COVID-19 Vaccination Rates and Google Search Data

Arianna Schmid and Stacey Frank

2021-12-15

Contents

Introduction **1**

Research Questions 2

Data Collection **2**

1. Google Trends and Keywords 2

2. Vaccination Rates 5

3. State-level Demographics 6

Analysis **7**

1. Correlation Analysis 7

2. Regression Analysis 9

Conclusion **14**

References **14**

Introduction

Vaccines to control the Coronavirus Disease 2019 (COVID-19) became available to the public in the first half of 2021. Rejection and indecision towards being vaccinated is evident across the United States. The motivation for this study is to provide a better understanding of reasons for COVID-19 vaccine refusal in the United States. This can help public health messaging campaigns be more targeted and effective when promoting vaccination.

Google data is useful for exploring this topic because there is previous research that people feel freer to search for socially stigmatized topics on Google than they would be to admit such opinions in a survey or another form of data collection. In his study of racial animus's relationship to voting behavior, Stephens-Davidowitz notes that Google searchers are likely to be alone and thus more likely to search for private topics (Stephens-Davidowitz 2014). Since we are interested in understanding how myths and conspiracies are playing into people's choice to receive the vaccine or not, Google searches are a useful source of data about the prevalence and impact of these ideas.

Research Questions

Our primary research question is what is the relationship, if any, between state-level COVID-19 vaccine rates and the types of Google searches that are made about vaccines in each state? To assist in answering that question, we have two secondary research questions:

1. Are vaccine myths more commonly searched for in states that also have low vaccination rates?
2. Does the relationship between COVID vaccine rates and Google searches change between June and September 2021?

We will use Google search data, state level COVID vaccination rate information from the Centers for Disease Control, and state-level demographic information to address these questions.

Data Collection

1. Google Trends and Keywords

The Centers for Disease Control provides a list of the most common questions about the COVID-19 vaccine, including mainstream questions and myths (CDC 2021). Similarly, the Mayo Clinic provides information on the most common myths surrounding the vaccine ("COVID-19 Vaccine Myths Debunked" 2021). Using these two data sources, we constructed a list of 12 keyword search terms. It consists of the two general searches, "covid vaccine" and "covid vaccine near me," five mainstream questions, such as "covid vaccine side effects," and 5 myth-related searches such as "covid vaccine microchip."

We created a vector called "k" to signify "keywords" and referenced this vector in later code to loop over the search terms for which we wanted to collect data. Note that each element in "k" will be renamed based on its index (hits.1, hits.2, ... hits.12) for code efficiency.

Table 1: Google Search Terms in Vector 'k'

Search Term
covid vaccine
covid vaccine near me
covid vaccine safe
covid vaccine ingredients
covid vaccine pregnant
covid vaccine protect
covid vaccine side effects
covid vaccine microchip
covid vaccine dna
covid vaccine fetal
covid vaccine infertility
covid vaccine magnet

We are interested in studying the Google search hit rate for all 12 terms in "k" for all 50 states and Washington, D.C. Since vaccines were made available to states at different points in time, and the nature of people's concerns about the vaccine may have changed over time, we pulled search hit rates from 3 different time periods: 1/1/21-9/20/21, 4/1/21-6/20/21, and 7/1/21-9/20/21.The gtrendsR package was used to work with Google Trends queries.

We created the custom function get.hit.results() to iterate through all the Google Trends queries we wanted

to run without repeating code. The function takes in the date range as an argument, calls gtrends() once for each of the 12 search terms, and returns the hit results by state based on the given date range. The hit rates by state for each search term are then extracted from the list initially generated by the gtrendsr() query, and saved into a single tibble containing the hit rates for all 12 search terms for the specified time period. The function is called 3 times, once for each date range, and the result is saved in the 3 objects hits.results.jan, hits.results.june, and hits.results.sept.

```
#User-defined function to run all needed Google Trends queries

get.hits.results <-  function(date){
    for (i in 1:length(k)){
          new_frame <- paste("Keyword",i,sep = "")
          assign(new_frame, gtrends(k[i], geo = "US",
                   time = date, low_search_volume = T)
                 )
    }

    hits_results <- Keyword1$interest_by_region %>%
      left_join(Keyword2$interest_by_region, by = "location") %>%
      left_join(Keyword3$interest_by_region, by = "location") %>%
      left_join(Keyword4$interest_by_region, by = "location") %>%
      left_join(Keyword5$interest_by_region, by = "location") %>%
      left_join(Keyword6$interest_by_region, by = "location") %>%
      left_join(Keyword7$interest_by_region, by = "location") %>%
      left_join(Keyword8$interest_by_region, by = "location") %>%
      left_join(Keyword9$interest_by_region, by = "location") %>%
      left_join(Keyword10$interest_by_region, by = "location") %>%
      left_join(Keyword11$interest_by_region, by = "location") %>%
      left_join(Keyword12$interest_by_region, by = "location") %>%
      as_tibble() %>%
      select(c(1,2,6,10,14,18,22,26,30,34,38,42,46))

    hits_results %<>% rename( hits.1 = hits.x,
                          hits.2 = hits.y,
                          hits.3 = hits.x.x,
                          hits.4 = hits.y.y,
                          hits.5 = hits.x.x.x,
                          hits.6 = hits.y.y.y,
                          hits.7 = hits.x.x.x.x,
                          hits.8 = hits.y.y.y.y,
                          hits.9 = hits.x.x.x.x.x,
                          hits.10 = hits.y.y.y.y.y,
                          hits.11 = hits.x.x.x.x.x.x,
                          hits.12 = hits.y.y.y.y.y.y)
    print(hits_results)

}

hits.results.jan <- get.hits.results("2021-01-1 2021-09-20")
hits.results.june <- get.hits.results("2021-04-1 2021-06-20")
hits.results.sept <- get.hits.results("2021-07-1 2021-09-20")
```

