Coastal Analysis June 24

Summary

Confounding Variables

1. Population Density. Reflects the role of social distance in airborne propagation. We should in all our comparisons keep this variable as fixed as we can while avoiding the comparison of small sets of data.
2. All Ages in Poverty (
3. Median Income. Similar to (2) while an independent variable (poverty rate may be high and median income high or low dependent on the wealth gap).
4. Percent adult obesity. Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity.
5. Voter margin 2020 election. Reflects propensity to wear masks. Independent variable to (7).
6. Median age 2019. Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity.
7. Voting party in the 2020 presidential election. See (5).
8. Air pollution (PM 2.5) (Dominici lab data). Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity. Should use 2020 PM 2.5 data if available given the importance of the fire season in 2020.
9. Mean winter and summer humidity (Dominici lab data). Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity.

Analyses

- Atlantic coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).
- Atlantic urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).
- Atlantic rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).
- Pacific coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).
- Pacific urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).
- Pacific rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).

- Gulf coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).
- Gulf urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).
- Gulf rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).

```
library(readxl)
library(stringr)
library(gee)
library(sjPlot)
```

```
## Learn more about sjPlot with 'browseVignettes("sjPlot")'.
```

```
library(sjmisc)
library(sjlabelled)
```

Analyses

Read in data and additional confounding variables from Dominici lab (air pollution 2020 from aqs, humidity from previous Dominici lab confounding set)

```
# Summary sheet from FEND data
coastal <- read_excel("FIPS-based datasets_05232021.xlsx", sheet = 13)
```

```
## New names:
## * `` -> ...12
## * `` -> ...22
## * `` -> ...25
## * `` -> ...39
```

```
# Contains 2020 AQS air pollution data
pm = read.csv("aqs-pm25-annual-aggregated.csv")
pm$fips = paste(str_pad(pm$state_code, 2, pad = "0"), str_pad(pm$fips3,
    3, pad = "0"), sep = "")
colnames(pm)[3] = "mean_pm25"

# Contains humidity data and other confounders used in 2020 study
load("confounding.Rda")
```

