A note to the grader: After careful consideration — and much searching for a data set that containing the races of popular actors — our group decided to shift gears for this final project, and instead focus on a different topic. As such, we submit the following additional project proposal to show that we spent considerable time developing this idea before moving to the EDA/Baseline Model stage.

STAT 139 FINAL PROJECT PROPOSAL

Group Members: Daniel de Castro, Laura Appleby

Project Title: Characterizing the relationship between the religious affiliation and incidences of Covid-19 at U.S. universities.

Hypotheses of Interest:

1. Determine whether there is an association between a school's religious affiliation and the number of covid cases reported between July 2020 and May 2021.
2. Assess whether there remains such an association after controlling for potentially confounding predictors such as enrollment, student racial demographics, percent of students awarded financial aid, percent of students with disabilities, geographical information,
3. Building a best predictive model of Covid cases in our data set (using cross-validation techniques).

Variables of Interest:

Response: Number of Covid cases reported at each university from July 2020 to May 2021.

Predictors:

1. State
2. Public/Private (non-religious)/Private (religious) Institution categorical variable
3. Religious Affiliation
4. Tuition and Fees 2020-21
5. Total 12-month unduplicated headcount (students and staff)
6. Undergraduate 12-month unduplicated headcount
7. Percent of 12-month unduplicated headcount that are
    a. American Indian or Alaska Native
    b. Asian
    c. Black or African American
    d. Hispanic/Latino
    e. Native Hawaiian or Other Pacific Islander
    f. White
    g. Two or more races
    h. Ethnicity unknown
    i. Nonresident Alien
8. Percent of 12-month unduplicated headcount that are women
9. Average amount of grant and scholarship aid awarded 2020-21
10. Graduation rate

11. Institution provide on campus housing (categorical y/n)
12. Total dormitory capacity
13. Typical room charge for academic year

Sources: For this project, we will draw data from two different sources:

1. The response variable will be drawn from the New York Times data set of counts of Covid cases reported by over 1,900 universities, as can be found at https://github.com/nytimes/covid-19-data/tree/master/colleges.
2. The predictor variables will be drawn from the National Center for Education Statistics: Integrated Postsecondary Education Data System (https://nces.ed.gov/ipeds/datacenter/institutionlist.aspx?stepId=1). We sat down and looked at all of the available variables for the 2020-2021 academic year before deciding on the subset that we will consider in this project.
3. Data on mask mandates by state — which we will manipulate to create additional predictor variables — will be drawn from https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Public-Mask-Mandates-Fro/tzyy-aayg.

Analysis Plan:

We will fit a wide range of both regression and predictive models to our data set, drawing from the work that we have done across the Problem Sets completed for this course; these models will include straightforward multiple regression models, models created via sequential variable selection, penalized regression models, non-parametric models such as decision trees and random forests, etc. For each of these model types, we will try to identify a parsimonious model that best describes our data set without being overly complex or overfit. We will then interpret the relationship between religious affiliation and Covid cases in each model, using visuals when appropriate.

Potential Challenges:

Potential challenges for this project will include cleanly merging the tables from each of the two sources of data and dealing with incomplete cases in the data set. We also must be careful in interpreting our response variable in light of inconsistencies in the testing and reporting of Covid cases across the wide range of institutions considered in our data set. We also would have liked to include a predictor variable based on whether masking was required at each of the institutions considered, but this has been very difficult to come by so far — the best we could come up with was the number of days in the period from July 2020 to May 2021 in which a mask mandate was in place in the state in which each institution is located.

EDA: Characterizing the relationship between the religious affiliation and incidences of Covid-19 at U.S. universities.

Daniel de Castro and Laura Appleby

November 22, 2022

Description of data and source

Our data for this project comes from three sources:

1. NYTimes Covid-19 Data. This is publicly available on GitHub and was the source for some of the NYTimes maps and data visuals during the 2020-2021 era of the pandemic. It includes cases from 2020 - May 2021, and we have specifically selected cases at Universities. This dataset has 1948 entries and includes 2020 cases, 2021 cases, University IPEDS ID, University Name, State, etc.
2. IPEDS Data Center. This is publicly available data on colleges across the globe. It has many possible variables including demographics, admission rates, University affiliation, etc. The IPEDS data center allowed us to select certain Universities and variables. The smallest subset of Universities that included all from the NYTimes database (by IPEDS ID) was 6125 rows, with all US Universities.
3. Centers for Disease Control. This publicly available data set tracks mask mandates in each state from April 8, 2020, to August 15, 2021.

