Final Report

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Background and Significance

America, unlike other developed countries, does not have a universal healthcare program, meaning that not all individuals are granted free health insurance by the government. In America, Health insurance is purchased in the private marketplace or provided by the government only to certain groups, such as pregnant, low income, elderly, families with children.

The members of this project have personal experiences with United States health insurance. Having lived in Canada, where all citizens can apply for a public health insurance for free which grants them access to quality healthcare, Isabelle has never had to think of what it would be like without access to healthcare. In doing this research, Isabelle wanted to understand the effects of a lack of health insurance in the US, by finding the correlation between not having health insurance and the likelihood of contracting different diseases in 500 largest US cities. Maya worked at Westminster Free Clinic for four years, which offered healthcare services to the uninsured population in Ventura County, California. They witnessed how the obstacles our patients faced in accessing healthcare impacted their behaviors and healthcare outcomes.

Data Collection and Variables

The 500 cities dataset is provided by the Center for Disease Control and Prevention (CDC), Division of Population Health, Epidemiology and Surveillance Branch. Data from this dataset is sourced from 28,000 census tracts in "Census Bureau 2010 census population data, Behavioral Risk Factor Surveillance System (BRFSS) data (2017, 2016), and American Community Survey (ACS) 2013-2017, 2012-2016 estimates". All data was collected through the form of surveys. The meta dataset features data for a total of 5 "unhealthy behaviors", 13 "health outcomes' ' and 9 "preventive services" related to 27 types of chronic disease in 500 largest cities in the US. Within the datasets for diabetes, coronary heart disease, mental health outcomes and health insurance, variables include city, state, state abbreviation, year, datasource, TractFIPS, CityFIPS, Geographic Level, data value, low confidence unit, high confidence unit, coordinate of geographical location of city.

The original dataset includes about 29,000 observations, with multiple measurements for each city based on the data source (census, BRFSS, ACS). We restricted our dataset to only include variables on percent of city with lack of insurance, visiting the doctor, taking high blood pressure medications, smoking, reporting binge drinking, not having physical activity, with heart disease, with diabetes, and with kidney disease. We took the mean of all the age-adjusted prevalence measurements within a city and filtered our dataset to these means. As a result, there was only one measurement per city. For ANOVA testing, we filtered our dataset to only include states with measurements for at least 10 cities and created logarithmic versions of all variables.

Research Questions

1) Do cities with a greater lack of healthcare access have poorer mental health and/or physical health outcomes?

2) Does healthcare access, mental health, and/or physical health outcomes vary by state?

Variables of Interest

1) Healthcare Access for Adults (18+): Percent of City Population that Lacks Insurance, Percent of City Population with visits to doctor for routine checkup within the past year, Percent of City Population who have high blood pressure and are taking medicine for high blood pressure control.
2) Geographic Distribution by State
3) Behavior for Adults (18+): Percent of city population currently smoking, percent of city population currently reporting binge drinking habits, percent of city population reporting No leisure-time physical activity
4) Health Outcomes for Adults (18+): Percent of city population with coronary heart disease, percent of population diagnosed with diabetes, percent of city population with kidney disease

