030	0.1824
MME rate for opioid analgesics	0.0004	0.0001	0.0030	0.1809
MME rate for MAT drugs	0.0004	0.0001	0.0010	0.1785
Violent crimes	0.0006	0.0003	0.0270	0.1748
Primary care providers	0.0050	0.0018	0.0050	0.1574
Percentage with no high school diploma	0.0170	0.0073	0.0190	0.1243
Mental health providers	0.0182	0.0089	0.0410	0.0581
Percentage of housing units that are crowded	-0.0003	0.0002	0.0990	-0.0936
Percentage of population that is unemployed	-0.0272	0.0101	0.0070	-0.1594
Rate of prescription opioid sales	-0.0038	0.0014	0.0050	-0.2008
Poor physical health days	-0.5266	0.1775	0.0030	-0.2058

VULNERABILITY INDEX

Following Van Handel et al. (2016), we used unstandardized coefficients obtained from our regression model to determine vulnerability for each ZCTA. The coefficient for each predictor was multiplied by the value for each ZCTA – if two years of data are available, the data were averaged; all variables were summed to create a vulnerability index. To ease interpretation, index scores were ranked, and ranks were reversed coded so that 1 = most vulnerable ZCTA and 510 = least vulnerable.

EXPERT FEEDBACK

Following construction of the vulnerability index and associated maps, we returned to the experts with whom we initially spoke about plausible indicators of risk in Louisiana to discuss the preliminary results. We reviewed the maps we constructed that illustrate the vulnerability index rankings and available high-impact resources and discussed the extent to which these maps comport with their knowledge of the opioid epidemic and available resources in Louisiana. We also discussed the utility of the maps and, of the vulnerability assessment more generally, what the state is currently doing to address the opioid epidemic, what they see as the biggest barriers to dealing with the epidemic, and the greatest areas of need in the state.

PREDICTED VULNERABILITY

In this section we present findings on the relative level of predicted vulnerability to the rapid spread of injection drug-related HIV, HCV, or overdose deaths in sub-Parish (ZCTA) regions across Louisiana. The predicted vulnerabilities are a probabilistic function of the processes and methods outlined in this report, the proxy selected (*chronic HCV for people under 40*), and the data that were available. We start by graphically illustrating predicted levels of vulnerability at the ZCTA level on a map of Louisiana. Predicted vulnerability is ordered and ranked by quintile according to the vulnerability index that is the result of our data reduction and statistical modeling procedures. Darker colors in the map are indicative of higher levels of predicted vulnerability, and the top 10% of vulnerable ZCTAs are bordered by yellow. Note, the white sections in the map do not have an associated ZIP Code; they are remote and rural areas without a mail route.[15] Following the map, we present select characteristics of those top 10% of

[15] For more information on places without ZIP Codes, see: https://www.unitedstateszipcodes.org/.

vulnerable ZCTAs. As can be seen in Figure 1, while pockets of vulnerability have been identified across the state, the most vulnerable areas tend to be concentrated in South East Louisiana, notably in Jefferson, Livingston, and Tangipahoa parishes. This corresponds closely to rates of chronic HCV in person under 40 across the state (see Health Outcome Maps in Appendix C). In addition, experts with whom we spoke agreed that this area corresponds relatively closely to where opioid overdoses are most prevalent. Looking at Table 1, the ZCTAs identified as most vulnerable (those in the top 10% of vulnerable cases) vary greatly in size, with populations ranging from 30 to over 50,000. Approximately one quarter are designated as rural, and most had an average chronic HCV incidence rate of between 5 and 15 per 10,000 individuals; a few had no new incidence of chronic HCV reported in 2016 and 2017, suggesting the index is identifying places that are in need of effective treatment, as well as those that are potentially in need of prevention services.

Figure 1. ZCTA-Level Vulnerability Index by Risk Quintile

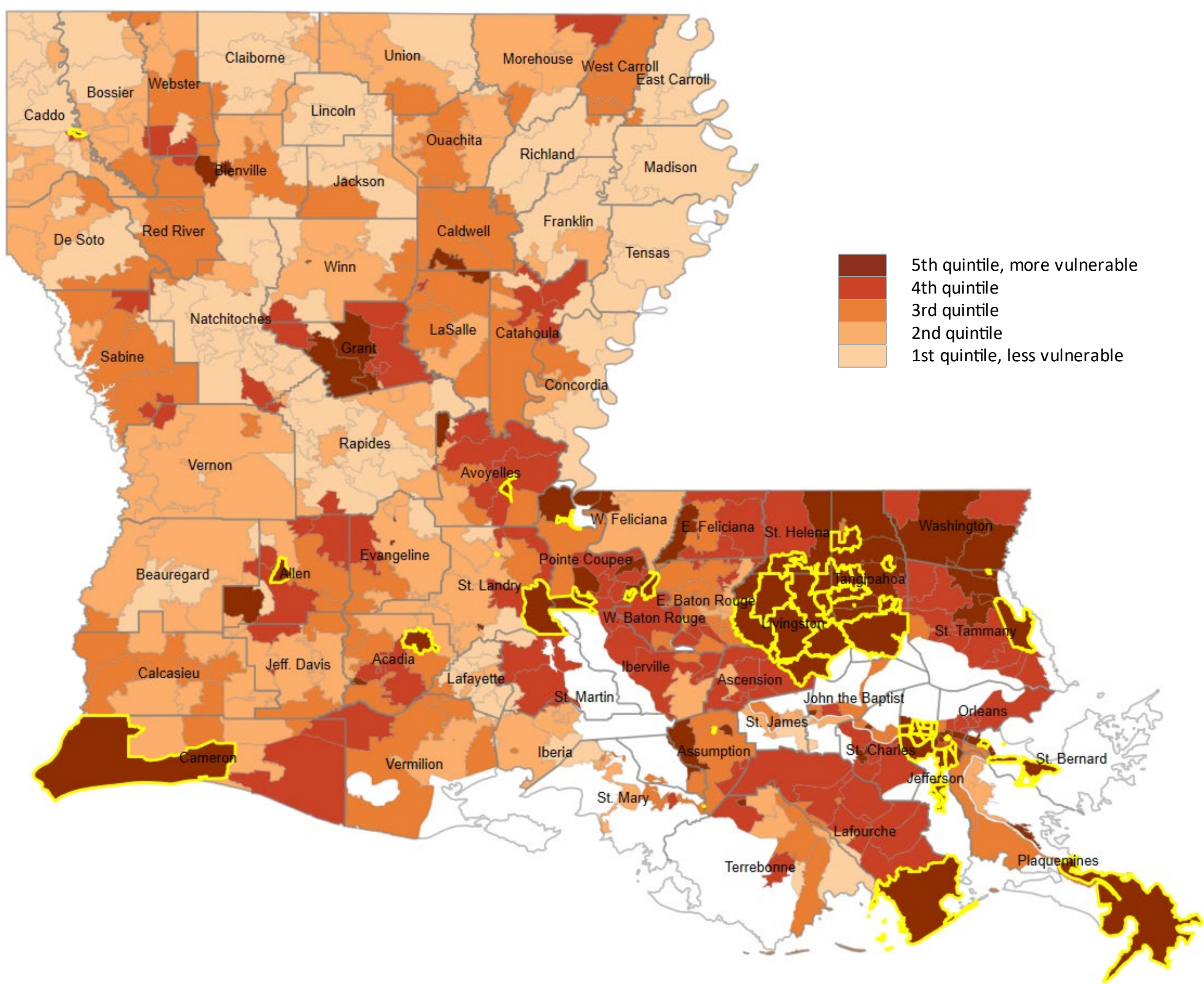


Table 2. Characteristics of Top 10% Vulnerable ZCTAS

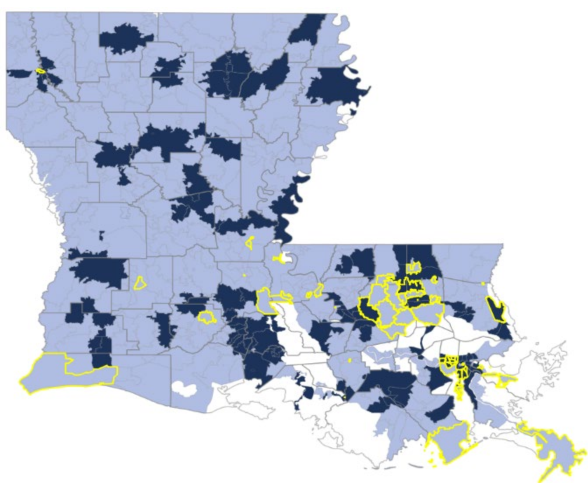
Rank	Parish	ZCTA	Population size	Rate of chronic HCV	Percent no HS diploma	Percent in poverty	Percent with a disability	Percent unemployed	Percent uninsured	Percent White, not Hispanic	Rural
1	E. Baton Rouge	70801	30	166.67	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	No
2	Acadia	70516	439	11.39	20.7%	0.0%	5.8%	0.0%	20.0%	88.6%	Yes
3	Tangipahoa	70442	68	0.00	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	No
4	Orleans	70112	2553	19.58	8.3%	35.5%	13.4%	10.5%	17.4%	43.5%	No
5	Tangipahoa	70455	936	16.03	17.1%	4.8%	11.3%	5.9%	5.6%	100.0%	No
6	St. Mary	70340	70	71.43	64.3%	100.0%	100.0%	6.8%	0.0%	0.0%	Yes
7	Jefferson	70067	2669	13.11	14.2%	20.3%	12.7%	4.4%	12.7%	90.4%	No
8	Jefferson	70358	760	13.16	11.1%	17.0%	18.5%	2.5%	14.2%	97.1%	No
9	Jefferson	70121	11503	6.09	7.3%	17.8%	17.6%	5.4%	11.7%	62.9%	No
10	St. Helena	70453	808	12.38	36.8%	31.7%	2.0%	2.2%	17.1%	43.7%	No
11	Cameron	70631	463	10.80	14.1%	15.2%	24.2%	4.1%	17.8%	96.5%	Yes
12	Livingston	70733	1556	6.43	18.5%	25.8%	16.8%	8.3%	10.2%	97.7%	No
13	Livingston	70744	5691	10.54	14.4%	26.6%	28.4%	1.8%	16.4%	98.0%	No
14	Livingston	70711	4726	8.46	8.5%	17.8%	18.8%	3.3%	6.2%	96.2%	Yes
15	Livingston	70462	5114	12.71	15.2%	18.9%	30.6%	9.2%	13.7%	82.6%	No
16	St. Tammany	70463	219	0.00	18.6%	14.2%	25.1%	5.9%	12.3%	90.4%	No
17	St. Landry	71345	167	0.00	46.2%	100.0%	0.0%	0.0%	0.0%	0.0%	Yes
18	Jefferson	70072	55586	6.03	14.7%	19.5%	15.4%	7.5%	12.0%	44.1%	No
19	Allen	70654	266	0.00	42.6%	11.3%	24.8%	16.4%	45.9%	100.0%	Yes
20	Jefferson	70062	16583	6.03	14.7%	20.9%	17.1%	6.0%	21.8%	36.5%	No
21	Jefferson	70094	30604	9.48	13.5%	25.5%	19.1%	10.5%	13.3%	37.9%	No
22	Livingston	70754	12768	12.92	13.2%	10.8%	12.6%	3.5%	9.6%	86.3%	No
23	Tangipahoa	70443	10362	5.79	18.9%	30.5%	22.9%	13.7%	19.7%	56.3%	Yes
24	Jefferson	70036	1146	4.36	22.3%	7.7%	15.4%	16.8%	14.0%	85.7%	No
25	St. Bernard	70075	5574	12.56	9.2%	8.2%	12.4%	6.1%	11.4%	74.0%	No
26	Tangipahoa	70402	1917	0.00	0.0%	16.0%	11.7%	16.7%	5.4%	63.0%	No
27	St. Tammany	70452	12678	11.44	11.0%	15.4%	20.6%	7.8%	14.3%	87.8%	No
28	Assumption	70391	196	51.02	4.1%	4.6%	34.2%	0.0%	29.6%	41.3%	Yes
29	Lafourche	70357	2395	6.26	18.9%	16.6%	24.6%	2.6%	19.0%	80.0%	Yes
30	St. Bernard	70085	4878	21.53	17.8%	25.9%	18.6%	19.3%	9.5%	81.5%	No
31	St. Landry	70750	1386	7.22	13.6%	27.7%	19.1%	2.9%	11.5%	98.9%	Yes
32	Jefferson	70006	16531	2.12	5.0%	13.4%	11.5%	5.4%	17.9%	64.8%	No
33	Plaquemines	70091	361	0.00	22.0%	32.7%	5.8%	0.0%	29.2%	66.5%	No
34	Jefferson	70053	16316	6.13	13.3%	20.7%	19.4%	8.8%	15.1%	41.8%	No
35	Tangipahoa	70456	2258	4.43	24.1%	20.6%	17.3%	10.1%	13.1%	38.2%	Yes
36	Jefferson	70058	38695	5.69	12.3%	19.0%	10.2%	5.6%	14.0%	26.8%	No
37	Jefferson	70001	39745	4.28	5.5%	14.9%	12.1%	5.0%	13.2%	68.4%	No
38	Pointe Coupee	70747	174	0.00	30.0%	10.9%	51.1%	28.4%	14.4%	23.0%	Yes
39	Livingston	70785	21366	8.89	9.7%	14.7%	11.2%	8.0%	10.6%	89.2%	No
40	Avoyelles	71339	156	0.00	0.0%	29.5%	0.0%	0.0%	29.5%	100.0%	Yes
41	Jefferson	70003	41056	4.02	6.9%	11.6%	12.7%	5.3%	11.3%	67.8%	No
42	Caddo	71101	7211	8.32	18.5%	42.6%	25.7%	14.8%	19.3%	17.0%	No
43	Pointe Coupee	70756	513	0.00	6.6%	9.4%	22.4%	0.0%	8.2%	100.0%	No
44	Jefferson	70123	27089	7.75	4.4%	7.6%	14.0%	3.2%	8.0%	78.8%	No
45	Livingston	70449	3844	11.71	6.9%	20.3%	15.0%	4.9%	12.8%	92.8%	No
46	Tangipahoa	70454	28597	6.12	8.8%	15.7%	17.7%	4.3%	8.2%	77.4%	No
47	Jefferson	70002	20437	3.18	4.2%	13.2%	13.2%	3.6%	15.3%	60.4%	No
48	Tangipahoa	70466	9579	6.26	15.4%	16.0%	18.1%	8.5%	20.3%	62.8%	No
49	Livingston	70726	55657	10.87	8.0%	11.4%	11.7%	5.6%	12.6%	84.4%	No
50	W. Baton Rouge	70729	747	0.00	27.4%	48.7%	14.5%	0.0%	30.5%	48.7%	No
51	Jefferson	70005	25767	2.91	3.3%	9.6%	12.7%	4.1%	11.2%	82.0%	No

RESOURCES AND GAPS

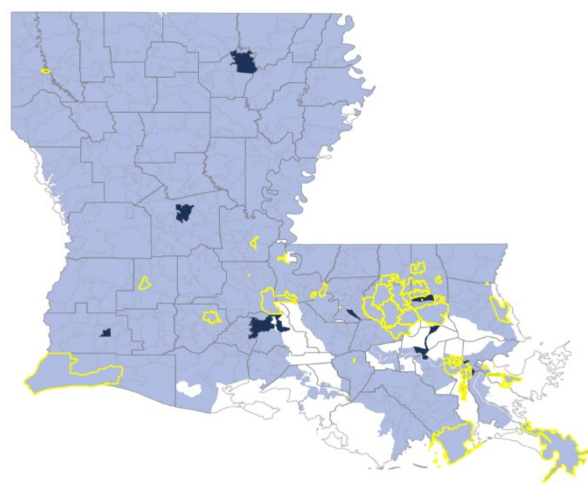
In the next set of maps, we illustrate the distribution of high-impact prevention and treatment interventions across the state. Light blue indicates absence of the resource, and dark blue indicates the resource is present; the top 10% most vulnerable ZCTAs are highlighted. Again, white areas do not have an associated ZIP Code. The purpose of these maps is to show how risk and availability of resources are geographically related. Gaps are areas in the state where a resource is not available; the most consequential are those where there is evident risk in a ZCTA (indicated as top 10% most vulnerable, highlighted in yellow) and evident absence of resources in the surrounding geographic areas. As can be seen, there are many resource gaps across the state. There are few methadone clinics and large pockets of the state without a buprenorphine or substance use disorder provide; only four syringe access programs exist – all are in Baton Rouge and New Orleans. Similarly, although HIV and HCV care can take place in many health care settings, providers that focus on the identification and treatment of these diseases are sparsely distributed across the state, including in the most vulnerable ZCTAs.