Next, we are interested in getting the count of states that actually have a Google Trends ranking for each search term. We do this to ensure we are using search terms that are popular enough to have generated a

hit rate, which will allow us to actually conduct our analysis. We accomplish this through the user-created get.search.terms() function. This function takes the hits results object from get.hit.results() as an argument, and returns the total number of states that have a reported hit rate for each search term in "k." Again, the function is called 3 times for each time period, and results are saved to the objects search.terms.jan, search.terms.june, and search.terms.sept. As an example, we see in Table 3 that for April-June, "covid vaccine," "covid vaccine near me," and "covid vaccine side effects" have reported hit rates in all 50 states and Washington DC. On the other hand, "covid vaccine microchip" was only searched often enough to generate a hit rate in 17 states.

Table 2: January-September: Number of States with Hit Rates by Search

Variable Name	Search Term	Number of States with Hit Rate
hits.1	covid vaccine	51
hits.2	covid vaccine near me	51
hits.3	covid vaccine safe	51
hits.4	covid vaccine ingredients	51
hits.5	covid vaccine pregnant	50
hits.6	covid vaccine protect	44
hits.7	covid vaccine side effects	51
hits.8	covid vaccine microchip	23
hits.9	covid vaccine dna	48
hits.10	covid vaccine fetal	31
hits.11	covid vaccine infertility	48
hits.12	covid vaccine magnet	43

Table 3: April-June: Number of States with Hit Rates by Search

Variable Name	Search Term	Number of States with Hit Rate
hits.1	covid vaccine	51
hits.2	covid vaccine near me	51
hits.3	covid vaccine safe	50
hits.4	covid vaccine ingredients	47
hits.5	covid vaccine pregnant	45
hits.6	covid vaccine protect	40
hits.7	covid vaccine side effects	51
hits.8	covid vaccine microchip	17
hits.9	covid vaccine dna	43
hits.10	covid vaccine fetal	26
hits.11	covid vaccine infertility	44
hits.12	covid vaccine magnet	40

Table 4: July-September: Number of States with Hit Rates by Search

Variable Name	Search Term	Number of States with Hit Rate
hits.1	covid vaccine	51
hits.2	covid vaccine near me	51
hits.3	covid vaccine safe	49
hits.4	covid vaccine ingredients	49
hits.5	covid vaccine pregnant	49

Variable Name	Search Term	Number of States with Hit Rate
hits.6	covid vaccine protect	42
hits.7	covid vaccine side effects	51
hits.8	covid vaccine microchip	10
hits.9	covid vaccine dna	41
hits.10	covid vaccine fetal	28
hits.11	covid vaccine infertility	42
hits.12	covid vaccine magnet	23

2. Vaccination Rates

We now have data for our Google search hits from January-September, April-June, and July-September. Next, we are interested in finding the corresponding information on vaccination rates for each state. This data is acquired by using RSocrata to pull COVID vaccine data from the Centers for Disease Control website via their API. After pulling the data into R, we did some basic data cleaning, including converting variables to a numeric type and dropping rows for U.S. territories and federal entities for which we did not have corresponding Google Trends data. We also recoded the state variable, which previously used the two-letter postal code for state (AK, AZ, etc.), to use the full state name. This was done so that the CDC data could be joined with the Google Trends data by state.

After cleaning, the datasets vax.June21 and vax.Sept21 are created, where vax.June21 will correspond to the Google Trends hit results from April-June, and vax.Sept21 will correspond to January-September and July-September Google Trends hit results. We are focusing on the vaccination rates in June and September 2021 because June is around the time when vaccines became widely available to anyone who wanted one, while September 21, 2021 is the day before boosters for some at-risk groups were approved by the CDC. By doing this, we are restricting our analysis to the time before boosters were available. Our variables of interest are series_complete_pop_pct, which is the percentage of the population in each state that has completed their vaccine series, and admin_per_100k, which is the number of vaccines administered in each state per 100,000 people.

The tables below list the top 10 states by percent of the population fully vaccinated in June and September 2021.

Table 5: Top 10 States for % Population Vaccinated: June 2021

State	Percent Pop. Fully vaccinated	Administered Per 100K
Vermont	64.3	134607
Massachusetts	60.0	125936
Maine	59.9	117770
Connecticut	59.0	121188
Rhode Island	57.3	118098
New Hampshire	54.9	110353
New Jersey	54.6	111391
Maryland	53.8	110157
Washington	52.9	109782
New Mexico	52.5	109500

Table 6: Top 10 States for % Population Vaccinated: September 2021

State	Percent Pop. Fully vaccinated	Administered Per 100K
Vermont	69.0	142674
Connecticut	68.0	139362
Maine	67.8	133752
Massachusetts	67.4	140598
Rhode Island	67.1	135818
New Jersey	63.6	128346
Maryland	63.4	129903
New York	62.7	130789
Washington	62.6	130222
New Mexico	62.3	130771

3. State-level Demographics

We now have our search hit results and vaccine rates. Before studying any correlations, we consider certain state-level demographic factors that could potentially have an impact on our analysis. Data of interest includes state population counts, voter information, household income, age group, and race.

