COVID-19 IMPACTS ON THE US

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2020-12-14

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BACKGROUND & QUESTIONS

COVID-19 IMPACTS ON THE US: 2020-12-14

>15M Infections

~300K Deaths

210% Black Americans’ relative risk of COVID-19 death

COVID-19 IMPACTS ON THE US: 2020-12-14

- Close to 300,000 Americans have died from COVID-19, with 2,500-3,000 dying each day from the disease as part of a fall/winter "spike"

- In June 2020, the Federal Reserve forecasted a 6.5% decline in GDP in 2020 amid a "collapse in employment" as a result of the pandemic and public health measures taken to address it (CEPAL, 2020).

- In addition to the death and morbidity caused by the disease, many have pointed to the devastating effects of the economic damage, closed schools, isolation due to public health measures, etc.

- Impacts have fallen disproportionately on Black, Hispanic, immigrant, and other disadvantaged communities due to the intersection of environmental racism, occupational hazards, inequalities in social determinants of health, and other factors.

“The COVID-19 crisis has also had differential impacts among various racial and ethnic groups. Inequities in the social determinants of health—income and wealth, health-care access and utilization, education, occupation, discrimination, and housing—are interrelated and put some racial and ethnic minority groups at increased risk of contracting and dying from COVID-19…. Black and Hispanic people are dying at much higher rates relative to their share of the U.S. population.”

(O’Donnell et al, 2020)

COVID-19 QUESTIONS OF INTEREST

- How much of the mortality toll of COVID-19 can be predicted by county-level characteristics such as the state, the geographic region, how rural or urban the county is, racial/ethnic composition, county median income and poverty rates, how educated the county inhabitants are, etc. while addressing multicollinearity? How have these trends changed over time?

- What is the “best model” to predict “lagged” COVID-19 deaths, or the rate of COVID-19 deaths per 100K people in a county population? What is the relationship between reported cases and “lagged” COVID-19 deaths?

- Is there any evidence in Google Mobility data at the county level that increased time spent at home may be related to reported deaths from COVID-19 per capita at the county level?

01

DATA SOURCES

DATA SOURCE BREAKDOWN

COVID-19 DATA

Time series of total reported cases and total reported deaths from COVID-19 at the county level

COUNTY DATA

Characteristics of US counties from the US Census, including ethnic/racial population percentage, income, education, etc.

MOBILITY DATA

Google has made mobility data at the county level available as a time series that shows percentage from baseline activity.

COVID-19 DATA

- Acquire data that is used by the COVID Tracking Project, Johns Hopkins University, using the Datahub package and infrastructure.
- Data is updated daily
- Data is not geocoded, and only has the county and/or city **text name**
- Data is collated by volunteers, and is sometimes inconsistently reported/has corrections
- Variables of interest are date, location, total cases as of that date, and total deaths as of the date

COUNTY DATA

- Data sources from the US Census, particularly the 5-Year Annual Community Survey, last performed in 2018
- Some data sourced using Census-provided API to retrieve information using FIPS codes; other data sourced from the USDA Economic Research Service via flat files
- All data is at county level, as defined by FIPS Code
- 64,000+ variables in the ACS alone
- I selected the variables total population, Black population, Native American population, Hispanic population (not mutually exclusive), percent in poverty, median income for county, and education variables (percent with high school diploma only, percent with Bachelor's degree or higher)

GOOGLE MOBILITY DATA

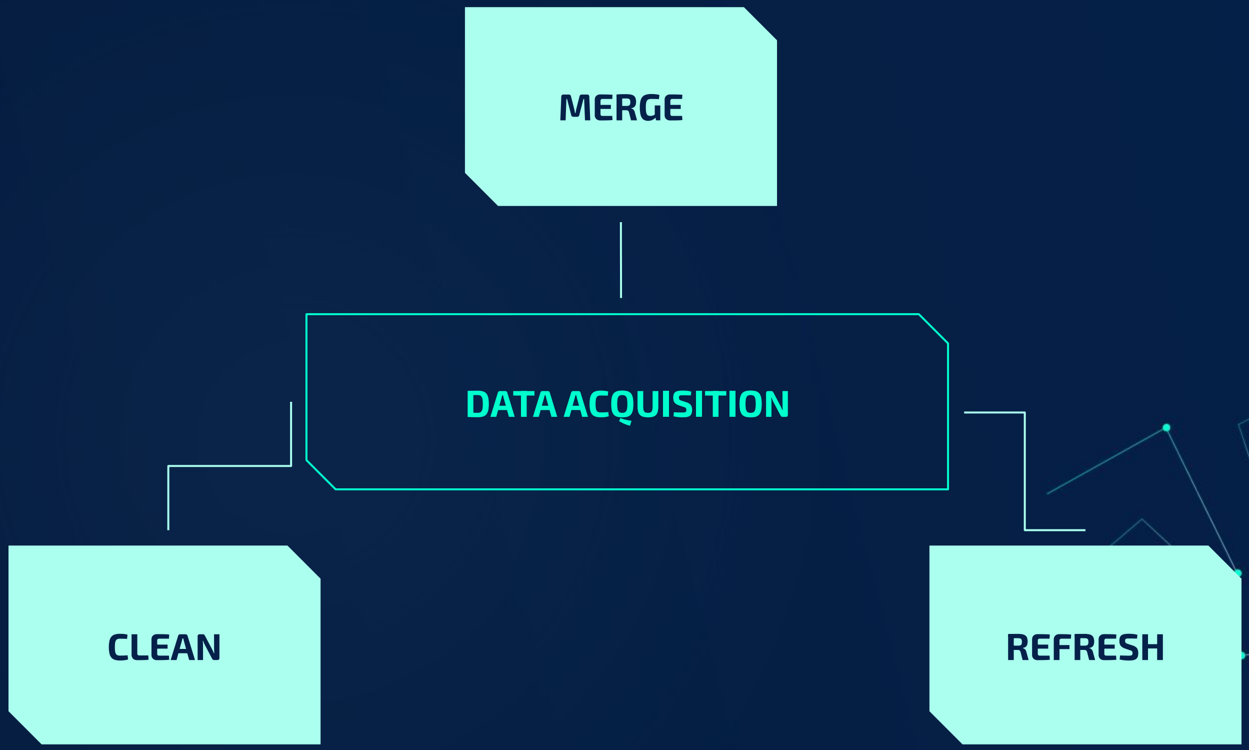
- Reports from Google from Google maps data, reported aggregated at county level as a time series
- Data is updated daily, I hand-downloaded the CSV
- Data is geocoded using FIPS
- Data is not reported for all counties, and this changes over time
- Data gap for ~50% of counties in September that I reached out to Google to ask about
- Variables of interest are percent change in activity from baseline in various settings (work, shopping, home, etc.) The most consistently reported was time at home spent relative to baseline, which was generally elevated (although not everywhere!)

