

Pandemic Politics: Physical Polling Place Usage and COVID-19 Cases in Wisconsin



Wisconsin voters wait to cast their ballots. Photo from the Philadelphia Inquirer.

Abstract:

On 04/07/2020, Wisconsin held in-person elections despite the COVID-19 pandemic, unique among U.S. states. In addition, fewer than typical polling stations opened. Given public health concerns, we investigated how polling place usage relates to COVID-19 case numbers three weeks later. We compiled data for Wisconsin's 73 counties and fit a multiple linear regression with $R^2_{adj} = .8431$ using county-by-county positive test numbers on election day, population, population density, proportion of people older than 65, median income, regional hospital bed availability / population, comorbidity prevalence rates, and rate of polling place usage to predict a response of $(\text{Cases as of April 27th} + 1)^{15}$. We found a statistically significant positive relationship between poll station usage and transformed cases, controlling for other predictors. Future studies could examine the impacts of public health measures, increased remote voting access, consider foreign in-person elections, and locate actual instances of election-day infections via contact tracing.

Additional information is available in the appendix, starting on page 6.

Background and Introduction

On Tuesday, April 7, 2020, Wisconsin held several elections, including a presidential primary and a Wisconsin Supreme Court contest. It is the only state to have held in-person elections during April. Additionally, Wisconsin's attempt to extend absentee ballot access was overruled by the U.S. Supreme Court (Neely).

We are interested in the relationship across counties between availability of physical polling stations and reported COVID-19 cases as of April 27th, controlling for compounding factors such as population density and comorbidity prevalence. Importantly, some locales closed more polling stations on April 7th than others. For example, the city of Madison had 66 polling locations compared to Milwaukee city's 5, despite the latter being more populated (Durr and Spicuzza).

Given the United States may administer federal elections before the COVID-19 outbreak subsides, questions have arisen over how local, state, and federal governments should adapt elections. Analyzing data on Wisconsin's experiences can thus inform vital policy decisions.

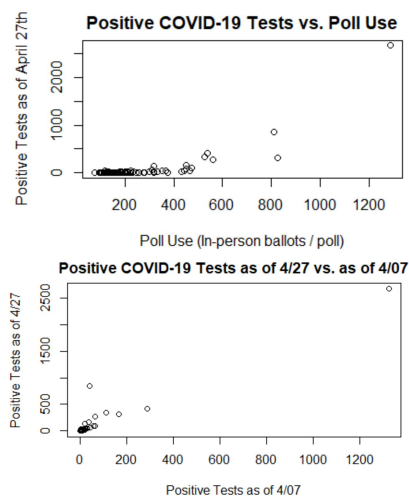
Data and Exploratory Analysis

Data and Variables

We collected county-by-county data for each of Wisconsin's 73 counties. We used U.S. Census data¹ to determine populations (total people) and population density (people per square mile). To measure physical polling place use, we used absentee vote numbers² and polling place quantities³ provided by the Wisconsin Election Commission as well as vote totals for the state Supreme Court race compiled by the *New York Times*⁴, which used to create "PollUse," equal to $(\text{total votes} - \text{absentees}) / (\text{number of polling places})$. PollUse is created to capture (i) infection variability due to an inability to social distance with fewer polling locations, and (ii) infection variability due to more in-person votes. Wisconsin's Department of Health Services (W-DHS) provided data on positive COVID-19 tests as of April 27th and April 7th⁵. We also sourced data on the percentage of the population over 65⁶, median incomes as of 2017 in current USD⁷, number of asthma hospitalizations from 2016 through 2018⁸, and hospitalizations from chronic obstructive pulmonary diseases (COPD) in 2017 from the W-DHS⁹. The W-DHS's Healthcare Emergency Readiness Coalition regions were potential categorical predictor.¹⁰ We also collected data on the number of hospital beds in each region.¹⁰ Data on hospital capacity for individual counties was unavailable, so counties were assigned the capacity of their region. Data on the percentage of the population with diabetes and annual HIV cases were sourced from the 2020 County Health Rankings and Roadmaps.¹¹ To aid parsimony, we combined data on COVID-19 comorbidities (COPD, Diabetes, and Asthma) into a single variable by summing their t-values, which may (wrongly) assume each comorbidity is equally influential. A further limitation of our data is non-independence with respect to state, given all data is from Wisconsin. For example, states have varying testing capacity and public health responses, which could influence reported COVID-19 cases.