State population numbers were web scraped from Wikipedia using Selector Gadget ("List of U.S. States by Population" 2021). These state counts were then joined with the vax.June21 and vax.Sept21 frames created in Part 2. In addition, information on the Trump vote share in the 2020 presidential election for each state was downloaded from the Cook Political Report ("2020 Popular Vote Tracker" n.d.). Unnecessary columns were deleted and columns of interest were renamed. The final spreadsheet was saved as vote.xlsx.

Median household income information from the 2018 Current Population Survey was downloaded from the U.S. Census Bureau website and saved as med.income.xlsx ("Current Population Survey 2019 Annual Social and Economic (ASEC) Supplement," n.d.). Unnecessary columns were deleted and columns of interest were selected: state (location) and median income (med.income).

Percent of state population by age group was pulled from the Kids Count Data Center ("Adult Population by Age Group" n.d.) The raw Excel data was downloaded. Columns from years 2011-2019 were deleted since we are focusing on the most recently available data, in this case 2020. The spread() function from the tidyr package was then used to reshape from long to wide so we can split up the categorical Age Group Variable into the 3 separate variables: ages 18 to 24, ages 25 to 64, and ages 65 and over. The final spreadsheet was saved as percent.age.xlsx.

Race data from the 2020 Current Population Survey was pulled as a csv file from the Kaiser Family Foundation website ("Population Distribution by Race/Ethnicity (CPS)" 2021). It was then converted from CSV to xlsx, unnecessary columns were deleted, columns of interest were renamed, and reported percentages of $<.01$ were replaced with 0 to make all cell values integers. Categories for American Indian/Alaska Native, Native Hawaiian/Other Pacific Islander, and Multiple Races were combined into a single 'Other' race category. This was saved as State Race Data.xlsx.

These four excel files were loaded into the FOCD Github public repository. They were then joined together in R and saved as the object "cov" (for covariates). This object was then joined with the two CDC vaccine rate data frames created in Part 2 (vax.June21 or vax.Sept21).

Finally, the three gtrends datasets from Part 1 (hits.results.jan, hits.results.june, hits.results.sept) are joined with the updated vax.June21 or vax.Sept21, depending on the dates the Trends are covering. A user-defined function called join.gtrends.vaccine() accomplishes this and saves the 3 final data sets as Jan01.analysis, Sept21.analysis, and June21.analysis. Now they are ready for analysis.

```
## This function joins the gtrends datasets with vaccine info datasets

join.gtrends.vaccine <- function (hits.results.month,vax.month){

  month.analysis <- vax.month %>%
      select(location,date, admin_per_100k, series_complete_pop_pct,
             pct.vote.rep, med.income, pct.18.to.24, pct.25.to.64, pct.65.over,
             pct.white, pct.black, pct.hispanic, pct.asian, pct.other.multiple) %>%
        full_join(hits.results.month, by = "location") %>%
        arrange(location)

  print(month.analysis)

}

Jan01.analysis <- join.gtrends.vaccine(hits.results.jan,vax.Sept21)
Sept21.analysis <- join.gtrends.vaccine(hits.results.sept,vax.Sept21)
June21.analysis <- join.gtrends.vaccine(hits.results.june,vax.June21)
```

Analysis

1. Correlation Analysis

The three data sets Jan01.analysis, Sept21.analysis, and June21.analysis are used as arguments for the user-defined function get.correlations() and results are saved to the three objects Jan01.correlations, Sept21.correlations, and June21.correlations respectively. This function calculates the correlation between each search term (as defined in vector "k") and series_complete_pop_pct (percentage of the population in each state that has completed their vaccine series) along with the p value.

```
## This function pulls the correlations for all 3 data sets
get.correlations <- function(month.analysis){
      #Loop for correlations for each search term
      j <- c("hits.1", "hits.2",
      "hits.3", "hits.4",
      "hits.5", "hits.6",
      "hits.7", "hits.8",
      "hits.9", "hits.10",
      "hits.11","hits.12")

      correlations <- data.frame(estimate=numeric(26), p.value=numeric(26))

      for(i in 15:ncol(month.analysis)){
        test <- cor.test(month.analysis[, i], month.analysis$series_complete_pop_pct)
        correlations$estimate[i] = test$estimate
        correlations$p.value[i] = test$p.value
      }

      correlations %<>%
        slice_tail(n=12) %>%
        cbind(j,k) %>%
        relocate(estimate, p.value,.after = k)
```

```
      correlations %<>% rename(var_name = j, search = k)

      print(correlations)
}

Jan01.correlations <- get.correlations(Jan01.analysis)
Sept21.correlations <- get.correlations(Sept21.analysis)
June21.correlations <- get.correlations(June21.analysis)
```