COUNTY SHAPE FILES (FOR TABLEAU)

- Shape file that uses FIPS to code counties
- Provides polygons and locations for US counties and states
- I hand loaded the .CSV and imported it into Tableau

02

DATA WRANGLING


MERGE
DATA ACQUISITION
CLEAN
REFRESH

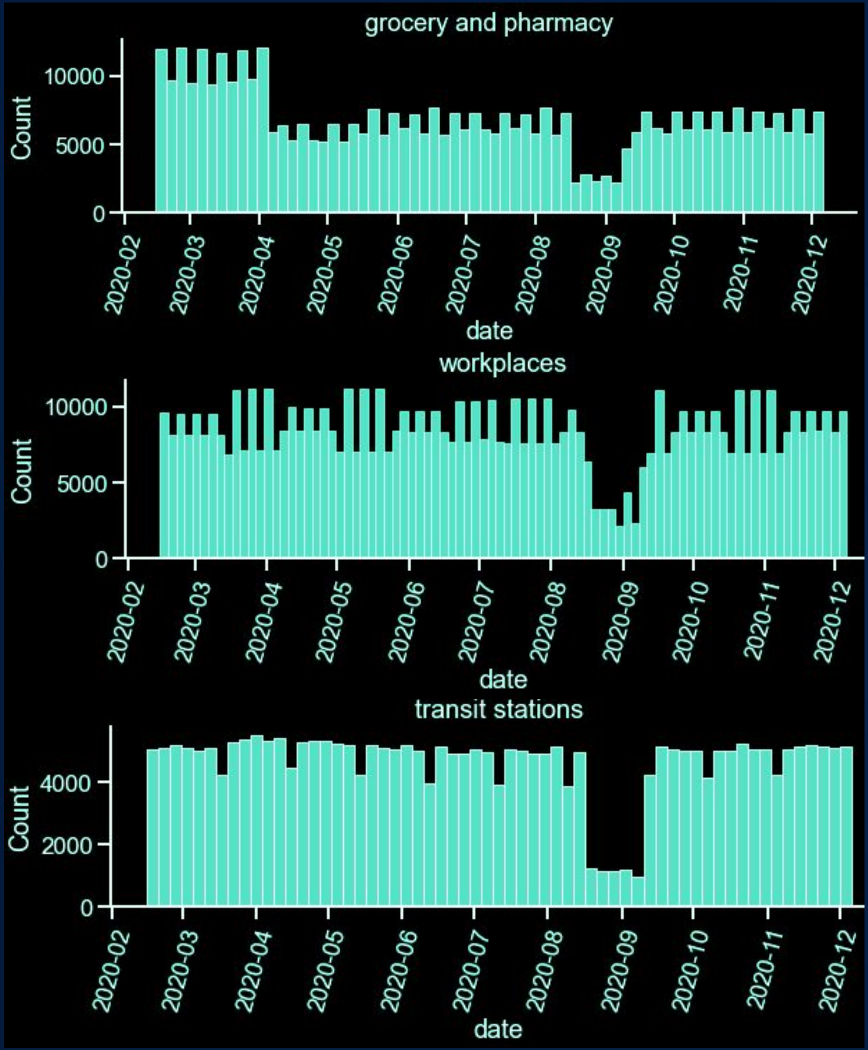
DATA ISSUES

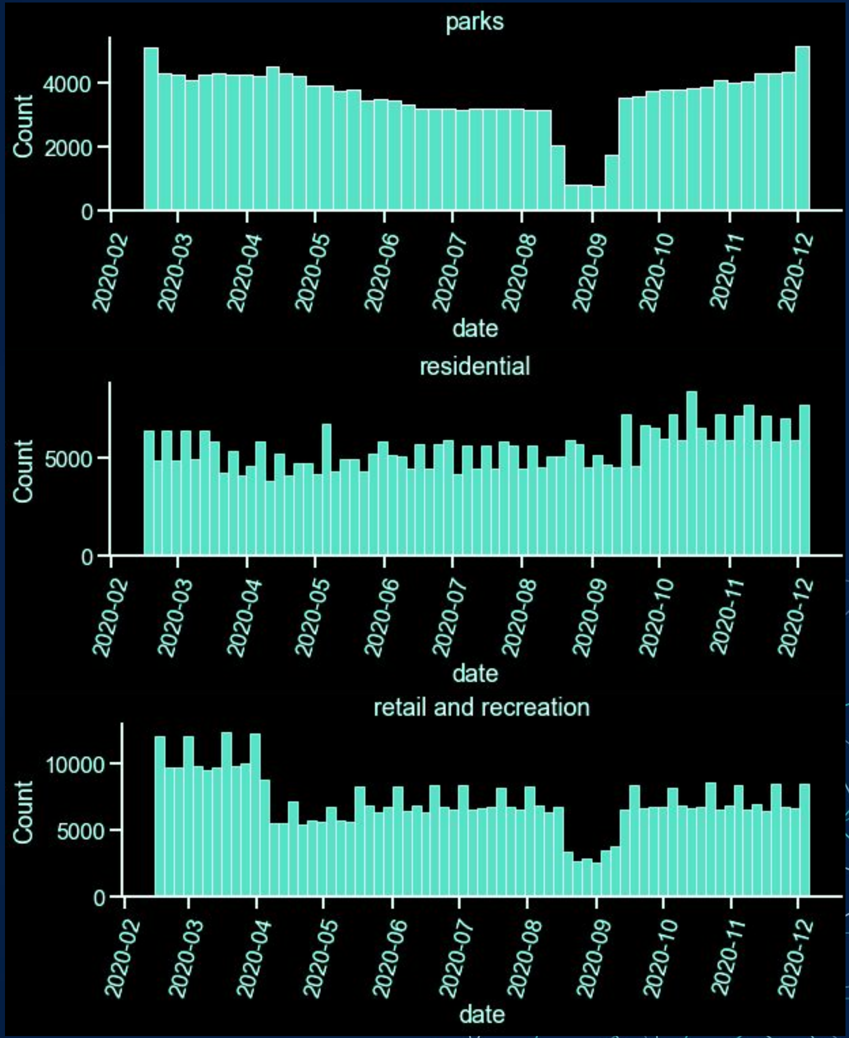
- Geocoding the county names in the COVID-19 Dataset
  - Some counties have the **same name as the state** that they are located in (New York County, Utah County, etc.) and geocoders tended to code these as states, not counties
  - Some areas were included in the COVID-19 dataset that are not at the county level at all (such as at the city level), and in some cases are places that used to be part of different FIPS codes, so the geocoder would sometimes get these codes wrong
- Data types
  - FIPS codes should be coded as strings and sometimes **contain leading zeroes**, but they are often implicitly read as **integers/floats** in both Excel, Python, and R leading to leading zero loss without **explicitly altering their data type during import**
- Geographic Data consistency
  - Although Puerto Rico was included in the COVID-19 data, and is available in many Census datasets, I was only able to find comprehensive data for educational attainment, poverty, and rural-urban divides in flat file format from the USDA Economic Research Service, which **omitted Puerto Rico** in their poverty estimates, which I used as the backbone of my counties dataset.