The data is 1,855 rows after removing Universities without stats or without matching IPEDS ids. It has 40 columns, including IPEDS id, university name, cases, and predictor variables based on college attributes.

Data Cleaning Procedures

For this exploratory data analysis, the first step is to read our data from CSV files into R data frames. The `colleges` data frame stores the NYT data on Covid cases at universities, while the `ipeds` data frame stores the data will most of our predictor variables (university characteristics) taken from IPEDS. We then rename most of the columns in `ipeds` to make them shorter and easier to work with.

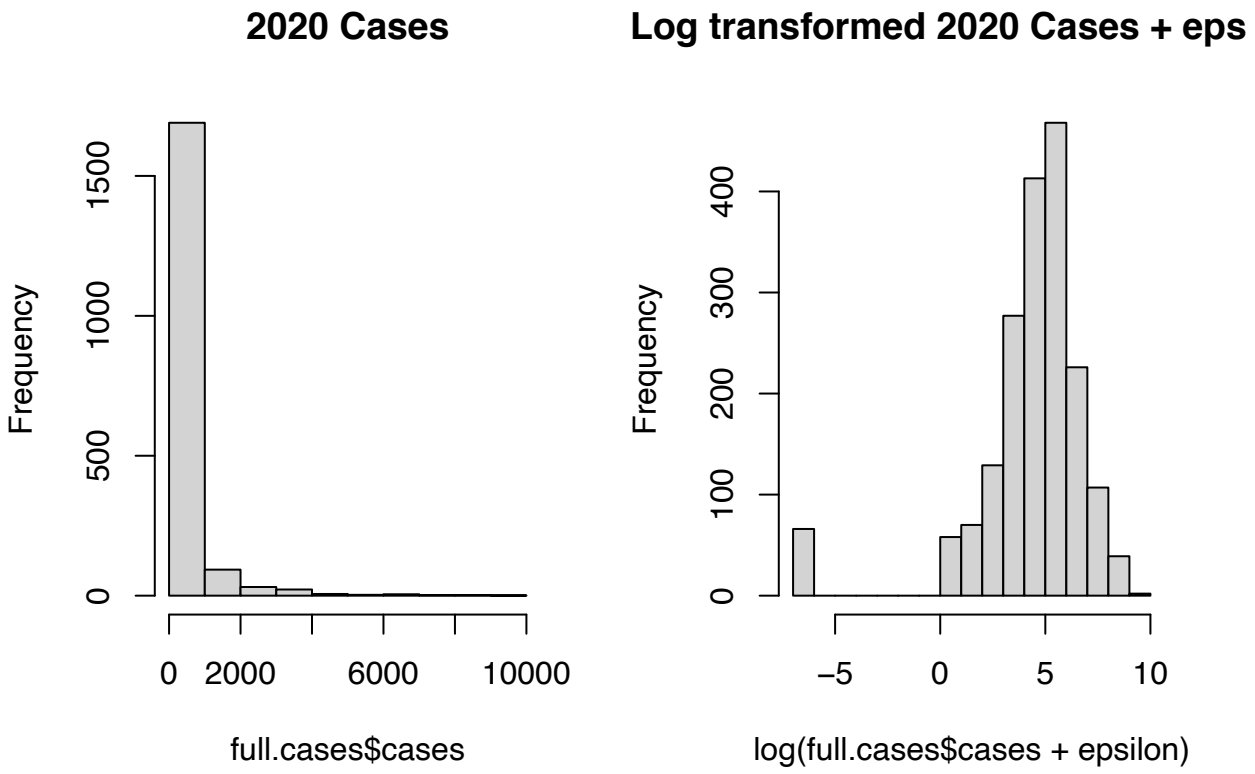
Next, we merge the `colleges` and `ipeds` data frames on the `ipeds_id` column and remove institutions with no IPEDS data. We then create the `religious`, `catholic`, and `private` columns, which are simply indicators for whether an institution has any religious affiliation, whether it has a catholic affiliation, and whether it is a private university. Finally, we drop the `control` column from the data frame, since it now contains redundant information.