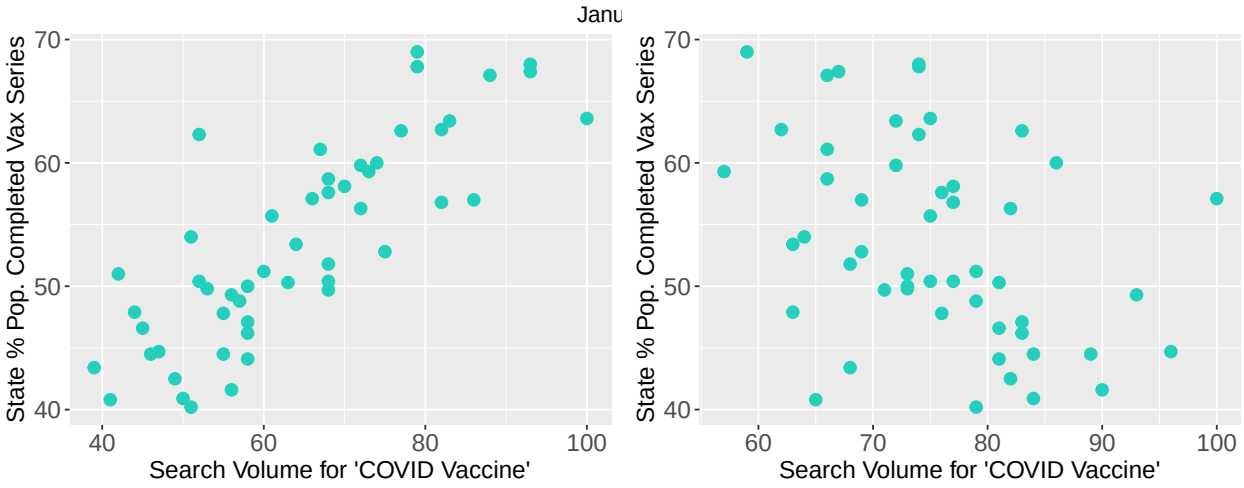
Results from Jan01.correlations and June21.correlations show that the correlation patterns are fairly similar for January-September and for April-June. In both cases, the more mainstream searches are positively correlated, and the myth-related searches are negatively correlated (with the exception of April-June, where infertility has a small positive correlation).

On the other hand, correlation patterns from Sept21.correlations are very different. Our results show for July-September searches, nearly all the search terms have a negative correlation. This is likely because most people in states with high vaccination rates had already been vaccinated by July. As a result, in these states, there are less people searching for vaccine information after July. Therefore in general, more of the vaccine searches (of all types) were happening in low vaccine rate states during July-September. This explains why 'covid vaccine' searches are positively correlated with vaccine rates when looking at the overall January-September searches– but when just looking at July-September, they are negatively correlated since vaccinated people were no longer searching for vaccine info. The table below shows these correlation patterns for all three time periods.

Table 7: Correlations Between Search Hits and % Population Vaccinated

var_name	search	Jan-Sept	Apr-June	Jul-Sept
hits.1	covid vaccine	0.8193496	0.9097244	-0.3974835
hits.2	covid vaccine near me	0.1540698	0.4214743	-0.2710663
hits.3	covid vaccine safe	0.2526902	0.3731780	-0.1539391
hits.4	covid vaccine ingredients	0.0666467	0.3254644	-0.0614900
hits.5	covid vaccine pregnant	0.5040617	0.2241392	0.0139224
hits.6	covid vaccine protect	0.0698830	0.2433504	-0.1907652
hits.7	covid vaccine side effects	0.2211306	0.6795389	-0.6420471
hits.8	covid vaccine microchip	0.2701688	0.2993866	0.0173331
hits.9	covid vaccine dna	-0.0620409	-0.1859246	-0.0965737
hits.10	covid vaccine fetal	-0.1729502	-0.1939630	-0.0250867
hits.11	covid vaccine infertility	-0.0892084	0.0743798	-0.2848799
hits.12	covid vaccine magnet	-0.1679615	-0.0600668	-0.3624079