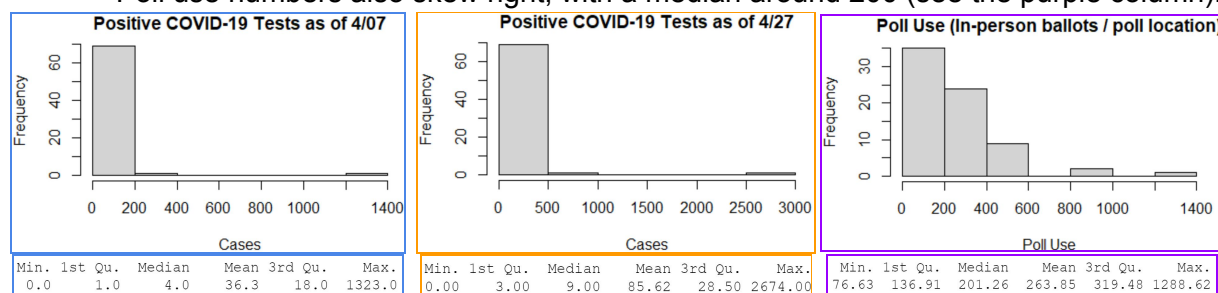
Exploratory Data Analysis

There appeared to be a positive, non-linear relationship between positive case numbers on April 24 and our poll-use metric (see right scatterplot). The high-leverage point in the upper right corner is Milwaukee County; it is a high-leverage outlier in both cases and poll use. There appeared to be a positive, roughly linear relationship between positive COVID-19 tests as of April 27th versus April 7th, with Milwaukee County a high-leverage outlier. The distributions of positive COVID-19 tests for both dates (see histograms below) are heavily



right-skewed, with median cases shifting from 4 on the 7th to 8 on the 24th. The range drastically increases from the 7th to 24th, from 0-1323 to 0-2431. This is due to significant growth in cases for Milwaukee County, the county with the highest case numbers on both dates.

Poll use numbers also skew right, with a median around 200 (see the purple column). It



ranges from about 77 at minimum to about 1289 at

maximum; this maximum, which is a visible outlier, corresponds to Milwaukee County.

In addition, we discovered that Iron County had invalid data: its recorded COPD-related hospitalizations are negative. Iron County is an outlier in two respects, Asthma Prevalence and Percent Over 65 (Appendix: 1). Finally, HIV data was missing for 12 counties.

Model and Results

Analytic Methods

Because we are using multiple variables to predict a quantitative response, we used a multiple linear regression model. Milwaukee's outlier status required special consideration. We reduced Milwaukee's influence by dividing Cases on April 7th by counties' populations and using population-adjusted rates when constructing our comorbidities variable. We considered doing similar for PollUse, but we found that doing so introduced non-normality regardless of Milwaukee County's omission (Appendix: 2). These measures are only partial, however, as Milwaukee remains an outlier in other respects such as population density. As such, analysis initially excludes Milwaukee County; however, we later examine the influence of the two omitted outliers, Iron and Milwaukee counties, on our model estimate and research conclusion (Appendix: 3). Finally, to avoid losing non-trivial statistical power by restricting analysis to 61 counties, HIV was excluded from our comorbidity variable.