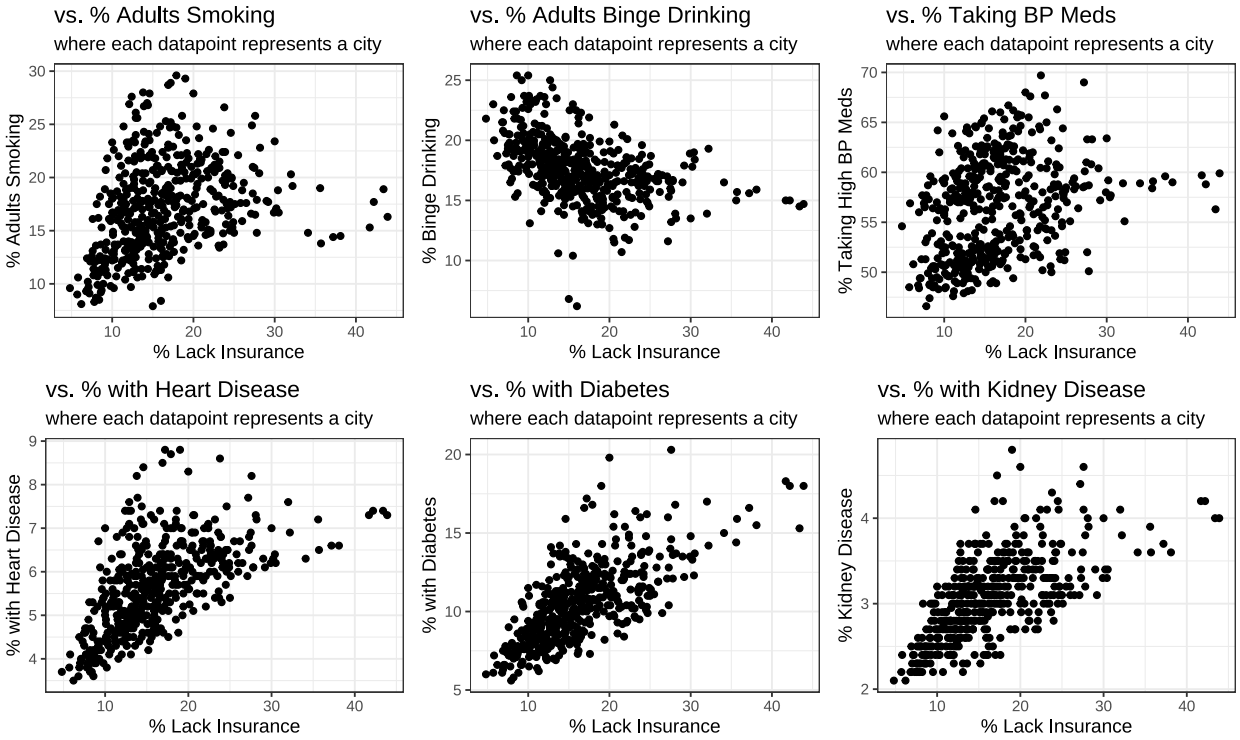
For Research Question 1, Healthcare Access Variables (1) are the explanatory variables, whereas Behavior (3) and Health Outcomes (4) are the response variables. For Research Question 2, Geographic Distribution by State (2) is the explanatory variable, and all health indicators (1, 3, 4) are the response variables.

Exploratory Data Analysis

Research Question 1

The following visuals are scatter plots between the insurance (the main explanatory variable we want to focus on) and a behavior or health outcome variable.

