Lead in the Water: The Effects of Blood Lead Levels on Incareration Rates

A Socio-Spatial Analysis

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Introduction

Could exposure to lead increase one's likelihood of going to prison? After our team's systematic review of studies, we have explored the potential effects of lead exposure on brain development in children and adults. Various existing studies highlight the detrimental effects of lead on different brain regions, noticeable in a decrease in executive control and cognitive control, thereby affecting memory, mood, behavior and comprehension skills. Such exposure to lead during the developmental years of children causes irreversible damage, the effects of which can be seen later on in life.

Studies in the past, such as one conducted by Talayero et al. (2023)[1], have highlighted a strong association between lead exposure during childhood and criminal tendencies during adulthood. One can be exposed to lead through different means, including water, which is the medium which we've chosen to investigate. Our research topic inquires about whether a relationship exists between a specified area's water lead levels and its incarceration rates, while also considering potential confounding effects of other demographic factors.

This research topic has important societal implications, namely the complicated intersection of crime, environmental racism, and more. It's an ever relevant question today and we hope to come to meaningful conclusions by the end of our analysis. Our initial hypothesis is that there is a positive relationship between water lead levels and the rate of incarceration with the existence of other interaction effects from things such as race and income. However, we acknowledge the intricate combination of social and institutional factors that increases one's likelihood of incarceration and are understand the possibility for inconclusive findings with the focus on lead exposure.

1. The association between lead exposure and crime: A systematic review

Exploratory Data Analysis

Our Data

We've chosen to create our dataframe from a variety of census data relating to California in 2020. Our data looks at different California census tracts and their respective statistics relating to blood lead levels, income, incarceration rates, and racial demographics. For our analysis, we are particularly focused on `perc_bll_indicator`, `med_income`, our age and race variables and how well they can predict `imprisonment_rt`. The demographic data was collected through the Census data collection process which involves online surveys, in-person questionnaires, and is self-reported. The blood lead level data was compiled using the mandatory reported data entered by laboratories and heathcare workers. The data was sorted into census tracts based on reported street address and observations deemed false positive or false negative by the California Department of Public Health (CDPH) have been omitted. To clean the data, we joined each dataset to each other based on census tract and renamed columns for clarity. In addition, we calculated new columns to simplify categories (i.e. age ranges, ethnicities) and omitted fields which would not be relevant for this investigation.

Note: All figures referenced throughout the report can be found in the Appendix section below.

Univariate Data Exploration

Blood Lead Levels (Figure 1): There are 94 census tracts that didn't test blood lead levels in this data. These will likely need to be removed because these observations are not useful in the analysis. Additionally, there is a large concentration of census tracts that have a percent blood level indicator of 0 (1899 observations). While these should probably be included in the final analysis, removing these for data visualization produces a unimodal distributon that is heavily right skewed. Overall, the median blood level is 1.6891892 and the IQR is NA.

Incarceration Rate (Figure 2): After removing extreme outliers (the top 1% incarceration rates - some may ultimately be removed because the census tract has an extremely low population ex. ~3 people), the shape of the distribution is unimodal and right skewed. The median incarceration rate is 267 out of 100,000 with an IQR of 257. This doesn't appear surprising - there are fewer census tracts with particularly high imprisonment rates.

Income (Figure 3): The shape of the income distribution is also unimodal with a less extreme right skew and a median value of 7.7225×10^4 and iqr of `r_inc_iqr`. This doesn't appear surprising - we'd expect median incomes of tracts to be concentrated towards the left.

Spatial Distribution (Figure 4): Given the spatial nature of this investigation, it is important to understand how the reported lead levels vary across the state. This map shows that there are contiguous series of tracts, especially in the Los Angeles region, where there may be

spatial correlation. This is not surprising, as we expect water conditions across tracts to be similar.

Bivariate Data Exploration (WE SHOULD EXPAND MORE ON THIS)

Imprisonment vs BLL Indicator (Figure 5): Imprisonment rate and the percentage of a census tract with a high bll has a generally positive correlation.

Imprisonment vs Median Income (Figure 6): Imprisonment rate and median income has a generally negative correlation.

Imprisonment vs Population Aged 15-29 (Figure 7): Imprisonment rate and percentage of population aged 15-29 in the census tract has a generally positive correlation.

Potential Interactions (Figure 8):

When comparing the relationship between median income and imprisonment rate, it appears that generally they have a negative correlation. This graph suggests there could be an interaction effect between race and income, as the relationship between median income and imprisonment rate differs by race. We created a categorical variable for the percentage of the census tract population that is black, native american, or "other race" that is categorically above or below the median in the data. The relationship between imprisonment rate and median income appears more negatively correlated when categorically above the median census tract population percentage of black, native american, and other_race. This supports that there could be an interaction effect between race and income.