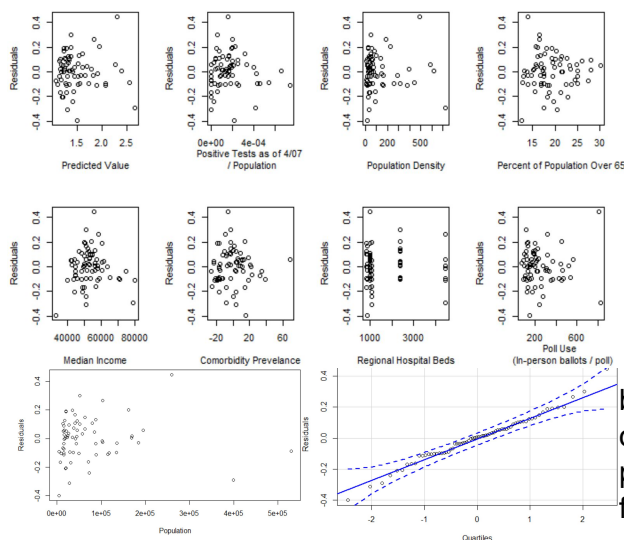
Because our goal was investigating PollUse's influence, not making predictions, we included all predictors that may explain COVID-19 case variability, using them as controls for our observational study. Region had to be dropped, however. Note that when considering region's inclusion, we had to change one variable: counties had their regional hospital capacity divided by their populations to eliminate collinearity with their region assignment. When performing a partial F-test for region's 40 interaction terms, inference diagnostics were severely, uncorrectably violated - we could not confidently conclude the hyperplanes for each region are parallel, precluding the use of only indicator terms (Appendix: 4). With at most 73 data-points, a model with 40 interaction terms is poised to overfit the data, eliminating that option, too.

Now we consider response transformation. Because some counties had no positive COVID-19 tests by April 27th, and Box-Cox transformations only function for positive response values, we added 1 to cases on the 27th and then used a Box-Cox transformation of $(\text{Cases as of 4/27} + 1)^{.15}$. We understand this is not the most interpretable transformation; however, none of Box-Cox's recommended transformations were (Appendix: 5).

Final model and Results

The estimated equation for our multiple-regression model is:

$$(\text{Positive Tests by 4/27} + 1)^{.15} = 1.521 + \frac{\text{Positive Tests by 4/7}}{\text{Population}} * 477.9 + \text{Population} * 1.062 \times 10^{-6} - \text{Population Density} * 7.8 \times 10^{-5} - \text{Percent Older Than Sixty Five} * 1.851 \times 10^{-2} - \text{Median Income} * 3.922 \times 10^{-6} + \text{Regional Hospital Beds} * 6.905 \times 10^{-5} + \text{Comorbidity Prevalance} * 8.759 \times 10^{-4} + \text{PollUse} * 1.094 \times 10^{-3}$$



Our model's assumptions are satisfied, as residuals are nearly-normal, the Residual vs. Predicted plot displays constant variance, and no residual plot displays a strong curved pattern, though because data is not independent of state, we should be cautious. The model's high R^2 of .8631 and the low s_e of .152 indicate high model performance: our model explains 86.31% of the variability in $(\text{Positive Tests by 4/27} + 1)^{15}$ with little variation. The R^2_{Adj} of .8431 indicates a good balance of performance and parsimony. Further, our model's R^2_{Adj} is comparable to the best possible model's .847 (Appendix: 6). The F-test for model effectiveness returns $p\text{-value} < 2.2 \times 10^{-16} < \alpha = .01$, enabling us to

reject the null hypothesis that our model performs no better than an intercept-only model, indicating an effective model. Turning to the variable of concern for our research, PollUse, we conduct a one-sided t-test for evidence that $\beta_{\text{PollUse}} > 0$. Because the t-statistic of 3.301 is positive, and the one-sided p-value $.00081 < \alpha = .01$, we reject the null hypothesis that $\beta_{\text{PollUse}} \leq 0$. We have evidence for the alternative hypothesis that PollUse has a positive, linear relationship with $(\text{Positive Tests by 4/27} + 1)^{15}$ accounting for our other predictors. The 99% confidence interval for β_{PollUse} is $(2.127758 \times 10^{-4}, 1.974911 \times 10^{-3})$, meaning that after accounting for other predictors' influence, we are 99% confident that increasing PollUse by one is associated with an average increase in $(\text{Positive Tests by 4/27} + 1)^{15}$ of between 2.127758×10^{-4} and 1.974911×10^{-3} .

Discussion and Conclusions

We investigated the relationship between poll usage and COVID-19 case numbers. We found that there was a statistically significant, positive correlation at the $\alpha = .01$ level between poll usage and $(\text{Positive Tests by 4/27} + 1)^{15}$, accounting for other variables such as case numbers on election day and the prevalence of select comorbidities. Our model explains a high proportion of variance in $(\text{Positive Tests by 4/27} + 1)^{15}$ without much variability in error sizes. While we cannot determine causation, we have found a statistically significant correlation.