OPIOID MISUSE AND ADDICTION TREATMENT

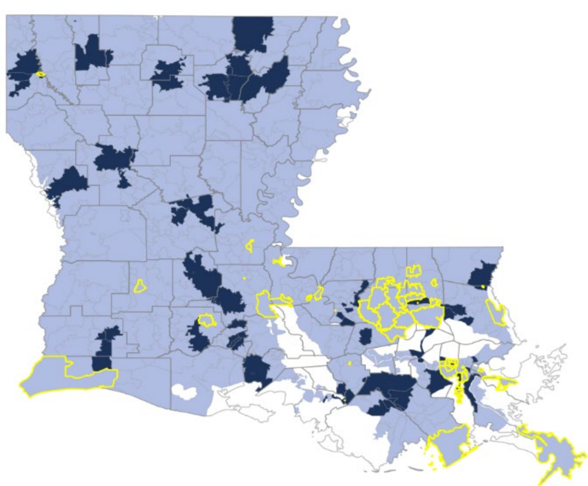
ZCTAs with at Least 1 Buprenorphine Prescriber, 2019



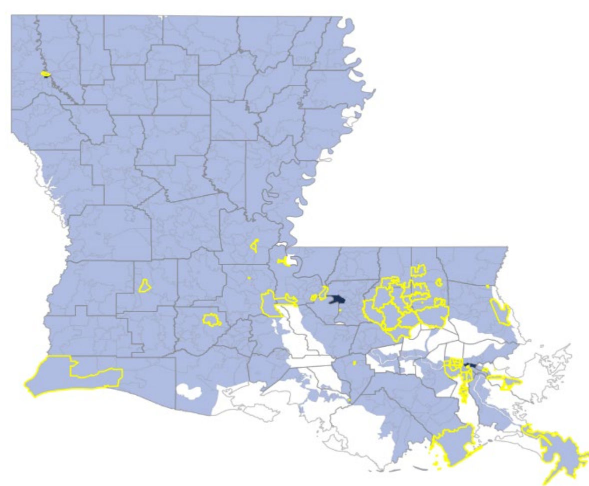
ZCTAs with at Least 1 Methadone Clinic, 2019



ZCTAs with at Least 1 Substance Use Disorder Provider, 2017

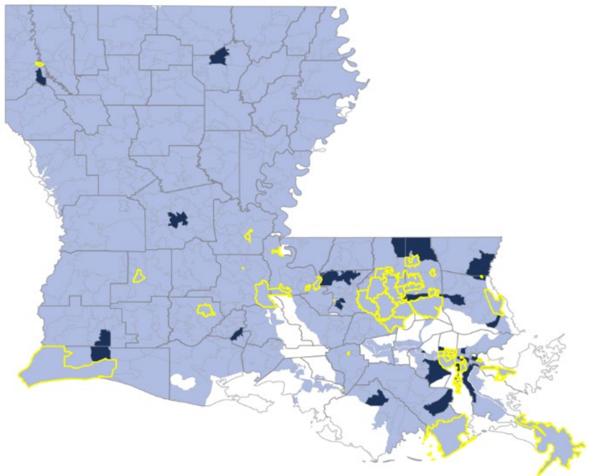


ZCTAs with Syringe Access Services, 2019

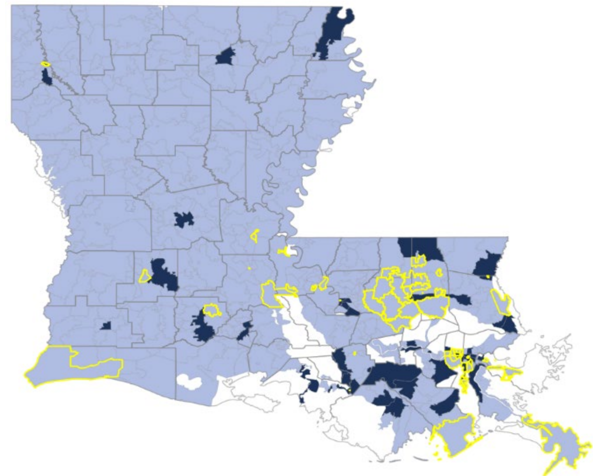


HCV AND HIV TREATMENT AND TESTING

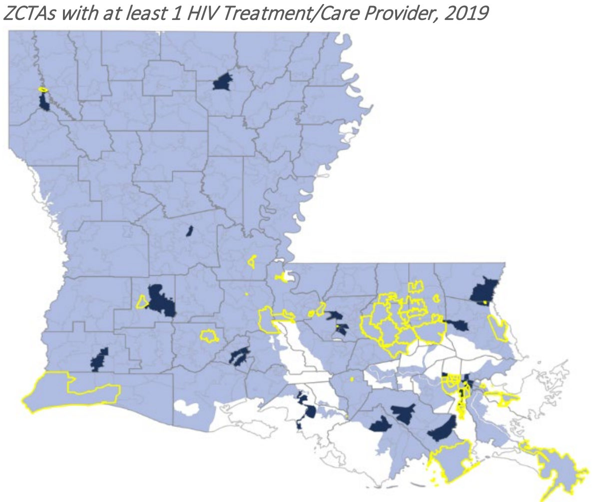
ZCTAs with at least 1 HCV Treatment/Care Provider, 2019



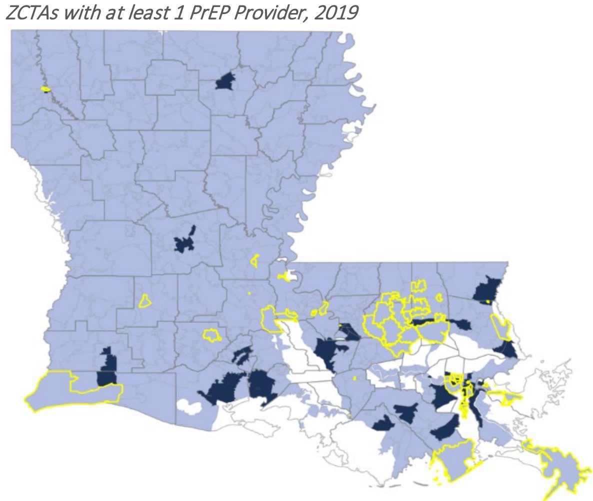
ZCTAs with at least 1 Low/No Cost HCV Testing Site, 2019



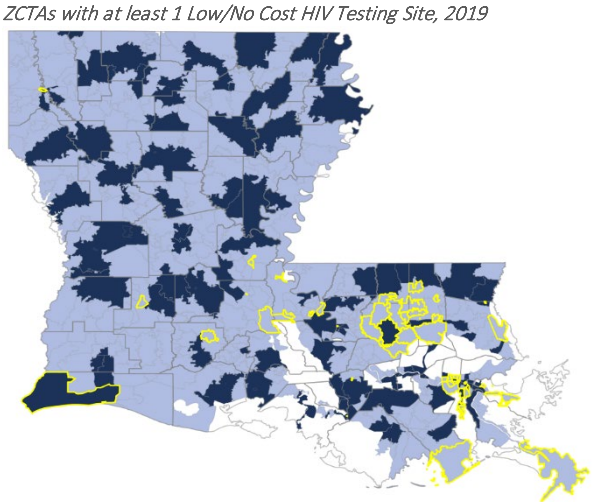
ZCTAs with at least 1 HIV Treatment/Care Provider, 2019



ZCTAs with at least 1 PrEP Provider, 2019



ZCTAs with at least 1 Low/No Cost HIV Testing Site, 2019



Feedback from Experts

Several themes emerged from our discussions with experts regarding the vulnerability assessment and the opioid epidemic in Louisiana, more generally. Discussions touched the utility of the vulnerability assessment, issues that make combatting the opioid epidemic in Louisiana particularly difficult, resources they feel are needed to effectively deal with the epidemic, and what Louisiana is doing and potentially needs to do to improve health outcomes across the state. Details on these points are provided below.

Utility of Vulnerability Assessment From a Public Health Perspective

Interviewees suggest that results of the vulnerability assessment, regarding predicted vulnerability, are useful from an educational point of view. Currently, understanding of risk factors for opioid use and addiction is incomplete - the epidemic is changing; who is using is changing; and the risk factors are changing. There have been noticeable increases in use among women and people of color in recent years, as well as in persons under the age of 35. And, while chronic pain is known as the biggest risk factors for use, what is driving these trends is not clear. The maps produced illustrating the geographic distribution of predicted vulnerability provide an interesting way of looking at the opioid epidemic and can be useful for starting discussions about what risk/vulnerability looks like. These maps can help stakeholders and researchers to start thinking about the characteristics of vulnerability and why some places and populations are more vulnerable than others. The maps are also effective vehicles for raising awareness of the extent of the opioid problem across the state and for helping specific jurisdictions to identify risk factors and resources that are needed to address the problem locally.

With this said, while mapping predicted vulnerability may be a useful educational and academic tool, they prove less so when it comes to deploying resources to address needs. First, the current quality and representativeness of data on important risk factors/measures of health are questionable. An example provided in our discussions is the fact that overdose data in Louisiana are known to be imperfect. Opioid use as a contributing cause of hospitalization, overdose, injury, or death is systematically underreported in certain hospitals and in certain jurisdictions across the state. This may lead to an underrepresentation of vulnerability in some places, and potentially an exaggerated depiction of vulnerability in others. Second, even if data were relatively complete/representative, to use the maps for resource allocation would require that they be kept up-to-date and available for community leaders and policy makers. This would require additional, and potentially unavailable, resources and funding. Finally, while examining vulnerability at a ZIP-code level provides a more nuanced understanding of where incidence is occurring and which places are predicted to be most vulnerable, it is not granular enough from an action and resource standpoint. In many cases, ZIP Codes cover a large swath of land and/or a large population. As such, it would take a team of outreach workers to go to a ZIP Code that has been identified as vulnerable to understand the extent of need in that area and what needs to be done. Realistically, analyses would need to be at a smaller geographic level – census tract or neighborhood – if community leaders/organizations were to use them to effectively target resources and interventions.

Barriers to Combatting the Opioid Epidemic

Experts mentioned several barriers in Louisiana that complicate efforts to address the opioid epidemic. These include stigma and attitudes surrounding opioid use and substance use treatment, incentivizing and providing support to providers, the cost of effective care, and accessibility of effective treatment options. Each of these is discussed briefly in subsequent sections.

Stigma and Attitudes

Many people in Louisiana see addiction and substance use disorders as moral weakness– that individuals choose to use drugs, and it is through their own willfulness or personal weakness that they do not quit. While there is general support for 12-step programs and substance use treatment that focus on abstinence, MAT, which is proven to be the most effective method of treatment for opioid addiction/misuse, is stigmatized. Many believe that substituting a less harmful drug, such as methadone or buprenorphine, for a more harmful drug only perpetuates the problem by incentivizing drug dependency. These attitudes make providing and receiving effective treatment difficult. Many physicians and prescribers who could treat patients for opioid addiction/misuse in a health care setting choose not to, as they do not want to be associated with these practices. Similarly, people who need help often do not seek it because they fear people will judge them.

Provider Incentives, Training, and Support

Potential prescribers who have established practices do not always see the benefit of MAT. Through Medicaid and some private insurance, billing for MAT services can be done only by certain specialists (e.g., psychiatrists). For other providers, including many primary care physicians, reimbursement for MAT services is not enough to offset other patient services for which providers could be reimbursed. In addition, prescribers often don't have the support they feel they need to provide MAT. Most are not trained counselors; they have not been trained in how to conduct behavioral health assessments, and they do not know how to support and manage individuals beyond providing a prescription for MAT drugs. This, coupled with the stigma surrounding MAT, makes providers question why they would want to add MAT to their service array.

Cost of Effective Care

Evidence-based treatment for opioid use/misuse is typically only covered for individuals who have behavioral health coverage as a part of a comprehensive health plan; obtaining and paying for treatment is hard for individuals who fall into health care coverage gaps. Methadone is the least expensive treatment choice for people who fall into health care coverage gaps, but it is also not as effective as MAT. Additionally, it is not widely available. For many individuals, seeking MAT services through a cash-only provider is the only means of treatment, and cost can be prohibitive for persons with limited economic means.

Access to Effective Care

Evidence-based practices for treating patients with opioid use disorders are not widely accessible across the state, especially for those living in rural places and for those who do not have the means to seek care (e.g., underinsured, homeless). What is more, though research suggests that comprehensive MAT services – use of medication (methadone, buprenorphine, suboxone) in conjunction with supportive services and counseling – is the most effective method of treating opioid use disorders, MAT services are typically not offered or allowed in most large clinics/hospitals and residential treatment settings. This results in a large gap in the quality of clinical care for opioid addiction/opioid use disorders.

What is Needed

Experts identified several strategies they feel are needed in Louisiana to effectively combat the opioid epidemic. Most strategies are related to preventing overdose and the transmission of HIV and HCV among persons who inject drugs (PWID) and increasing access to effective opioid addiction/misuse treatment. In addition, individuals discussed a need for destigmatizing opioid addiction and MAT services and for increasing focus on addiction prevention.

PREVENTING OVERDOSE

A large resource gap identified is availability of easy to administer forms of naloxone (specifically Narcan®), a fast-acting opioid overdose reversal drug. Currently, naloxone stands as the most immediate and effective way to save someone's life in an overdose situation, and the best way of ensuring it is available when needed is to distribute it to individuals who are at-risk themselves and/or who have contact with at-risk individuals. Across the state, there are agencies and community-based organizations (CBOs) that are ready to distribute Narcan®; however, they do not have access to enough of the drug to be able to distribute it. It is cost prohibitive for agencies and CBOs working with high-risk populations to obtain Narcan® themselves, and while there are some grants that allow organizations to purchase Narcan®, funds are limited.

It is also important that first responders are in a position to administer naloxone when needed. Many local police departments across the state have instituted policies mandating officers to carry Narcan®. While this has been very effective in limiting overdose deaths in some areas, it is not a universal policy in local departments, and currently state police are not mandated to carry it. Beyond the cost of the life-saving drug, attitudes stand as a barrier. Some individuals and organizations feel that naloxone is enabling addicts and increasing the likelihood of overdose. However, as more agencies institute policies to carry Narcan®, it is being destigmatized.

PREVENTING TRANSMISSION OF BLOODBORNE INFECTION

Two of the best options discussed for preventing transmission of bloodborne infection are syringe access service programs and universal opt-out testing for HCV and HIV. Syringe access service programs not only offer clean needles and injection equipment (works) to PWID; they also provide HCV/HIV testing, referrals to care, and other support services. While these programs are understood as an effective means of combatting negative health outcomes associated with IDU, they are currently only being implemented in New Orleans and Baton Rouge and are not available in many vulnerable areas.

Universal opt-out testing for HCV and HIV in emergency rooms, hospitals, and large clinics was also suggested as a much-needed prevention strategy. There have been discussions about this among stakeholders and experts and calls for the state to mandate this, but there is a wealth of obstacles that have prohibited a hard push for legislation that would make it possible.

INCREASED ACCESS TO MAT AND EFFECTIVE TREATMENT OPTIONS

Although the State has increased access to MAT for Medicaid patients (through Medicaid expansion, prior authorization for MAT drugs is not required and Medicaid is set to start reimbursement for methadone), there is still a shortage of providers, particularly those who will accept Medicaid or unfunded patients. MAT services are largely unavailable in residential treatment facilities, and most providers who have a waiver to prescribe buprenorphine/Suboxone are in private practice and accept cash-only for MAT services. Interviewees discussed several strategies they felt could alleviate some of these barriers and help increase access to effective opioid misuse/addiction treatment.

TREATMENT AT THE POINT OF CARE

Experts agree that comprehensive treatment at the point of care is needed. The places where people are most likely to receive medical care, including hospitals, large clinics, federally qualified health centers (FQHCs), and primary care practices, need to provide the full array of services that individuals with opioid use disorders need. This includes screening for opioid addiction/misuse, brief intervention, and evidence-based treatment (specifically MAT). If treatment is not readily available in these places, then providers need to be willing and able to refer their patients to providers who can provide MAT.

INCREASED SUPPORT FOR PRESCRIBERS

Two strategies that may serve to increase access to effective treatment at the point of care are increased consultative supports to buprenorphine prescribers and implementation of the Spoke and Hub model where smaller clinics and practices have a larger, central provider from which they can receive support or to which they can refer patients. Prescribers of buprenorphine often need consultative support. Since they are not trained counselors or behavioral health professionals, they need to be able to access those who are. One option is for prescribers to connect to experts who can advise them on client care. Currently Tulane University is providing these services through Project ECHO (Extension for Community Healthcare Outcomes). Through ECHO, prescribers and MAT providers can access experts at Tulane to anonymously discuss patient cases and get advice on how to best treat patients.[16] Another option discussed is for prescribers and small organizations to either have behavioral health counselors and clinicians from larger organizations come into their offices to provide direct support to clients or provide guidance to prescribers (similar to that provided through ECHO); alternatively, patients can be referred to these larger clinics, especially if they are close enough in proximity to make access possible.