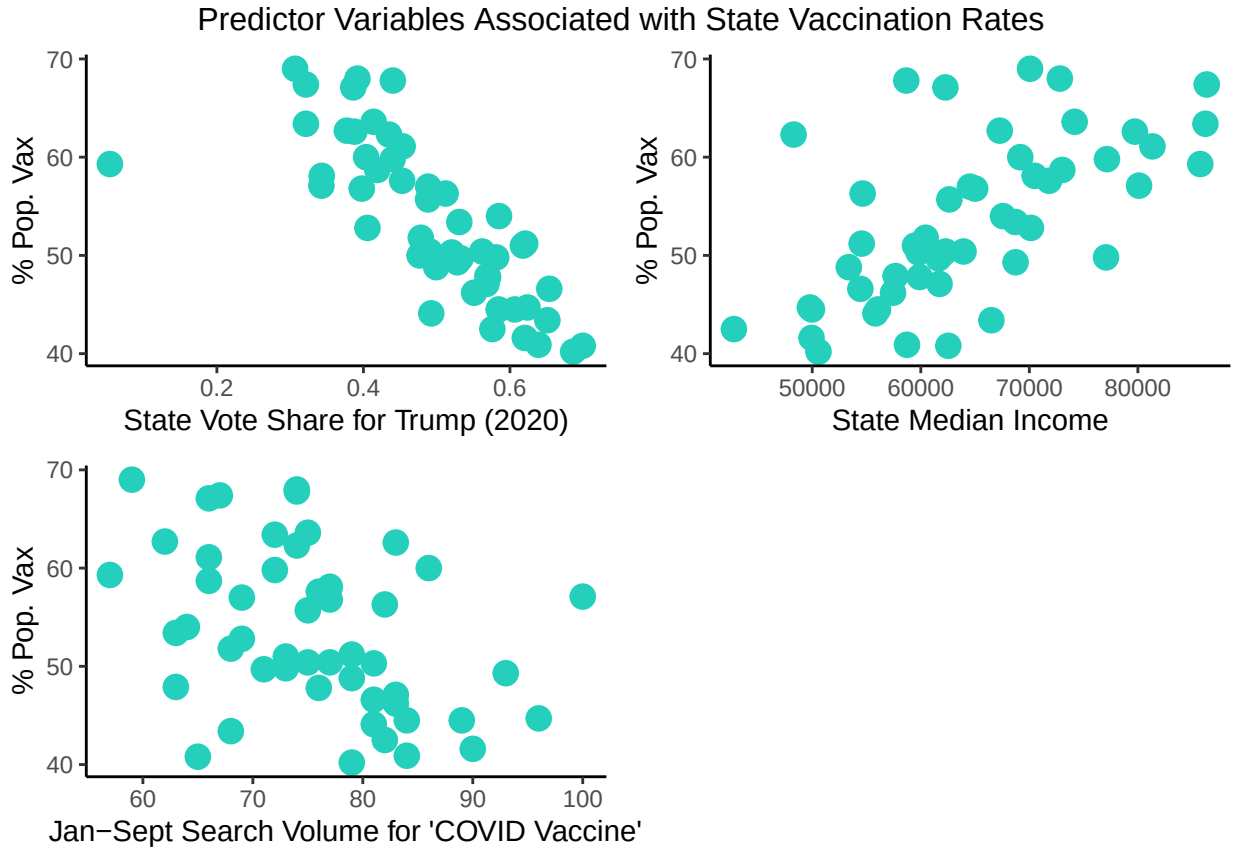
The tables below show the different correlation patterns between searches for 'COVID Vaccine' and State Vaccination rates in both time periods January-September and July-September. We see a statistically significant positive correlation for the entire span of Jan-Sept, and a negative correlation when we restrict ourselves to July-Sept.



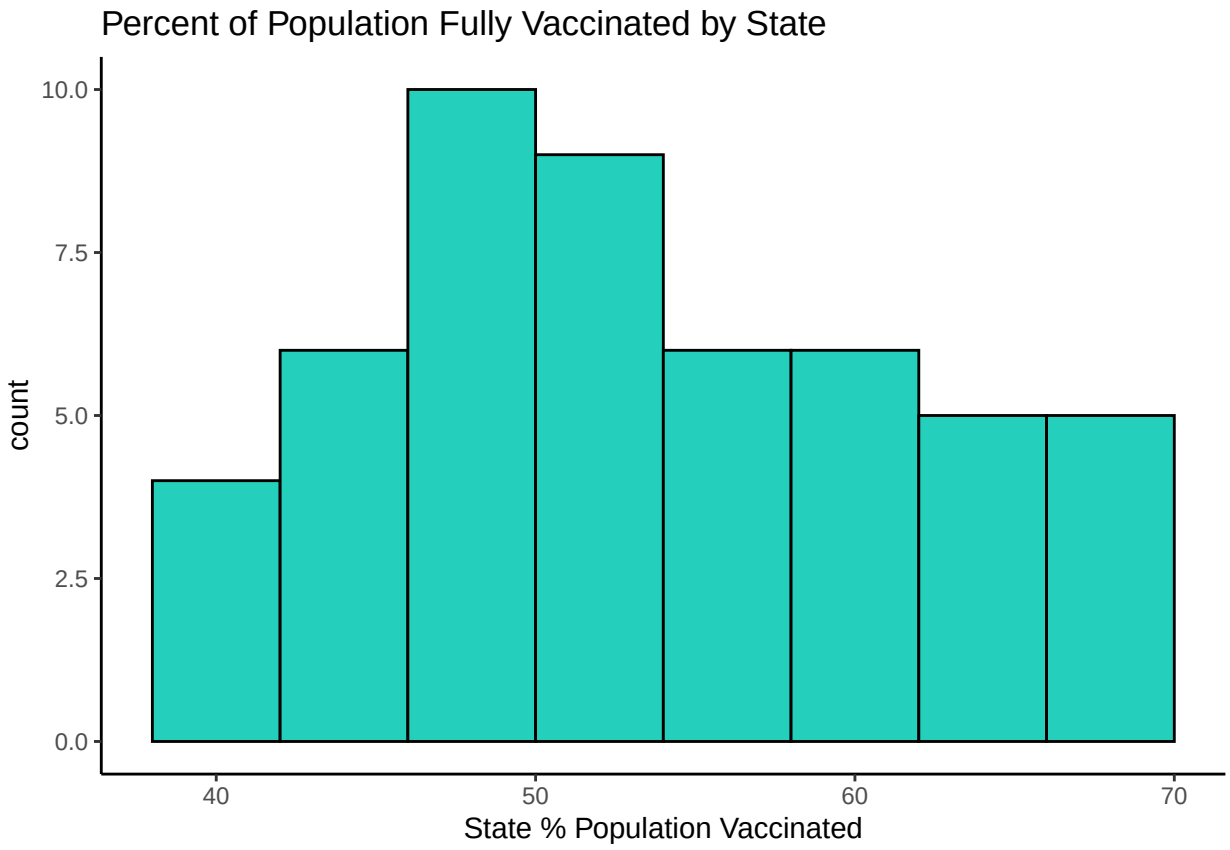
Very few of the correlations are statistically significant at level .05. Hence, we will incorporate the social demographic variables from Data Collection Part 3 as covariates for a regression analysis.