Finally, we look to add a column to the data frame that addresses the extent to which mask mandates were present in the state in which each institution is located. Below, we read out the mask mandates data from the CDC into a data frame from the CSV file, treat the appropriate columns as factors, and convert `date` into R's `Date` type.

We then create a new simpler data frame to merge with `md`. This data frame contains only two columns: One with the name of each state, and the other with the number of days between July 1, 2020, and May 26, 2021, during which face masks were required in public in that state. We then merge this data frame with `md` to create `full.cases`, and finally create a column `total.cases` in `full.cases` that sums the `cases` and `cases_2021` columns.

EDA / Data Visualizations

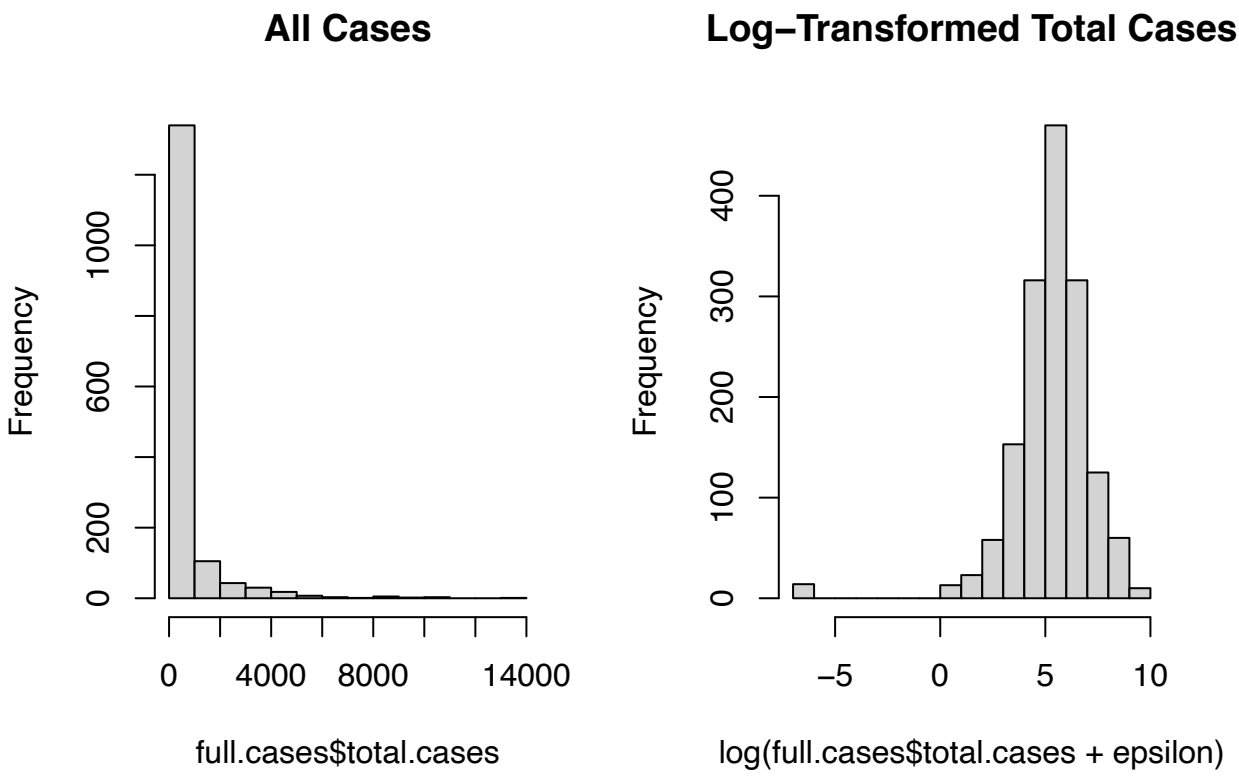
We will first look at the distribution of the total cases from the NYT data.




```
## [1] 39
```

From the above graphs we see that the un-transformed NYT case data from 2020 is strongly right skewed. In particular, there are 39 universities in the data set that recorded 0 Covid cases in 2020. Log-transforming this data (and the inclusion of the arbitrary constant `epsilon = 0.001`) results in a more symmetrically distributed distribution with some negative outliers on the left. These outliers correspond to those observations with zero Covid cases in 2020.