INTEGRATED CARE IN TREATMENT FACILITIES

Related to comprehensive treatment at the point of medical care, residential treatment facilities need to either directly provide MAT to clients or allow prescribers from the community to access their clients. They also need to ensure clients have access to primary and mental health care while they are in treatment – so that they stay in treatment and increase the likelihood of achieving improved behavioral and health outcomes.

TELEMEDICINE

A final strategy mentioned for increasing access to MAT services is the use of Telemedicine. Through Telemedicine, clinics and providers that do not have on-site MAT services can access prescribers through an online interface. Primary health care and support services (e.g., case management and counseling) can be provided on site, and addiction specialists or MAT service providers can remotely assess patients and prescribe medication. Telemedicine is especially important as a treatment strategy for rural, more remote locations. While there is a lot of promise in Telemedicine, there are some potential downsides. First, state law stipulates that a patient's initial exam must be done in person. This means that to be compliant with the state law, Telemedicine prescribers will periodically need to travel to the facilities where they are prescribing medications to conduct exams, or patients in these places will have to travel to the prescriber. This will be especially problematic in remote areas and for people with limited means of transportation. Another potential issue is service provision. There are large, out-of-state organizations that provide Telemedicine services. Though cost-effective, these organizations do not have cultural knowledge that may be necessary for providing effective care. In addition, some fear that large providers may not be as invested in clients' wellbeing as local providers would be, which may decrease the quality of care patients receive.

[16] For more information see: https://libguides.tulane.edu/ECHO/Topics.

Education

Increased education surrounding the opioid epidemic may lead to a de-stigmatization of MAT services and to a change in opioid prescribing practices. Health providers and the general public need to be made aware of the extent and consequences of the opioid epidemic and the fact that evidence indicates MAT encourages people to stay in treatment longer, which, in turn, decreases that likelihood that individuals engage in high risk behaviors and overdose. The state, as well as local agencies and CBOs, are doing a lot to increase awareness, including holding Action Summits, participating in the National Judicial Opioid Task Force and holding *Screening, Brief Intervention, and Referral to Treatment* (SBIRT) trainings for prescribers and practitioners that teach them how to screen for substance use disorders and refer to appropriate care. While progress is being made, more training and education is needed. In particular, education and training related to pain management will help prescribers to limit the duration and amount of opioids prescribed and to provide patients with non-opioid alternatives.

Preventing Addiction

In the long term, effective prevention is critical. The state has made strides by instituting a limit on the duration of opioid prescriptions to seven days and integrating monitoring into hospitals and electronic health records. However, the state has not provided alternatives to opioids for pain management. Alternative modalities are often not covered by Medicaid, and hospitals are not equipped to prescribe less.

A focus on prevention also entails increased efforts towards understanding and addressing social determinants of risk and addiction. It is well understood that chronic pain is a correlate and predictor of opioid use, however, other social determinants such as poverty that might also play an important role are not well understood.

Discussion

The purpose of this project was to produce a statewide Opioid and Infectious Diseases Vulnerability Assessment based on existing data sources as well as interviews and group discussions with experts in the local and statewide opioid crisis. Following guidance from the CDC, we undertook a “step-wise” approach, collecting data on plausible indicators of vulnerability to outbreak and implementing a model-based approach to identifying vulnerable places and resource gaps across the state.

Results from the assessment indicate that the southeast region of the state is most vulnerable to outbreak; though; there are pockets of vulnerability throughout. Jefferson, Livingston, and Tangipahoa Parishes appear to be particularly at risk; together, these account for nearly 60% (30 of 51) of ZCTAs identified as most vulnerable. Discussions with experts suggest that this depiction of vulnerability is largely representative of HCV-incidence and corresponds well (although not perfectly) with opioid-related overdoses and deaths across the state.

Additional analyses presented in Table C1 in Appendix C, indicate that the areas with highest predicted vulnerability tend to rank highly in a number of negative substance use and health outcomes. Of the 51 ZCTAs identified as most vulnerable in this assessment, 85% rank in the top 10% of ZCTAs with the following health risk outcomes: new chronic HCV infections in persons under 40, MME rate for opioid analgesics, HIV prevalence, rate of injury-related deaths, drug overdose deaths, and rate of drug involved death, opioids only; more than 40% of vulnerable ZCTAs rank in the top 10% of at least 2 of these outcomes.

Regarding resources and resource gaps, results indicate that there is a dearth of many high-impact prevention and treatment services across the state. Maps of resources illustrate that few areas have immediate access to a methadone clinic or syringe access services, and while buprenorphine prescribers and substance use disorder providers are more widely distributed across the state, they are not available in many areas, including many of those identified as most vulnerable to an opioid-related outbreak of disease or overdose. With regard to HCV and HIV services, there also appear to be gaps in access to low/no-cost testing and to service providers who explicitly provide treatment and care for these illnesses. Experts agreed that there are a number of gaps in effective care and treatment across the state; the greatest needs mentioned are increased access to resources such as naloxone and syringe access services, which are aimed at preventing overdose and the transmission of HIV/HCV, and more effective opioid addiction/misuse treatment, especially with regard to increased access to buprenorphine/MAT services.

Ultimately, any plan of action intended to curb the ill effects of the opioid epidemic needs to distinguish between places with high incidence of negative outcomes (e.g., overdose, HCV, HIV) and those that are not experiencing high incidence but may be at risk. State and local governments/agencies/CBOs need to identify places where overdose, opioid related deaths, and outbreaks of HIV/HCV are happening. These places need to be assessed and should be prioritized for the immediate allocation of resources and attention. In terms of prevention, more needs to be done to understand vulnerability, what puts a place at risk, and which places are most vulnerable to increased incidence of opioid-related negative health outcomes. Places that are considered vulnerable need to be assessed to see what resources are needed to prevent overdoes death/infectious disease from occurring.

While interviewees contend that predicted vulnerability maps do not yet provide a sound basis for resource allocation, they do understand and appreciate its educational value. Results of this report can be used to prompt conversations among stakeholders about where the most critical resource gaps are across the state and what needs to be done to address those gaps. They can also be used as a starting point for conversations about what makes places and populations vulnerable and what can and should be done to prevention disease outbreak and opioid overdose in these areas.

LIMITATIONS

This vulnerability assessment is premised on selecting a predictive, interpretable, and (relatively) parsimonious model to predict HCV and, in turn, places vulnerable to an outbreak of HCV/HIV or opioid overdose. We have employed this method because it is similar in approach to that used previously by the CDC (Van Handel et al. 2016), and it is a transparent process with clear and identifiable decision criteria. Further, it is our understanding that it is the variables themselves that are of substantive interest. If only prediction were of primary interest (i.e., if we were not interested in which predictor variables were associated with chronic HCV) a machine learning algorithm may have been more appropriate. There is a burgeoning array of supervised learning techniques that may select a more predictive model, but require high dimensionality and/or non-interpretability of coefficients (Hastie, Tibshirani, Friedman, 2009).[17] With these concerns in mind, we conducted several sensitivity analyses to better understand the robustness and potential limitations of our methodological approach. Specifically, using our benchmark approach, we estimated a predictive model using our "full" set of predictor variables (all 23 candidate variable remaining after data reduction from which we selected the final, parsimonious model), a model that permits second order and interaction effects, as well as a parish-

[17] Hastie, T., Tibshirani, R., Freidman, J. (2001). The Elements of Statistical Learning Data Mining, Inference, and Prediction (2nd ed). Springer Science + Business Media. New York.

level predictive model. In addition, we implemented a machine-learning algorithm and LASSO (Least Absolute Shrinkage and Selection Operator) methods to select a final parsimonious model from our full set of predictor variables. Though results of these analyses were largely consistent with those of our benchmark approach, there was enough variation in identification of vulnerable places – especially regarding the machine learning approach – to warrant future investigation of different modeling approaches. Methods and results are discussed and presented in Appendix A and Appendix D, respectively.

Another limitation of the approach we have used is that spatial autocorrelation has not been incorporated into the analysis – although evidence (Moran's I) suggests that such correlation exists in the data. The reason for not including spatial considerations in the analysis is that a guiding principle of this initial analysis was to keep the model and analysis as straightforward as possible. Nevertheless, if resources permit and there is an interest in improving the predictive validity of the model, integrating spatial autocorrelation (e.g., via spatial autoregressive or spatial error models) in subsequent analytical models would be productive.

Finally, there are known limitations to the data used in analysis. Data on health outcomes of interest are not consistently reported or gathered across the state, and there is a lag in reporting, which means that even the most recently available data may not be up-to-date and representative of actual incidence in an area. Due to this, especially given the short time-period of data considered in the statistical analysis, we are not sure how generalizable the current model is. We are unsure to what extent we are predicting the true (but latent) regional vulnerability to high-risk IDU or just a short-term covariance of chance. The same analysis, given a longer duration of time, should permit for the exclusion of some of the spurious correlation that may exist in the current model.

APPENDIX A: DETAILED METHODS

DESIGN AND SETTING

The purpose of this study was to identify areas in Louisiana that are at risk of an outbreak of bloodborne illness or overdose due to high-risk injection drug use (IDU). Our methods and analysis are intended to parallel a nationwide study conducted by the *Centers for Disease Control and Prevention* (CDC) that examined county-level vulnerability across the nation (Van Handel et al. 2016).[18] Our vulnerability assessment is similar in methods to the nationwide study but uses more recent and more granular data (ZIP Code level) in order to identify pockets of vulnerability across the state. Our approach involved a multi-stage variable selection process, use of a multi-level regression model to predict the rate of chronic hepatitis C (HCV) among individuals under the age of 40, creation of a vulnerability index that is used to identify areas of high vulnerability, and descriptive analyses of health outcomes and resource gaps across the state of Louisiana.

The unit of analysis is the ZIP Code Tabulation Area (ZCTA).[19] We were initially interested in the census tract because it would allow a more nuanced understanding of where risk occurs and how it potentially clusters. In addition, Flanagan et al. (2011) suggest they are relevant from a policy and planning perspective as they "are commonly used to collect and analyze data for policy and planning in government and public health." [20] However, due to confidentiality concerns with smaller geographic areas, we were only able to obtain HCV data at the ZIP Code-level. Even so, we feel the ZIP Code is a meaningful geography as research (especially related to social determinants of health) shows that the ZIP Code in which a person resides is a strong predictor of their own health outcomes, in large part because it captures the environment in which people live, the resources they are able to access, and the risks to which they are exposed on a continual basis.[21] Methodologically speaking, with 510 observations, ZCTA is also sufficiently granular to explore the large number of plausible predictors identified.[22]

To be an accurate reflection of current vulnerability, we used the most recent data possible in analyses. While HCV data were obtained for 2016-2018, many other data points were available only for 2016 and/or 2017. To keep consistency across variables, we restricted data to those collected for 2016 or 2017, or which are period measures that include these time points (e.g., *American Community Survey* (ACS) 5-year population estimates released in 2017).

---

[18] Van Handel, M. M., Rose, C. E., Hallisey, E. J., Kolling, J. L., Zibbell, et al. (2016). County-level Vulnerability Assessment for Rapid Dissemination of HIV or HCV infections among Persons who Inject Drugs, United States. *Journal of Acquired Immune Deficiency Syndromes, 73*(3), 323-331.

[19] According to the U.S. Census Bureau, "ZIP Codes identify the individual Post Office or metropolitan area delivery station associated with mailing addresses … ZIP Codes are not areal features but a collection of mail delivery routes." In order to create geographic units that better correspond to census statistical units, the Census Bureau uses addresses within census blocks to define ZCTAs, which are "generalized areal representations of ZIP Codes." For more information on how ZCTAs correspond to ZIP Codes see: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html.

[20] Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A Social Vulnerability Index for Disaster Management. Journal of Homeland Security and Emergency Management, 8(1). doi:10.2202/1547-7355.1792).

[21] See Slade-Sawyer P. 2014. Is health determined by genetic code or zip code? Measuring the health of groups and improving population health. *North Carolina Medical Journal*. 75(6):394-7. doi: 10.18043/ncm.75.6.394, and https://www.healthaffairs.org/do/10.1377/hblog20150806.049730/full/.

[22]Though there is much disagreement on the subject of appropriate sample size for the analytic techniques employed in this assessment (principal components analysis, factor analysis, regression modeling), we feel a sample size of over 500 and an item-to-observation ratio of roughly 10:1 is adequate considering our primary purpose in using these methods is variable reduction and considering that Hilbe (2014). indicates there is evidence that the rule of 10:1 or even 5:1 is appropriate for count modeling. Hilbe, J. M. (2014). *Modeling Count Data*. New York: Cambridge University Press.

IDENTIFYING PLAUSIBLE PREDICTOR VARIABLES

We began with the list of 78 variables identified by Rickels et al. (2017), which includes the predictors identified by Van Handel et al. (2016). We then held interviews and group discussions with individuals who were identified as experts on opioid use and addiction, the opioid epidemic, and/or infectious disease in Louisiana to discuss plausible predictors of vulnerability specific to Louisiana.[23] From this process, all initial predictors were retained and the following were added to our variable list: *number of people within flood zones, calls to suicide hotline, acute hepatitis B* (HBV), *chronic HBV, percentage of blue-collar workers, education desert, chronic HCV in persons under 40, extent of homelessness in an area; access to HIV treatment/care; access to HCV treatment/care; access to HIV and HCV testing; access to substance use disorder provider; access to Pre-Exposure Prophylaxis (*PrEP*); and access to syringe services*.

DATA AND DATA SOURCES

Data were obtained through a number of different sources; of particular note: HIV, hepatitis, and STI data, available through the Louisiana Office of Public Health, STD/HIV/Hepatitis Program (OPH SHP); drug-related death and hospitalization data available through the *Louisiana Department of Health* (LDH), *Louisiana Opioid Data and Surveillance System* (LODSS), prescription drug data available through the *Louisiana Board of Pharmacy Prescription Monitoring Program* (PMP); and health care and high-impact prevention (HIP) intervention service data available through *Center for Medicare and Medicaid Services* (CMS) *National Provider Identification* (NPPES) and through *National Prevention Information Network* (NPIN) organizations database. Much of the other data used in analysis were retrieved from *County Health Rankings and Roadmaps* and ACS*.*

We attempted to obtain data for the full list of identified predictors; however, we were unable for nine variables identified in Rickels et al. (2017) and one additional predictor identified by experts.[24,25] Once we compiled the data, we constructed one measure for each of the plausible predictors. In several cases, Rickels et al. (2017) considered both counts and rates of several predictors, and they considered logged and unlogged versions of predictors. To simplify an already complicated variable selection process, we did not operationalize the count or log variables in these instances. In all, we constructed 73 variables for modeling purposes – including the outcome of interest.[26] Appendix B provides a table detailing all 73 variables we constructed for analysis. The table categorizes variables into 8 domains: demographic characteristics, social characteristics, economic characteristics, housing characteristics, health outcomes, opioid and medication-assisted treatment (MAT) prescriptions, access to health care, and high impact prevention and intervention services. Included in the table are details on data

---

[23] We first conducted online searches to identify Louisiana-based opioid epidemic and/or substance abuse-content area experts with documented long-term experience working on opioid task forces, working groups, or committees. An initial list of eleven individuals was compiled and vetted by our project partner, the Louisiana Department of Health Office of Public Health's STD/HIV Program (OPH SHP), to identify individuals who they felt would be the most useful with whom to speak. Emails were sent to six of the individuals and responses were received from three who agreed to participate in a 30-60-minute key informant interview. These three individuals recommended we reach out to an additional six people or entities with expertise in the topic area. A total of nine experts were consulted for this study.

[24] Rickles, M., Rebeiro, P. F., Sizemore, L., Juarez, P., Mutter, M., Wester, C., & McPheeters, M. (2017). Tennessee's In-state Vulnerability Assessment for a "Rapid Dissemination of Human Immunodeficiency Virus or Hepatitis C Virus Infection" Event Utilizing Data About the Opioid Epidemic. *Clinical Infectious Diseases, 66*(11), 1722-1732.

[25] We could not obtain data for the following variables identified in Rickels et al. (2017): *highway access*; *multiple provider episodes*; *certified pain management clinics*; *nonfatal overdoses, opioids only*; *nonfatal overdoses, heroin only*; *substance abuse treatment beds*; *substance abuse treatment beds, per capita*; *admissions for injection drug use treatment*; *rate of acute hepatitis C infections.* In addition, we could not obtain data on *extent of homelessness* in an area which was identified by experts.

[26] For a few predictors, we operationalized variables differently for the model and maps presented in the report. In these instances, both operationalizations are presented in Appendix B.

sources/data availability, variable operationalization and analysis, and geographic-level and year of data obtained.

While data needed for many of the measures were available at the ZIP Code or ZCTA level, several variables were only available at the parish (county) level. Though ZIP Codes, and correspondingly ZCTAs, are not always bounded by parishes or counties, we decided inclusion of parish-level predictors was important as the characteristics of a parish are likely to influence or correspond to the characteristics of ZCTAs that are close in proximity (within and around them).