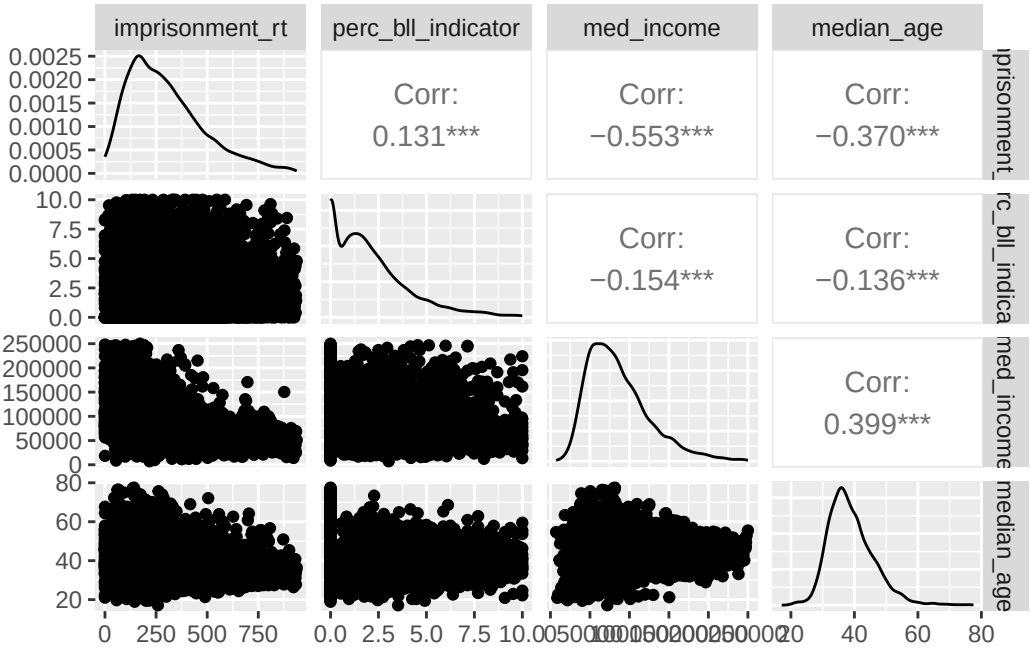
Checking Initial Modelling Conditions

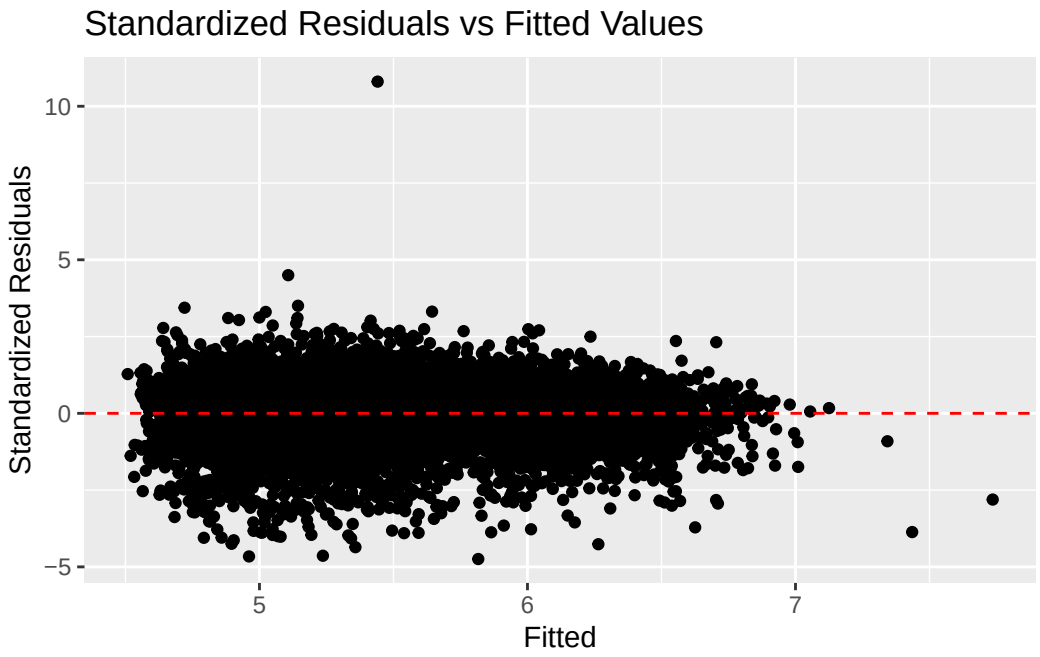
term	estimate	std.error	statistic	p.value
(Intercept)	-357.488	162.353	-2.202	0.028
perc_bll_indicator	-1.802	2.848	-0.633	0.527
POC_other	6.274	0.989	6.345	0.000
med_income	-0.001	0.000	-4.522	0.000
median_age	-3.145	1.379	-2.281	0.023
perc_male	17.270	2.859	6.041	0.000
POC_other:med_income	0.000	0.000	-3.974	0.000

```
perc_bll_indicator            POC_other           med_income
          1.047454             6.401602             2.310705
        median_age            perc_male POC_other:med_income
          1.631162             1.030406             3.966140
```

Using the residual vs fitted plot **(Figure 9),** we can assess the model conditions. From this graph, we find

1. Normality condition can be relaxed.
2. Linearity condition not satisfied. Points not randomly scattered around the x = 0 line.
3. Constant variance condition not satisfied. Points fan out across the x = 0 line.
4. Independence condition also may not be satisfied. Census tracts next to each other could be more likely to have similar incarceration rates or blood lead levels.

