Prediction and Intervention Models for Combating the Opioid Crisis

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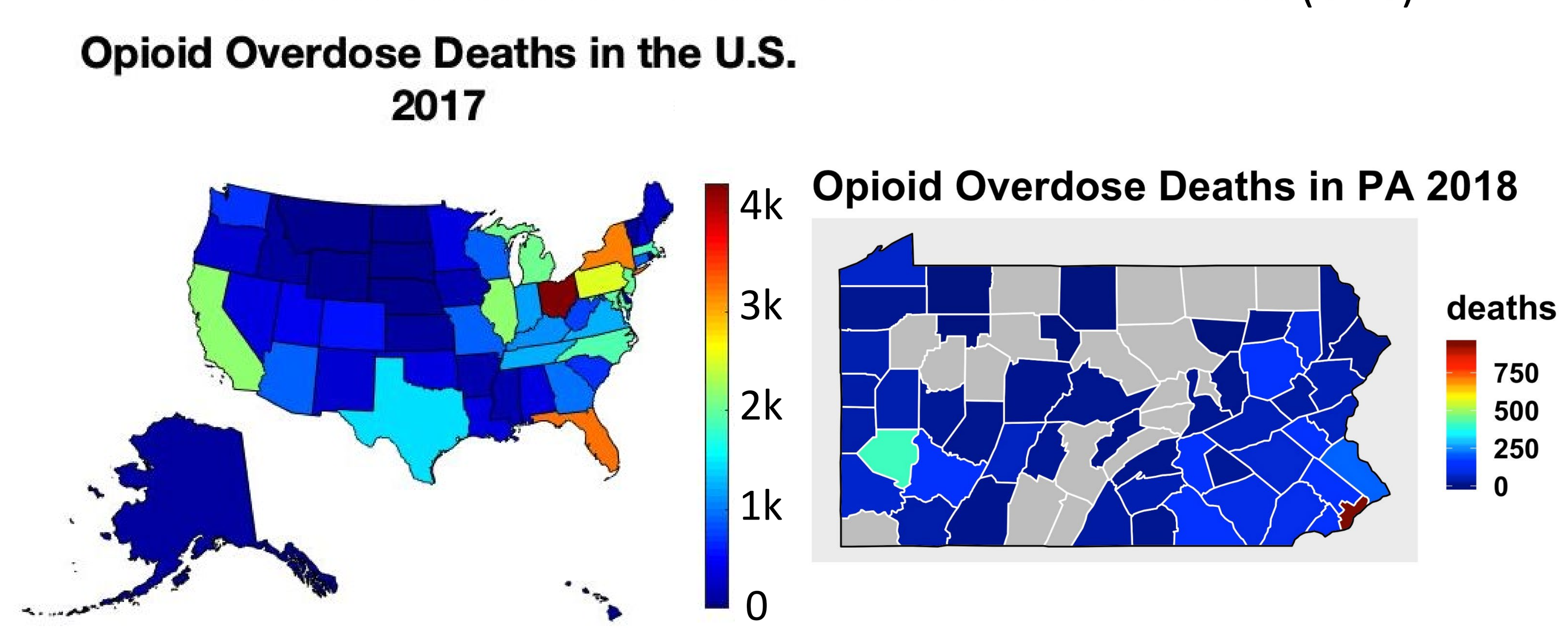
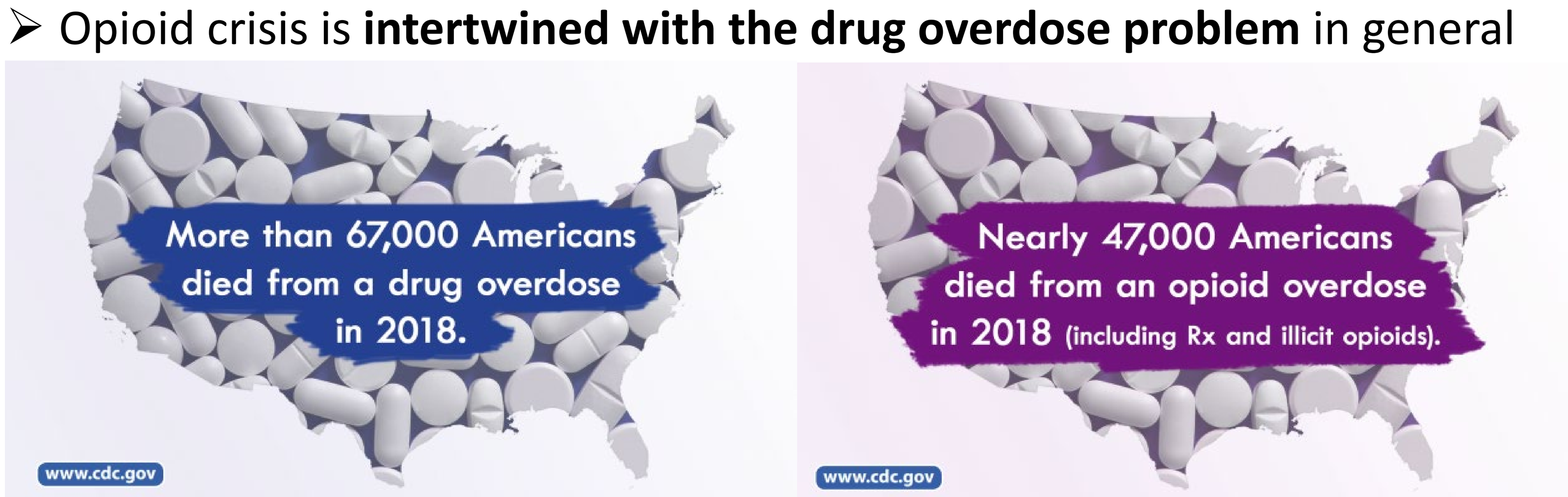
Motivation and Background