In order to produce a ZCTA-level dataset, we used geography relationship files, or crosswalks, to link ZIP Codes and parishes to 2010 Census ZCTAs. In all, 714 ZIP Codes were matched to 510 residential ZCTAS; 396 ZIP codes were exact matches to a ZCTA, and 318 were spatially matched to a ZCTA. [27,28,29] After matching all ZIP Codes to ZCTAs, data were aggregated to the ZCTA level, such that each ZCTA observation represents the sum of all ZIP Codes mapped to it. Since ZCTAs can cross parish lines, we consider a ZCTA linked to a parish if the ZCTA to County crosswalk indicated at least 51% of the ZCTA population resided in that parish.[30] In all, 386 of the residential ZCTAs located in Louisiana were located entirely within one parish; the remaining 114 cases were linked based on population distribution.[31]

VARIABLE SELECTION

We conducted a multi-step variable selection process in order to identify the best subset of plausible predictors with which to model the of rate of chronic HCV for persons under 40. While our methodological approach is primarily guided by Van Handel et al. (2016) and Rickels et al. (2017), we also relied on other relevant literature to inform our methods and to plan our analyses.

COMPREHENSIVE VARIABLE REVIEW

Our initial step was a comprehensive review of the data. For this, we reviewed and categorized the variables in terms of what they measure, recency, missingness, and variability. To be considered for inclusion in our predictive model, variables must: 1) be reflective of the 2016-2017 time period (data must have been gathered in 2016, 2017, or be period measures that include these time points); 2) have a percentage of missingness below 50%; and 3) not be a “zero-variance” or “near-zero variance predictor.”[32] Following the comprehensive variable review, 16 variables were removed from consideration in the model because they did not meet these criteria.

---

[27]The ZIP Code to ZCTA crosswalk was developed by John Snow, Inc. for Uniform Data Service (UDS) service area data. The crosswalk and explanation of its use can be found on the UDS Mapper website. See https://www.udsmapper.org/zcta-crosswalk.cfm for more information.
[28] Not considered in analysis are six ZCTAs included in the ZIP Code to ZCTA crosswalk as Post Offices or large volume postal customers (e.g., large businesses) that ACS data indicate have no residential population.
[29] The 318 ZIP Codes that are not exact matches to a ZCTA are all identified as Post Offices or large volume postal customers. According to the UDS Mapper website, JCI “assures that every valid ZIP Code maps to the ZCTA that best fits its location (based on centroid).” See https://www.udsmapper.org/faqs.cfm.
[30] We used the 2010 ZCTA to County relationship file produced by the U.S. Census Bureau to link ZCTAs to parishes. The crosswalk and a brief explanation of its intended use can be found on the U.S. Census Bureau website. See https://www.census.gov/geographies/reference-files/2010/geo/relationsh ip-files.html#par_textimage_674173622 for more information.
[31] The breakdown of ZCTAs linked to a parish by percentage of population residing in the parish is as follows: 100% of population residing in parish = 386 (76%); 90-99% of population residing in parish = 58 (11%); 80-89% of population residing in parish = 33 (6%); 70-79% of population residing in parish = 19 (4%); 60-69% of population residing in parish =11 (2%); 50-51% of population residing in parish = 3 (1%).
[32] A zero-variance predictor has only one value, while a near-zero variance predictor may have multiple values. But, the frequency for one value is very high, and the frequency for the others is very low. According to Kuhn and Johnson (2013), predictors such as these are “uninformative” and can be problematic in regression modeling. Following the “rule of thumb” suggested by Kuhn and Johnson (2013; 467), we consider a variable to be a near-zero variance predictor if “the fraction of unique values over the sample size is low” (less than or equal to 10%), and “the ratio of the frequency of the most prevalent value to the frequency of the second most prevalent value is large” (20 or higher). All variables identified as near-zero variance predictors were removed from consideration in the model. See: Kuhn, M. and Johnson, K. (2013). *Applied Predictive Modeling*. New York: Springer.

MISSING DATA IN PREDICTOR VARIABLES

While most of the data we obtained were complete, several variables retained during the variable selection process had missing observations. Observations were missing because 1) low values (values between 1 and 5) in incidence variables and their derived rates were suppressed due to confidentiality issues, or 2) valid values were not provided in the datasets we received. Since the purpose of our analyses was prediction and not hypothesis testing and we had very little missing data, we decided the simplest and most straightforward approach was best for our needs. Suppressed observations were imputed to the median of the range of suppressed values (value of 3). Data which were missing because they were not provided were imputed to the median of the variable, given the parish in which the ZCTA was located and rural status of the ZCTA. To ensure the all observations were included in our data reduction and modeling analyses, imputation was conducted following the initial variable selection process and prior to data reduction. Table A.1 provides details on variables with imputed data and the extent of missingness or suppression in the ZCTA level within each.

Table A.1 Number and Percentage of Imputed Values, by Variable

	Observations Imputed	
Variable with Missing Observations	**Number**	**Percent**
Violent crimes	38	7.4%
Property crimes	53	10.3%
Gini coefficient	7	1.4%
Per capita income	8	1.6%
Percentage of mobile homes	3	0.6%
Percentage of homes with no phone service	3	0.6%
Percentage with no high school diploma	1	0.2%
Percentage living in poverty	3	0.6%
Percentage of population that is unemployed	4	0.8%
Percentage of female-headed households	3	0.6%
Teen birth rate	49	9.5%
Drug overdose death	23	4.5%
Percentage of housing units that are crowded	3	0.6%
Percentage of workers in blue-collar occupation	7	1.4%
Percentage with vehicle access	3	0.6%
Variables with Suppressed Values		
Rate of drug involved death, 2016	129	25.0%
Rate of drug involved death, 2017	151	29.3%
Rate of opioid involved death, 2016	197	38.2%
Rate of opioid involved death, 2017	199	38.6%
Neonatal abstinence syndrome cases	170	32.9%
Nonfatal overdoses, all drugs	209	40.5%
Rate of new acute HBV infections, 2016	255	49.4%
Rate of new acute HBV, 2017	144	27.9%
Rate of new chronic HBV, 2016	114	22.1%
Rate of new chronic HBV, 2017	112	21.7%
MME rate for MAT drugs, 2016	37	7.2%
MME rate for opioids, 2016	21	4.1%
Total MME for all drugs, 2016	37	7.2%
MME rate for MAT drugs, 2017	36	7.0%
MME rate for opioids, 2017	26	5.0%
Total MME for all drugs, 2017	36	7.0%
Rate of heroin and opioid involved death, 2016	250	48.4%
Rate of heroin and opioid involved death, 2017	244	47.3%

DATA REDUCTION

The next step in the variable selection process was to reduce the number of plausible predictors into a smaller set that adequately captures the domain content and information contained in the original set. For this step, in tandem, we did the following:

1. **Performed Principal Components Analysis** (PCA) to identify the set of underlying components that explain the most variance across plausible predictor variables and identify the variable that contributes most to each component (i.e., has the largest coefficient or component loading).[33]
2. **Performed a Factor Analysis** to identify variables that contribute the most unique information to the set of plausible predictor variables.[34]
3. **Conduct simple regression**, regressing the outcome of interest on each plausible predictor variable, to identify potentially significant predictors of the outcome[35].
4. **Construct a correlation matrix** of all plausible predictor variables to identify variables that were highly correlated with one another.[36]

We performed these analyses across multiple sets of data and looked for consistency across results.[37] We identified variables that consistently explained the most variance in a particular principal component and/or were contributing information that was unique as compared to other plausible predictors; we then examined each of these variables to ensure they were not highly correlated with other variables considered for inclusion in the model.[38] In the event two or more variables explained a similar degree of variance in a particular component, or in the event two or more variables were highly correlated, we examined regression results and retained the variable that was most consistently significant. Following this data reduction step, 33 plausible predictors were removed and 22 (not including population offset) were retained for the final model selection.

FINAL SELECTION OF PREDICTORS

To select the final set of predictors needed to construct the vulnerability index, we used part of an algorithm developed by Imbens and Rubin (2015) for estimating a propensity score. We are interested in selecting an interpretable and parsimonious model that maximizes the predictive accuracy of incidence of chronic HCV in persons under 40. So rather than logistic regression, we use a multilevel negative binomial model (with population size as the exposure or offset term) to estimate the rate of chronic HCV

---

[33] PCA is a common data reduction technique used to identify linear combinations of predictors, or principal components (PCs), that explain variance in the full set of predictors (Kuhn and Johnson, 2013). There are as many PCs as there are variables in the subset – eigenvalues are used to determine the amount of variation that each PC explains. Following methods discussed in Joliffe (2002), we performed an initial PCA on plausible predictors and retained those with eigenvalues above .7. If there was little difference in the eigenvalue of the last retained PC and the first omitted PC, we would also consider inclusion of that PC. Next, we would perform PCA again using rotation and identify the variable (or variables) with the largest coefficient or component loading. See: Jolliffe, I. T. (2002). *Principal component analysis*. (2nd ed.) New York: Springer.

[34] Because PCA only considers the relationships of the predictor variables and does not consider their relationship with the dependent variable, Joliffe (2002) warns against omitting PCs with the least explained variance when trying to identify a subset of predictors to include in a regression model. This may lead to omitted variable bias – it may be the case that a variable is providing unique information that is relevant to the outcome. To account for potentially unique information provided by the plausible predictors, we also ran a factor analysis to identify variance that is unique to a specific variable. We considered a variable to be contributing unique information if factor analysis results indicated it had uniqueness of at least 0.4.

[35] Since the outcome of interest is a count variable, we conducted negative binomial regression, using ZCTA population as the exposure or offset variable.

[36] We consider variables to be highly correlated if correlation coefficients are .7 or greater for continuous variables and .3 or greater for dichotomous variables.

[37] Several datasets were constructed to reflect the longitudinal nature of many of the variables. Where there were two years of data, we constructed a dataset that contained only 2016 data, one that contained 2017 data, one that contained variables averaged across years, and for simple regressions, a longitudinal dataset. Period measures and variables collected in only one year were included in each dataset.

[38] We omitted highly correlated variables from our model as they can lead to difficulties estimating regression coefficients. According to Kuhn and Johnson (2013; pg. 46), "In general, there are good reasons to avoid data with highly correlated predictors. First, redundant predictors frequently add more complexity to the model than information they provide to the model…[Second] Using highly correlated predictors in techniques like linear regression can result in highly unstable models, numerical errors, and degraded predictive performance."

and iteratively add to and select the set of predictors that maximizes the likelihood function and is above a likelihood ratio statistic of 2.71, which corresponds to a z-statistic of 1.645. In brief, the algorithm starts with a constant model (intercept only) and then iteratively considers and tests the added predictive value (based on the likelihood ratio statistic and Akaike information criterion (AIC)) for each candidate predictor. If at least some of the likelihood ratio statistics are above the pre-set threshold (LR > 2.71), we include the candidate variable with the highest likelihood ratio statistic (or equivalently, given the comparison is nested, the lowest AIC). The algorithm then tests the inclusion of all remaining predictive terms against the unrestricted model that includes the selected predictor. This routine continues until no remaining variables meet the inclusion threshold.

Following this final selection of predictors, we retained 12 variables from our original list of plausible predictors, plus a measure *year*, which is an indicator of the year of the observation (2016 or 2017) for variables with multiple observation time points.

STATISTICAL MODEL

We modeled the rate of chronic HCV infection using a multi-level generalized linear model (GLM) with a log link and a negative binomial distribution. We employed a three-level model where time (two annual observations, 2016 and 2017) is nested in ZCTAs, and ZCTAs are nested in parish, with ZCTA population included in the model as an offset.[39]

MODEL SPECIFICATION

The equation for the empirical model is as follows:

Level 1: ZCTA:

$$\ln\,(\eta_{ijk}) = \ln\!\left(p_j\right) + \beta_0 + \beta_{1p}ZTV_{pijk} + \beta_{2l}ZTI_{ljk} + \beta_{3m}PTV_{mik} + \beta_{4o}PTI_{ok} + \beta_5 Year_{ijk}$$

Where:

η_{ijk} = the predicted count of chronic HCV for persons under 40 at time *i* for ZCTA *j* in parish *k;*

$\ln(p)$ = the natural log of the population in ZCTA *j*, which is the offset variable; this allows us to interpret the outcome η_{ijk} as a rate.

$Year_{ijk}$ = the time variant indicator (fixed effect) of year of observation for ZCTA *j* at time *i* in parish *k*;

ZTV_{pijk} = a p-vector of time-variant ZCTA-level predictor variables, detailed in Appendix B;

ZTI_{ljk} = an l-vector of time-invariant ZCTA-level predictor variables, detailed in Appendix B;

PTV_{mik} = an m-vector of time-variant parish-level predictor variables, detailed in Appendix B;

[39] According to Hilbe (2014, pg. 63), "Statisticians use an offset with a model to adjust for counts of events over time periods, areas, and volumes. The model is sometimes referred to as a proportional intensity model." Using an offset not only adjusts for potential correlations in observations, but it also allows the outcome of the model to be interpreted as a rate. See: Osgood, D., W. (2000). Poisson-Based Regression Analysis of Aggregate Crime Rates *Journal of Quantitative Criminology* 16(1), 21-43.

PTI_{ok} = an o-vector of time-invariant parish-level predictor variables, detailed in Appendix B;

β_0 = the intercept;

$\beta_{1p}, \beta_{2l}, \beta_{3m}, \beta_{4o}$ = vectors of coefficients for the predictors entered in the model; each represents the predicted change in the log rate of chronic HCV in person under 40 in a ZCTA that is associated with a one-unit increase in the selected predictor, holding all other predictors constant;

β_5 = represents the change in the log rate of chronic HCV in persons under 40 from 2016 to 2017, when all other predictors are held constant;

MODEL DIAGNOSTICS

The outcome of interest, chronic HCV incidence among persons under 40, is a count variable. Prior to conducting the model-based variable selection procedures described above, we assessed which count model would be most appropriate for our data using methods suggested by Hilbe (2014).[40] We estimated single-level Poisson and negative binomial models regressing our outcome of interest on the set of retained plausible predictors. The Pearson dispersion statistic values for both models (4.59 and 1.92, respectively) indicated the data were overdispersed.[41] Next, we ran model fit diagnostics (*countfit* in Stata) and determined that the negative binomial model was the preferred model on the basis of goodness of fit statistics (AIC and Bayesian information criterion (BIC)) and predicted and observed values. Finally, we estimated a series of two- and three-level Poisson and negative binomial mixed regression models with ZCTA (level 2) and parish (level 3) modeled as random effects, and assessed AIC, BIC, and log likelihood ratio test statistics associated with each model to assess which was best fit.[42] The three-level, negative binomial model had the lowest scores on all three measures, indicating it was most appropriate for our data.

CONSTRUCTION OF VULNERABILITY INDEX

We used coefficients obtained from our regression model to determine vulnerability for each ZCTA. Following Van Handel et al. (2016), the coefficient for each predictor was multiplied by the value for that predictor for each ZCTA. In instances where two years of data were available, the data were averaged. Variables were then summed to create a vulnerability index – for which lower values indicated less vulnerability and higher values indicated greater vulnerability. To increase the interpretability of the index, we ranked the index scores for each of the ZCTAs, and then reverse coded the ranks so that a value of 1 indicates the most vulnerable ZCTA and a value of 510 indicates the least vulnerable ZCTA.

[40]According to Hilbe (2014), count data are non-negative counts of items or events that have occurred. Often count variables are limited in range as compared to continuous variables, with only a small to moderate number of distinct values. Due to this, count data are often not appropriate for statistical models, such as ordinary least squares (OLS) regression, that assume a normal distribution of residual errors. Instead, count data are typically better suited for count models that are based on the Poisson distribution – including Poisson and negative binomial models. See: Hilbe, J. M. (2014). Modeling count data. New York: Cambridge University Press.

[41] Overdispersion was likely because our data are grouped or nested (each ZCTA has two annual observations, and each parish has multiple ZCTAs nested within).

[42] AIC, BIC, and Likelihood ratio tests are all used to compare the fit of nested models. According to Hilbe (2014, 112) "Poisson is often considered a reduced version of negative binomial;" therefore, these goodness-of-fit tests can help assess whether or not one model is preferred over the other.

CHOROPLETH MAPS

Choropleth maps were constructed in Stata 15 using the built-in command *grmap* and the user-written command *shp2dta.*[43,44] Cartographic boundary files for ZCTAs and parishes in Louisiana were obtained from the Census Bureau's MAF/TIGER geographic database.[45] Choropleth maps simplify the predicted vulnerability estimates by illustrating the degree of predicted vulnerability (orange maps) in quintiles, from lowest risk (light orange) to highest risk (dark orange). Similar maps are constructed for resources; however, in these cases, maps depict the presence (dark blue) or absence (light blue) of a resource in a ZCTA.