Create smaller datasets from previous datasets, dataclean, merge with PM25 and humidity data.

```
coastal.new = data.frame(coastal$`FIPS as Text`, coastal$state, coastal$cases,
    coastal$deaths, coastal$`Country REGION`, coastal$`Coastal Distance`,
    coastal$`Population 2019 Estimate`, coastal$`Population Density`, coastal$`All Ages in Poverty (%)`
    coastal$`Median Income`, coastal$`percent adult obesity`, coastal$`diff/total`,
    coastal$`Politcal alignment 2020 election`, coastal$`median age 2019`)
colnames(coastal.new) = c("fips", "state", "cases", "deaths", "region",
    "coastal.distance", "population2019", "popdensity", "poverty", "median_income",
    "pct_obesity", "voter_margin_2020", "party", "median_age")

# Change NAs in coastal.distance to level 4, and save as factor with
```

```r
# reference level 4.
coastal.new$coastal.distance[is.na(coastal.new$coastal.distance)] <- 4
coastal.new$coastal.distance = as.factor(coastal.new$coastal.distance)
coastal.new <- within(coastal.new, coastal.distance <- relevel(coastal.distance,
    ref = 4))

# Change NAs in coastal region to Inland, and save as factor with
# reference level Inland
coastal.new$region[is.na(coastal.new$region)] <- "Inland"
coastal.new$region[coastal.new$region == "0"] <- "Inland"
coastal.new$region[coastal.new$coastal.distance != 1] <- "Inland"
coastal.new$region = tolower(coastal.new$region)
coastal.new$region = factor(coastal.new$region, levels = c("inland", "atlantic",
    "gulf of mexico", "pacific"))
# coastal.new <- within(coastal.new, region <- relevel(region, ref =
# 'inland'))

## Create indicator for being a coast (degree 1)
coastal.new$indicatorcoast = ifelse(coastal.new$coastal.distance == "1",
    "Coastal", "NonCoastal")
coastal.new$indicatorcoast = as.factor(coastal.new$indicatorcoast)
coastal.new <- within(coastal.new, indicatorcoast <- relevel(indicatorcoast,
    ref = "NonCoastal"))

# Merge with humidity and mean_pm25
coastal.new = merge(coastal.new, cbind.data.frame(fips = confounding$fips,
    mean_summer_rm = confounding$mean_summer_rm, mean_winter_rm = confounding$mean_winter_rm),
    by = "fips")
coastal.new = merge(coastal.new, pm, by = "fips")

nrow(coastal.new)
```

```
## [1] 601
```

```r
summary(coastal.new)
```

```
##      fips              state               cases             deaths
##  Length:601         Length:601         Min.   :     53   Min.   :    0.0
##  Class :character   Class :character   1st Qu.:   4743   1st Qu.:   80.0
##  Mode  :character   Mode  :character   Median :  14439   Median :  234.0
##                                        Mean   :  33038   Mean   :  573.6
##                                        3rd Qu.:  36119   3rd Qu.:  579.0
##                                        Max.   :1219237   Max.   :23101.0
##            region    coastal.distance population2019       popdensity
##  inland        :481   4:390            Min.   :     928   Min.   :    0.5
##  atlantic      : 45   1:120            1st Qu.:   54987   1st Qu.:   63.0
##  gulf of mexico: 20   2: 57            Median :  161075   Median :  243.7
##  pacific       : 25   3: 34            Mean   :  360181   Mean   :  654.0
##  NA's          : 30                    3rd Qu.:  413538   3rd Qu.:  618.4
##                                        Max.   :10039107   Max.   :17179.1
##     poverty        median_income     pct_obesity    voter_margin_2020
##  Min.   :0.0270   Min.   : 30309   Min.   :13.60   Min.   :-0.86752
##  1st Qu.:0.0970   1st Qu.: 51603   1st Qu.:26.90   1st Qu.:-0.16533
```

```
##  Median :0.1270   Median : 59253   Median :30.40   Median : 0.08237
##  Mean   :0.1307   Mean   : 62841   Mean   :30.09   Mean   : 0.07122
##  3rd Qu.:0.1580   3rd Qu.: 69528   3rd Qu.:33.50   3rd Qu.: 0.32811
##  Max.   :0.3660   Max.   :151806   Max.   :43.10   Max.   : 0.80967
##     party             median_age      indicatorcoast mean_summer_rm
##  Length:601         Min.   :24.80   NonCoastal:481    Min.   :31.64
##  Class :character   1st Qu.:35.80   Coastal   :120    1st Qu.:85.63
##  Mode  :character   Median :38.80                     Median :90.12
##                     Mean   :39.17                     Mean   :86.38
##                     3rd Qu.:42.10                     3rd Qu.:93.23
##                     Max.   :56.50                     Max.   :99.42
##  mean_winter_rm    state_code        fips3          mean_pm25
##  Min.   :58.16   Min.   : 1.00   Min.   :  1.00   Min.   : 1.322
##  1st Qu.:83.12   1st Qu.:17.00   1st Qu.: 27.00   1st Qu.: 6.357
##  Median :87.28   Median :29.00   Median : 59.00   Median : 7.474
##  Mean   :86.29   Mean   :29.64   Mean   : 83.31   Mean   : 7.727
##  3rd Qu.:90.47   3rd Qu.:42.00   3rd Qu.:111.00   3rd Qu.: 8.410
##  Max.   :96.85   Max.   :56.00   Max.   :810.00   Max.   :24.562
##      min
##  Length:601
##  Class :character
##  Mode  :character
##
##
##
```

Analysis 1, 4, 7:

Atlantic coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water). Pacific coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water). Gulf coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).

```
model.byregion.cases = gee(cases ~ region + offset(log(population2019)) +
    scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
    scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
    mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.new,
    id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
```

```
## running glm to get initial regression estimate
```

```
##               (Intercept)            regionatlantic      regiongulf of mexico
##              -1.421545722               0.203473055              -0.113013140
##             regionpacific         scale(popdensity)            scale(poverty)
##              -0.050529779               0.001679485              -0.029614318
## scale(log(median_income))        scale(pct_obesity)  scale(voter_margin_2020)
##              -0.116342218              -0.051311894               0.143955432
##         scale(median_age)   factor(party)Republican                 mean_pm25
##              -0.110853751              -0.028071795               0.014058307
##            mean_summer_rm            mean_winter_rm
##               0.004696333              -0.017088021
```

```
summary(model.byregion.cases)$coefficients
```

```
##                               Estimate  Naive S.E.     Naive z Robust S.E.
## (Intercept)               -1.421545722 0.105854069 -13.4292970 0.285235406
## regionatlantic             0.203473055 0.029803252   6.8272097 0.065772691
## regiongulf of mexico      -0.113013140 0.042679842  -2.6479278 0.052700035
## regionpacific             -0.050529779 0.035029829  -1.4424786 0.094797833
## scale(popdensity)          0.001679485 0.008202978   0.2047408 0.010094173
## scale(poverty)            -0.029614318 0.026610503  -1.1128808 0.043889272
## scale(log(median_income)) -0.116342218 0.025103911  -4.6344259 0.050118619
## scale(pct_obesity)        -0.051311894 0.015213321  -3.3728266 0.043865231
## scale(voter_margin_2020)   0.143955432 0.021315682   6.7534988 0.041637322
## scale(median_age)         -0.110853751 0.015575312  -7.1172732 0.020979921
## factor(party)Republican   -0.028071795 0.032536518  -0.8627781 0.057350347
## mean_pm25                  0.014058307 0.004598447   3.0571855 0.007711324
## mean_summer_rm             0.004696333 0.001126754   4.1680185 0.002670373
## mean_winter_rm            -0.017088021 0.001770602  -9.6509647 0.005774099
##                             Robust z
## (Intercept)               -4.9837632
## regionatlantic             3.0935796
## regiongulf of mexico      -2.1444605
## regionpacific             -0.5330267
## scale(popdensity)          0.1663816
```

```
## scale(poverty)            -0.6747507
## scale(log(median_income)) -2.3213372
## scale(pct_obesity)        -1.1697623
## scale(voter_margin_2020)   3.4573653
## scale(median_age)         -5.2838021
## factor(party)Republican   -0.4894791
## mean_pm25                  1.8230730
## mean_summer_rm             1.7586805
## mean_winter_rm            -2.9594265
```

```
model.byregion.deaths = gee(deaths ~ region + offset(log(population2019)) +
    scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
    scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
    mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.new,
    id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
## running glm to get initial regression estimate
```

```
##               (Intercept)            regionatlantic      regiongulf of mexico
##              -4.592226641               0.199290912              -0.072272466
##             regionpacific         scale(popdensity)            scale(poverty)
##              -0.167801308               0.016844149               0.268192434
## scale(log(median_income))        scale(pct_obesity)  scale(voter_margin_2020)
##               0.101659060               0.050308705               0.115115176
##         scale(median_age)   factor(party)Republican                 mean_pm25
##               0.197834845              -0.118582408               0.021638047
##            mean_summer_rm            mean_winter_rm
##               0.008991931              -0.031696350
```

```
summary(model.byregion.deaths)$coefficients
```

```
##                               Estimate  Naive S.E.    Naive z Robust S.E.
## (Intercept)               -4.592226641 0.164792505 -27.866720 0.332187823
## regionatlantic             0.199290912 0.043822710   4.547663 0.070580315
## regiongulf of mexico      -0.072272466 0.065100402  -1.110169 0.056099103
## regionpacific             -0.167801308 0.056084684  -2.991927 0.097542478
## scale(popdensity)          0.016844149 0.011566114   1.456336 0.023598236
## scale(poverty)             0.268192434 0.040024291   6.700742 0.091924101
## scale(log(median_income))  0.101659060 0.037956084   2.678334 0.090042315
## scale(pct_obesity)         0.050308705 0.023673224   2.125131 0.027867873
## scale(voter_margin_2020)   0.115115176 0.032551064   3.536449 0.048806675
## scale(median_age)          0.197834845 0.024521617   8.067773 0.034900100
## factor(party)Republican   -0.118582408 0.051265974  -2.313082 0.060638301
## mean_pm25                  0.021638047 0.007355935   2.941577 0.010860243
## mean_summer_rm             0.008991931 0.001829755   4.914282 0.004916046
## mean_winter_rm            -0.031696350 0.002910036 -10.892084 0.008510842
##                             Robust z
## (Intercept)               -13.8241872
## regionatlantic              2.8236047
## regiongulf of mexico       -1.2882999
## regionpacific              -1.7202896
```

```
## scale(popdensity)           0.7137885
## scale(poverty)              2.9175421
## scale(log(median_income))   1.1290143
## scale(pct_obesity)          1.8052581
## scale(voter_margin_2020)    2.3585949
## scale(median_age)           5.6686040
## factor(party)Republican    -1.9555694
## mean_pm25                   1.9924092
## mean_summer_rm              1.8290982
## mean_winter_rm             -3.7242322
```