There are many, mutually compatible explanations of the relationship identified. First, more people voting in-person could enable more COVID-19 spread. Second, polling place closures may have limited people's ability to practice social distancing. Third, high poll use rates may have occurred in places susceptible to COVID-19 for reasons besides those we controlled for; for example, Milwaukee county is closer to Chicago, a dense urban hub, than most of Wisconsin, which might have influenced spread in Milwaukee.

Our data is limited by its county-level nature: we suspect variation within counties, especially those containing both urban and rural locales. Further, our hospital capacity data was not specific to counties, limiting explanatory power within regions. Additionally, we did not take into account different polling place characteristics such as drive-through voting availability and varying county health policies. Finally, because all data is for Wisconsin, the relationships identified may not manifest in the same way elsewhere. Future research focused on our question could account for additional factors—for example, distance to nearby disease hotspots—and also consider the election experiences of foreign countries to identify consistent trends.

References

Background:

Neely, Brett. 6 April 2020. "Wisconsin Plans to Vote In Person Tuesday After Last Minute Chaos," NPR,

<https://www.npr.org/2020/04/06/828191015/wisconsin-governor-effectively-reschedules-tuesday-s-primary-election>

Durr, Allison and Spicuzza, Mary. 9 April 2020. "What we know so far about why Milwaukee only had 5 voting sites for Tuesday's election while Madison had 66," Milwaukee Journal Sentinel,

<https://www.jsonline.com/story/news/politics/elections/2020/04/09/wisconsin-election-milwaukee-had-5-voting-sites-while-madison-had-66/2970587001/>

Data Sources:

1. "Wisconsin Counties by Population," Cubit Planning, Inc. Data from the U.S. Census Bureau. https://www.wisconsin-demographics.com/counties_by_population
2. "Absentee Ballot Report - April 7, 2020 Spring Election and Presidential Preference Primary," Wisconsin Elections Commission. <https://elections.wi.gov/node/6825>
3. "Spring 2020 Election and Presidential Preference Primary," Wisconsin Elections Commission. <https://elections.wi.gov/node/6524>. (see: "Polling Place List-2020 April Election as of 4-4-20.xlsx")
4. "Live: Wisconsin Supreme Court and Statewide Election Results," *New York Times*. <https://www.nytimes.com/interactive/2020/04/07/us/elections/results-wisconsin-spring-elections.html>
5. "COVID-19 Historical Data Table," Wisconsin Department of Health Services. <https://data.dhsgis.wi.gov/datasets/covid-19-historical-data-table/data?where=GEO%20%3D%20%27State%27>
6. "Demographics of Aging in Wisconsin," Wisconsin Department of Health Services. <https://www.dhs.wisconsin.gov/aging/demographics.htm>
7. "Wisconsin Public Health Profiles," Wisconsin Department of Health Services. <https://www.dhs.wisconsin.gov/stats/pubhealth-profiles.htm>
8. "Age-Adjusted Asthma Hospitalization Rate and 95% Confidence Intervals (CIs) for Wisconsin Counties and Overall State, 2016-2018," Wisconsin Department of Health Services. <https://www.dhs.wisconsin.gov/asthma/county-level-asthma-hospitalization-rates.pdf>
9. "Environmental Public Health Tracking: COPD Data," Wisconsin Department of Health Services. <https://www.dhs.wisconsin.gov/epht/copd.htm>
10. "COVID-19: Hospital Capabilities," Wisconsin Department of Health Services. <https://www.dhs.wisconsin.gov/covid-19/hosp-data.htm>
11. "Wisconsin," County Health Rankings and Roadmaps. <https://www.countyhealthrankings.org/app/wisconsin/2020/overview>

Appendix

(1) Outlier Analysis for Iron County

Below are the ranges for not being considered an outlier; each interval equals (Median - 1.5 * IQR, Median + 1.5 * IQR). Note that Iron County lies outside two intervals: Asthma Prevalence, for having a lower ratio of Asthma Hospitalizations to Population than the interval minimum, and Percent Over 65, for having a larger percentage of its population over 65 years of age than the interval maximum.