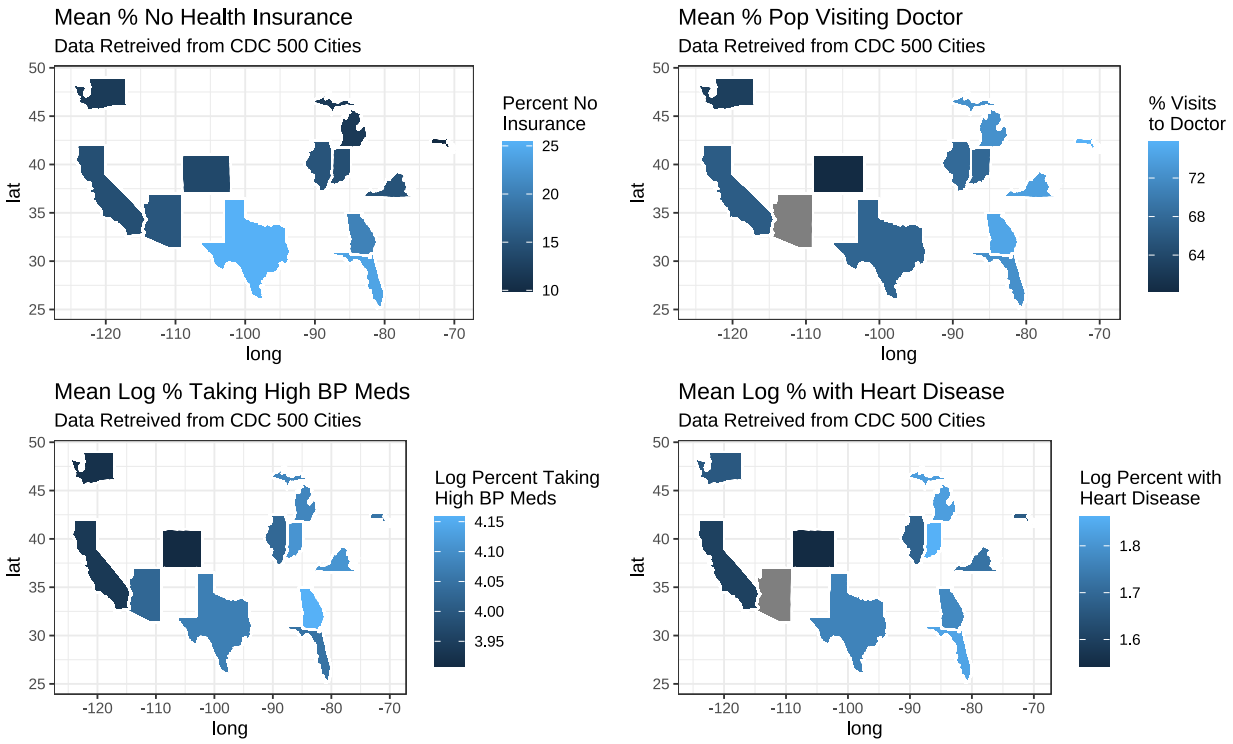
Figure 1: % Lacking Insurance vs. Behavior and Health Outcome Variables



Research Question 2

The maps below visualize the distribution healthcare access, behavior, and outcome variables by state. Only states that have at least ten observations are included, and only four variables that fit the assumptions for ANOVA testing.

Figure 2: State Distribution of Healthcare Access, Behavior, and Health Outcome Variables



Analytic Methods

Research Question 1

We modeled our data with a linear regression to determine if there were significant correlations between healthcare access variables and mental health and physical health outcomes. We did not add any interactions to our linear models because all the explanatory variables are numerical, and the course does not encompass an analysis of interactions between two numerical variables. To determine whether a linear regression model would be appropriate, we made residual plots for each health outcome to check for any patterns in the residuals. For smoking, binge drinking, physical activity, and diabetes, there didn't seem to be a significant pattern in the residual plot, so a linear regression model was appropriate. However, for coronary heart disease and kidney disease, there was a pattern in the residual plot where the higher the predicted percentage of adults with diabetes, the larger the magnitude of the residual, such that a linear regression model would not be appropriate.

Research Question 2

We conducted ANOVA testing to determine if there was variance within and between states for the healthcare access, behavior, and health outcome variables. We determined that state distributions of % lack of insurance, % visiting the doctor, log % with heart disease, and log % taking high BP medications had normal distributions within groups and homoscedastic variance and therefore fit the assumptions for ANOVA testing. It is highly unlikely that the samples groups within an ANOVA test are independent; for example, certain states may

share similar political contexts and could be more likely to share simliar health outcomes. We employed a Bonferroni correction with a subsequent significance level of p = 0.000641025641.

Results

Research Question 1

1) Holding all other variables constant when evaluating each explanatory variable, we expect a 0.0523 percentage increase in adults smoking in a city for every percent increase in a city lacking access to health insurance, a 0.0966 percentage decrease in adults smoking in a city for each percent decrease of people in a city visiting doctor for routine checkup within the past year, and a 0.674 percentage increase in adults in a city smoking for each percent increase in adults in city with high blood pressure had access to high blood pressure medication. The coefficients for all three variables are statistically significant (p-value < 0.05), meaning there is less than a 5% chance such a coefficient or more extreme would be found in the data if percentage of adults smoking and the healthcare access variables were not associated.