2. Regression Analysis

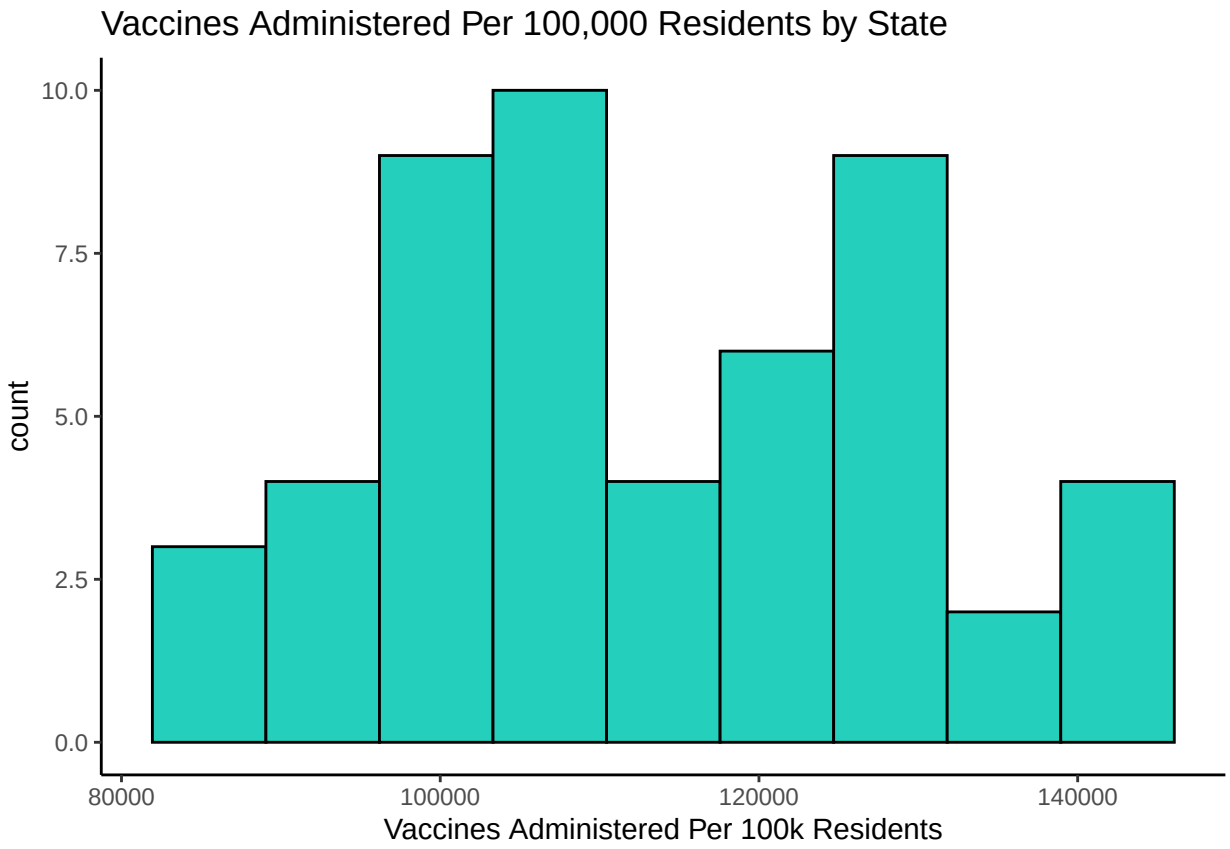
Given the lack of significant results in our correlation analysis, we next sought to use linear regression to determine the primary predictors of state vaccination rates.



```
##histogram of outcome variable

ggplot(Jan01.analysis) + geom_histogram(aes(series_complete_pop_pct), color = "black", fill = '#24d0bc'
      ggtitle("Percent of Population Fully Vaccinated by State") +
      labs(x = "State % Population Vaccinated") +
      theme_classic()
```




```
ggplot(Jan01.analysis) + geom_histogram(aes(admin_per_100k), color = "black", fill = '#24d0bc', binwidt
      ggtitle("Vaccines Administered Per 100,000 Residents by State") +
      labs(x = "Vaccines Administered Per 100k Residents") +
      theme_classic()
```