Cases on 4/07 / Population: -9.655371e-05 0.0003792544
 Iron County: 0.0001749781

Population: -62350.5 143896.5
 Iron County: 5715

Population Density: -111.6219 212.7169
 Iron County: 7.54

Percent Over 65: 10.19199 26.13814
 Iron County: 29.308

Median Income: 39790.62 64097.38
 Iron County: 42328

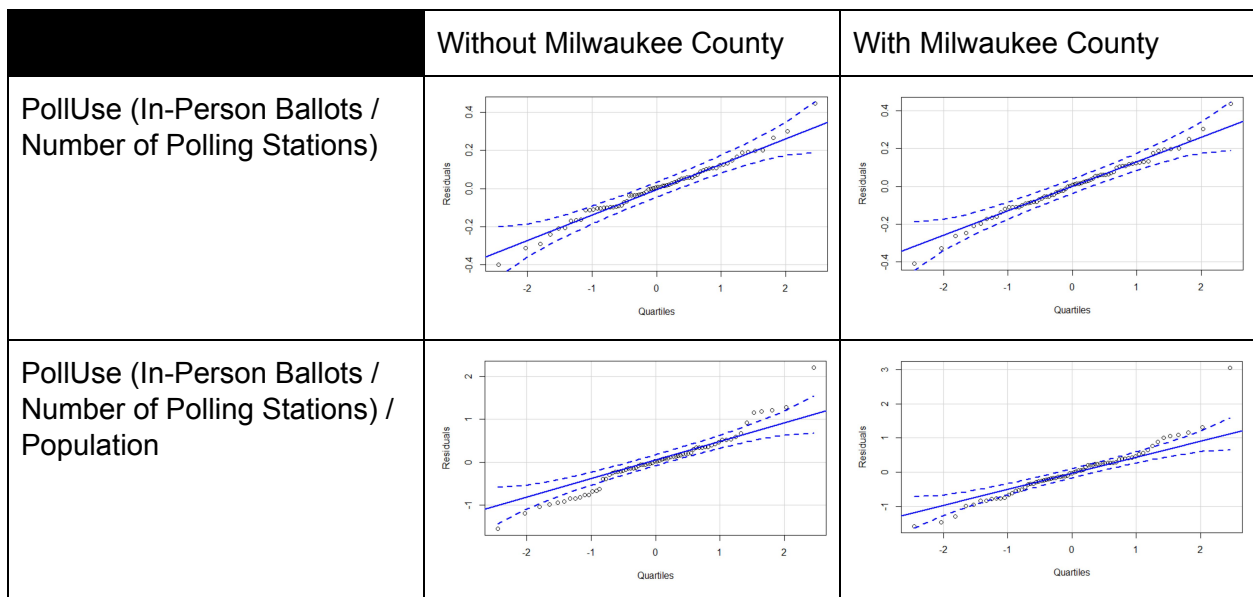
Regional Hospital Beds: -1352.5 3288.5
 Iron County: 1050

Asthma Prevalance: 0.01015959 0.1335779
 Iron County: 0.0006999125

Diabetes Prevalance: 5.125 14.875
 Iron County: 11

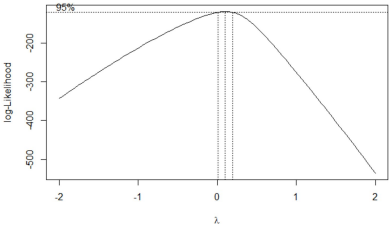
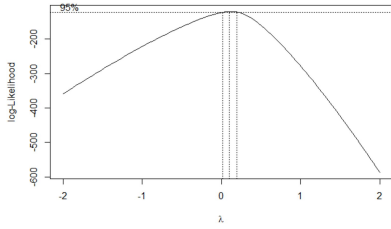
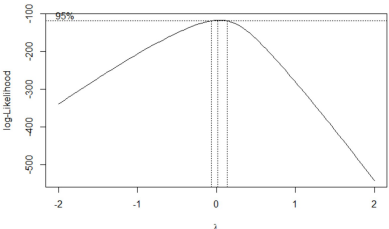
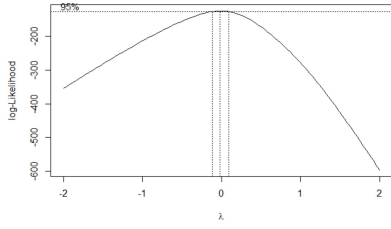
Poll Use: -74.95862 455.0843
 Iron County: 75