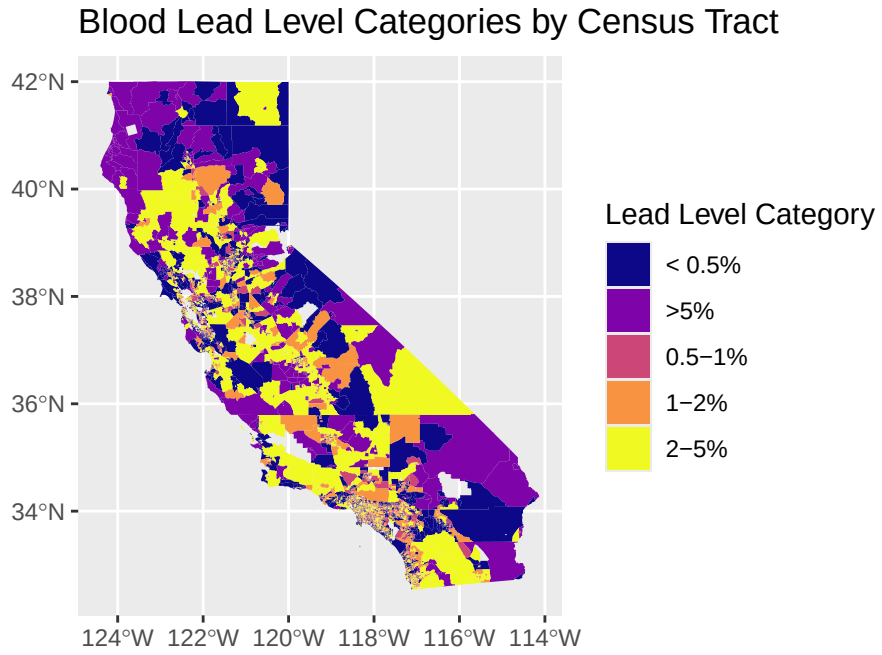


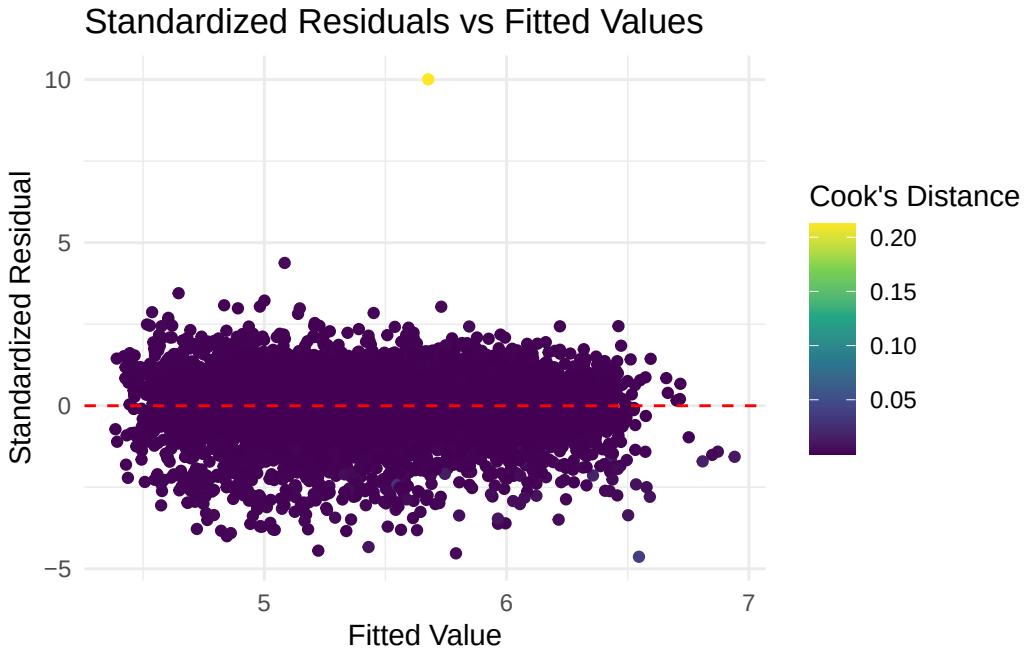



```
log_med_income perc_bll_indicator          POC_other         median_age
      1.674443           1.065711           2.182680           1.644827
perc_male
      1.030724
```