SENSITIVITY ANALYSES

We acknowledge there are limitations to our data and to our benchmark approach detailed above. To test the robustness of our approach, we developed alternative vulnerability indices based on different model specifications and compared results with the results of our parsimonious-benchmark model. [46] Specifically, did the following:

1. We estimated a predictive model of chronic HCV in persons under 40 using the "full" set of 22-variables (not including population size) that were selected after data reduction from which we selected the final, parsimonious model.
2. Using the final, parsimonious set of 13 predictors identified in the benchmark model, we estimated a model of chronic HCV incidence that permits second order and interaction effects of the selected linear terms in the benchmark approach. The algorithm is otherwise identical to the benchmark model. The additional variables produce a model that has better goodness-of-fit statistics but is less parsimonious than the benchmark one.
3. We implemented a machine learning, boosted decision-tree algorithm (*boost* in Stata) using a Poisson (not negative binomial) distribution.[47]
4. We implemented Least Absolute Shrinkage and Selection Operator (LASSO), which is a common regression-based approach for prediction and model selection (Joliffe 2002; Kuhn and Johnson 2013). While it is less transparent than the simple benchmark algorithm used above, predictors and coefficients are meaningful in a LASSO framework and recoverable postestimation. As an additional means of sensitivity testing the benchmark approach, we fit a Poisson LASSO model with adaptive selection and produce the set of predictor variables.[48]
5. We conducted the benchmark variable selection process on parish-level predictors and estimated a parish-level model of chronic HCV in persons under 40.

Using coefficients from each of these alternative models, we constructed separate vulnerability indices. We then generated a choropleth map of vulnerability for each index as well as a comparative table indicating whether or not each of the top 51 most vulnerable ZCTAs identified in the benchmark index is

---

[43] According to the Stata *grmap* manual, "*grmap* is lightly adapted from *spmap*, which was written by Maurizio Pisati (2007) of the Universita degli Studi di Milano-Bicocca and which was preceded by his *tmap* command (2004)." See: https://www.stata.com/manuals/sp*grmap*.pdf

[44] Kevin Crow, 2006. "SHP2DTA: Stata module to converts shape boundary files to Stata datasets," Statistical Software Components S456718, Boston College Department of Economics, revised 17 Jul 2015.

[45] According to the Census Bureau, "Cartographic boundary files are simplified representations of selected geographic areas from the Census Bureau's MAF/TIGER geographic database. These boundary files are specifically designed for small scale thematic mapping." Shapefiles and related information can be found at: https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html.

[46] In addition to testing separate indices, following the work of Van Handel et al. (2016), we used a simulation to estimate 90% confidence intervals for each ZCTAs rank. Results of the simulation suggest our rankings are quite robust – no additional ZCTAs were identified as vulnerable using this simulation method, and 98% of the top 51 most vulnerable ZCTAs identified in the benchmark model are also identified in the simulation.

[47] The *boost* command in Stata does not permit the use of the negative binomial distribution.

[48] The *lasso* command in Stata does not fit a negative binomial model.

also identified as vulnerable in the alternative indices. Comparative results of the benchmark and alternative models are presented in Appendix D.

Except for the boost model, for which predicted vulnerability varies considerably, results of the alternative indices are largely consistent with that of the benchmark model. Each of the choropleth maps presented in Appendix D show a large concentration of vulnerability in the southeast region of the state – especially in Livingston and Tangipahoa parishes. Considering the most vulnerable ZCTAs identified by each model, the full model and LASSO specifications most closely approximate the benchmark model. In terms of the top 10% of vulnerable ZCTAs identified, these models correspond to the benchmark model in 82% and 84% of cases, respectively. The boost model corresponds the least to the benchmark model. The divergence may be attributable to factors other than the predictive algorithms (e.g., distributions), but in any case, less than one third of the ZCTAs identified as being most vulnerable (top 10%) by the benchmark approach are identified as most vulnerable by the boosted algorithm. The results of the interaction model show that – in terms of comparability with the benchmark approach – this model produces results that are somewhere in between the boosted and LASSO approaches. This model does not agree as consistently with the benchmark as does the LASSO model, but it identifies approximately half of the same ZCTAs as the benchmark as highly vulnerable (i.e., top 10%). While the map shows many of the most vulnerable ZCTAs identified in the benchmark model are located within the areas of high vulnerability, additional analysis shows that two parishes (Iberville and East Feliciana), which are identified in the top 10% of vulnerable parishes have no ZCTAs identified as highly vulnerable in the benchmark model.

APPENDIX B. VARIABLE DESCRIPTIONS

Included in the table below are descriptions of all plausible variables (except for *year*) considered for analysis. The table is broken down by domain and provides details on data sources, variable operationalization, and geographic-level and year of data received. Measures in bold are included in the final model (as the outcome of interest, predictors, or population offset); asterisks indicate measures that are represented in choropleth maps in the report or in Appendices C and D.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
Demographic characteristics				
1. Percentage of population never married*	**Percentage of population 15 years and over who have never been married. No calculations made; the measure was obtained from ACS data tables.**	***American Community Survey* (ACS), 5-year estimates**[49] ***Table S1201 - Marital Status***	**ZCTA and parish**	**2017**
2. Percentage with no high school diploma*	**Percentage of ZCTA population aged 25 or older with less than 12th grade education (including persons with 12 grades but no diploma). No calculations made; the measure was obtained from ACS data tables.**	**ACS, 5-year estimates** ***Table S1501 – Educational Attainment***	**ZCTA and parish**	**2017**
3. Percentage of population that is non-Hispanic white	Percentage of population who identify as white alone, non-Hispanic. Percentage was calculated by dividing the total number identified as white, non-Hispanic by the ZCTA population estimate; the quotient was multiplied by 100 to obtain the percentage. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table C27001H - Health Insurance Coverage Status by Age (White Alone, Not Hispanic Or Latino)*	ZCTA and parish	2017
4. Percentage of population with a disability	Percentage of population with a disability (civilian noninstitutionalized population). No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates Table S1810 – Disability Characteristics	Parish	2017
5. Percentage of population aged 18-29	Percentage of ZCTA population age 18 to 29 years old out of total population. ACS provides estimates of the percentage of individuals ages 18 to 24 and the percentage ages 25 to 29. The estimates were summed to create the measure. *Removed as predictor during data reduction process*	ACS, 5-year estimates Table S0101 - Age and Sex	ZCTA and parish	2017
Economic characteristics				
6. Percentage of population that is unemployed*	**Percentage of ZCTA civilian population 16 years and older who are unemployed. No calculations made; the measure was obtained from ACS data tables.**	**ACS, 5-year estimates Table S2301 – Employment Status**	**ZCTA and parish**	**2017**
7. Percentage of workers in blue-collar occupation	Percentage of civilian employed population 16 years or older working in one of the following occupations: building, grounds cleaning, and maintenance; construction and extraction; installation; maintenance, and repair; or production, transportation, and material moving occupations.[50] No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table S2401: Occupation by Sex and Median Earnings in the Past 12 Months*	ZCTA and parish	2017

[49] All ACS data retrieved June 2019 through American Fact Finder Data Download Center. See: https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml.

[50] Blue collar occupations are those Fronzcek and Johnson (2003) categorize as the "traditional blue collar group," represented by construction, extraction, and maintenance occupations. See Fronzcek and Johnson (2003). Occupations: 2000 Census 2000 Brief. Prepared for the U.S. Census Bureau. Retrieved from: https://www.census.gov/prod/2003pubs/c2kbr-25.pdf.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
8. Per capita income	Mean income of all persons living in the ZCTA. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table B19301 - Per Capita Income in the Past 12 Months*	ZCTA and parish	2017
9. Percentage living in poverty	Percentage of ZCTA population living below the poverty level. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table S1701 - Poverty Status in the Past 12 Months*	ZCTA and parish	2017
10. Percentage uninsured	Percentage of civilian noninstitutionalized ZCTA population that is uninsured. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table S2701 - Selected Characteristics of Health Insurance Coverage in The United States*	ZCTA and parish	2017
11. Percentage with vehicle access	Percentage of ZCTA workers 16 years or older with vehicle access. ACS provides the number of workers 16 years or older without vehicle access. To calculate percentage with vehicle access we divided the total number without access by the ZCTA population estimate and subtracted the quotient from 1; the difference was multiplied by 100 to obtain the percentage. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table B08141 - Means of Transportation to Work by Vehicles Available*	ZCTA and parish	2017
Social characteristics				
12. Population size	**Estimated number of individuals living in the ZCTA. No calculations made; the measure was obtained from ACS data tables.** *Included in final model as exposure term or population offset.*	**ACS, 5-year estimates** ***Table B01003 -Total Population***	**ZCTA and parish**	**2017**
13. Violent crimes*	**Count of violent crimes, which include murder and nonnegligent manslaughter, rape, robbery, and aggravated assault, as reported by law enforcement in parishes.**	**Louisiana Uniform Crime Reporting (UCR) Program[51]**	**Parish**	**2016**
14. Drug-related crimes	Count of drug/narcotic offenses (except driving under the influence) which include the violation of laws prohibiting the production, distribution, and/or use of certain controlled substances and the equipment or devices utilized in their preparation and/or use. No calculations made; the measure was calculated by the Louisiana UCR. *Removed as predictor during comprehensive variable review*	Louisiana UCR Program[52]	Parish	2016
15. Property crimes	Count of summed total of reported burglary, larceny-theft, and motor vehicle theft crimes as reported by law enforcement agencies in parishes that contribute to the UCR program. No calculations made; the measure was calculated by the Louisiana UCR. *Removed as predictor during data reduction process*	Louisiana UCR Program [53]	Parish	2016

[51] Louisiana Commission on Law Enforcement and Administration of Criminal Justice. (2018). *Crime in Louisiana 2016*. Retrieved June 2019 from: http://lcle.la.gov/programs/uploads/CIL_2016.pdf.
[52] Retrieved July 2019 from: http://www.lcle.la.gov/programs/SAC.asp.
[53] Louisiana Commission on Law Enforcement and Administration of Criminal Justice. (2018). *Crime in Louisiana 2016*. Retrieved June 2019 from: http://lcle.la.gov/programs/uploads/CIL_2016.pdf.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
16. High intensity drug trafficking area	Dichotomous variable indicating if the parish has a High intensity drug trafficking area (1) or not (0).[54] *Removed as predictor during data reduction process*	Office of National Drug Control Policy, High Intensity Drug Trafficking Area Map[55]	Parish	2017
17. Is there a drug coalition?	Dichotomous variable indicating whether or not the parish has a Drug and Safety Coalition (1) or not (0). *Removed as predictor during comprehensive variable review*	Louisiana Department of Health (LDH), Bureau of Health Informatics [56]	Parish	2019
18. Gini coefficient	A measure of household inequality. Values range from 0 (perfect equality) to 1 (perfect inequality), higher values indicate higher inequality.[57] No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table B19083 - GINI Index of Income Inequality*	ZCTA and parish	2017
19. Is parish an education desert?	Dichotomous variable indicating a parish is considered an education desert (1) or not (0).[58] *Removed as predictor during data reduction process*	N. Hilman and T. Weichman (report authors)[59]	Parish	2016
20. Population decline [2011 to 2017]	A dichotomous measure indicating whether or not there was population decline in the ZCTA since 2011 (1) or not (0). [60] Population decline was calculated as the difference between the 2011 and 2017 ACS 5-year population estimates. If the difference was negative, the measure was coded as 1, otherwise it is coded as 0. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table B01003 -Total Population*	ZCTA and parish	2017
21. Rate of church adherence	Rate of adherence per 1,000 parish population. No calculations made; the measure was obtained from the Religious Congregations and Membership Study dataset. *Removed as predictor during comprehensive variable review*	U.S. Religion Census: Religious Congregations and Membership Study[61]	Parish	2010

[54] Information on high intensity drug trafficking areas can be found at: https://www.dea.gov/high-intensity-drug-trafficking-areas-hidta.
[55] Retrieved June 2019 from: https://www.dea.gov/hidta.
[56] Information on Drug Coalitions received June 2019.
[57] According to ACS documentation, "The Gini ranges from zero (perfect equality) to one (perfect inequality), and it is calculated by measuring the difference between a diagonal line (the purely proportionate distribution) and the distribution of actual values (a Lorenz curve). This measure is presented for household income." For more information see: https://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2017_ACSSubjectDefinitions.pdf.
[58] According to Hillman and Weichman, education deserts are areas where there are no colleges or universities nearby or where there is one community college and no other higher education institutions nearby. Hillman, N, and Weichman, T. (2016). Education Deserts: The Continued Significance of "Place" in the Twenty-First Century. Viewpoints: Voices from the Field. Washington, DC: American Council on Education. Retrieved from: https://www.acenet.edu/Documents/Education-Deserts-The-Continued-Significance-of-Place-in-the-Twenty-First-Century.pdf.
[59] Upon request, Hilman and Weichman provided data from their 2016 report in June 2019.
[60] Population decline does not represent observed decline between the years 2011 and 2017, but rather the decline in five-year population estimates for those years.
[61] Grammich, C., Hadaway, K., Houseal, R., Jones, D. E., Krindatch, A., Stanley, R., & Taylor, R. H. (2018, December 11). U.S. Religion Census Religious Congregations and Membership Study, 2010 (County File). Distributed by Association of Religion Data Archives: www.thearda.com. doi: 10.17605/OSF.IO/QUN29.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
22. Population density	ZCTA population per square mile of land area. The measure was calculated by dividing the ZCTA population estimate by the ZCTA land area[62] *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table B01003 – Total Population* Census Bureau 2010 ZCTA to County Relationship File[63]	ZCTA and parish	2017
23. Percentage of female-headed households	Percentage of occupied housing units in each ZCTA with female householder, no husband present. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table S2501 - Occupancy Characteristics*	ZCTA and parish	2017
24. Urban/Rural status	A dichotomous measure indicating a ZCTA is defined by the Federal Office of Rural Health Policy as rural (1) or not (0).[64] *Removed as predictor during data reduction process*	Health Resources & Services Administration (HRSA), Federal Office of Rural Health Policy (FORHP) Data Files[65]	ZIP code	2017
Housing characteristics				
25. Percentage of housing units that are crowded*	**Percentage of housing units in each ZCTA with more than 1 occupant per room.[66] ACS provides the number of units with 1.01 to 1.5 occupants and the number with 1.51 or more occupants per room. These measures were summed and divided by the number of total housing units in each ZCTA; the quotient is multiplied by 100 to obtain percent.**	**ACS, 5-year estimates** ***Table DP04 – Select Housing Characteristics***	**ZCTA and parish**	**2017**
26. Housing units	Total housing units in each ZCTA. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table DP04 – Select Housing Characteristics*	ZCTA and parish	2017
27. Occupied housing units	Total occupied housing units in each ZCTA. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table DP04 – Select Housing Characteristics*	ZCTA and parish	2017
28. Vacant housing units	Total vacant housing units in each ZCTA. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table DP04 – Select Housing Characteristics*	ZCTA and parish	2017
29. Percentage of mobile homes	Percentage of total housing units in each ZCTA that are mobile homes. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table DP04 – Select Housing Characteristics*	ZCTA and parish	2017