2) Holding all other variables constant when evaluating each explanatory variable, we expect a 0.162 percentage decrease of adults in a city reporting binge drinking for every percent increase of adults in a city lacking access to health insurance, a 0.0565 percentage increase in adults in a city reporting binge drinking for each percentage increase of adults in a city visiting doctor for routine checkup within the past year, and a 0.137 percentage decrease in adults in a city reporting binge drinking for each percent increase in adults in a city with high blood pressure had access to high blood pressure medication. The coefficient for all three variables are statistically significant (p-value < 0.05).

3) Holding all other variables constant when evaluating each explanatory variable, we expect a 0.533 percentage increase of adults in a city reporting no physical activity for each percent increase of adults in a city lacking health insurance, a 0.0625 percentage decrease in of adults in a city reporting no physical activity for each percent increase of adults in a visiting doctor for routine checkup within the past year, and a 0.738 percentage increase of adults in a city reporting no physical activity for each percent increase of adults in a city with high blood pressure had access to high blood pressure medication. The coefficient for all three variables are statistically significant (p-value < 0.05).

4) Holding all other variables constant when evaluating each explanatory variable, we expect a 0.239 percentage increase in population diagnosed with diabetes for each percent increase of adults in a city lacking health insurance, a 0.065 percentage decrease in population diagnosed with diabetes for each percent increase of adults in a visiting doctor for routine checkup within the past year, and a 0.171 percentage increase in population diagnosed with diabetes for each percent increase of adults in a city with high blood pressure had access to high blood pressure medication. The coefficient for all three variables are statistically significant (p-value < 0.05).

Figure 3: Percent Lacking Insurance vs. Response Variables (Titled in Quadrants)

Linear Regression Considers Visits to Doctor and High BP Meds as Explanatory Variables