Splitting the Data

We were concerned about spatial correlation, so originally split the data with 20% in training and 80% testing to minimize this effect. We received abysmal R squared values when doing this. We are going to perform a form of cross validation called spatial cross validation to address model overfitting and independence issues within our data. Because we are addressing the independence problem using this method, we can now do 80% training and 20% testing. For this, we used ChatGPT to suggest solutions. It suggested spatial cross validation, which we researched further using this source: https://r.geocompx.org/spatial-cv





term	estimate	std.error	statistic	p.value
(Intercept)	11.971	0.330	36.315	0.000
log_med_income	-0.663	0.026	-25.624	0.000

term	estimate	std.error	statistic	p.value
perc_bll_indicator	-0.003	0.003	-1.045	0.296
POC_other	-0.027	0.009	-2.929	0.003
median_age	0.005	0.001	4.476	0.000
perc_male	0.008	0.003	2.915	0.004
log_med_income:POC_other	0.004	0.001	4.522	0.000

```
Start:  AIC=-7536.27
log_imprisonment_rt ~ log_med_income + perc_bll_indicator + POC_other +
    median_age + perc_male + POC_other * log_med_income

                          Df Sum of Sq    RSS     AIC
<none>                                  1925.7 -7536.3
- perc_male                1    2.5847 1928.3 -7529.8
- median_age               1    6.0945 1931.8 -7518.2
- log_med_income:POC_other 1    6.2204 1931.9 -7517.8



Call:
lm(formula = log_imprisonment_rt ~ log_med_income + perc_bll_indicator +
    POC_other + median_age + perc_male + POC_other * log_med_income,
    data = bll_train)

Residuals:
    Min      1Q  Median      3Q     Max
-2.5390 -0.2884  0.0555  0.3615  5.4796

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              11.9709416  0.3296440  36.315  < 2e-16 ***
log_med_income           -0.6631090  0.0258782 -25.624  < 2e-16 ***
perc_bll_indicator       -0.0026630  0.0025478  -1.045  0.29596
POC_other                -0.0274528  0.0093714  -2.929  0.00341 **
median_age                0.0053888  0.0012039   4.476 7.73e-06 ***
perc_male                 0.0079678  0.0027333   2.915  0.00357 **
log_med_income:POC_other  0.0038170  0.0008441   4.522 6.23e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5515 on 6331 degrees of freedom
Multiple R-squared:  0.4201,    Adjusted R-squared:  0.4195
```

```
F-statistic: 764.3 on 6 and 6331 DF,  p-value: < 2.2e-16
```

term	estimate	std.error	statistic	p.value
(Intercept)	11.971	0.330	36.315	0.000
log_med_income	-0.663	0.026	-25.624	0.000
perc_bll_indicator	-0.003	0.003	-1.045	0.296
POC_other	-0.027	0.009	-2.929	0.003
median_age	0.005	0.001	4.476	0.000
perc_male	0.008	0.003	2.915	0.004
log_med_income:POC_other	0.004	0.001	4.522	0.000

Table 4: Model Performance (RMSE and R-squared)

.metric	.estimator	.estimate
rmse	standard	184.971
rsq	standard	0.495

```
Start:  AIC=-9001.12
log_imprisonment_rt ~ log_med_income + perc_bll_indicator + POC_other +
    median_age + perc_male + POC_other * log_med_income

                          Df Sum of Sq    RSS     AIC
<none>                                 1983.0 -9001.1
- perc_male                1    1.6252 1984.6 -8997.3
- median_age               1   12.1954 1995.2 -8959.7
- log_med_income:POC_other 1   15.4345 1998.4 -8948.2
```

Table 5: Random-Split Model Performance (RMSE and R-squared)

.metric	.estimator	.estimate
rmse	standard	158.152
rsq	standard	0.442

```
[1] 0.4200831
```

```
[1] 0.47341
```