Analysis 2, 5, 8

Atlantic urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water). Pacific urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water). Gulf urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).

```
coastal.urban = subset(coastal.new, coastal.new$popdensity >= 1500)

model.byregion.cases.urban = gee(cases ~ region + offset(log(population2019)) +
    scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
    scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
    mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.urban,
    id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
```

```
## running glm to get initial regression estimate
```

```
##               (Intercept)            regionatlantic      regiongulf of mexico
##              -0.0852311638              0.0836632777             -0.1313487202
##              regionpacific          scale(popdensity)            scale(poverty)
##              -0.1679560020             -0.0316965733             -0.0002881448
## scale(log(median_income))          scale(pct_obesity)  scale(voter_margin_2020)
##              -0.0545560279              0.0296049522              0.1337628622
##          scale(median_age)   factor(party)Republican                 mean_pm25
##              -0.0267402195              0.0927747140              0.0173391422
##             mean_summer_rm             mean_winter_rm
##              -0.0061643103             -0.0236921411
```

```
summary(model.byregion.cases.urban)$coefficients
```

```
##                               Estimate  Naive S.E.      Naive z Robust S.E.
## (Intercept)              -0.0852311638 0.581569044 -0.146553818 0.430463337
## regionatlantic            0.0836632777 0.068383148  1.223448760 0.081279960
## regiongulf of mexico     -0.1313487202 0.103117173 -1.273781239 0.079968785
## regionpacific            -0.1679560020 0.115645728 -1.452332086 0.116138929
## scale(popdensity)        -0.0316965733 0.031579245 -1.003715365 0.021901843
## scale(poverty)           -0.0002881448 0.078394969 -0.003675552 0.040913315
## scale(log(median_income)) -0.0545560279 0.080106625 -0.681042649 0.032018179
## scale(pct_obesity)        0.0296049522 0.045434431  0.651597297 0.030778974
## scale(voter_margin_2020)  0.1337628622 0.035423651  3.776089072 0.021071203
## scale(median_age)        -0.0267402195 0.029715816 -0.899864889 0.034416819
## factor(party)Republican   0.0927747140 0.114510806  0.810183048 0.118990753
## mean_pm25                 0.0173391422 0.024685308  0.702407360 0.023092696
## mean_summer_rm           -0.0061643103 0.005459300 -1.129139319 0.002647607
## mean_winter_rm           -0.0236921411 0.005598259 -4.232054934 0.004876039
##                             Robust z
## (Intercept)              -0.197998660
## regionatlantic            1.029322323
## regiongulf of mexico     -1.642499891
```

```
## regionpacific              -1.446164552
## scale(popdensity)          -1.447210338
## scale(poverty)             -0.007042812
## scale(log(median_income)) -1.703907876
## scale(pct_obesity)          0.961856382
## scale(voter_margin_2020)    6.348136111
## scale(median_age)          -0.776952088
## factor(party)Republican     0.779680030
## mean_pm25                   0.750849622
## mean_summer_rm             -2.328257517
## mean_winter_rm             -4.858891285
```

```r
model.byregion.deaths.urban = gee(deaths ~ region + offset(log(population2019)) +
    scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
    scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
    mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.urban,
    id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
## running glm to get initial regression estimate
```

```
##               (Intercept)            regionatlantic       regiongulf of mexico
##               -2.22609193                0.13219270                -0.02919697
##             regionpacific         scale(popdensity)             scale(poverty)
##               -0.41495483                0.01826963                 0.16524613
## scale(log(median_income))        scale(pct_obesity)   scale(voter_margin_2020)
##                0.09747730                0.08478289                 0.11867685
##         scale(median_age)   factor(party)Republican                  mean_pm25
##                0.22510216               -0.04184826                 0.01181252
##            mean_summer_rm            mean_winter_rm
##               -0.01436105               -0.03633786
```

```r
summary(model.byregion.deaths.urban)$coefficients
```

```
##                              Estimate Naive S.E.    Naive z Robust S.E.
## (Intercept)               -2.22609193 1.08766139 -2.0466773 0.999480080
## regionatlantic             0.13219270 0.11890296  1.1117697 0.129991732
## regiongulf of mexico      -0.02919697 0.19437423 -0.1502101 0.158926873
## regionpacific             -0.41495483 0.21143311 -1.9625821 0.165174034
## scale(popdensity)          0.01826963 0.05461672  0.3345061 0.038399822
## scale(poverty)             0.16524613 0.14385491  1.1486999 0.090603545
## scale(log(median_income))  0.09747730 0.14704975  0.6628865 0.111561864
## scale(pct_obesity)         0.08478289 0.08390154  1.0105046 0.073142376
## scale(voter_margin_2020)   0.11867685 0.06766146  1.7539798 0.036164396
## scale(median_age)          0.22510216 0.05221094  4.3113986 0.047781305
## factor(party)Republican   -0.04184826 0.20259557 -0.2065606 0.202158533
## mean_pm25                  0.01181252 0.04476009  0.2639075 0.052770255
## mean_summer_rm            -0.01436105 0.01067483 -1.3453186 0.008940204
## mean_winter_rm            -0.03633786 0.01090980 -3.3307547 0.008584142
##                             Robust z
## (Intercept)               -2.2272499
## regionatlantic             1.0169316
```

```
## regiongulf of mexico      -0.1837132
## regionpacific             -2.5122280
## scale(popdensity)          0.4757738
## scale(poverty)             1.8238373
## scale(log(median_income))  0.8737511
## scale(pct_obesity)         1.1591487
## scale(voter_margin_2020)   3.2815935
## scale(median_age)          4.7110928
## factor(party)Republican   -0.2070071
## mean_pm25                  0.2238481
## mean_summer_rm            -1.6063449
## mean_winter_rm            -4.2331387
```