[62] Land area measures reflect the size of ZCTA in square meters. We convert the measures to square miles so that population density reflects population per square mile.
[63] Relationship file and explanation files can be downloaded from the Census Bureau website: https://www.census.gov/geographies/reference-files/2010/geo/relationship-files.html.
[64] According to FORHP, "Any ZIP code where more than 50% of its population resides in either a Non-Metro County and/or a rural Census Tract was" designated as rural. For FORHP definition of rural, see: https://www.hrsa.gov/rural-health/about-us/definition/index.html; for explanation of FORHP Data Files, see: https://www.hrsa.gov/rural-health/about-us/definition/datafiles.html.
[65] FORHP Eligible ZIP Codes (a spreadsheet containing all ZCTAs identified as "rural" according to FORHP classifications) retrieved June 2019 from: https://www.hrsa.gov/rural-health/about-us/definition/datafiles.html.
[66] Occupants per room reflects the number of individuals in each occupied housing unit divided by the number of rooms in the unit. According to Blake et al .(2007), persons per room is a standard measure of overcrowding because it gives a sense of how much privacy individuals in housing unit have – if occupancy is greater than one person per room, this indicates individuals are likely sharing bedrooms and/or individuals are utilizing shared living space (e.g., living room) as sleeping quarters. For more information see: Blake, K., Kellerson, R., and Simic, A. (2007) Measuring Overcrowding in Housing. Prepared for: U.S. Department of Housing and Urban Development Office of Policy Development and Research. Retrieved 9/1/19 from: https://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2017_ACSSubjectDefinitions.pdf.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
30. Percentage of homes with no phone service	Percentage of total housing units in each ZCTA with no telephone service. No calculations made; the measure was obtained from ACS data tables. *Removed as predictor during data reduction process*	ACS, 5-year estimates *Table DP04 – Select Housing Characteristics*	ZCTA and parish	2017
31. Number of people within flood hazard area	Number of parish residents within a FEMA designated special flood hazard area. No calculations made; the measure was obtained from CDC National Environmental Health Tracking Network. *Removed as predictor during data reduction process*	Centers for Disease Control (CDC) National Environmental Public Health Tracking Network[67]	Parish	2011
Health outcomes				
32. New chronic HCV infections in persons under 40*	**Number of new chronic HCV infections in persons under 40 in the ZCTA.** ***<u>Outcome of interest; dependent variable in final model</u>*** Note: For mapping purposes, variable constructed as a rate by dividing the number of cases in the ZCTA by the ACS ZCTA population estimate and multiplying the quotient by 10,000.	**Louisiana Office of Public Health, STD/HIV/Hepatitis Program (OPH SHP)[68]**	**ZCTA and parish**	**2016, 2017**
33. Poor physical health days*	**Parish average number of physically unhealthy days reported in past 30 days (age-adjusted). No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*.**	***County Health Rankings and Roadmaps*[69]**	**Parish**	**2016**
34. Rate of injury-related deaths*	**Number of deaths due to injury per 100,000 parish population. No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*.**	***County Health Rankings and Roadmaps***	**Parish**	**2013-2017**
35. HIV cases related to injection drug use (IDU) *	Number of PLWH in a ZCTA for whom the mode of transmission was related to IDU. *Removed as predictor during comprehensive variable review*	Louisiana OPH SHP	ZIP Code and parish	2018
36. HIV prevalence*	Rate of persons living with HIV (PLWH) per 10,000 ZCTA population. Measure calculated by dividing the number of PLWH living in the ZCTA by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate. *Removed as predictor during comprehensive variable review*	Louisiana OPH SHP	ZIP Code and parish	2018
37. Drug overdose death*	Number of drug poisoning deaths per 10,000 parish population. *Removed as predictor during data reduction process*	*County Health Rankings and Roadmaps*	Parish	2014-2016

[67] Data retrieved June 2019 from: https://ephtracking.cdc.gov/DataExplorer/index.html?c=22&i=106&m=-1#/.
[68] Data from Louisiana OPH, STD/HIV/Hepatitis Program received August 2019.
[69] All *County Health Rankings and Roadmap* data retrieved June 2019 from: https://www.countyhealthrankings.org/app/louisiana/2019/downloads.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
38. Rate of drug involved death, opioids only*	Age-standardized rate of opioid-involved deaths per 100,000 individuals (residence). Drug-involved death is defined as the presence of a formal listing of drug poisoning anywhere in the death certificate record. This means that drugs were present in the body and/or contributed to but did not directly cause the death of the individual. No calculations made; the measure was calculated by the LDH LODSS. *Removed as predictor during final selection of predictors*	LDH, Louisiana Opioid Data and Surveillance System (LODSS)[70]	Parish	2016, 2017
39. Rate of new chronic hepatitis B (HCB) infections*	Rate of new chronic HBV infections per 10,000 parish population. Measure calculated by dividing the number of new cases in the ZCTA by the ACS parish population estimate; the quotient was multiplied by 10,000 to obtain the rate. *Removed as predictor during data reduction process*	LDH - Infectious Disease Epidemiology Program[71]	Parish	2016-2017
40. Premature age-adjusted mortality	Number of deaths among residents under age 75 per 100,000 parish population (age-adjusted). No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*. *Removed as predictor during data reduction process*	*County Health Rankings and Roadmaps*	Parish	2015-2017
41. Years of potential life lost	Age-adjusted years of potential life lost before age 75 per 100,000 parish population. No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*. *Removed as predictor during data reduction process*	*County Health Rankings and Roadmaps*	Parish	2016
42. Adults reporting poor/fair health	Percentage of adults in a parish who consider themselves to be in poor or fair health (age adjusted). No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*. *Removed as predictor during data reduction process*	*County Health Rankings and Roadmaps*	Parish	2016
43. Poor mental health days	Parish average number of mentally unhealthy days reported in past 30 days. No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*. *Removed as predictor during data reduction process*	*County Health Rankings and Roadmaps*	Parish	2016
44. Percentage of adults who smoke	Percentage of adults in parish who are current smokers. No calculations made; the measure was obtained from *County Health Rankings and Roadmaps*. *Removed as predictor during data reduction process*	*County Health Rankings and Roadmaps*	Parish	2016
45. Teen birth rate	Rate per 1,000 of births among female adolescents (ages 15 to 19) in ZCTA. No calculations made; the measure was obtained from ACS Data Table. *Removed as predictor during final selection of predictors*	ACS, 5-year estimates *Table S1301 - Fertility*	ZCTA and parish	2017
46. Rate of drug-involved death, all drugs	Age-standardized rate of drug-involved deaths per 100,000 individuals (residence). Drug-involved death is defined as the presence of a formal listing of drug poisoning anywhere in the death certificate record. This means that drugs were present in the body and/or contributed to but did not directly cause the death of the individual. No calculations made; the measure was calculated by the LDH LODSS. *Removed as predictor during data reduction process*	LDH LODSS	Parish	2016, 2017

[70] All LDH LODSS data received July 2019.
[71] Data on HBV received July 2019.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
47. Rate of drug involved death, heroin and opioids only	Age-standardized rate of opioid- or heroin-involved deaths attributed to heroin and opioids only per 100,000 individuals (residence). Drug-involved death is defined as the presence of a formal listing of drug poisoning anywhere in the death certificate record. This means that drugs were present in the body and/or contributed to but did not directly cause the death of the individual. No calculations made; the measure was calculated by the LDH LODSS. *Removed as predictor during data reduction process*	LDH LODSS	Parish	2016, 2017
48. Nonfatal overdoses, all drugs	Number of all hospital admissions and emergency department visits that were indicated as drug-poisoning related. The measure was constructed by summing the number of drug poisoning-related emergency department visits and hospital admissions. *Removed as predictor during data reduction process*	LDH LODSS	Parish	2016, 2017
49. Neonatal opioid withdrawal cases	Number of Neonatal Opioid Withdrawal Syndrome (NOWS)-related inpatient visits. No calculations made; the measure was obtained from LDH - Bureau of Health Informatics. *Removed as predictor during data reduction process*	LDH - Bureau of Health Informatics[72]	Parish	2016, 2017
50. HIV incidence	Number of new HIV diagnoses in a parish from 2013 to 2018. No calculations made; the measure was obtained from OPH SHP. *Removed as predictor during comprehensive variable review*	Louisiana OPH SHP	Parish	2013-2018
51. Rate of sexually transmitted infections	Rate of sexually transmitted infections (STIs), (specifically, gonorrhea and chlamydia) per 10,000 ZCTA population. Measure calculated by dividing the number of cases in the ZCTA by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate. *Removed as predictor during data reduction process*	Louisiana OPH SHP	ZIP Code and parish	2016, 2017
52. Rate of syphilis infections	Rate of syphilis infections per 10,000 ZCTA population. Measure calculated by dividing the number of cases in the ZCTA by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate. *Removed as predictor during data reduction process*	Louisiana OPH SHP	ZIP Code and parish	2016, 2017
53. Rate of new acute HBV infections	Rate of acute HBV infections per 10,000 parish population. Measure calculated by dividing the number of cases in the ZCTA by the ACS parish population estimate; the quotient was multiplied by 10,000 to obtain the rate. *Removed as predictor during data reduction process*	LDH - Infectious Disease Epidemiology Program	Parish	2016-2017
54. Calls to suicide hotline	Number of calls initiated from parish-based phone numbers to the National Suicide Prevention Lifeline. No calculations made; the measure was obtained from the National Suicide Prevention Lifeline/Vibrant Emotional Health. *Removed as predictor during data reduction process*	National Suicide Prevention Lifeline/Vibrant Emotional Health[73]	Parish	2017

[72] Data on NOWS received June 2019.
[73] Data on number of calls received August 2019.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
Opioid and Medication Assisted Treatment (MAT) prescriptions				
55. MME rate for opioids*	**The mean morphine milligram equivalent (MME) prescribing rate per person for opioids in a year. No calculations made; the measure was obtained from the Louisiana Board of Pharmacy PMP.**	**Louisiana Board of Pharmacy, Prescription Monitoring Program (PMP)[74]**	**ZCTA**	**2016, 2017**
56. MME rate for MAT drugs*	**The mean MME prescribing rate per person in a ZCTA for MAT drugs in a year. No calculations made; the measure was obtained from the Louisiana Board of Pharmacy PMP.**	**Louisiana Board of Pharmacy, PMP**	**ZCTA**	**2016, 2017**
57. Rate of prescription opioid sales*	**Number of opioid prescriptions per 100 persons (2016). No calculations made; the measure was obtained from the Louisiana Board of Pharmacy PMP.**	**Louisiana Board of Pharmacy, PMP**	**Parish**	**2016**
58. Total MME for all drugs	The MME prescribing rate per person in the ZCTA for all drugs in a year.[75] No calculations made; the measure was obtained from the Louisiana Board of Pharmacy PMP. *Removed as predictor during data reduction process*	**Louisiana Board of Pharmacy, PMP**	ZCTA	2016, 2017
Access to Health Care				
59. Mental health providers*	**Rate of mental health providers per 10,000 ZCTA population. Mental health providers include individuals working in psychiatry, psychology, mental health counseling, or clinical social work as well as agencies that provide mental health care or treatment. The measure was calculated by dividing the number of providers by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate.[76]** Note: For mapping purposes, variable constructed as a dichotomous measure indicating whether or not there is at least 1 mental health provider in the ZCTA (1) or not (0).	**Center for Medicare and Medicaid Services (CMS), National Plan and Provider Enumeration System (NPPES)[77]**	**ZIP code**	**2017**

[74] All data from Louisiana Board of Pharmacy PMP received July 2019.

[75] For an explanation of MMEs and their import, see: https://www.cdc.gov/drugoverdose/pdf/calculating_total_daily_dose-a.pdf; for opioid oral MME conversion factors, see: https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Oral-MME-CFs-vFeb-2018.pdf.

[76] Included in the measure are providers in the *Health Care Provider Taxonomy Code Set* coded as Psychiatry, Nurse in Psychiatric/Mental Health (this includes nurses, clinical nurse specialists, and nurse practitioners), Clinical Neuropsychologist, Mental Health Counselor, Psychologist, Clinical Social Worker, or Ambulatory Mental Health Care Facilities (those designated as mental health, adult mental health, psychiatric hospital, intermediate care facility for mental illness, community based residential facility for mental illness, psychiatric residential facility, or adolescent and children mental health). For taxonomy codes, see: http://www.wpc-edi.com/reference/codelists/healthcare/health-care-provider-taxonomy-code-set/.

[77] All NPPES data retrieved June 2019. Up-to-date weekly and monthly NPPES Data Dissemination files, that contain information on all providers in the National Provider Identifier (NPI) Registry can be downloaded through CMS at: http://download.cms.gov/nppes/NPI_Files.html . Older NPEES Data Dissemination Files are maintained by the National Bureau for Economic Research; data for December 2017 can be found at: http://data.nber.org/npi/2017/. For information on NPI, see: https://www.cms.gov/Regulations-and-Guidance/Administrative-Simplification/NationalProvIdentStand/index.html.

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
60. Primary care providers*	**Rate of primary care physicians per 10,000 ZCTA population. The measure was calculated by dividing the number of providers by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate.[78]** Note: For mapping purposes, variable constructed as a dichotomous measure indicating whether or not there is at least 1 primary care provider in the ZCTA (1) or not (0).	**CMS NPPES**	**ZIP code**	**2017**
61. Is there an urgent care facility?	A dichotomous measure indicating whether or not there is an Ambulatory Health Care Clinic/Center (outside hospital setting) in the ZCTA (1) or not (0). The measure was calculated by dividing the number of Urgent Care facilities by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate.[79] *Removed as predictor during data reduction process*	CMS NPPES	ZIP code	2017
62. Rate of specialty care providers	Rate of specialty care providers per 10,000 ZCTA population. Specialty care providers are non-primary care providers (e.g., not general practice, family practice, or internal medicine) who can provide specialized care for hepatitis and HIV; this includes providers in gastroenterology, hepatology, and infectious disease. The measure was calculated by dividing the number of providers by the ACS ZCTA population estimate; the quotient was multiplied by 10,000 to obtain the rate. [80] *Removed as predictor during data reduction process*	CMS NPPES	ZIP code	2017
High Impact Prevention and Intervention Services				
63. Is there a buprenorphine prescriber? *	A dichotomous measure indicating whether or not there is at least 1 buprenorphine prescriber in the ZCTA (1) or not (0). A ZCTA is considered to have a prescriber if data retrieved from SAMHSA or Suboxone indicates there is a prescriber in the area. *Removed as predictor during comprehensive variable review*	Substance Abuse and Mental Health Services Administration (SAMHSA) Buprenorphine Treatment Practitioner Locator[81] Suboxone Treatment Provider Locator[82]	ZIP code	2019

[78] Included in the measure are providers in the *Health Care Provider Taxonomy Code Set* coded as Family Practice (as well as sub codes Adolescent Medicine, and Adult Medicine), Federally Qualified Health Centers (FQHCs), General Practice, Internal Medicine (as well as sub code adolescent medicine), Nurse Practitioners, OB/GYNs, Pediatrics, Rural Health Clinics, Primary Care Clinics, or Critical Access Hospitals. For taxonomy codes, see: http://www.wpc-edi.com/reference/codelists/healthcare/health-care-provider-taxonomy-code-set/

[79] Included in the measure are all facilities in the *Health Care Provider Taxonomy Code Set* coded as Ambulatory Health Care Clinic/Centers (as well as sub codes Urgent Care and Emergency Care). For taxonomy codes, see: http://www.wpc-edi.com/reference/codelists/healthcare/health-care-provider-taxonomy-code-set/

[80] Included in the measure are all providers coded in the *Health Care Provider Taxonomy Code Set* under Internal Medicine as Gastroenterology, Hepatology, and Infectious Disease or under Registered Nurse as Gastroenterology. For taxonomy codes, see: http://www.wpc-edi.com/reference/codelists/healthcare/health-care-provider-taxonomy-code-set/

[81] Data retrieved July 2019 from: https://www.samhsa.gov/medication-assisted-treatment/practitioner-program-data/treatment-practitioner-locator?field_bup_physician_us_state_value=LA

[82] Data retrieved November 2019 from: https://www.suboxone.com/

Table B1. *Plausible Predictor Variable Descriptions*

Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
64. Is there a methadone clinic? *****	Dichotomous variable indicating whether or not there is a methadone clinic in the ZCTA (1) or not (0). *Removed as predictor during comprehensive variable review*	SAMHSA Behavioral Health Treatment Services Locator[83]	ZIP code	2019
65. Is there a substance use disorder provider? *****	Dichotomous variable indicating whether or not there is a substance use disorder provider in the ZCTA (1) or not (0). Substance use disorder providers are individuals or agencies who specialize in addiction or substance use disorders/treatment. [84] *Removed as predictor during comprehensive variable review*	CMS NPPES	ZIP code	2019
66. Is there an HCV treatment/ care organization? *****	Dichotomous variable indicating whether or not there is an organization that explicitly provides HCV treatment or care in the ZCTA (1) or not (0). *Removed as predictor during comprehensive variable review*	National Prevention Information Network (NPIN) Organizations Database[85]	ZIP code	2019
67. Is there an organization that provides low/no cost HCV testing? *****	Dichotomous variable indicating whether or not there is an organization that provides free or low/cost HCV testing in the ZCTA (1) or not (0). Organizations are considered to provide low/no cost testing if the NPIN database indicates they a) provide low-cost HCV testing or b) they provide HCV testing and they provide no fee or services on a sliding scale. *Removed as predictor during comprehensive variable review*	NPIN Organizations Database	ZIP code	2019
68. Is there a HIV treatment/ care organization? *****	Dichotomous variable indicating whether or not there is an organization that explicitly provides HIV treatment or care in the ZCTA (1) or not (0).[86] A ZCTA is considered to have a treatment or care organization if data received from NPIN or OPH indicate there is an organization in the area. *Removed as predictor during comprehensive variable review*	NPIN Organizations Database Louisiana OPH SHP	ZIP code	2019
69. Is there an organization that provides PrEP? *****	Dichotomous variable indicating whether or not there is an organization that explicitly provides Pre-exposure prophylaxis (PrEP)or care in the ZCTA (1) or not (0).[87] *Removed as predictor during comprehensive variable review*	NPIN Organizations Database	ZIP code	2019
70. Is there an organization that provides low/no cost HIV testing? *****	Dichotomous variable indicating whether or not there is an organization that provides free or low/cost HIV testing in the ZCTA (1) or not (0). Organizations are considered to provide low/no cost testing if the NPIN database indicates they a) provide low-cost HIV testing or b) they provide HIV testing and they provide no fee or services on a sliding scale. *Removed as predictor during comprehensive variable review*	NPIN Organizations Database	ZIP code	2019

[83] Data retrieved June 2019 from: https://dpt2.samhsa.gov/treatment/directory.aspx
[84] Included in the measure are individuals/agencies in the *Health Care Provider Taxonomy Code Set* coded as Addiction Medicine, Addiction Psychiatry, Addiction (Substance Use Disorder) as Methadone, Rehabilitation, Substance Use Disorder/Unit, Substance Abuse Rehabilitation Facility. For taxonomy codes, see: http://www.wpc-edi.com/reference/codelists/healthcare/health-care-provider-taxonomy-code-set/
[85] All NPIN data were received in November 2019.
[86] Data received from NPIN for measures of HCV and HIV testing and treatment do not reflect all testing and services providers, only those explicitly providing HIV or HCV services. According to NPIN, "Not all organizations are included in the database. To be included in the database, organizations must focus their services on one or more of the disease areas of NPIN (HIV/AIDS, viral hepatitis, STDs, or TB) or offer specific programs targeting one or more of these diseases."
[87] PrEP is an anti-HIV medication that can help prevent HIV, when taken daily. According to the CDC, "Among people who inject drugs, PrEP reduces the risk of getting HIV by at least 74% when taken daily." See: https://www.cdc.gov/hiv/basics/prep.html.