Appendix

Univariate EDA

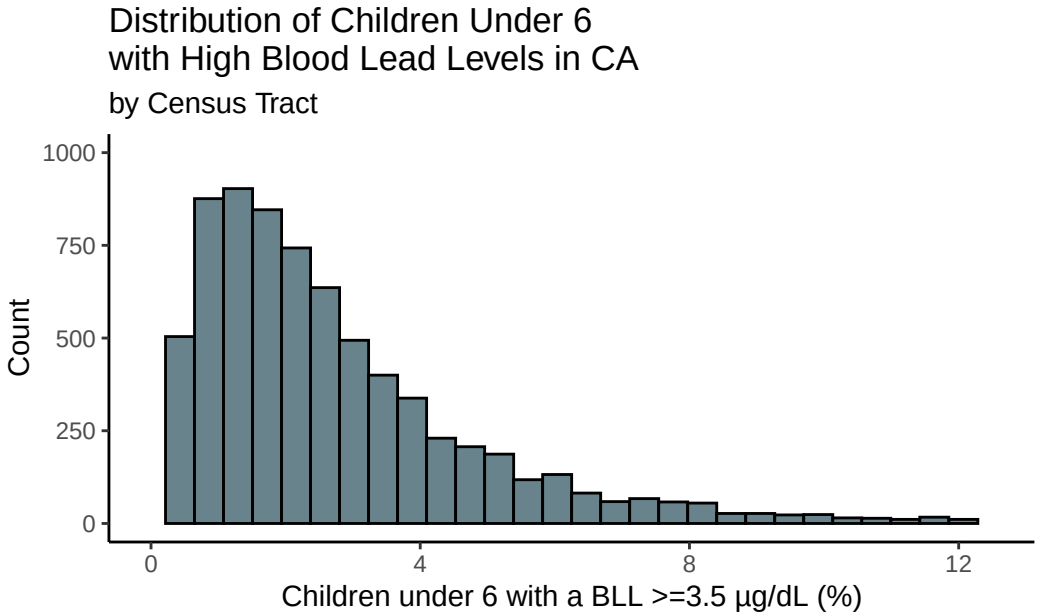


Figure 1: Figure 1: Distribution of lead in children

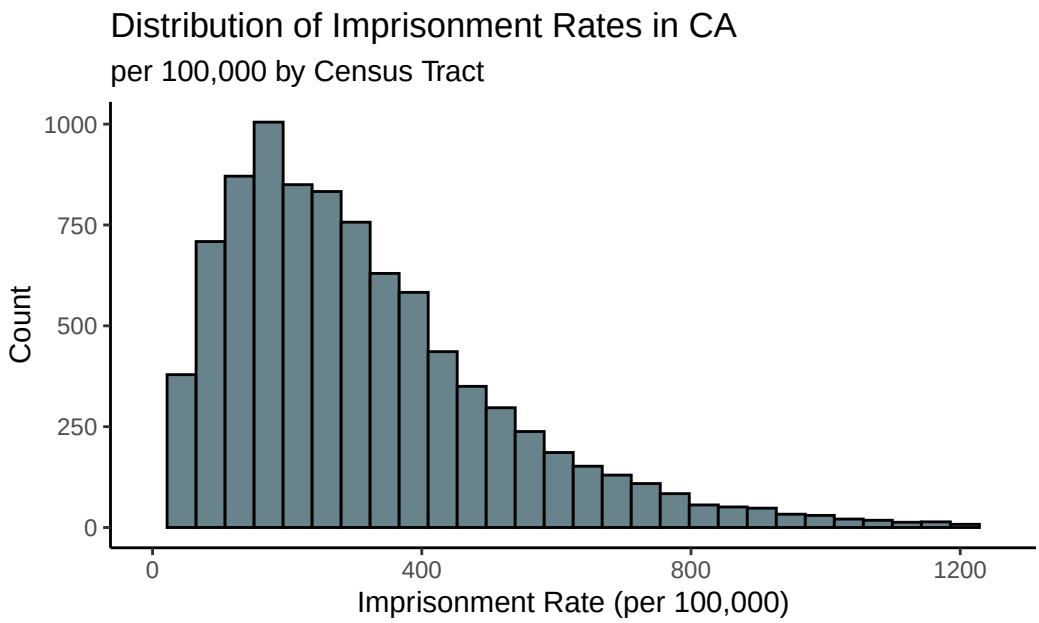


Figure 2

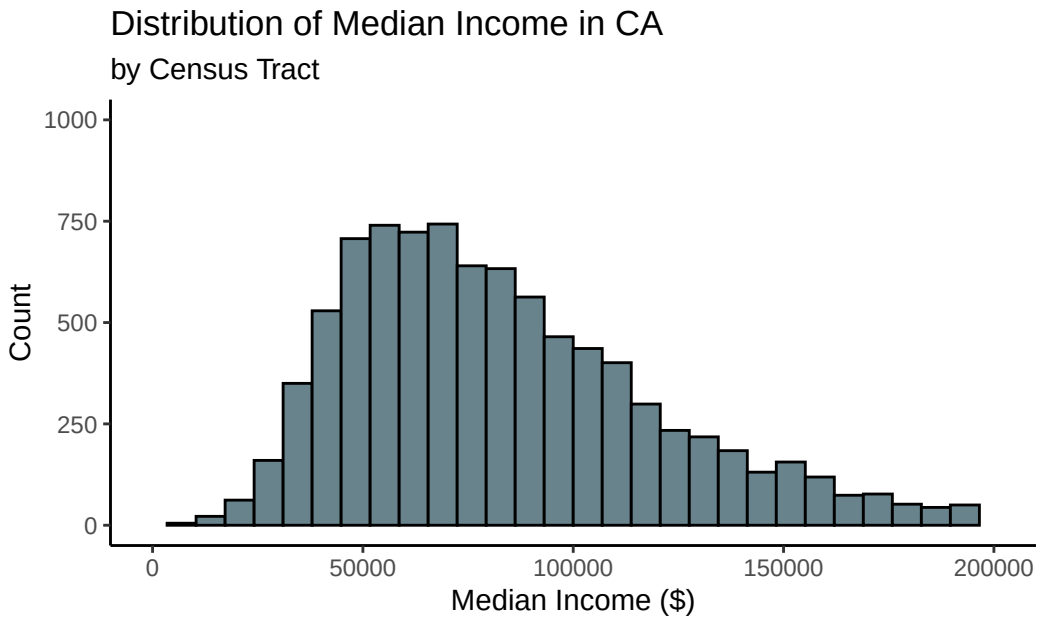