DATA ISSUES

- API performance
  - Using the Census API, the average call/response time for a single variable for a single county that I clocked was about **1.5 seconds,** so for roughly 3300 counties, it took about 80 minutes to look up a single variable
  - Looking up several variables took many hours (overnight)
  - This illustrates the performance benefit of using a .CSV for this purpose, but finding .CSVs was difficult

- Google Mobility Data
  - Google mobility data was n**ot available for every county for every day**
  - This may have been because there were not enough Google users in that county on a specific day to a) protect the privacy of users and b) calculate valid measurements
  - There was also a "revision" made to the files which I found may have resulted in a fair amount of missing data during mid-August into early September
  - I reached out to Google via Twitter and email (thanks Vivian!) but since this was late in the game,I was never able to determine what the issue was/is
  - The residential change from baseline was a) the most reliably populated, and b) unaffected by this issue, so I ended up using it in my regression to avoid dropping tons of data


grocery and pharmacy
Count
0
5000
10000
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
date
workplaces
Count
0
5000
10000
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
date
transit stations
Count
0
2000
4000
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
date


parks
Count
0
2000
4000
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
date
residential
Count
0
5000
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
date
retail and recreation
Count
0
5000
10000
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
date

TOOLS USED

- Data Wrangling - Python Jupyter Notebooks
  - Download the day's COVID data (final analysis done on 2020-12-09
  - Import mobility data using flat files
  - Import county data using flat files and API
  - Geocode and clean the COVID dataset
  - Merge the datasets together
  - Unit tests using Pytest to ensure that counties weren't duplicated or missing
  - Subset different datasets to feed into Tableau

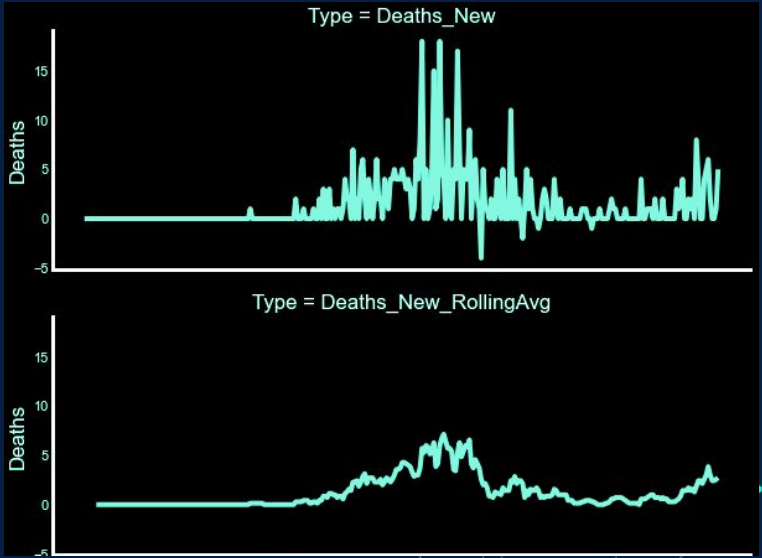
- Analysis - Python JuPyter Notebook using R-style regression
  - Assess multicollinearity using VIF and corrplot
  - Python implementation of all-subsets regression
  - Selecting models using BIC and Adjusted R-Squared as well as logic and judgment

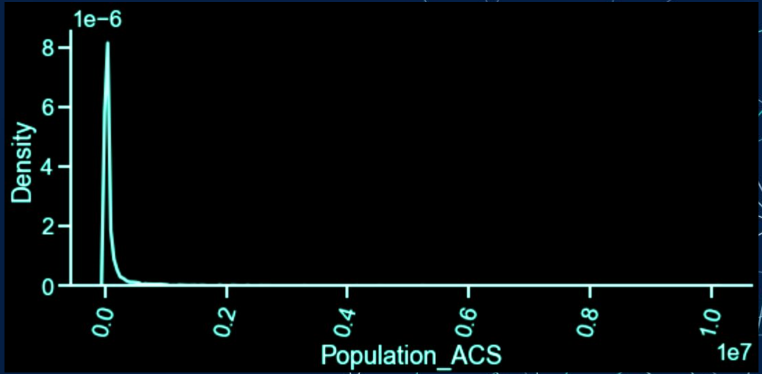
- Visualization - Python using Seaborn, Tableau
  - Custom color scheme to match this presentation

```
for i in list_frames:
    plt.rcParams.update({"grid.linewidth":0.5, "grid.alpha":0.5})
    sns.set(style="ticks", context="talk")
    plt.style.use("dark_background")
    sns.displot(i[0].date, height=3, aspect=3, color="#00ffcd")
    plt.xticks(rotation=75)
    plt.title("{x}".format(x=i[1]))
```

DATA TRANSFORMATION

- Data change over time
  - New deaths
  - New cases
- Rolling Averages
  - Helps to eliminate spikiness and data anomalies (negative counts due to revisions, holidays, weekend effects, etc.)
- Data lag
  - Deaths 7, 14, 21 days after the cases reported on day T
- Per capita measures
  - Deaths, cases, by 100K population
  - Population by county is very right-tailed, with a median of 25K, a mean of 101K, and a standard deviation of 325K
  - Raw measures by themselves are not always very helpful, but inherent tension here because reporting by 100K population can also skew human impact