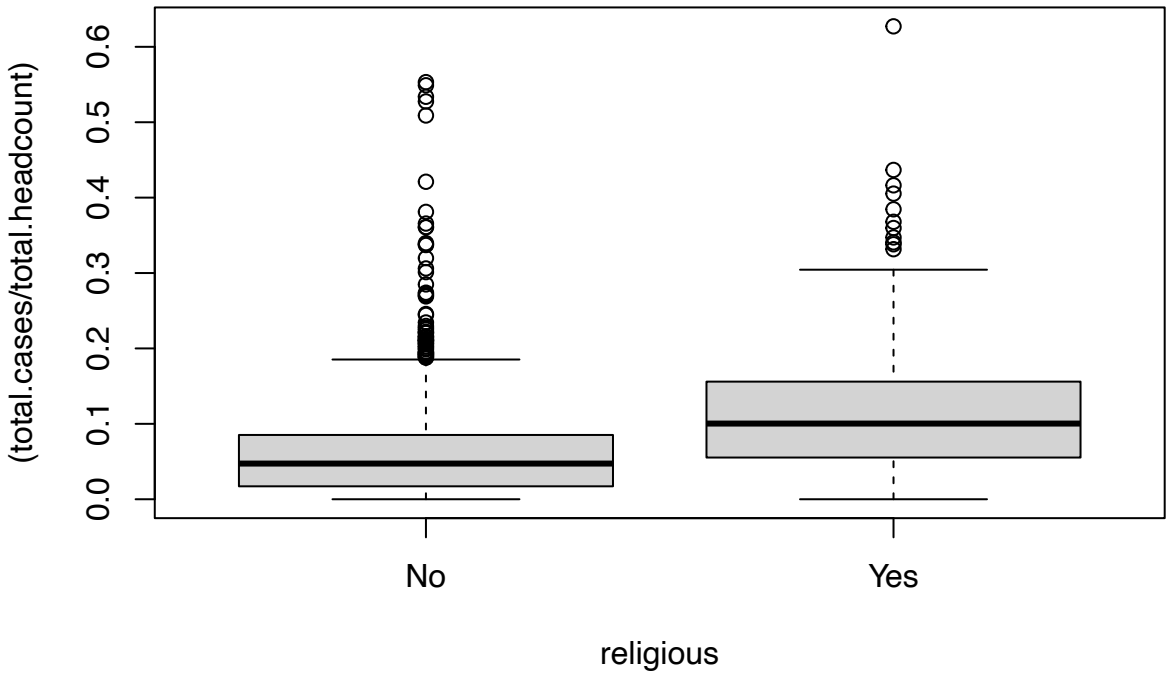
We will now have a look at the distribution of `total.cases` below.




```
## [1] 39
```

There are still 39 institutions with no reported Covid cases. The resulting plots are nearly identical to the plots for only the cases reported in 2020. The main difference between the two sets of plots is that the magnitude of the observations in `total.cases` is generally larger, which makes sense given that `total.cases` also includes case counts from the first five months of 2021. Thus, the histogram of the log-transformed distribution of `total.cases` is shifted slightly to the right compared to the log-transformed distribution of `cases`.

Given that we are focusing on the relationship between the religious affiliation of an institution and the number of Covid cases it reported in the 2020-21 academic year, we will also find it useful to look at a boxplot comparing case counts between religious and non-religious institutions:




```
##
##   No  Yes
## 1372  483
```

Above we see that the median number of cases as a fraction of total headcount (to account for differing school sizes) at religious universities is slightly higher than that of non-religious schools, and the 75th quartile much higher. Thus, there does seem to be some sort of difference in terms of case counts between the groups. In our actual project, we could formalize this observation by performing a parametric test for a difference in sample means, or some sort of non-parametric test (such as a rank-based test). Both distributions also appear to be somewhat right-skewed, but the distribution for non-religious institutions is possibly more so. This is likely because there are more non-religious institutions in the data set (1372 vs 483 religious) and they likely represent a more diverse pool: non-religious schools can be large public institutions (i.e. The UC schools) or small private institutions (i.e. Wesleyan). Religious schools are always private based on IPEDS classifications.