(2) Normality Analysis of PollUse vs. (PollUse / Population)



Note that the blue bands mark the 95% confidence interval for where we expect points to lie if we indeed have a normal distribution of residuals. These comparisons utilize the same predictor

variables as discussed in the final model section (except PollUse, of course); however, because Box-Cox recommendations vary, we adjust our response transformation accordingly. Below are the Box-Cox plots and chosen transformations for the above combinations. We can see on the QQPlots that, post Box-Cox transformation, the nearly-normal condition is more strongly violated by the models that divide PollUse by Population.

	Without Milwaukee County	With Milwaukee County
PollUse (In-Person Ballots / Number of Polling Stations)		
Response Transformation:	$(\text{Positive Tests as of } 4/27 + 1)^{.15}$	$(\text{Positive Tests as of } 4/27 + 1)^{.15}$
PollUse (In-Person Ballots / Number of Polling Stations) / Population		
Response Transformation:	$\log(\text{Positive Tests as of } 4/27 + 1)$	$\log(\text{Positive Tests as of } 4/27 + 1)$

(3) Analyzing the Influence of Milwaukee County & Iron County

The following table utilizes the same predictors and transformed response as in our final model for the last two columns. Iron County has erroneous COPD data, which means our combined comorbidity variable must be adjusted for it. To do so, we utilize a different approach to combining comorbidities, which adds t-statistics for the following two values: (Asthma Hospitalizations / Population) & (Percent of people in county with Diabetes). A table with summary output for the three models appears on the following page. With respect to model statistics, all three models are similar, with R^2 and R^2_{Adj} all falling between .83 and .89. s_e hovers around .15 for each model as well, and all three models' F-statistics result in $p\text{-value} < 2.2 \times 10^{-16}$ indicating each is effective at $\alpha = .01$. The model including Milwaukee is the one that maximizes both R^2 and R^2_{Adj} , likely because of how significant an outlier Milwaukee is with respect to PollUse, Population, and Population Density. Two models, the final model and the model including Milwaukee County, show positive t-statistics and one-sided p-values (half the p-values for the two-sided t-tests given in the summary outputs) below $\alpha = .01$ when considering PollUse. This confirms we can reject the null hypothesis that $\beta_{PollUse} \leq 0$, providing evidence for the alternative hypothesis that there is a positive, linear relationship between PollUse and $(\text{Positive Tests by } 4/27 + 1)^{.15}$ after accounting for other predictor variables. The

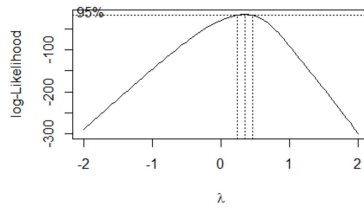
negative t-value for the model that includes Iron County could indicate our conclusion is not robust to outliers, but the different method for combining comorbidities in that case could also explain this difference.