03

FINAL DATASET

VARIABLES

DATE

COUNTY FIPS

COUNTY DATA

CASES

DEATHS

MOBILITY

1.01 M Rows / Observations

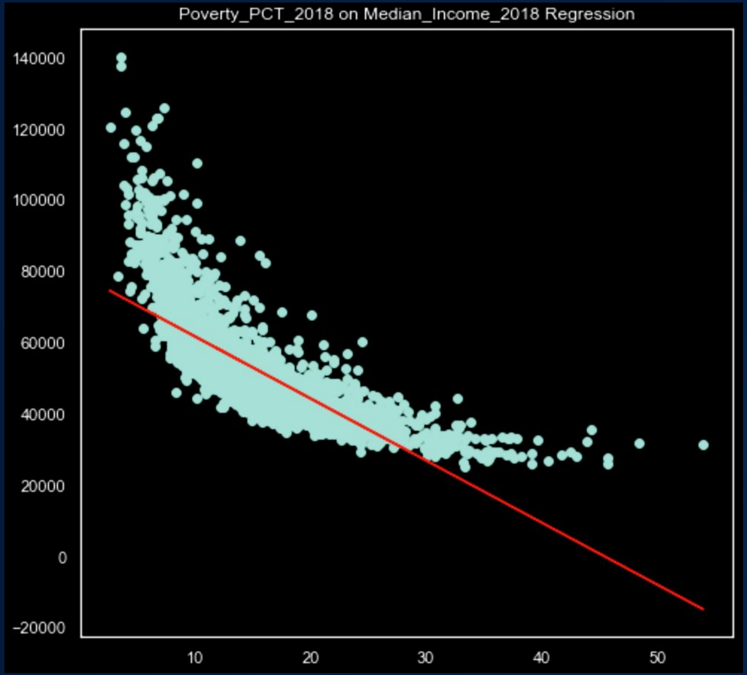
68 Columns / Variables

3130 Counties represented in the data

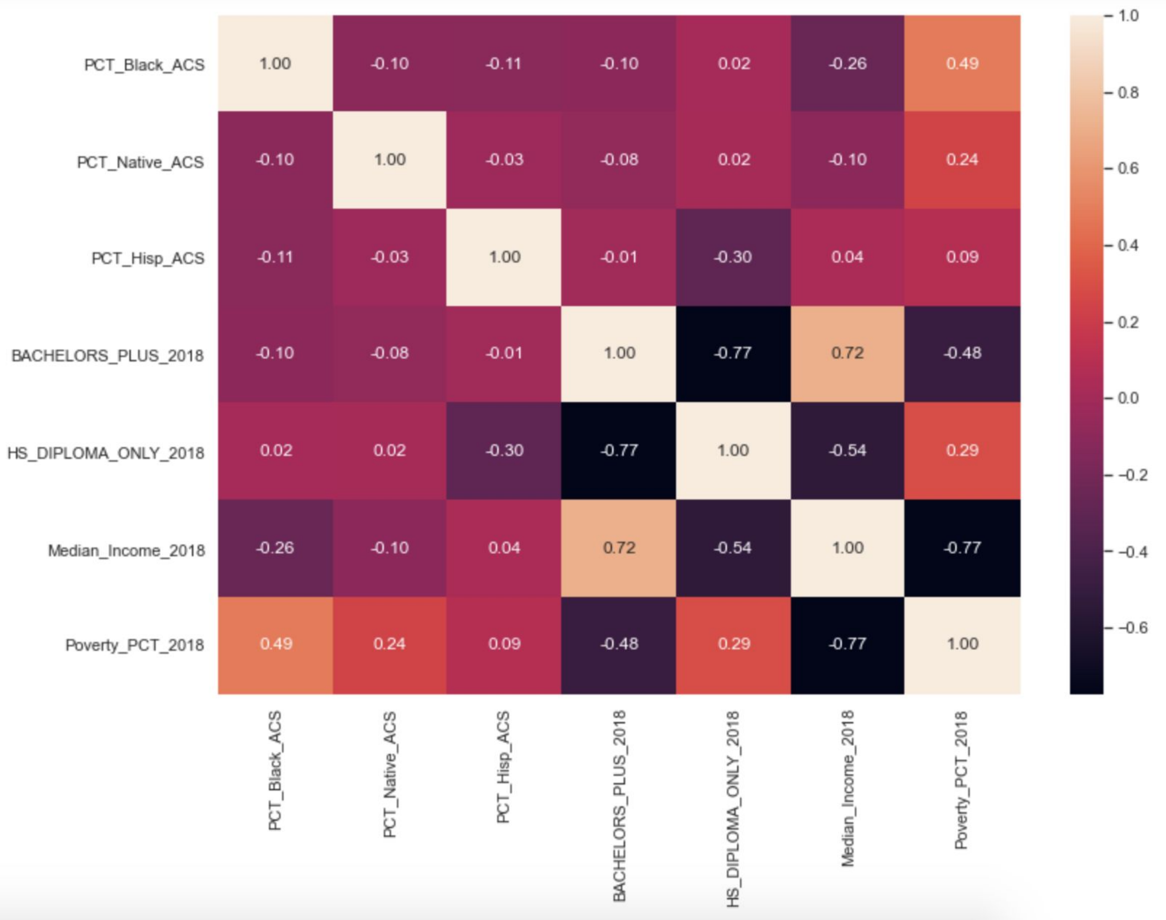
04

FINDINGS

MULTICOLLINEARITY / NONLINEARITY




```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.594
Model:                            OLS   Adj. R-squared:                  0.594
Method:                 Least Squares   F-statistic:                     4574.
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        10:25:36   Log-Likelihood:                -32886.
No. Observations:                3131   AIC:                         6.578e+04
Df Residuals:                    3129   BIC:                         6.579e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       7.914e+04    420.792    188.083      0.000    7.83e+04       8e+04
x1         -1739.3686     25.718    -67.632      0.000   -1789.795   -1688.942
==============================================================================
Omnibus:                     1509.945   Durbin-Watson:                   1.563
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            10807.420
Skew:                           2.180   Prob(JB):                         0.00
Kurtosis:                      10.990   Cond. No.                         43.8
==============================================================================
```



	VIF Factor	features
62	13.00	HS_DIPLOMA_ONLY_2018
61	12.70	BACHELORS_PLUS_2018
63	8.80	Median_Income_2018
64	5.40	Poverty_PCT_2018
60	3.10	PCT_Hisp_ACS
58	2.70	PCT_Black_ACS
4	2.10	Metro[T.Smaller_metro]
1	2.10	Metro[T.Micropolitan]
59	1.60	PCT_Native_ACS
65	1.40	residential_PCT_CFB_RollingAvg
2	1.20	Metro[T.Noncore_adjacent]
3	1.10	Metro[T.Noncore_remote]
0	0.00	Intercept