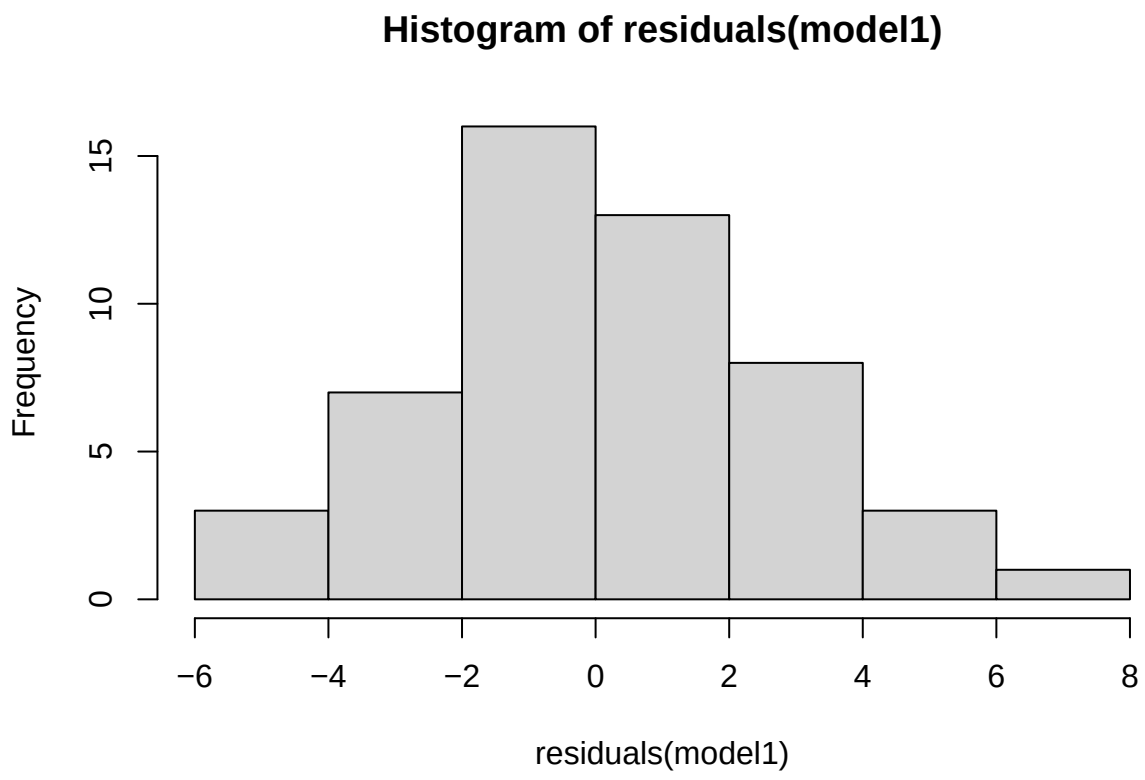



```
##Linear model

model1 <- lm(series_complete_pop_pct ~ pct.vote.rep + pct.white + pct.black + hits.1 + hits.2 + hits.3 +

summary(model1)
```