- **Opioid Epidemic:** American's public health catastrophe that has been hidden by the coronavirus pandemic but has not disappeared yet.
  - **130/day** opioid overdose deaths per day in 2017,
    Source: Centers for Disease Control and Prevention (CDC)

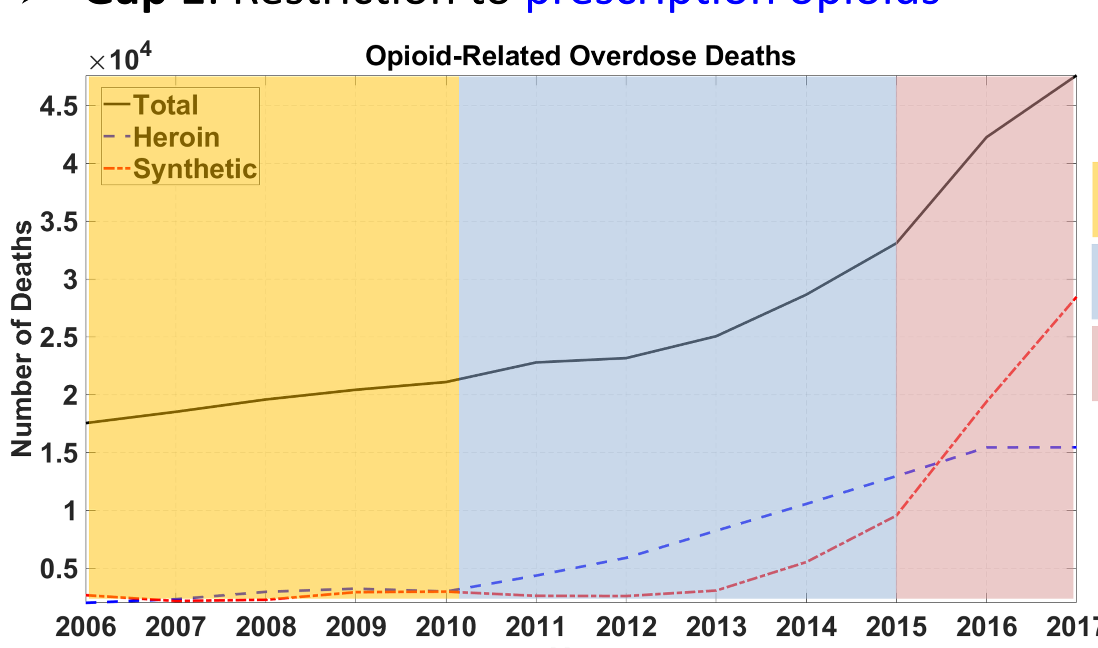


- Opioid crisis is **intertwined with the drug overdose problem** in general



Gaps in Current Approaches

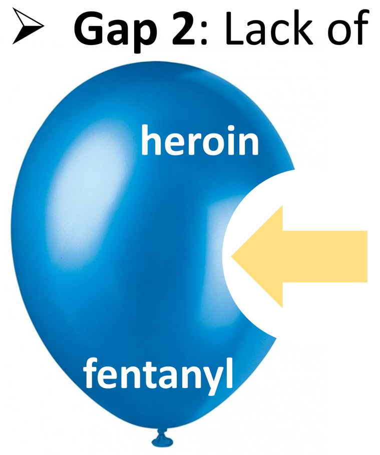
- To date, efforts to combat the opioid crisis have been focused on **restricting the supply of