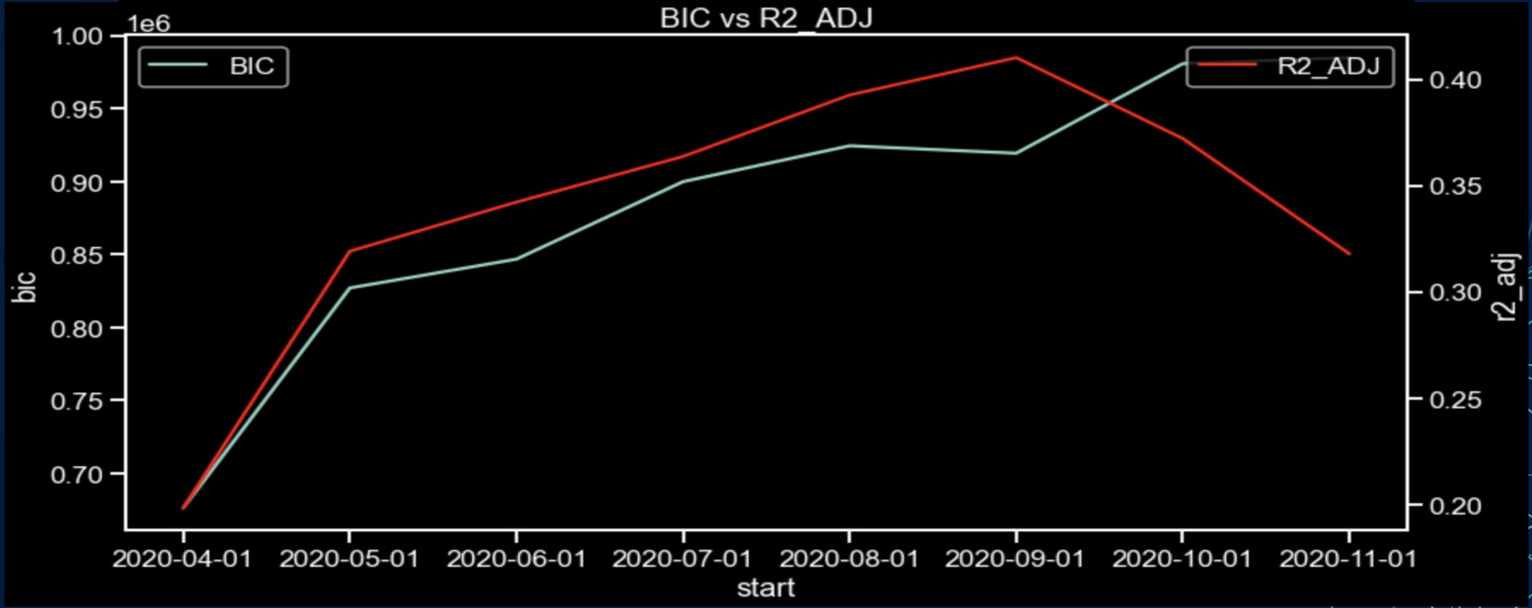
COVID-19 QUESTIONS OF INTEREST

- How much of the mortality toll of COVID-19 can be predicted by county-level characteristics such as the state, the geographic region, how rural or urban the county is, racial/ethnic composition, county median income and poverty rates, how educated the county inhabitants are, etc. while addressing multicollinearity? How have these trends changed over time?

formula	bic	aic	r2_adj	num_var
Deaths_PER_100K ~ C(Metro) + PCT_Black_ACS + BACHELORS_PLUS_2018 + Poverty_PCT_2018 + Median_Income_2018 + C(StateCD)	5934307.63	5933643.70	0.27	6
Deaths_PER_100K ~ C(Metro) + PCT_Black_ACS + Poverty_PCT_2018 + Median_Income_2018 + C(StateCD)	5935424.33	5934771.65	0.27	5
Deaths_PER_100K ~ C(Metro) + PCT_Black_ACS + BACHELORS_PLUS_2018 + Poverty_PCT_2018 + C(StateCD)	5935511.80	5934859.12	0.27	5
Deaths_PER_100K ~ PCT_Black_ACS + BACHELORS_PLUS_2018 + Poverty_PCT_2018 + Median_Income_2018 + C(StateCD)	5935485.40	5934866.48	0.27	5
Deaths_PER_100K ~ C(Metro) + PCT_Black_ACS + Poverty_PCT_2018 + C(StateCD)	5935811.75	5935170.32	0.27	4
Deaths_PER_100K ~ PCT_Black_ACS + Poverty_PCT_2018 + Median_Income_2018 + C(StateCD)	5936775.65	5936167.98	0.27	4
Deaths_PER_100K ~ PCT_Black_ACS + BACHELORS_PLUS_2018 + Poverty_PCT_2018 + C(StateCD)	5938020.65	5937412.98	0.27	4
Deaths_PER_100K ~ PCT_Black_ACS + Poverty_PCT_2018 + C(StateCD)	5938067.90	5937471.48	0.26	3

```
Deaths_PER_100K ~ C(Metro) + PCT_Black_ACS + Poverty_PCT_2018 + C(StateCD)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Deaths_PER_100K   R-squared:                       0.268
Model:                            OLS   Adj. R-squared:                  0.268
Method:                 Least Squares   F-statistic:                     3725.
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        13:44:16   Log-Likelihood:            -2.9675e+06
No. Observations:              569842   AIC:                         5.935e+06
Df Residuals:                  569785   BIC:                         5.936e+06
Df Model:                          56
Covariance Type:            nonrobust
```