Figure 3

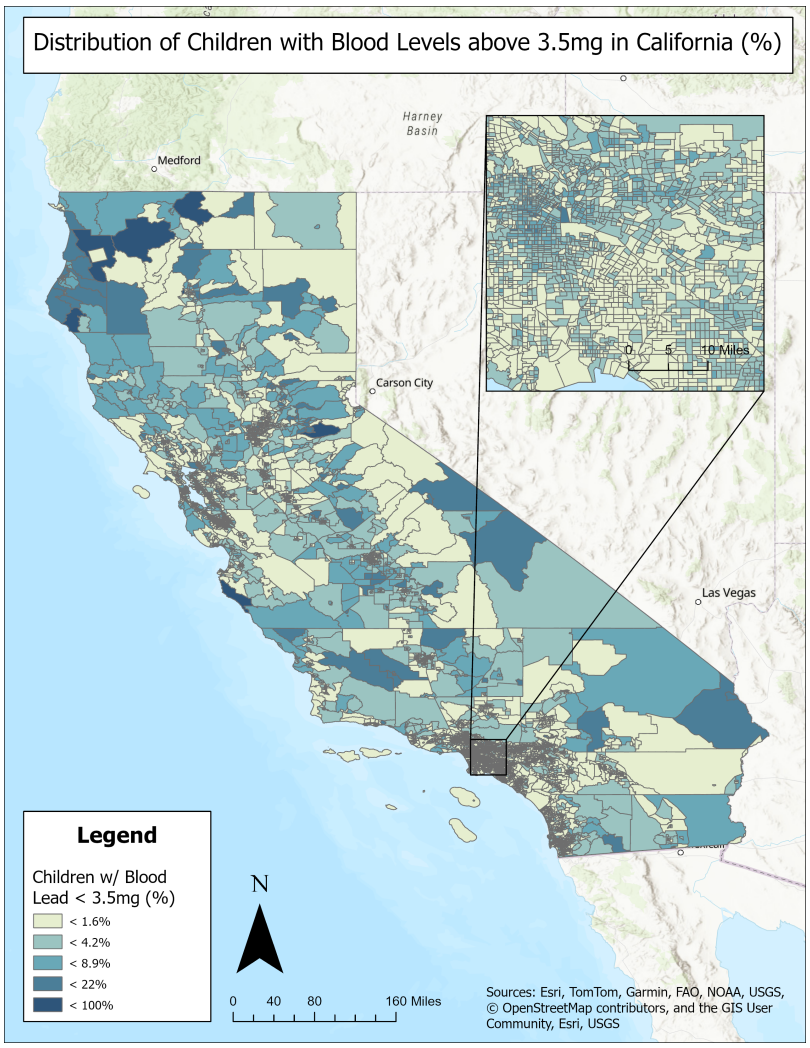


Figure 2: Figure 4: Spatial Distribution of BLL in California

Bivariate EDA

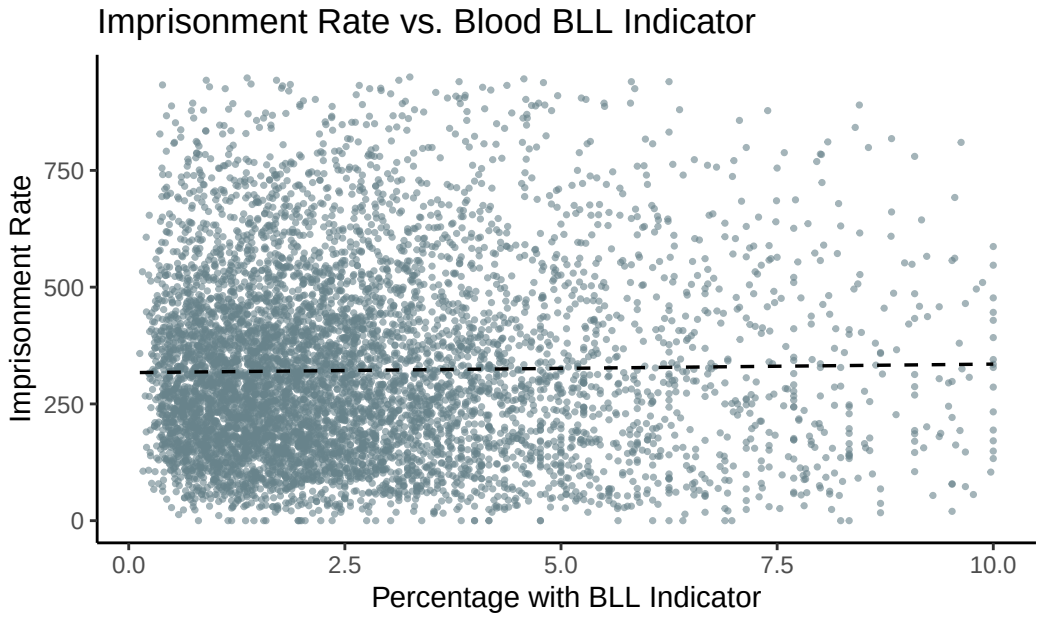


Figure 5