prescription opioids** such as 1) CDC Prescription Guideline, 2) Dose limit, 3) Drug take-back days, and 4) Law enforcement
- **Gap 1**: Restriction to prescription opioids



- Three waves of the opioid crisis
  1. Prescription opioid
  2. Heroin
  3. Synthetic opioid
- Increasing number of people initially start abusing opioid with illicit opioids

⇒Need to consider illicit opioids such as heroin and synthetic opioid along with prescription opioids

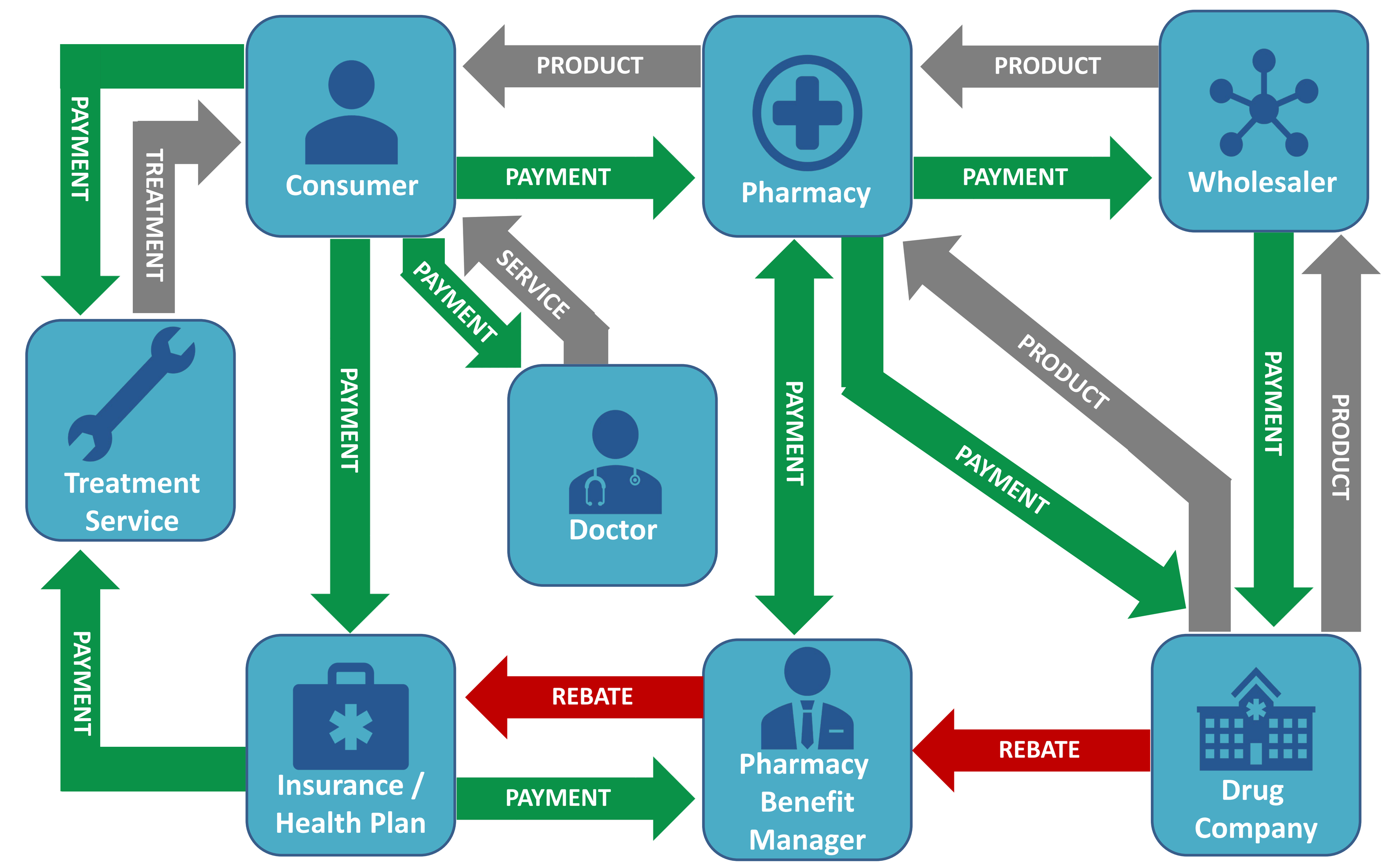
- **Gap 2**: Lack of demand-side analysis