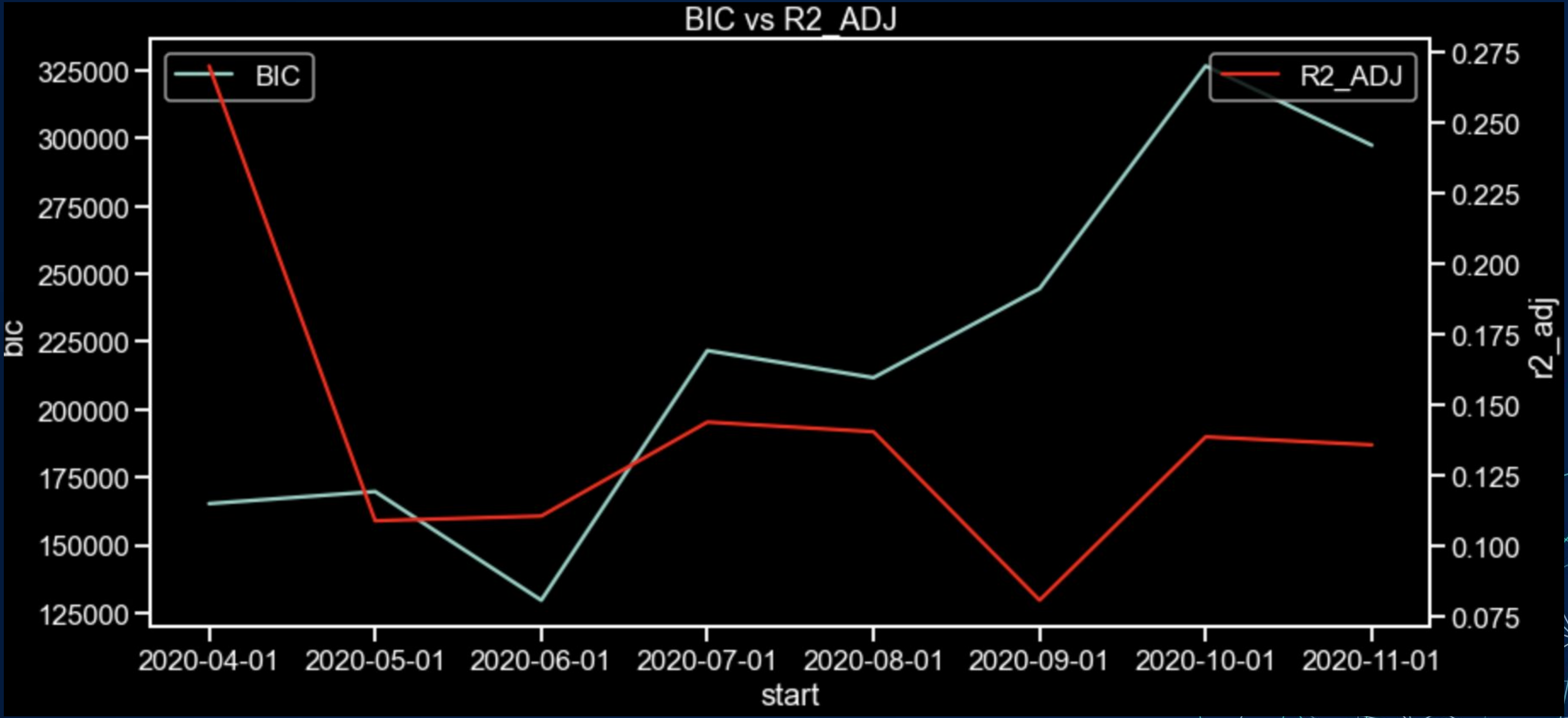
Deaths_PER_100K ~ C(Metro) + PCT_Black_ACS + Poverty_PCT_2018 + C(StateCD)

```
OLS Regression Results
==============================================================================
Dep. Variable:        Deaths_PER_100K   R-squared:                       0.268
Model:                            OLS   Adj. R-squared:                  0.268
Method:                 Least Squares   F-statistic:                     3725.
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        16:51:39   Log-Likelihood:            -2.9675e+06
No. Observations:              569842   AIC:                         5.935e+06
Df Residuals:                  569785   BIC:                         5.936e+06
Df Model:                          56
Covariance Type:            nonrobust
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
Intercept                      -2.0887      0.667     -3.132      0.002      -3.396      -0.782
C(Metro)[T.Micropolitan]       -7.7215      0.229    -33.735      0.000      -8.170      -7.273
C(Metro)[T.Noncore_adjacent]   -7.7845      0.220    -35.367      0.000      -8.216      -7.353
C(Metro)[T.Noncore_remote]    -12.7244      0.291    -43.683      0.000     -13.295     -12.153
C(Metro)[T.Smaller_metro]      -8.7221      0.213    -40.913      0.000      -9.140      -8.304
C(StateCD)[T.AZ]               65.9668      1.065     61.915      0.000      63.879      68.055
C(StateCD)[T.CT]               81.9050      1.325     61.817      0.000      79.308      84.502
C(StateCD)[T.DE]               45.1777      2.001     22.575      0.000      41.255      49.100
C(StateCD)[T.LA]               56.5112      0.782     72.233      0.000      54.978      58.045
C(StateCD)[T.MA]               91.8183      1.084     84.682      0.000      89.693      93.943
C(StateCD)[T.MS]               46.3816      0.772     60.107      0.000      44.869      47.894
C(StateCD)[T.NJ]              136.4193      0.968    140.872      0.000     134.521     138.317
C(StateCD)[T.NY]               43.7536      0.764     57.273      0.000      42.256      45.251
C(StateCD)[T.RI]               48.7492      1.607     30.328      0.000      45.599      51.900

..... OMMITTING STATES WITH COEFS LESS THAN +40

Poverty_PCT_2018                1.1389      0.014     82.477      0.000       1.112       1.166
PCT_Black_ACS                   0.8315      0.007    124.151      0.000       0.818       0.845
==============================================================================
Omnibus:                   371955.911   Durbin-Watson:                   0.030
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          7991721.154
Skew:                           2.820   Prob(JB):                         0.00
Kurtosis:                      20.458   Cond. No.                     1.70e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.7e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

COVID-19 QUESTIONS OF INTEREST

- What is the “best model” to predict “lagged” COVID-19 deaths, or the rate of COVID-19 deaths per 100K people in a county population? What is the relationship between reported cases and “lagged” COVID-19 deaths?

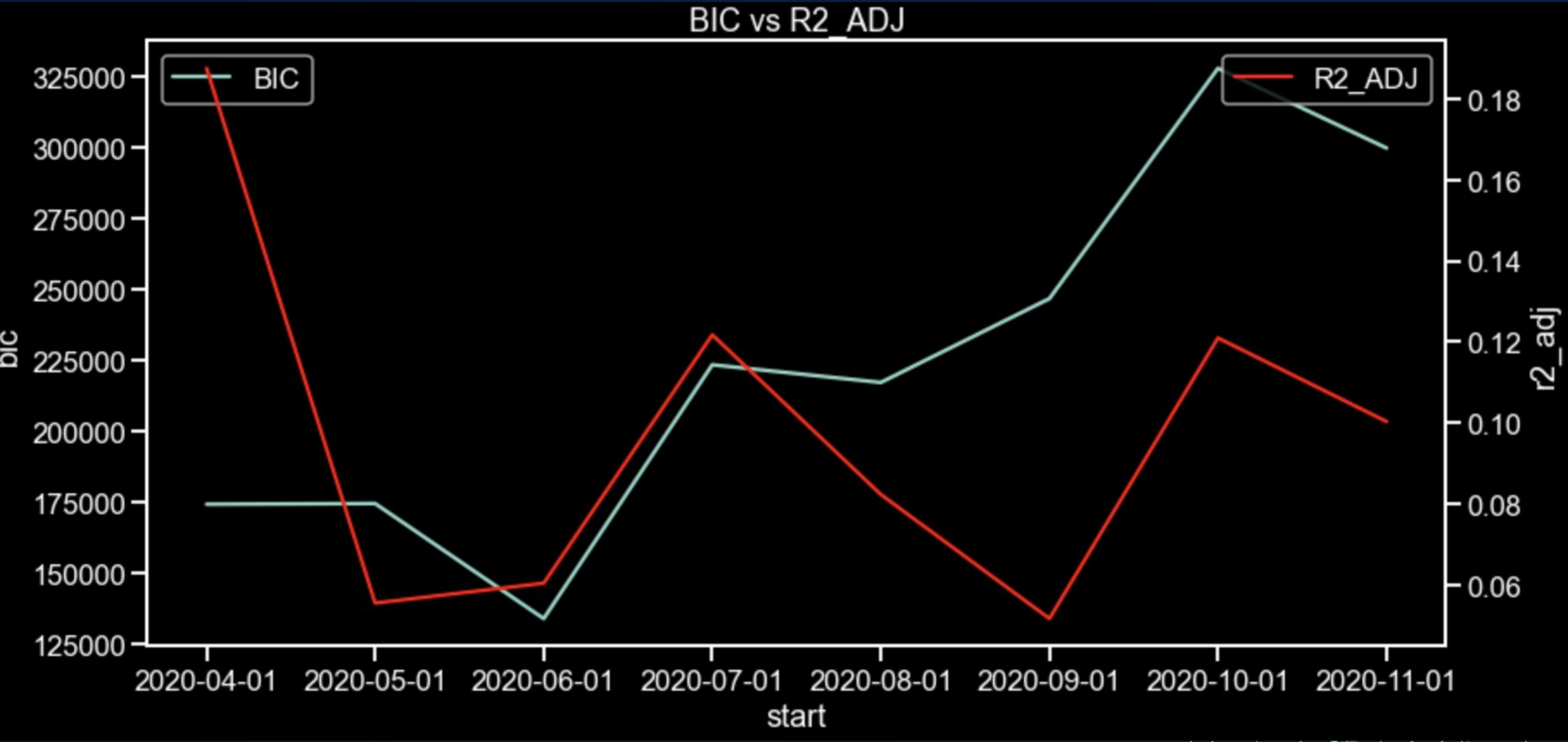
```
Deaths_New_14_RollingAvg_PER_100K ~ C(Metro) + Confirmed_New_RollingAvg_PER_100K + C(StateCD)
```



Deaths_New_14_RollingAvg_PER_100K ~ C(Metro) + Confirmed_New_RollingAvg_PER_100K + C(StateCD)