Baseline Model

To establish that our predictors would have a relationship with `total.cases`, we fit a simple linear model that predicts `total.cases` from the predictors that we are the most interested in.

```
##
## Call:
## lm(formula = log(total.cases + epsilon) ~ religious + FIPS.state.code +
##     total.headcount + undergrad.headcount + percent.american.native +
##     percent.asian + percent.black + percent.hispanic.latino +
##     percent.pacific.islander + percent.white + percent.two.more.races +
##     percent.NA.race + percent.disability + catholic + dorm.capacity +
##     private + mask.mandated.days, data = full.cases)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.4839  -0.3591   0.1022   0.5268   2.0884
```

```
##
## Coefficients: (1 not defined because of singularities)
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        5.329e+00  7.470e-01   7.134 2.25e-12 ***
## religiousYes                       7.737e-02  1.088e-01   0.711 0.477397
## FIPS.state.codeAlaska             -2.364e+00  1.040e+00  -2.273 0.023324 *
## FIPS.state.codeArizona            -1.002e+00  5.631e-01  -1.780 0.075463 .
## FIPS.state.codeArkansas            1.090e-01  4.041e-01   0.270 0.787426
## FIPS.state.codeCalifornia         -1.267e+00  3.651e-01  -3.472 0.000546 ***
## FIPS.state.codeColorado            1.750e-01  4.027e-01   0.435 0.663915
## FIPS.state.codeConnecticut         6.864e-02  3.738e-01   0.184 0.854345
## FIPS.state.codeDelaware            2.450e-01  6.048e-01   0.405 0.685556
## FIPS.state.codeDistrict of Columbia -5.084e-01  5.032e-01  -1.010 0.312673
## FIPS.state.codeFlorida            -8.978e-02  3.522e-01  -0.255 0.798830
## FIPS.state.codeGeorgia            -2.601e-02  3.587e-01  -0.072 0.942226
## FIPS.state.codeHawaii             -9.086e-01  1.120e+00  -0.811 0.417664
## FIPS.state.codeIdaho               1.302e-01  5.569e-01   0.234 0.815156
## FIPS.state.codeIllinois           -2.984e-01  3.309e-01  -0.902 0.367519
## FIPS.state.codeIndiana            -4.909e-01  3.545e-01  -1.385 0.166508
## FIPS.state.codeIowa               -5.817e-01  3.810e-01  -1.527 0.127164
## FIPS.state.codeKansas             -3.469e-01  4.995e-01  -0.695 0.487564
## FIPS.state.codeKentucky           -3.945e-01  3.540e-01  -1.114 0.265431
## FIPS.state.codeLouisiana          -4.320e-01  4.023e-01  -1.074 0.283342
## FIPS.state.codeMaine              -6.353e-01  4.350e-01  -1.461 0.144539
## FIPS.state.codeMaryland           -4.506e-01  3.806e-01  -1.184 0.236731
## FIPS.state.codeMassachusetts      -8.964e-01  3.206e-01  -2.796 0.005304 **
## FIPS.state.codeMichigan           -3.232e-01  3.361e-01  -0.962 0.336582
## FIPS.state.codeMinnesota          -3.176e-01  3.541e-01  -0.897 0.370037
## FIPS.state.codeMississippi        -1.270e-01  4.993e-01  -0.254 0.799330
## FIPS.state.codeMissouri           -2.952e-01  3.582e-01  -0.824 0.410070
## FIPS.state.codeMontana            -1.028e-01  6.057e-01  -0.170 0.865208
## FIPS.state.codeNebraska           -3.362e-02  4.476e-01  -0.075 0.940145
## FIPS.state.codeNevada              6.058e-01  7.306e-01   0.829 0.407228
## FIPS.state.codeNew Hampshire      -2.209e-01  4.341e-01  -0.509 0.610990
## FIPS.state.codeNew Jersey         -2.156e-01  3.517e-01  -0.613 0.539939
## FIPS.state.codeNew Mexico          1.727e-01  9.828e-01   0.176 0.860539
## FIPS.state.codeNew York           -5.616e-01  3.008e-01  -1.867 0.062260 .
## FIPS.state.codeNorth Carolina     -2.245e-01  3.342e-01  -0.672 0.501821
## FIPS.state.codeNorth Dakota       -5.545e-01  6.032e-01  -0.919 0.358282
## FIPS.state.codeOhio               -4.964e-01  3.231e-01  -1.536 0.124834
## FIPS.state.codeOklahoma           -1.006e-02  6.220e-01  -0.016 0.987095
## FIPS.state.codeOregon             -1.092e+00  3.981e-01  -2.744 0.006220 **
## FIPS.state.codePennsylvania       -4.945e-01  3.026e-01  -1.634 0.102679
## FIPS.state.codeRhode Island        1.374e-01  4.354e-01   0.316 0.752428
## FIPS.state.codeSouth Carolina      3.377e-02  3.661e-01   0.092 0.926530
## FIPS.state.codeSouth Dakota       -1.319e-01  9.619e-01  -0.137 0.890949
## FIPS.state.codeTennessee          -1.500e-01  3.791e-01  -0.396 0.692392
## FIPS.state.codeTexas              -3.538e-02  3.525e-01  -0.100 0.920077
## FIPS.state.codeUtah                3.805e-01  5.434e-01   0.700 0.484023
## FIPS.state.codeVermont            -1.258e+00  4.610e-01  -2.730 0.006482 **
## FIPS.state.codeVirginia           -3.001e-01  3.376e-01  -0.889 0.374352
## FIPS.state.codeWashington         -1.238e+00  3.766e-01  -3.286 0.001060 **
## FIPS.state.codeWest Virginia      -4.189e-01  4.318e-01  -0.970 0.332239
## FIPS.state.codeWisconsin          -5.312e-01  3.445e-01  -1.542 0.123503
```

```
## FIPS.state.codeWyoming              -3.383e-01  7.095e-01  -0.477 0.633591
## total.headcount                      2.866e-05  1.465e-05   1.955 0.050894 .
## undergrad.headcount                  2.177e-06  1.771e-05   0.123 0.902186
## percent.american.native             -6.335e-03  2.777e-02  -0.228 0.819597
## percent.asian                       -8.831e-03  1.393e-02  -0.634 0.526169
## percent.black                       -1.179e-02  7.767e-03  -1.518 0.129424
## percent.hispanic.latino             -6.108e-03  8.642e-03  -0.707 0.479919
## percent.pacific.islander             1.340e-02  1.275e-01   0.105 0.916358
## percent.white                        9.443e-03  6.961e-03   1.357 0.175319
## percent.two.more.races              -4.699e-02  2.290e-02  -2.051 0.040565 *
## percent.NA.race                     -1.746e-02  8.493e-03  -2.056 0.040154 *
## percent.disability                  -1.393e-02  6.090e-03  -2.288 0.022416 *
## catholicYes                          2.441e-01  1.209e-01   2.019 0.043793 *
## dorm.capacity                        2.555e-04  2.348e-05  10.885  < 2e-16 ***
## privateYes                          -2.779e-02  1.096e-01  -0.254 0.799876
## mask.mandated.days                         NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9153 on 769 degrees of freedom
##   (1020 observations deleted due to missingness)
## Multiple R-squared:  0.6274, Adjusted R-squared:  0.5959
## F-statistic: 19.92 on 65 and 769 DF,  p-value: < 2.2e-16
```