Table B1. *Plausible Predictor Variable Descriptions*

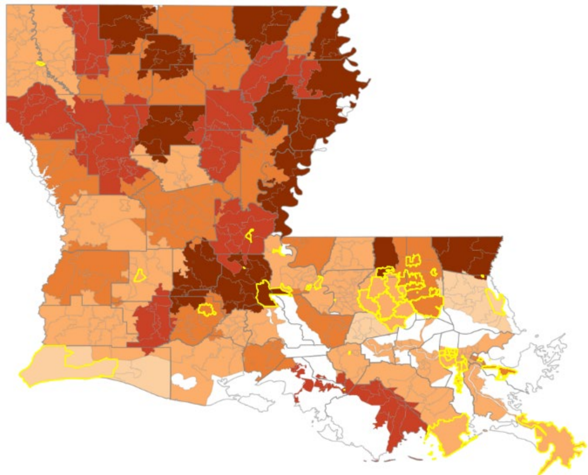
Variable	Description/Operationalization/Analysis Notes	Data Source	Geographic unit	Year
71. Are there syringe access services? *	Dichotomous variable indicating whether or not there is an organization that provides syringe access services in the ZCTA (1) or not (0). *Removed as predictor during comprehensive variable review*	Louisiana Health Hub[88]	ZIP code	2019
72. Is there an HIV testing site?	Dichotomous variable indicating whether or not there is an organization that explicitly provides HIV testing in ZCTA (1) or not (0). A ZCTA is considered to have a testing site if data received from NPIN or OPH indicate there is an organization that provides testing in the area. *Removed as predictor during comprehensive variable review*	NPIN Organizations Database Louisiana OPH SHP	ZIP code	2019
73. Substance use disorder providers	Rate of Substance use disorder providers per 10,000 ZCTA population. No calculations made; the measure was obtained from CMS NPPES. *Removed as predictor during final selection of predictors*	CMS NPPES	ZIP code	2017

[88] Information retrieved October 2019 from: https://www.louisianahealthhub.org/sexual-health-and-stds/hepatitis/syringe-service/.

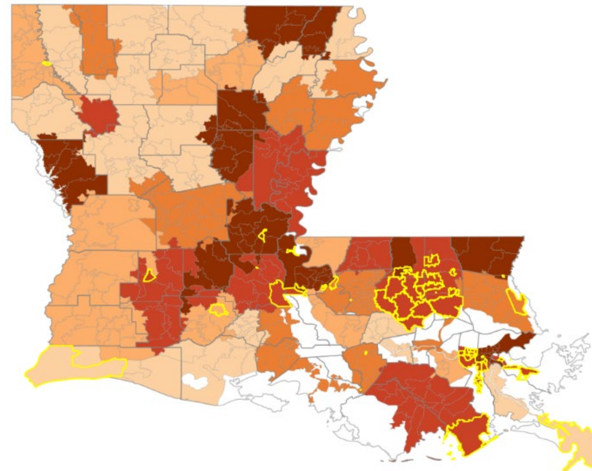
APPENDIX C: ADDITIONAL RESULTS

PREDICTORS INCLUDED IN PARSIMONIOUS MODEL

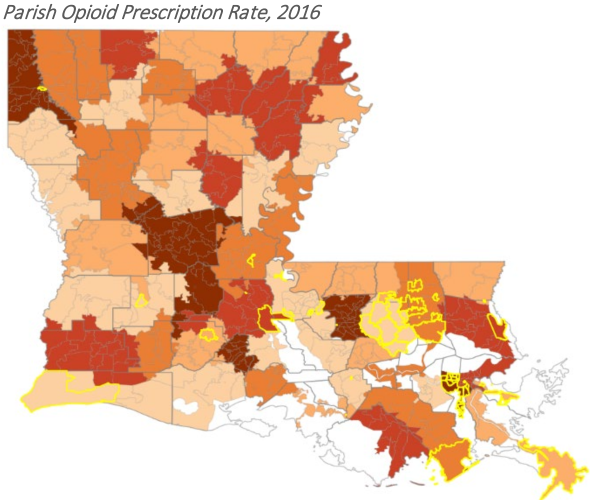
Parish Mean-Reported Poor Physical Health Days, 2016



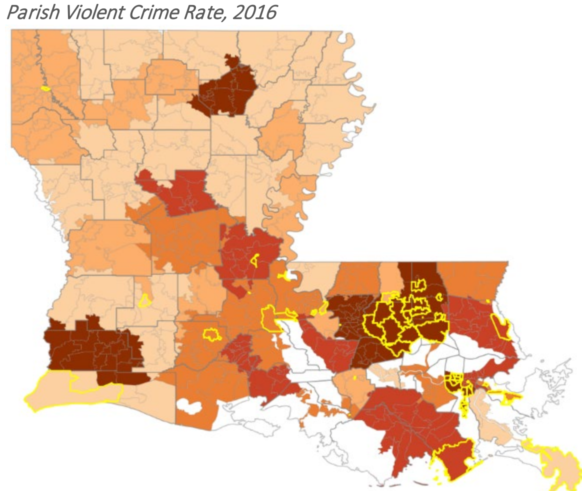
Parish Injury Mortality Rate, 2017



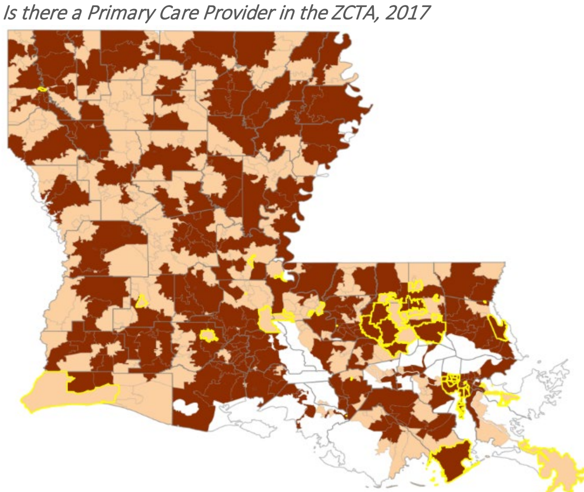
Parish Opioid Prescription Rate, 2016



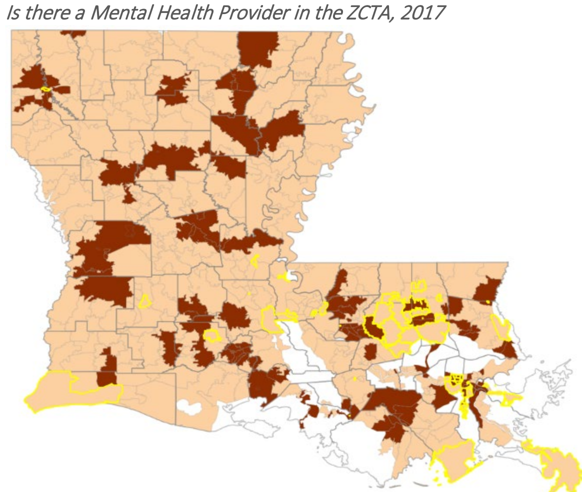
Parish Violent Crime Rate, 2016



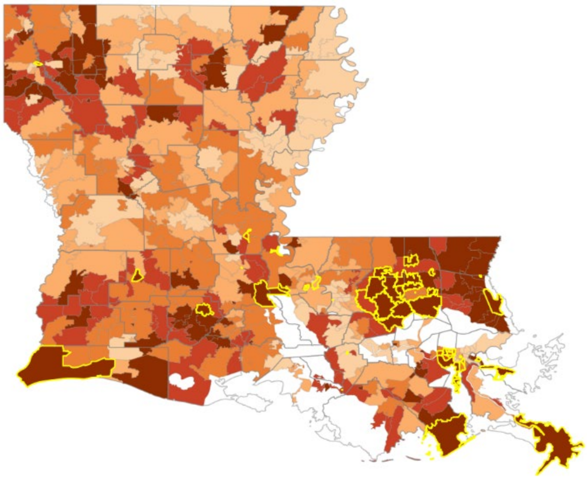
Is there a Primary Care Provider in the ZCTA, 2017



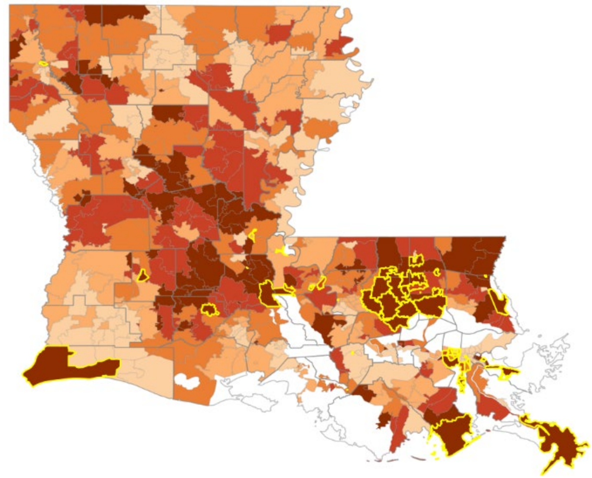
Is there a Mental Health Provider in the ZCTA, 2017



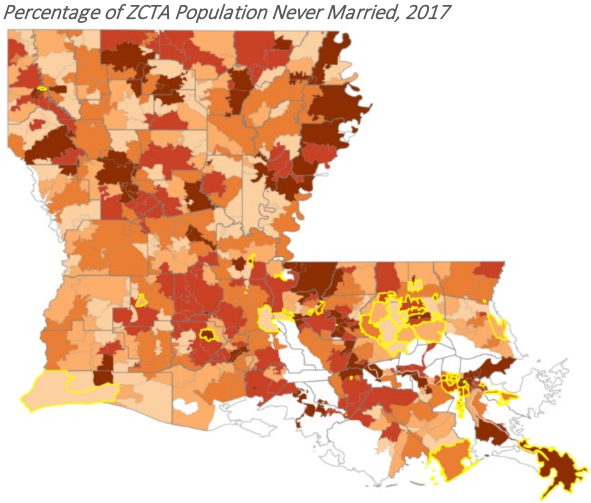
ZCTA MME Rate for MAT, 2016-17 average



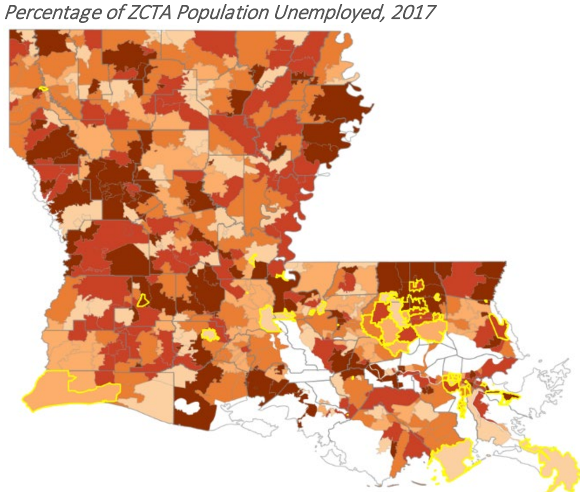
ZCTA MME Rate for Opioids, 2016-17 average



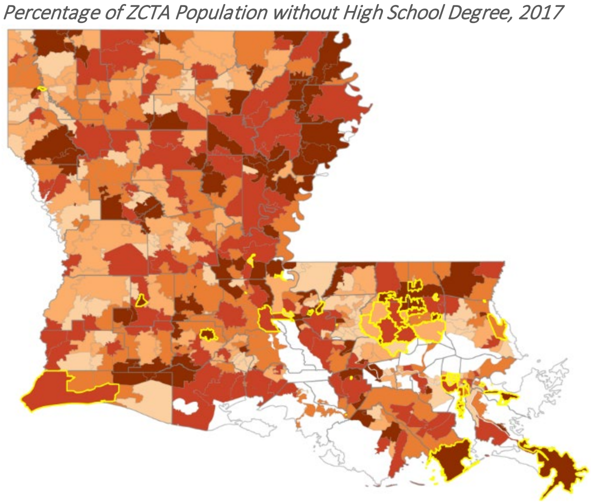
Percentage of ZCTA Population Never Married, 2017



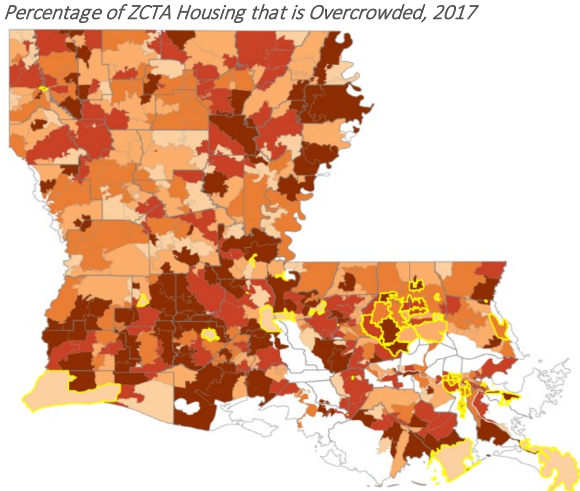
Percentage of ZCTA Population Unemployed, 2017



Percentage of ZCTA Population without High School Degree, 2017

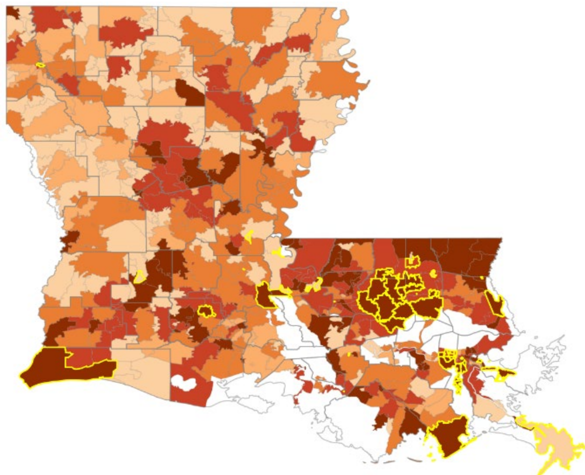


Percentage of ZCTA Housing that is Overcrowded, 2017

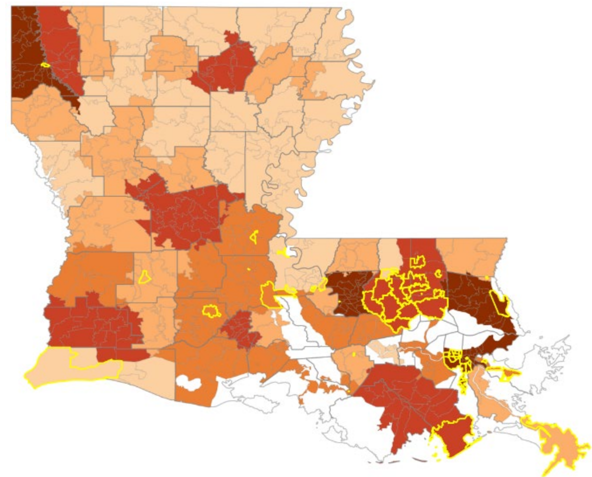


HEALTH RISK OUTCOMES

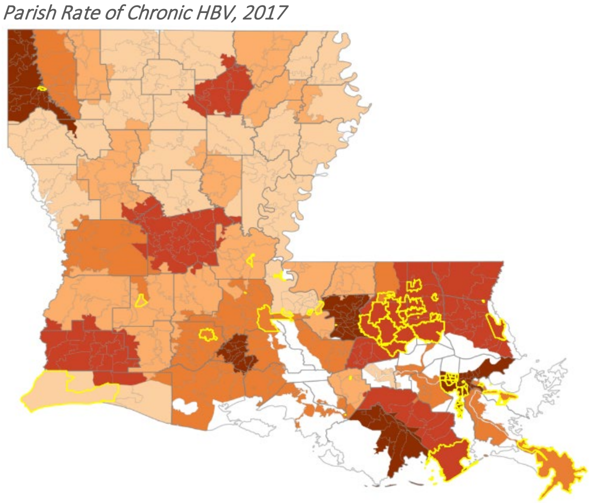
ZCTA Rate of HCV for Persons Under 40, average 2016-2017