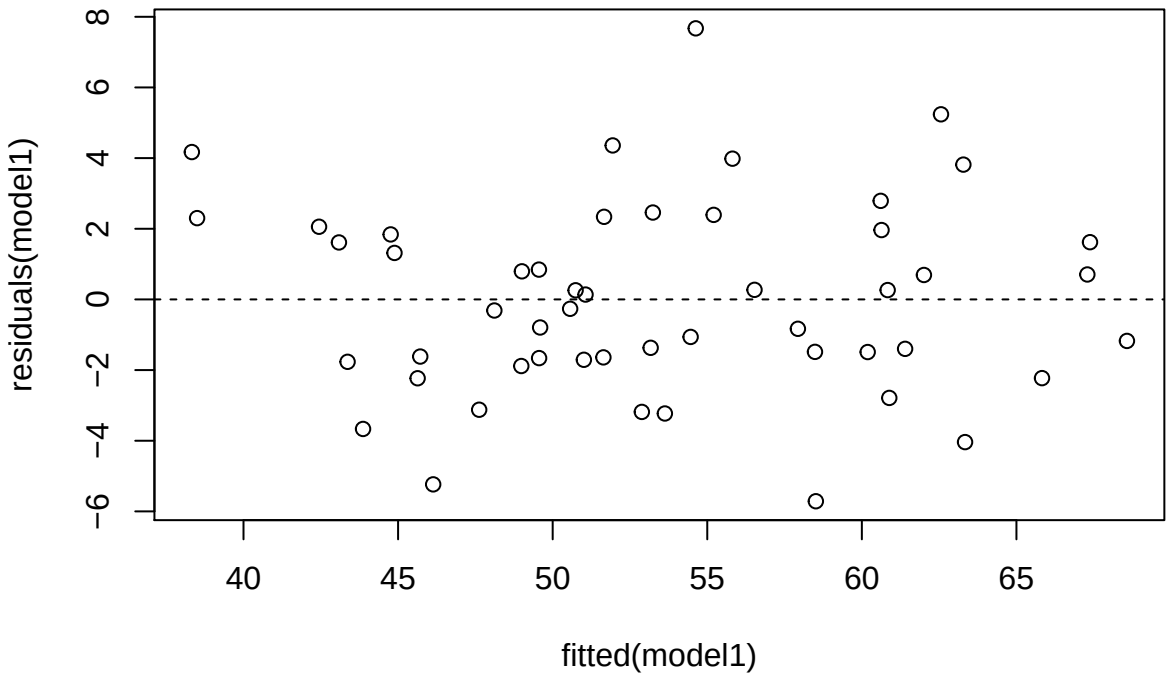
```
##
## Call:
## lm(formula = series_complete_pop_pct ~ pct.vote.rep + pct.white +
##     pct.black + hits.1 + hits.2 + hits.3 + hits.4 + hits.5 +
##     hits.6 + hits.7 + hits.8 + hits.9 + hits.10 + hits.11 + hits.12,
##     data = Jan01.analysis)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7127 -1.6852 -0.2653  1.9016  7.6727
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5.577e+01  6.716e+00   8.303 8.67e-10 ***
## pct.vote.rep -2.851e+01  9.199e+00  -3.099 0.003814 **
## pct.white    -1.523e+00  5.263e+00  -0.289 0.774004
## pct.black    -2.223e+01  6.187e+00  -3.593 0.000995 ***
## hits.1        3.474e-01  8.097e-02   4.290 0.000134 ***
## hits.2       -8.337e-02  6.730e-02  -1.239 0.223675
## hits.3       -8.722e-02  5.140e-02  -1.697 0.098609 .
```

```
## hits.4       -7.262e-03  3.543e-02  -0.205 0.838762
## hits.5        5.730e-02  4.619e-02   1.241 0.222954
## hits.6       -4.797e-02  4.233e-02  -1.133 0.264723
## hits.7        4.173e-04  8.533e-02   0.005 0.996126
## hits.8        5.368e-03  2.026e-02   0.265 0.792645
## hits.9        1.086e-02  3.036e-02   0.358 0.722698
## hits.10      -4.966e-03  2.417e-02  -0.205 0.838416
## hits.11       3.135e-02  4.718e-02   0.664 0.510760
## hits.12       2.003e-02  2.701e-02   0.742 0.463288
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.261 on 35 degrees of freedom
## Multiple R-squared:  0.8867, Adjusted R-squared:  0.8381
## F-statistic: 18.26 on 15 and 35 DF,  p-value: 2.981e-12
```

```
#Check that residuals are normally distributed

hist(residuals(model1))
```




```
#Check for homoskedasticity in residual variances (looks ok)

plot(fitted(model1), residuals(model1))
abline(h = 0, lty = 2)
```




```
#Linear model with interaction
#When adding interaction between hits.1 and % who voted republican, the main effects and the interactio

model2 <- lm(series_complete_pop_pct ~ pct.vote.rep + pct.black + hits.1  + hits.1*pct.vote.rep, data =

summary(model2)
```

```
##
## Call:
## lm(formula = series_complete_pop_pct ~ pct.vote.rep + pct.black +
##     hits.1 + hits.1 * pct.vote.rep, data = Jan01.analysis)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.5878 -2.1744 -0.2679  2.5307  7.9335
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           52.3502    12.8896   4.061 0.000188 ***
## pct.vote.rep         -25.7923    23.4115  -1.102 0.276326
## pct.black            -25.3249     4.7632  -5.317 3.01e-06 ***
## hits.1                 0.3237     0.1778   1.821 0.075133 .
## pct.vote.rep:hits.1   -0.1366     0.3496  -0.391 0.697849
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 3.381 on 46 degrees of freedom
## Multiple R-squared:   0.84,  Adjusted R-squared:  0.826
## F-statistic: 60.36 on 4 and 46 DF,  p-value: < 2.2e-16
```

```
save.image(file = "shared_work_space.RData")
```

Conclusion

Include a link to the github repository

References

"2020 Popular Vote Tracker." n.d. *Cook Political Report*. Accessed December 15, 2021. https://www.cookpolitical.com/2020-national-popular-vote-tracker.

"Adult Population by Age Group." n.d. *KIDS COUNT Data Center*. Accessed December 15, 2021. https://datacenter.kidscount.org/data/tables/6538-adult-population-by-age-group.

CDC. 2021. "COVID-19 Vaccine Facts." *Centers for Disease Control and Prevention*. https://www.cdc.gov/coronavirus/2019-ncov/vaccines/facts.html.

"COVID-19 Vaccine Myths Debunked." 2021. *Mayo Clinic Health System*. https://www.mayoclinichealthsystem.org/hometown-health/featured-topic/covid-19-vaccine-myths-debunked.

"Current Population Survey 2019 Annual Social and Economic (ASEC) Supplement." n.d. United States Census Bureau. https://www2.census.gov/programs-surveys/cps/tables/time-series/historical-income-households/h08.xls.

"List of U.S. States by Population." 2021. *Wikipedia, the Free Encyclopedia*. https://simple.wikipedia.org/w/index.php?title=List_of_U.S._states_by_population&oldid=7809509.

"Population Distribution by Race/Ethnicity (CPS)." 2021. *Kaiser Family Foundation*. https://www.kff.org/other/state-indicator/population-distribution-by-race-ethnicity-cps/.

Stephens-Davidowitz, Seth. 2014. "The Cost of Racial Animus on a Black Candidate: Evidence Using Google Search Data." *Journal of Public Economics* 118 (October): 26–40. https://doi.org/10.1016/j.jpubeco.2014.04.010.