- **Balloon effect**: Restricting the supply of prescription opioids leads to an increase in the usage of other drugs

⇒To eradicate the opioid epidemic, we need to understand what drive people to abuse opioids and try to decrease the demand

- **Gap 3**: More investigation into the dynamics of the supply chain of prescription opioids



- Pharmaceutical products have a more complex supply chain compared to other goods, as actors such as insurance companies and doctors are involved

⇒Need to model complexity of the prescription opioid supply chain

Research Objective and Rationale

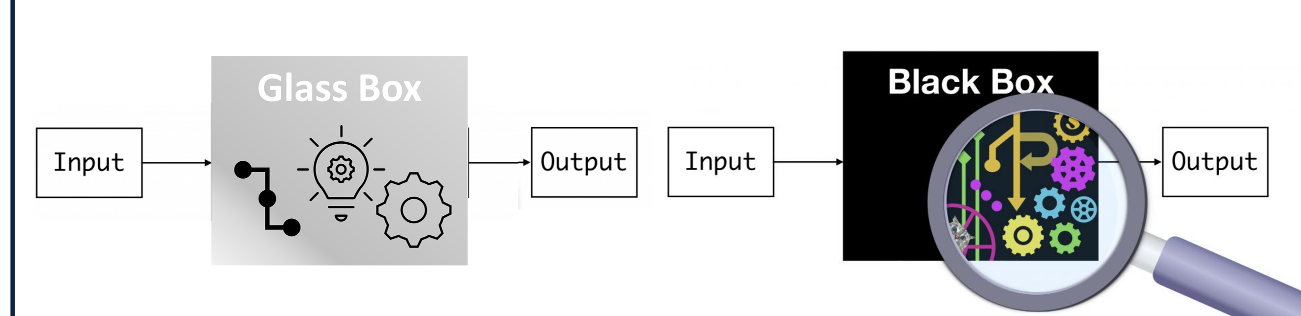
- This project aims to develop **a machine learning-based decision supporting system** that bridge the pointed gaps, providing not only the **prediction of risk factors** but also **effective intervention strategies**
- A data-driven decision supporting system is critical to combat the opioid crisis effectively
- It is hard to analyze complex dynamics of the opioid supply and demand chain manually
- We need to extract knowledge from publicly available data to perform the demand-side analysis and investigation of the prescription opioid supply chain

⇒Machine learning-based approach is suitable to harness publicly available data and build and optimize a complex data-driven model