```
                                  OLS Regression Results
=======================================================================================
Dep. Variable:     Deaths_New_14_RollingAvg_PER_100K   R-squared:                   0.140
Model:                                           OLS   Adj. R-squared:              0.140
Method:                                Least Squares   F-statistic:                 1644.
Date:                               Mon, 14 Dec 2020   Prob (F-statistic):           0.00
Time:                                       16:23:51   Log-Likelihood:        -8.3027e+05
No. Observations:                             554187   AIC:                    1.661e+06
Df Residuals:                                 554131   BIC:                    1.661e+06
Df Model:                                         55
Covariance Type:                           nonrobust
=======================================================================================================
                                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------------
Intercept                            -0.2587      0.016    -15.772      0.000      -0.291      -0.227
C(Metro)[T.Micropolitan]              0.1088      0.005     20.355      0.000       0.098       0.119
C(Metro)[T.Noncore_adjacent]          0.1732      0.005     34.638      0.000       0.163       0.183
C(Metro)[T.Noncore_remote]            0.1790      0.007     26.623      0.000       0.166       0.192
C(Metro)[T.Smaller_metro]             0.0577      0.005     11.237      0.000       0.048       0.068
Confirmed_New_RollingAvg_PER_100K     0.0121   4.53e-05    266.321      0.000       0.012       0.012
==============================================================================
Omnibus:                   836189.423   Durbin-Watson:                   0.256
Prob(Omnibus):                  0.000   Jarque-Bera (JB):        866035413.769
Skew:                           9.092   Prob(JB):                         0.00
Kurtosis:                     195.807   Cond. No.                     3.13e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.13e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
Deaths_New_14_RollingAvg_PER_100K ~ C(Metro) + Confirmed_New_RollingAvg_PER_100K
```



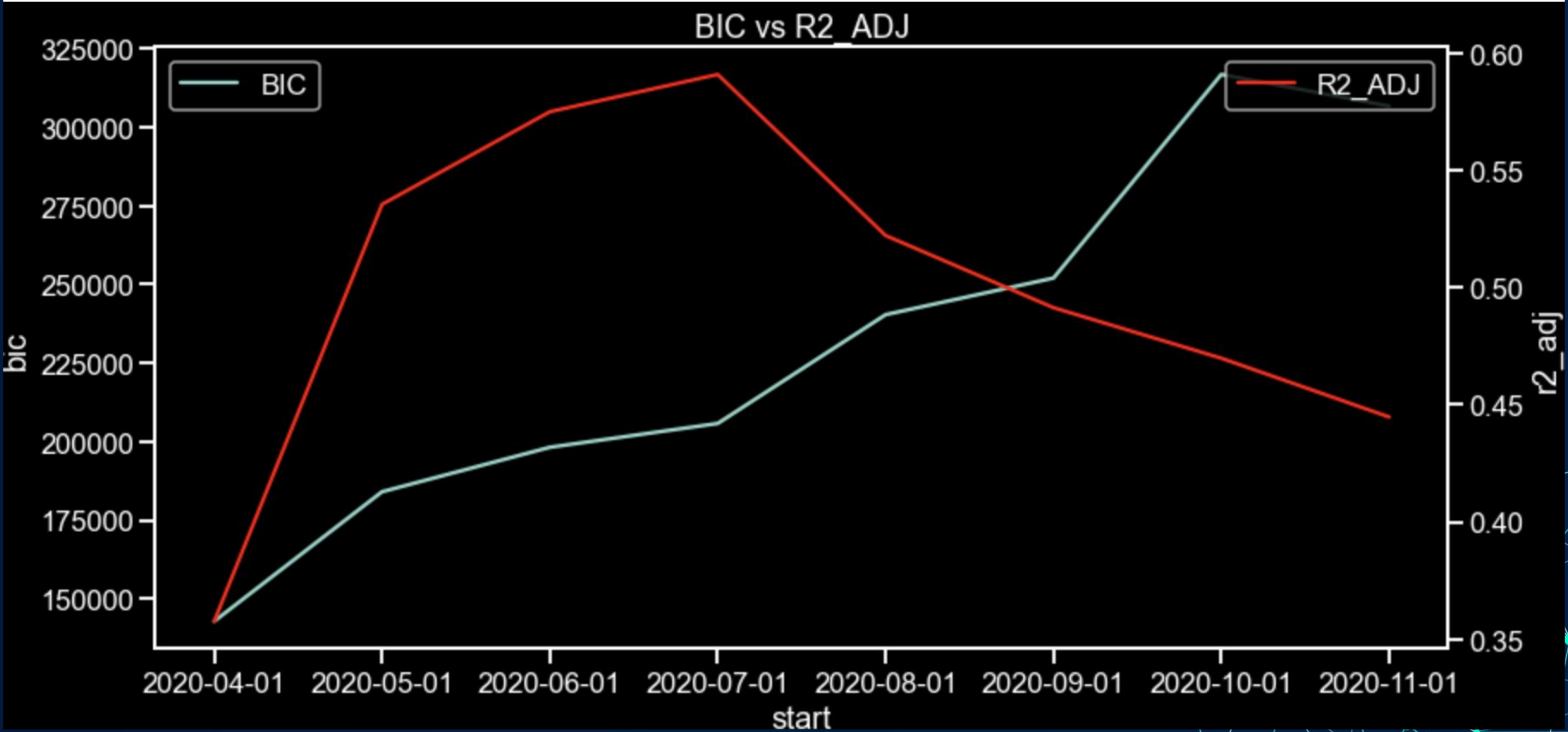
Deaths_New_14_RollingAvg_PER_100K ~ C(Metro) + Confirmed_New_RollingAvg_PER_100K

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Deaths_New_14_RollingAvg_PER_100K   R-squared:                       0.127
Model:                            OLS   Adj. R-squared:                  0.127
Method:                 Least Squares   F-statistic:                 1.619e+04
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        16:26:37   Log-Likelihood:            -8.3438e+05
No. Observations:              554187   AIC:                         1.669e+06
Df Residuals:                  554181   BIC:                         1.669e+06
Df Model:                           5
Covariance Type:            nonrobust
======================================================================================================
                                         coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------------
Intercept                              0.0482      0.004     11.982      0.000       0.040       0.056
C(Metro)[T.Micropolitan]               0.0861      0.005     16.801      0.000       0.076       0.096
C(Metro)[T.Noncore_adjacent]           0.1587      0.005     33.618      0.000       0.149       0.168
C(Metro)[T.Noncore_remote]             0.1256      0.006     20.436      0.000       0.114       0.138
C(Metro)[T.Smaller_metro]              0.0495      0.005      9.924      0.000       0.040       0.059
Confirmed_New_RollingAvg_PER_100K      0.0123   4.41e-05    278.886      0.000       0.012       0.012
==============================================================================
Omnibus:                   833597.351   Durbin-Watson:                   0.253
Prob(Omnibus):                  0.000   Jarque-Bera (JB):        835128245.965
Skew:                           9.047   Prob(JB):                         0.00
Kurtosis:                     192.313   Cond. No.                         255.
==============================================================================
```