As we can see from the R output above, a handful of these predictors were found to be significant at the $\alpha = 0.05$ level in this model, including `catholic`, `percent.disability`, and `dorm.capacity`. Importantly, `catholic` addresses our hypothesis, since it makes a specific claim about the religious affiliation about a particular institution. In this model, we find that `catholic` has a positive association with log-transformed `total.cases`. We also find that the coefficient estimates for `percent.disability` and `dorm.capacity` are negative, which is somewhat surprising: Our gut feeling would be to expect both of these predictors to have positive associations with `total.cases`, since having more immunocompromised students on campus (`disabled` is a somewhat flawed measure of this predictor) and having more students living in dorms on campus might be thought to increase Covid-19 transmission and case counts. It could be the case, however, that having more immunocompromised students and more students living on campus might prompt a university to take precautions against Covid more seriously.

It is also interesting that the model failed to produce coefficient estimates for `mask.mandated.days`. This is likely due to strong — indeed, almost perfect — collinearity between this predictor and `FIPS.state.code`, since each value of `FIPS.state.code` does indeed correspond to some specific and unchanging value in `mask.mandated.days`. Thus, it appears that, in the models that we will prepare for the final paper, we either need to include a more nuanced predictor variable reflecting mask mandates at each institution, or decide that we are happy with the representation of the presence of mask mandates at each school that is captured by a predictor such as state or county. To that end, performing an ANOVA to test whether the mean of `total.cases` is different for institutions grouped by state or even county might be an interesting exercise as we put together this final paper.