	Summary Results
<p>Include Iron County but not Milwaukee County</p>	<pre>Call: lm(formula = Cases.trans ~ InitCases + Population + PopDensity + Over65 + MedianIncome + HospitalBeds + ComorbidCpt + PollUse, data = wisconsinCOVID) Residuals: Min 1Q Median 3Q Max -0.29711 -0.12202 0.00287 0.06881 0.41509 Coefficients: Estimate Std. Error t value Pr(> t) (Intercept) 1.490e+00 2.165e-01 6.880 3.47e-09 *** InitCases 5.330e+02 1.626e+02 3.278 0.00172 ** Population 1.997e-06 4.624e-07 4.318 5.78e-05 *** PopDensity 8.832e-04 2.746e-04 3.216 0.00206 ** Over65 -1.587e-02 5.572e-03 -2.849 0.00595 ** MedianIncome 6.228e-07 3.276e-06 0.190 0.84987 HospitalBeds 5.997e-05 2.144e-05 2.797 0.00686 ** ComorbidCpt 5.396e-04 1.343e-03 0.402 0.68912 PollUse -6.492e-04 2.176e-04 -2.984 0.00407 ** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.1569 on 62 degrees of freedom Multiple R-squared: 0.8511, Adjusted R-squared: 0.8319 F-statistic: 44.3 on 8 and 62 DF, p-value: < 2.2e-16</pre>
<p>Include Milwaukee County but not Iron County</p>	<pre>Call: lm(formula = Cases.trans ~ InitCases + Population + PopDensity + Over65 + MedianIncome + HospitalBeds + ComorbidCpt + PollUse, data = wisconsinCOVID) Residuals: Min 1Q Median 3Q Max -0.40701 -0.08627 0.00835 0.08779 0.43858 Coefficients: Estimate Std. Error t value Pr(> t) (Intercept) 1.495e+00 2.088e-01 7.160 1.14e-09 *** InitCases 4.906e+02 1.735e+02 2.827 0.006313 ** Population 1.117e-06 4.088e-07 2.732 0.008200 ** PopDensity -3.983e-04 1.081e-04 -3.686 0.000481 *** Over65 -1.930e-02 5.587e-03 -3.455 0.000999 *** MedianIncome -3.806e-06 3.329e-06 -1.143 0.257321 HospitalBeds 7.601e-05 2.229e-05 3.410 0.001146 ** ComorbidCpt 1.069e-03 1.341e-03 0.797 0.428263 PollUse 1.309e-03 2.401e-04 5.453 9.14e-07 *** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.1518 on 62 degrees of freedom Multiple R-squared: 0.8924, Adjusted R-squared: 0.8786 F-statistic: 64.3 on 8 and 62 DF, p-value: < 2.2e-16</pre>
<p>Omit Both Iron County and Milwaukee County (Final Model)</p>	<pre>Call: lm(formula = Cases.trans ~ InitCases + Population + PopDensity + Over65 + MedianIncome + HospitalBeds + ComorbidCpt + PollUse, data = wisconsinCOVID) Residuals: Min 1Q Median 3Q Max -0.39755 -0.09524 0.00694 0.08491 0.44754 Coefficients: Estimate Std. Error t value Pr(> t) (Intercept) 1.521e+00 2.108e-01 7.216 9.87e-10 *** InitCases 4.779e+02 1.742e+02 2.743 0.00798 ** Population 1.062e-06 4.133e-07 2.569 0.01265 * PopDensity -7.800e-05 3.564e-04 -0.219 0.82748 Over65 -1.851e-02 5.655e-03 -3.273 0.00176 ** MedianIncome -3.922e-06 3.335e-06 -1.176 0.24406 HospitalBeds 6.905e-05 2.350e-05 2.939 0.00464 ** ComorbidCpt 8.759e-04 1.358e-03 0.645 0.52119 PollUse 1.094e-03 3.314e-04 3.301 0.00161 ** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 0.152 on 61 degrees of freedom Multiple R-squared: 0.8613, Adjusted R-squared: 0.8431 F-statistic: 47.35 on 8 and 61 DF, p-value: < 2.2e-16</pre>

(4) Analyzing the 'Region' Categorical Variable

Because Northwest is the most common region, we use it as our baseline for the Region variable.

Fox Valley Area 8 North Central 11 Northeast 7 Northwest 15 South Central 14 Southeast 8 Western 7

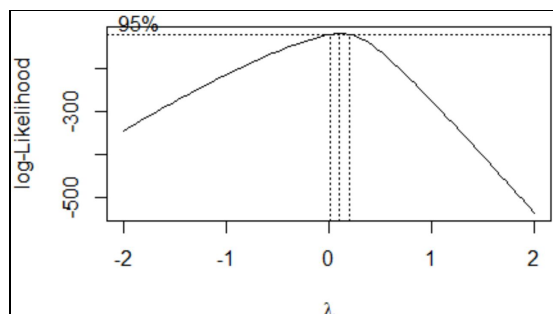


After fitting our model to include the predictors of our final model, along with Region indicators and Region interaction terms, we get the boxcox plot at left. Then, we apply a number of valid response transformations according to the plot, finding that none of them result in a satisfactory QQPlot for evaluating the nearly-normal condition. While some might deem them usable, we were not

confident in the validity of a partial F-test on Region's interaction terms, which is necessary to test the null hypothesis that the hyperplanes for the different regions do not intersect. Our reticence is motivated by the severity of the nearly-normal condition's violations (see below). And, without evidence for the parallel hyperplanes assumptions, including only indicator terms would be invalid, so we dropped Region.