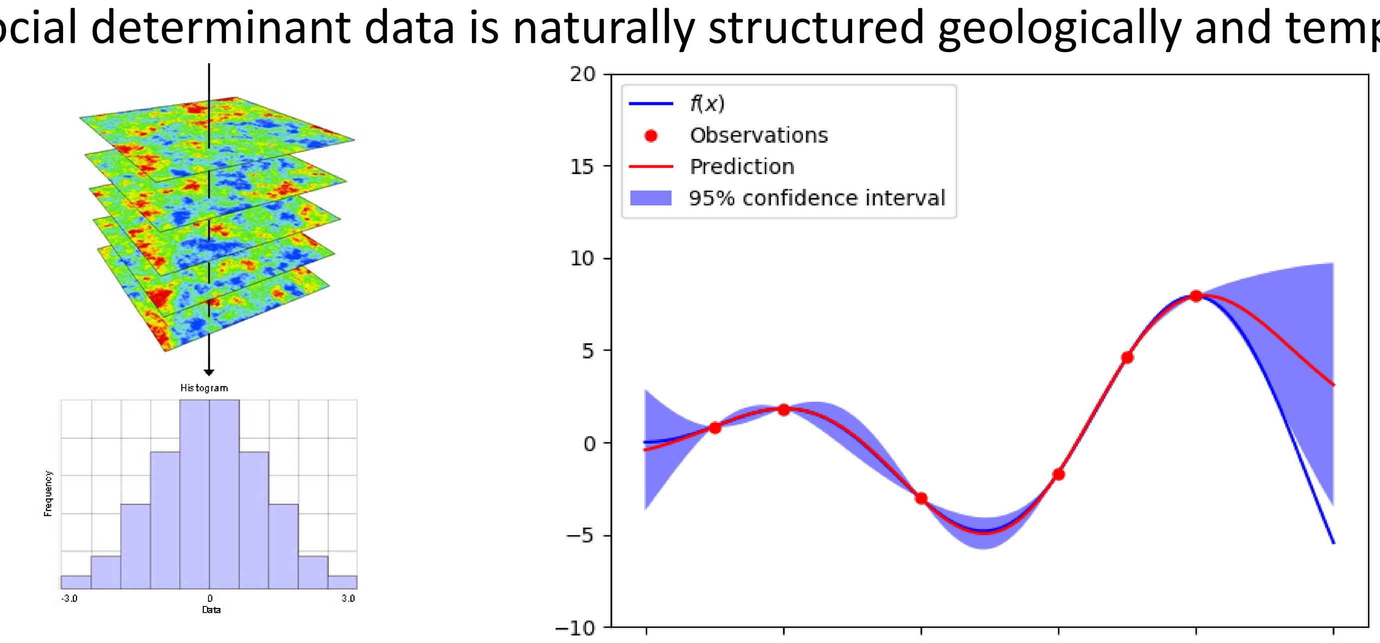
Methodology

- **Data**: We collect data of number of opioid overdose-related deaths by types of opioids, social determinants, public health environment, and opioid supply
- **Modeling**: To serve as a supporting decision system, models should provide **interpretability**

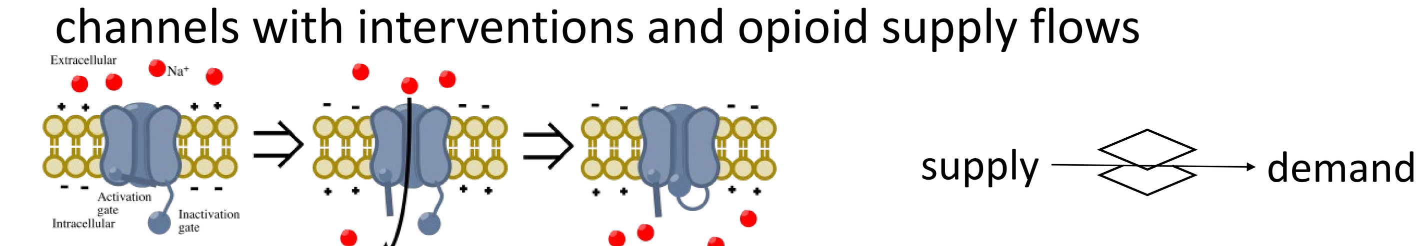
⇒Use "Glass-box" models or unbox "black-box" models