COVID-19 QUESTIONS OF INTEREST

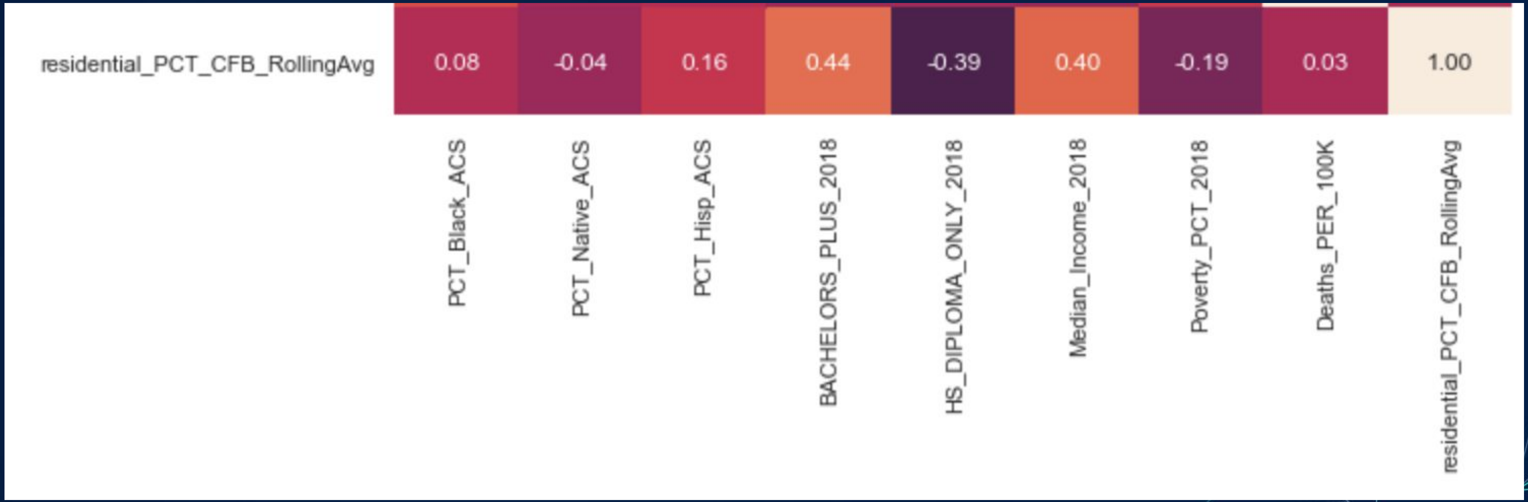
- Is there any evidence in Google Mobility data at the county level that increased time spent at home may be related to reported deaths from COVID-19 per capita at the county level?

```
Deaths_PER_100K ~ residential_PCT_CFB_RollingAvg + Poverty_PCT_2018 + C(StateCD)        +PCT_Black_ACS
```



Deaths_PER_100K ~ residential_PCT_CFB_RollingAvg + Poverty_PCT_2018 + C(StateCD) +PCT_Black_ACS

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Deaths_PER_100K   R-squared:                       0.398
Model:                            OLS   Adj. R-squared:                  0.398
Method:                 Least Squares   F-statistic:                     2011.
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        16:43:59   Log-Likelihood:            -8.0615e+05
No. Observations:              161394   AIC:                         1.612e+06
Df Residuals:                  161340   BIC:                         1.613e+06
Df Model:                          53
Covariance Type:            nonrobust
====================================================================================================
                                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------------
Intercept                        -24.4891      1.573    -15.570      0.000     -27.572     -21.406
C(StateCD)[T.CT]                  79.3385      1.805     43.964      0.000      75.802      82.876
C(StateCD)[T.DE]                  44.6101      2.177     20.491      0.000      40.343      48.877
C(StateCD)[T.LA]                  57.5136      1.686     34.107      0.000      54.209      60.819
C(StateCD)[T.MA]                 103.4900      1.734     59.696      0.000     100.092     106.888
C(StateCD)[T.NY]                  57.1343      1.602     35.663      0.000      53.994      60.274
C(StateCD)[T.RI]                  63.3194      2.093     30.248      0.000      59.217      67.422

... OMMITTING STATES WITH COEFS LESS THAN +40

residential_PCT_CFB_RollingAvg     1.5640      0.032     48.717      0.000       1.501       1.627
Poverty_PCT_2018                   2.1519      0.024     89.496      0.000       2.105       2.199
PCT_Black_ACS                      0.5107      0.011     47.544      0.000       0.490       0.532
==============================================================================
Omnibus:                    59679.520   Durbin-Watson:                   0.025
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           419925.592
Skew:                           1.610   Prob(JB):                         0.00
Kurtosis:                      10.216   Cond. No.                     2.57e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.57e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```


residential_PCT_CFB_RollingAvg
0.08
-0.04
0.16
0.44
-0.39
0.40
-0.19
0.03
1.00
PCT_Black_ACS
PCT_Native_ACS
PCT_Hisp_ACS
BACHELORS_PLUS_2018
HS_DIPLOMA_ONLY_2018
Median_Income_2018
Poverty_PCT_2018
Deaths_PER_100K
residential_PCT_CFB_RollingAvg

SUMMARY OF FINDINGS

- Multicollinearity between many measures poses challenges to analysis
- Data at a county level is rather imprecise
  - Ex: Boston, Newton, Lowell, and Weston are in the same county but are very different communities
- Percentage of population identifying as Black is a significant predictor of death toll for COVID-19, although this measure is correlated with other measures that also act as predictors for higher per capita death toll from COVID-19
  - A model with multiple interactions would be a good next step to analyze this
- There are omitted variables in this analysis, such as the rate of true disease prevalence, the rate of hospitalization, different rates of reporting cases and deaths, and many others
- 100 reported cases seem to predict roughly .5 - 1.5 deaths from COVID reported 14-21 days later, and this seems pretty stable over time since approximately June 1
- Many models of deaths (either new deaths or total death toll from COVID-19 show an increase in R squared up until the early Fall of 2020, and then falls in R squared later. This may be due to a more widespread disease toll that is affecting nearly all US counties more “equally” than before (at the county level)

05

TABLEAU

QUESTIONS

Code and zipped data files are on Github slidesgo

Fonts & colors used

This presentation has been made using the following fonts:

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(https://fonts.google.com/specimen/Roboto+Condensed)

#092a5c

#00ffcd

#ffffff