Box-Cox Transformations	QQ-Plots
(Positive Tests by $4/27 + 1$) ¹⁵	
(Positive Tests by $4/27 + 1$) ^(1/4)	
(Positive Tests by $4/27 + 1$) ^(1/2)	

(5) Large Box-Cox plot for Final Model Response Transformation



We would have preferred a more characteristically interpretable response transformation than $(\text{Positive Tests by } 4/27 + 1)^{.15}$. For example, $\log(\text{Positive Tests by } 4/27 + 1)$ is at least contextually relevant given the expected exponential spread of diseases, but the below Box-Cox plot restricts us to various sub-.5 (i.e. sub-square root) transformations without including 0 (and therefore a natural log) in the 95% confidence interval for the value of λ that maximizes log-likelihood.

(6) Best Subset Model

Below is our code and output for finding the best possible model using the best-subset automated selection procedure.

```
# Leaps library provides 'regsubsets' function, which is used to find the best subset of predictors
library(leaps)
```

```
# Apply final model's Box-Cox transformation for consistency
wisconsinCOVID$Cases.trans<-wisconsinCOVID$Cases.trans^.15
```

```
# Construct full model on all predictors (identical to final model)
```

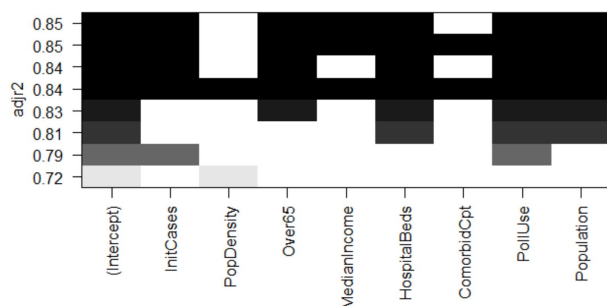
```
MLR.out<-
```

```
  regsubsets(Cases.trans ~ InitCases + PopDensity + Over65 + MedianIncome + HospitalBeds
+ ComorbidCpt + PollUse + Population, method = "exhaustive",
  data = wisconsinCOVID)
```

```
# Output Plot that displays the predictors used for the model maximizing adjusted-R2
plot(MLR.out, scale = "adjr2")
```

```
# Output summary for the adjusted-R2 maximizing model
```

```
MLR.best<-lm(Cases.trans ~ InitCases + Over65 + MedianIncome + HospitalBeds + PollUse +
Population, data = wisconsinCOVID)
summary(MLR.best)
```



```
Call:
lm(formula = Cases.trans ~ InitCases + Over65 + MedianIncome +
  HospitalBeds + PollUse + Population, data = wisconsinCOVID)

Residuals:
    Min       1Q   Median       3Q      Max
-0.38760 -0.09433  0.00368  0.08915  0.44945

Coefficients:
(Intercept)  1.550e+00  2.035e-01  7.616  1.68e-10 ***
InitCases    4.504e+02  1.656e+02  2.720  0.00842 **
Over65      -1.750e-02  5.370e-03  -3.260  0.00180 **
MedianIncome -4.718e-06  2.993e-06  -1.576  0.11999
HospitalBeds  7.035e-05  2.190e-05  3.213  0.00207 **
PollUse      1.046e-03  2.301e-04  4.547  2.53e-05 ***
Population   1.056e-06  3.893e-07  2.711  0.00863 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.15 on 63 degrees of freedom
Multiple R-squared:  0.8603,    Adjusted R-squared:  0.847
F-statistic: 64.68 on 6 and 63 DF,  p-value: < 2.2e-16
```