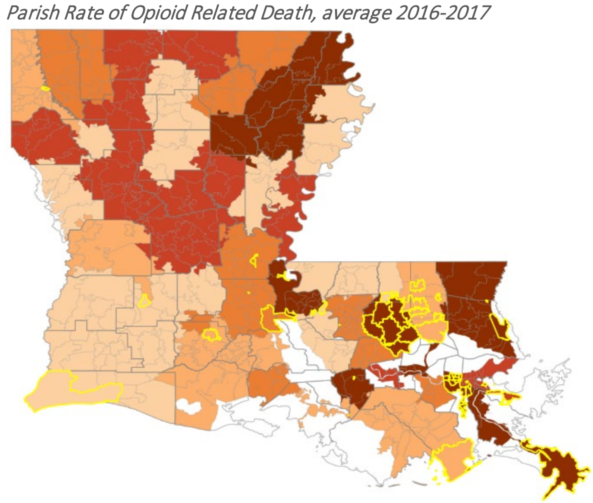
Parish Drug Poisoning Count, 2016



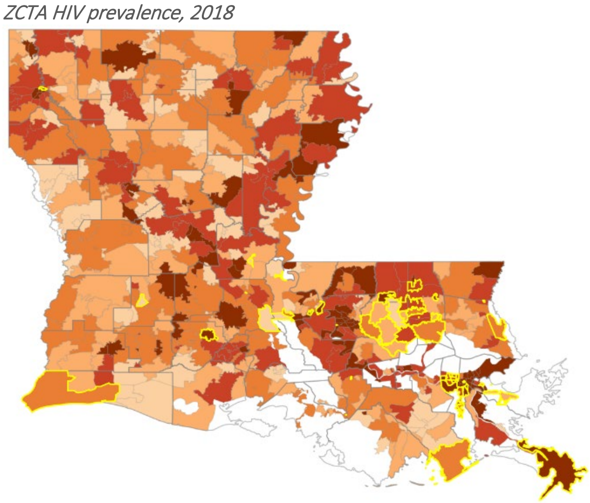
Parish Rate of Chronic HBV, 2017



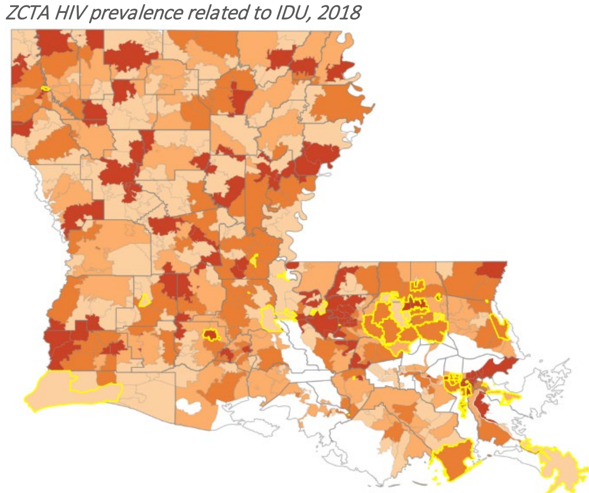
Parish Rate of Opioid Related Death, average 2016-2017



ZCTA HIV prevalence, 2018



ZCTA HIV prevalence related to IDU, 2018



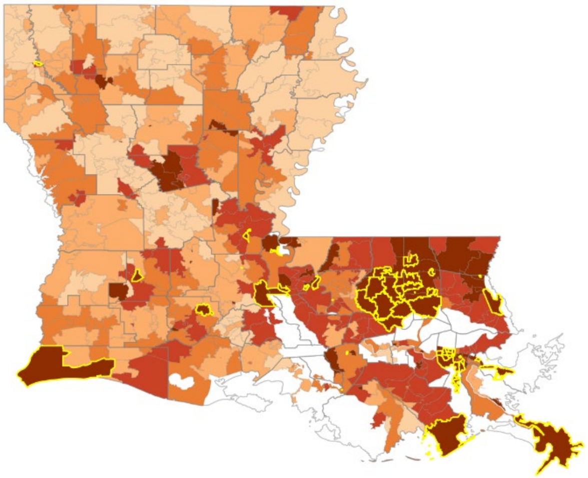
ADDITIONAL ANALYSIS OF MOST VULNERABLE 10% OF ZCTAS

Table C.1. *Correspondence between Top 10% Vulnerable ZCTAs and Top 10% Health Risk Outcomes*

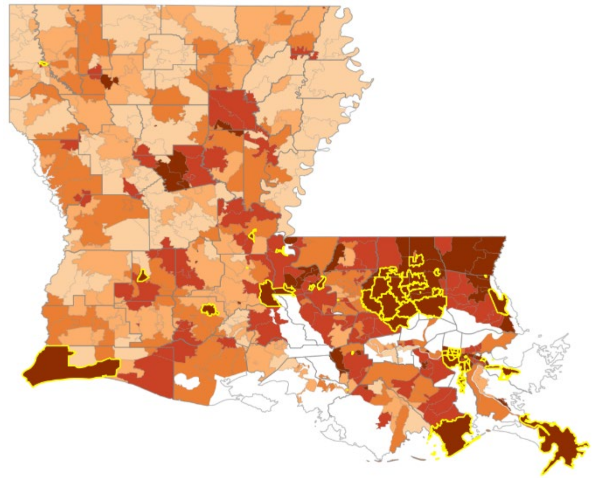
Rank	Parish	ZCTA	New HCV under 40	New HCV All	New HCV Over 55	PLWH	MME Rate Opioids	MME Rate MAT	Number Top 10 Vulnerable
1	E. Baton Rouge	70801	Yes	Yes	Yes	Yes	No	No	4
2	Acadia	70516	Yes	No	No	Yes	Yes	Yes	4
3	Tangipahoa	70442	No	Yes	No	Yes	Yes	Yes	4
4	Orleans	70112	Yes	Yes	Yes	Yes	No	No	4
5	Tangipahoa	70455	Yes	Yes	No	No	Yes	Yes	4
6	St. Mary	70340	Yes	Yes	No	Yes	Yes	Yes	5
7	Jefferson	70067	Yes	Yes	No	No	Yes	Yes	4
8	Jefferson	70358	Yes	Yes	Yes	No	Yes	Yes	5
9	Jefferson	70121	No	No	No	No	No	No	0
10	St. Helena	70453	Yes	No	No	Yes	Yes	No	3
11	Cameron	70631	Yes	Yes	Yes	No	No	Yes	4
12	Livingston	70733	No	No	No	No	Yes	Yes	2
13	Livingston	70744	Yes	Yes	No	No	Yes	Yes	4
14	Livingston	70711	No	No	No	No	Yes	Yes	2
15	Livingston	70462	Yes	Yes	No	No	Yes	Yes	4
16	St. Tammany	70463	No	No	No	Yes	Yes	Yes	3
17	St. Landry	71345	No	No	No	Yes	No	No	1
18	Jefferson	70072	No	No	No	No	No	No	0
19	Allen	70654	No	No	No	No	Yes	Yes	2
20	Jefferson	70062	No	No	No	No	No	No	0
21	Jefferson	70094	Yes	No	No	No	No	No	1
22	Livingston	70754	Yes	No	No	No	Yes	Yes	3
23	Tangipahoa	70443	No	No	No	No	Yes	Yes	2
24	Jefferson	70036	No	No	No	No	No	Yes	1
25	St. Bernard	70075	Yes	No	No	No	Yes	Yes	3
26	Tangipahoa	70402	No	No	No	No	No	No	0
27	St. Tammany	70452	Yes	Yes	No	No	Yes	Yes	4
28	Assumption	70391	Yes	Yes	No	No	Yes	Yes	4
29	Lafourche	70357	No	No	No	No	Yes	No	1
30	St. Bernard	70085	Yes	Yes	No	No	Yes	Yes	4
31	St. Landry	70750	No	No	No	No	Yes	Yes	2
32	Jefferson	70006	No	No	No	No	No	No	0
33	Plaquemines	70091	No	Yes	Yes	No	No	No	2
34	Jefferson	70053	No	No	No	No	No	No	0
35	Tangipahoa	70456	No	No	No	No	Yes	No	1
36	Jefferson	70058	No	No	No	No	No	No	0
37	Jefferson	70001	No	No	No	No	No	No	0
38	Pointe Coupee	70747	No	No	No	No	No	No	0
39	Livingston	70785	Yes	No	No	No	No	Yes	2
40	Avoyelles	71339	No	No	No	No	No	No	0
41	Jefferson	70003	No	No	No	No	No	No	0
42	Caddo	71101	No	Yes	Yes	Yes	No	No	3
43	Pointe Coupee	70756	No	No	No	No	No	Yes	1
44	Jefferson	70123	No	No	No	No	No	No	0
45	Livingston	70449	Yes	No	No	No	Yes	No	2
46	Tangipahoa	70454	No	No	No	No	No	No	0
47	Jefferson	70002	No	No	No	No	No	No	0
48	Tangipahoa	70466	No	No	No	No	No	No	0
49	Livingston	70726	Yes	No	No	No	No	No	1
50	W. Baton Rouge	70729	No	No	No	No	No	No	0
51	Jefferson	70005	No	No	No	No	No	No	0

APPENDIX D: SENSITIVITY ANALYSES RESULTS

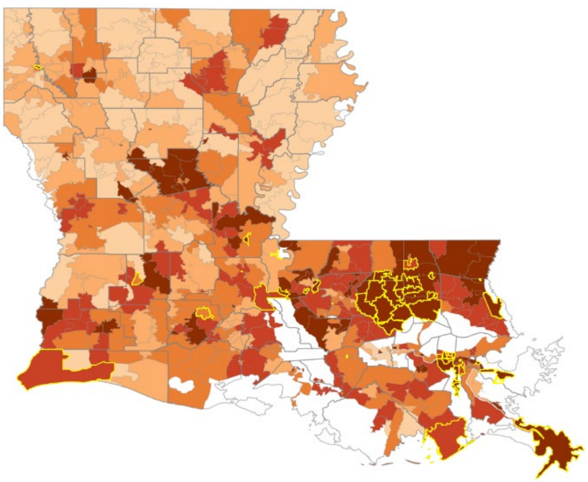
Benchmark Model



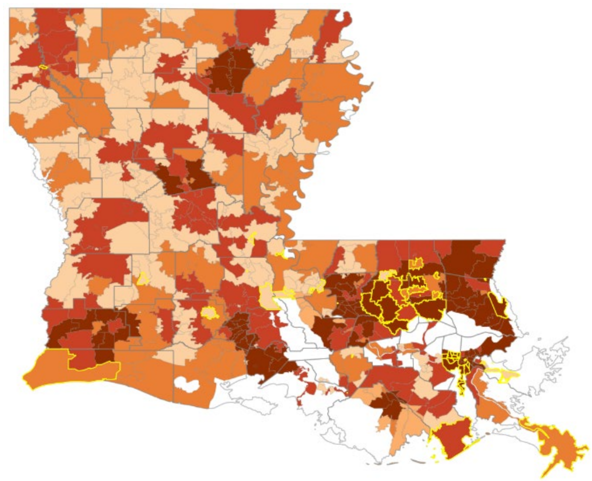
Full Model



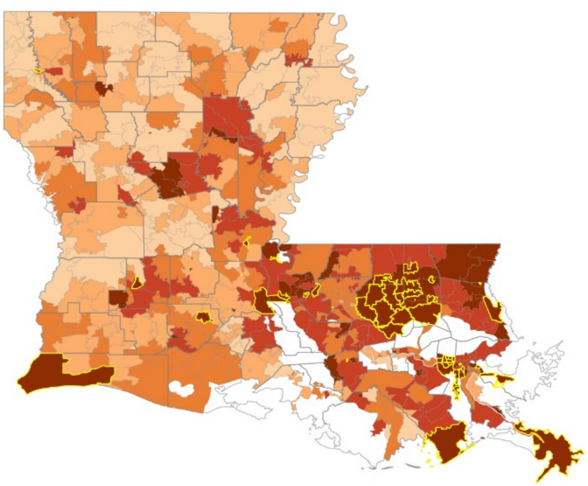
Interaction Model



Boosted Model



Lasso Model



Parish-Level Model

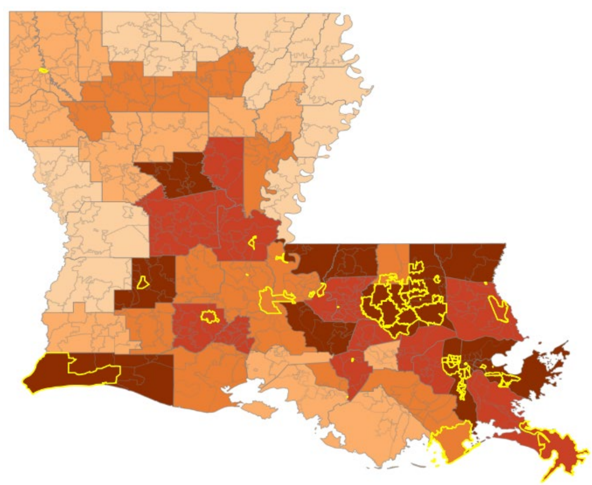


***Table D.1.** Correspondence between Top 10% Vulnerable ZCTAs in Benchmark and Alternative Models*

Rank	Parish	ZCTA	Top 10% of full model	Top 10% in Boost model	Top 10% in LASSO model	Top 10% in Interaction model
1	E. Baton Rouge	70801	Yes	No	No	No
2	Acadia	70516	Yes	No	Yes	No
3	Tangipahoa	70442	Yes	No	Yes	Yes
4	Orleans	70112	Yes	Yes	Yes	Yes
5	Tangipahoa	70455	Yes	No	Yes	Yes
6	St. Mary	70340	Yes	No	Yes	No
7	Jefferson	70067	Yes	No	Yes	Yes
8	Jefferson	70358	Yes	No	Yes	Yes
9	Jefferson	70121	Yes	Yes	Yes	No
10	St. Helena	70453	Yes	No	Yes	Yes
11	Cameron	70631	Yes	No	Yes	No
12	Livingston	70733	Yes	No	Yes	Yes
13	Livingston	70744	Yes	No	Yes	Yes
14	Livingston	70711	Yes	No	Yes	Yes
15	Livingston	70462	Yes	No	Yes	Yes
16	St. Tammany	70463	Yes	No	Yes	Yes
17	St. Landry	71345	Yes	No	Yes	Yes
18	Jefferson	70072	Yes	Yes	Yes	No
19	Allen	70654	Yes	No	Yes	No
20	Jefferson	70062	Yes	No	Yes	No
21	Jefferson	70094	Yes	Yes	Yes	No
22	Livingston	70754	Yes	Yes	Yes	Yes
23	Tangipahoa	70443	Yes	Yes	Yes	No
24	Jefferson	70036	Yes	No	Yes	Yes
25	St. Bernard	70075	Yes	No	Yes	Yes
26	Tangipahoa	70402	Yes	No	Yes	No
27	St. Tammany	70452	Yes	No	Yes	Yes
28	Assumption	70391	Yes	No	Yes	Yes
29	Lafourche	70357	No	No	No	No
30	St. Bernard	70085	Yes	No	Yes	Yes
31	St. Landry	70750	Yes	No	No	No
32	Jefferson	70006	Yes	Yes	No	No
33	Plaquemines	70091	Yes	No	Yes	Yes
34	Jefferson	70053	Yes	No	Yes	No
35	Tangipahoa	70456	No	No	Yes	No
36	Jefferson	70058	Yes	No	Yes	No
37	Jefferson	70001	Yes	Yes	Yes	No
38	Pointe Coupee	70747	Yes	No	No	No
39	Livingston	70785	Yes	Yes	Yes	Yes
40	Avoyelles	71339	Yes	No	Yes	Yes
41	Jefferson	70003	Yes	Yes	Yes	No
42	Caddo	71101	No	No	Yes	Yes
43	Pointe Coupee	70756	No	No	No	No
44	Jefferson	70123	Yes	Yes	Yes	No
45	Livingston	70449	No	Yes	No	Yes
46	Tangipahoa	70454	Yes	No	Yes	Yes
47	Jefferson	70002	No	Yes	Yes	No
48	Tangipahoa	70466	No	No	Yes	Yes
49	Livingston	70726	Yes	Yes	Yes	Yes
50	W. Baton Rouge	70729	No	No	No	Yes
51	Jefferson	70005	No	Yes	Yes	No