- **Linear mixed-effect multi-level modeling** to analyze statistically significant social determinants to the number of opioid-overdose deaths
  - It will provide preliminary demand-side analysis of the opioid crisis
  - A random effect term considers geological differences in X
- **Gaussian process-based spatiotemporal modeling** to further analyze the demand of opioid abuse and predict risk factors
  - Gaussian process (GP) is a popular nonparametric machine learning algorithm due to its interpretability in term of statistical uncertainty
  - GP can address spatiotemporal characteristics in data
  - Social determinant data is naturally structured geologically and temporal



- **Bioinspired simulation modeling** of the supply-demand chain to optimize interventions with incorporating predicted risk factors
  - Analogy between the gating mechanism and current flows in cell ion-channels with interventions and opioid supply flows



Progress

- H. Kim and H. Yang, "Statistical Analysis of County-Level Contributing Factors to Opioid-Related Overdose Deaths in the United States," 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)
- We analyzed the statistical significance of **county-level contributing factors to the opioid-overdose deaths** to examine demand-side characteristics of the opioid epidemic

County Feature	No.	All Opioids		Heroin		Fentanyl	
		Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI
Intercept	1	12.54	(5.80, 19.21)	1.37	(-5.97, 8.75)	-28.96	(-40.53 -16.05)
Demographic group							
Population	2	21.82	(20.25, 23.45)	9.42	(8.21, 10.64)	7.04	(5.46, 8.57)
% Male	3	5.88	(-1.47, 13.01)	3.82	(-5.49, 13.38)	6.86	(-5.71, 19.28)
% Age between 15 to 44	4	-0.99	(-7.65, 6.07)	-9.19	(-16.93, -0.85)	12.99	(0.31, 25.31)
% White	5	-59.99	(-84.76, -34.04)	-30.50	(-61.62, 2.04)	-34.01	(-92.76, 26.36)
% Black/African-American	6	-41.94	(-62.76, -20.41)	-21.79	(-47.55, 4.92)	-19.31	(-68.32 30.02)
% Asian-American	7	-24.7	(-33.52, -15.80)	-13.80	(-23.96, -3.34)	-15.90	(-33.32, 1.67)
% Other Races	8	-21.78	(-32.65, -10.50)	-7.79	(-21.45, 5.85)	-13.60	(-39.41 11.90)
Socio-economic group							
Median Household Income	9	8.27	(3.58, 12.96)	2.79	(-2.01, 7.64)	4.99	(-2.96, 12.73)
% Poverty	10	4.51	(-1.48, 10.56)	10.58	(3.35, 17.78)	-7.33	(-20.23, 5.73)
% Labor Force Participation	11	1.07	(-4.47, 6.67)	-8.85	(-15.86, -1.03)	-4.23	(-15.02, 7.17)
% Unemployed	12	0.51	(-2.94, 3.92)	-5.75	(-9.87, -1.66)	-18.74	(-27.15, -10.16)
Old Dependency Ratio	13	7.07	(0.16, 14.38)	-2.68	(-10.44, 5.78)	24.94	(12.89, 37.29)
Child Dependency Ratio	14	-6.95	(-11.73, -1.97)	-6.35	(-11.25, -0.91)	1.37	(-6.78, 9.19)
% Not Complete High School	15	-1.47	(-6.82, 3.74)	-13.50	(-20.22, -6.79)	-4.62	(-15.59, 6.13)
% Higher than B.S. Degree	16	3.14	(-2.70, 9.02)	2.46	(-3.91, 8.89)	4.66	(-4.36, 14.10)
% Veteran over Age 18	17	-10.92	(-14.24, -7.41)	-10.67	(-14.35, -6.68)	-13.92	(-19.33, -8.15)
% Female Household	18	7.71	(-0.17, 15.82)	9.77	(0.71, 19.56)	24.84	(11.06, 40.42)
% Divorce	19	2.78	(-1.63, 7.38)	-0.95	(-6.02, 4.31)	7.67	(-0.37, 15.28)
Health care environmental group							
% Uninsured	20	-9.44	(-13.16, -5.73)	-8.40	(-12.40, -4.39)	-22.91	(-30.39, -14.89)