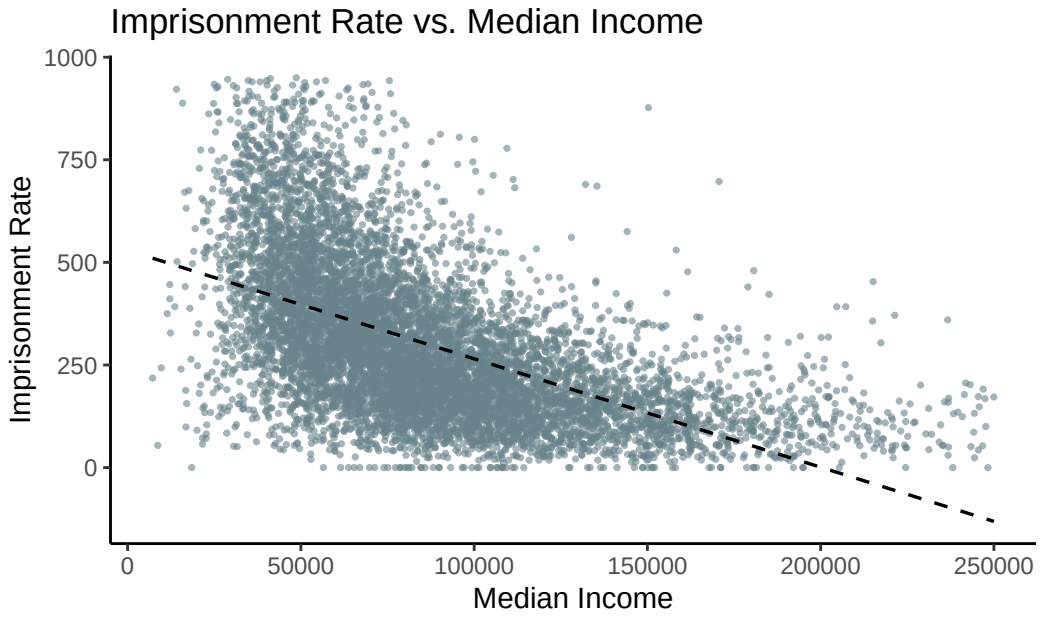


Figure 6

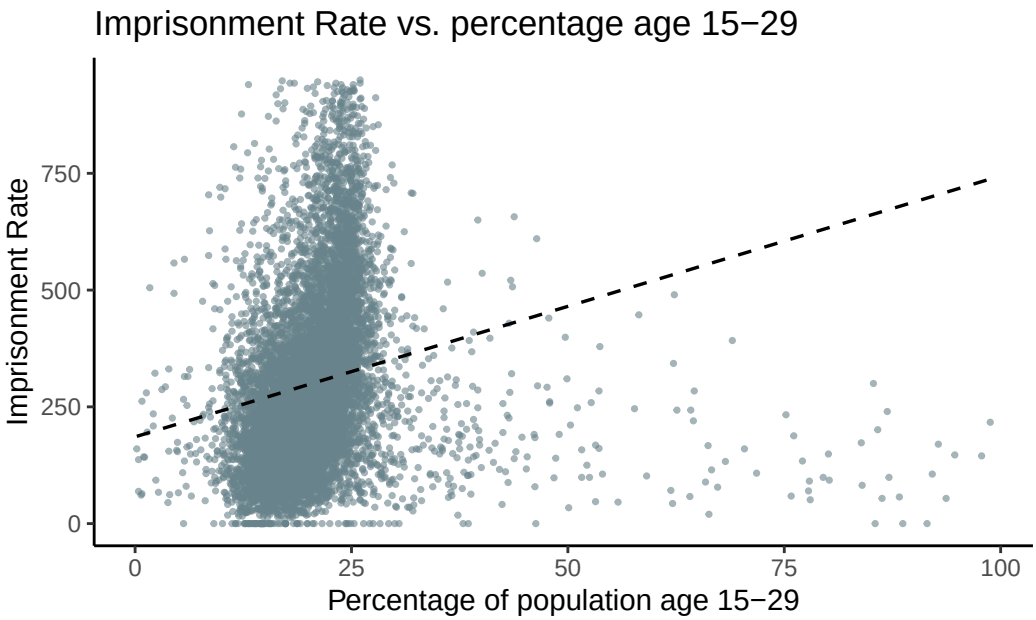


Figure 7

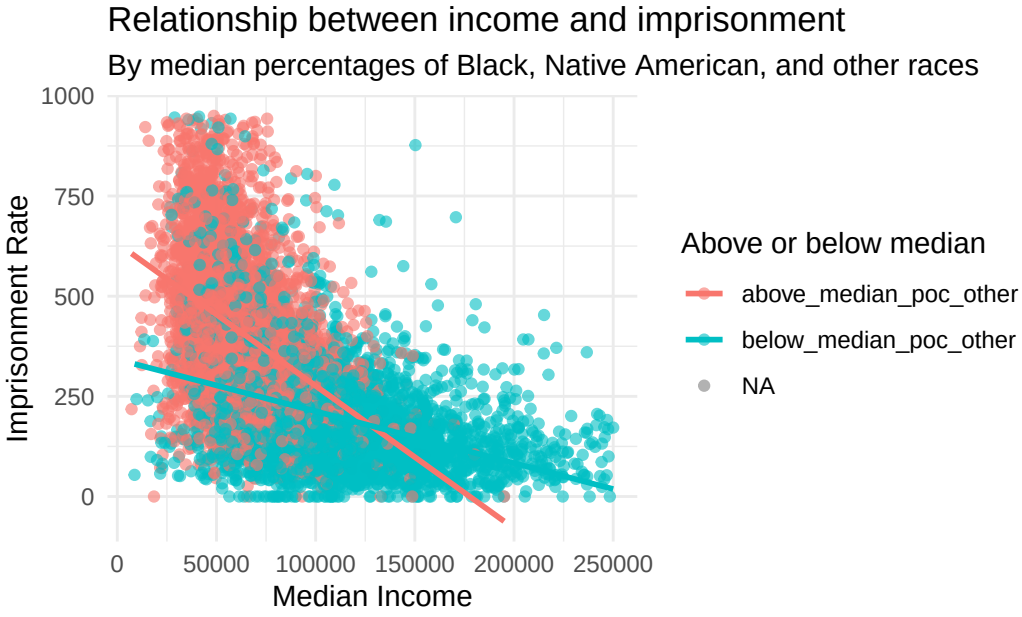


Figure 8

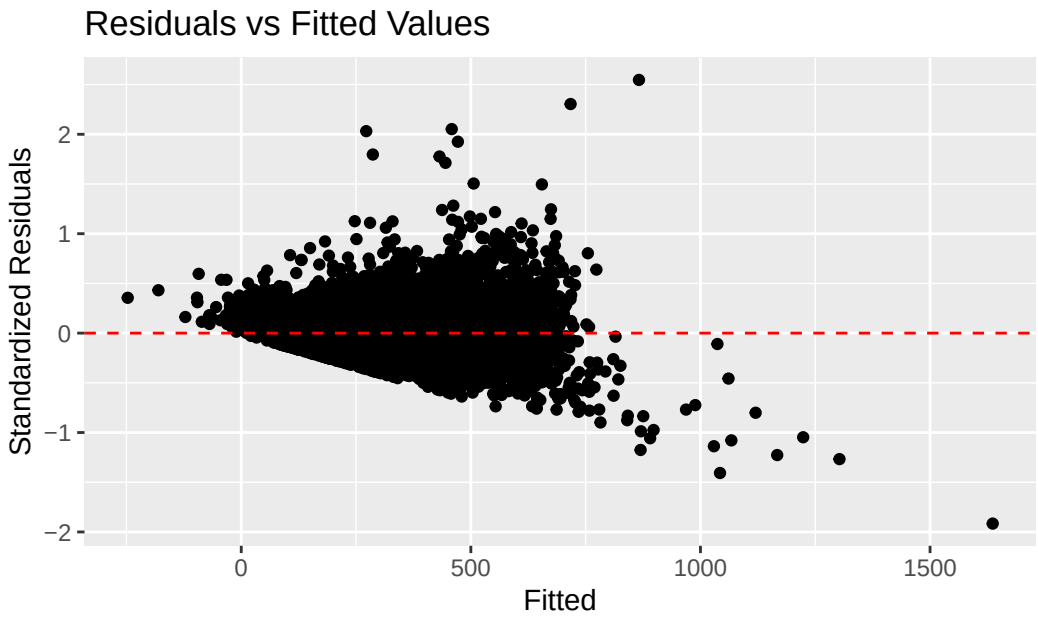


Figure 9

```
perc_bll_indicator            POC_other           med_income
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        median_age           perc_male POC_other:med_income
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