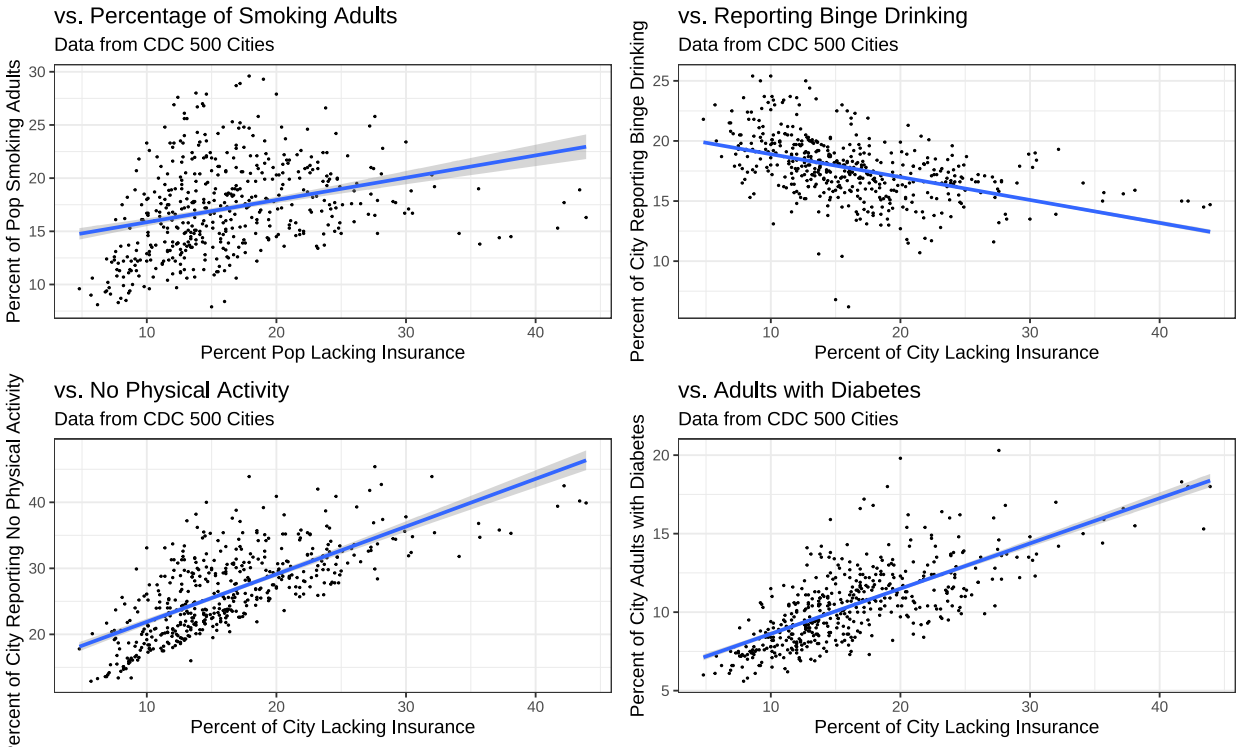


Table 1: Intercepts and Coefficients for Linear Regressions

Coefficients	Smoking	Binge Drinking	Physical Activity	Diabetes
Intercept	-15.0000	24.2000	-28.1000	-7.570
Insurance	0.0523	-0.1620	0.5330	0.239
Visits to Doctor	-0.0966	0.0565	0.0625	0.065
High BP Meds	0.6740	-0.1370	0.7380	0.171

Table 2: P-Values of Intercepts and Coefficients for Linear Regressions

Significance Value	Smoking	Binge Drinking	Physical Activity	Diabetes
Intercept P-Value	0.0000000	0.0000000	0.0000000	0.0000000
Insurance P-Value	0.0279000	0.0000000	0.0000000	0.0000000
Visits to Doctor P-Value	0.0308000	0.0945000	0.0995000	0.0021300
High BP Meds P-Value	0.0000000	0.0000439	0.0000000	0.0000000
Adjusted R-Squared Value	0.5150724	0.2367489	0.8369087	0.6797326

Research Question 2

ANOVA tests provided evidence that there is significant variances between and within states for % lack of insurance, % visiting the doctor, log % with heart disease, and log % taking high BP medications. The step down tests demonstrated that there are 19 significant pairs for % lack of insurance, 47 significant pairs for % visiting doctor, 39 significant pairs for log % taking high BP meds, and 7 significant pairs for log % with heart disease. Florida and Texas had the most significant pairs (9 each) for the insurance step down tests, Colorado and Washington had the most significant pairs (10 each) for the visits to doctor step down tests, California, Colorado, Georgia, and Washington (9 each) had the most significant pairs for the log medicine

high BP step down tests, and Colorado had the most significant pairs (3) for the log % heart disease step down tests. The only step-down test that had states with no significant pairs was for log % heart disease.

Table 3: ANOVA Summary Table Including F-Statistics and Significant Pairs

...1	Insurance	Visits to Doctor	log Medications	log Heart Disease
F-Statistic (Overall)	25.2	90.03	113.3	10.3
Overall Sig Pairs	19.0	47.00	39.0	7.0
Arizona Sig Pairs	2.0	7.00	6.0	0.0
California Sig Pairs	2.0	7.00	9.0	4.0
Colorado Sig Pairs	2.0	10.00	9.0	3.0
Florida Sig Pairs	9.0	8.00	6.0	2.0

Discussion

Research Question 1

Research Question 2

The ANOVA testing demonstrated that there is variance within and across states for lack of insurance, visits to doctor, heart disease, and taking High BP medication rates. Based on their higher F-squared values and greater number of significant pairs, visits to doctor and High BP Medication rates seemed to have more variance than lack of insurance and heart disease.

These results are significant in supporting Zuckerman's article on how there are differences in insurance coverage across states, with California, Texas, and Colorado having disproportionately high uninsurance rates (Zuckerman 1999, 8). These variances for health insurance correspond with state based variances for doctors' visits, heart disease prevalence, and people taking high blood pressure medications. Although the ANOVA testing does not depict which states have disproportionately high or low insurance rates, the fact that California, Texas, and Colorado commonly appear in significant pairs for the step-down tests supports Zuckerman's results.

A Bonferroni correction is implemented on the ANOVA testing because it is unlikely that the state distributions are independent from each other, but the research is limited in identifying what exactly causes a lack of independence. Identifying this cause could allow one to correct the lack of independence more accurately.

Further research should investigate the socioeconomic and policy factors that contribute to differences between and within states. Are the differences due to differing statewide healthcare policies or the result of inherent economic inequality between states?

References

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