Analysis 3, 6, 9

Atlantic rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water). Pacific rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water). Gulf rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).

```
coastal.rural = subset(coastal.new, coastal.new$popdensity < 1500)

model.byregion.cases.rural = gee(cases ~ region + offset(log(population2019)) +
    scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
    scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
    mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.rural,
    id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
```

```
## running glm to get initial regression estimate
```

```
##               (Intercept)            regionatlantic      regiongulf of mexico
##              -1.535567551               0.205367713              -0.023805275
##            regionpacific         scale(popdensity)            scale(poverty)
##              -0.188901171               0.044528820               0.021817099
## scale(log(median_income))         scale(pct_obesity)  scale(voter_margin_2020)
##              -0.068162949              -0.033117866               0.172171546
##         scale(median_age)   factor(party)Republican                 mean_pm25
##              -0.127498765              -0.040988963              -0.001230517
##            mean_summer_rm            mean_winter_rm
##              -0.000178165              -0.009452678
```

```
summary(model.byregion.cases.rural)$coefficients
```

```
##                              Estimate  Naive S.E.     Naive z Robust S.E.
## (Intercept)              -1.535567551 0.103649687 -14.8149752 0.234866830
## regionatlantic            0.205367713 0.034468166   5.9581852 0.066431463
## regiongulf of mexico     -0.023805275 0.050290191  -0.4733582 0.052643389
## regionpacific            -0.188901171 0.044202609  -4.2735299 0.126219416
## scale(popdensity)         0.044528820 0.010736339   4.1474864 0.022119752
## scale(poverty)            0.021817099 0.028516587   0.7650670 0.045663986
## scale(log(median_income)) -0.068162949 0.027336658  -2.4934631 0.031705372
## scale(pct_obesity)       -0.033117866 0.015183210  -2.1812163 0.041328024
## scale(voter_margin_2020)  0.172171546 0.024205498   7.1129107 0.032397071
## scale(median_age)        -0.127498765 0.015844305  -8.0469773 0.023224484
## factor(party)Republican  -0.040988963 0.036482710  -1.1235175 0.041726801
## mean_pm25                -0.001230517 0.004651052  -0.2645674 0.006920822
## mean_summer_rm           -0.000178165 0.001227545  -0.1451393 0.002847345
## mean_winter_rm           -0.009452678 0.001892123  -4.9958052 0.005060983
##                             Robust z
## (Intercept)              -6.53803498
## regionatlantic            3.09142238
## regiongulf of mexico     -0.45219875
```

```
## regionpacific              -1.49660946
## scale(popdensity)           2.01307955
## scale(poverty)              0.47777473
## scale(log(median_income)) -2.14988646
## scale(pct_obesity)        -0.80134162
## scale(voter_margin_2020)   5.31441698
## scale(median_age)         -5.48984277
## factor(party)Republican   -0.98231741
## mean_pm25                 -0.17779923
## mean_summer_rm            -0.06257233
## mean_winter_rm            -1.86775525
```

```r
model.byregion.deaths.rural = gee(deaths ~ region + offset(log(population2019)) +
    scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
    scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
    mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.rural,
    id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
## running glm to get initial regression estimate
```

```
##               (Intercept)            regionatlantic      regiongulf of mexico
##              -4.851261740               0.181033127               0.039009199
##             regionpacific         scale(popdensity)            scale(poverty)
##              -0.336656816               0.034886901               0.329605666
## scale(log(median_income))        scale(pct_obesity)  scale(voter_margin_2020)
##               0.130128355               0.076029702               0.161988007
##         scale(median_age)   factor(party)Republican                 mean_pm25
##               0.156555160              -0.162203724              -0.001117394
##            mean_summer_rm            mean_winter_rm
##               0.002665545              -0.019919905
```

```r
summary(model.byregion.deaths.rural)$coefficients
```

```
##                               Estimate  Naive S.E.     Naive z Robust S.E.
## (Intercept)               -4.851261740 0.155826355 -31.1324854 0.284057013
## regionatlantic             0.181033127 0.050018263   3.6193405 0.067124236
## regiongulf of mexico       0.039009199 0.071421913   0.5461797 0.099302043
## regionpacific             -0.336656816 0.071800896  -4.6887551 0.091851734
## scale(popdensity)          0.034886901 0.016184735   2.1555435 0.024214515
## scale(poverty)             0.329605666 0.040714911   8.0954535 0.074408588
## scale(log(median_income))  0.130128355 0.040155532   3.2406084 0.061160184
## scale(pct_obesity)         0.076029702 0.022656681   3.3557298 0.021398241
## scale(voter_margin_2020)   0.161988007 0.036243478   4.4694388 0.041578817
## scale(median_age)          0.156555160 0.023979775   6.5286335 0.043672944
## factor(party)Republican   -0.162203724 0.055375308  -2.9291706 0.067562280
## mean_pm25                 -0.001117394 0.007101572  -0.1573446 0.009673003
## mean_summer_rm             0.002665545 0.001921014   1.3875717 0.004315413
## mean_winter_rm            -0.019919905 0.003021841  -6.5919762 0.006394443
##                              Robust z
## (Intercept)               -17.0784790
## regionatlantic              2.6969860
```

```
## regiongulf of mexico        0.3928338
## regionpacific              -3.6652201
## scale(popdensity)           1.4407433
## scale(poverty)              4.4296724
## scale(log(median_income))   2.1276645
## scale(pct_obesity)          3.5530819
## scale(voter_margin_2020)    3.8959263
## scale(median_age)           3.5847174
## factor(party)Republican    -2.4008030
## mean_pm25                  -0.1155168
## mean_summer_rm              0.6176802
## mean_winter_rm             -3.1151897
```

Some splits

```
table(coastal.new$region)
```

```
##
##           inland         atlantic gulf of mexico         pacific
##              481               45              20              25
```

```
table(coastal.urban$region)
```

```
##
##           inland         atlantic gulf of mexico         pacific
##               37               14               3               5
```

```
table(coastal.rural$region)
```

```
##
##           inland         atlantic gulf of mexico         pacific
##              444               31              17              20
```

```
tab_model(model.byregion.cases, dv.labels = "Cases (All)", robust = T,
    digits = 3)
tab_model(model.byregion.deaths, dv.labels = "Deaths (All)", robust = T,
    digits = 3)
tab_model(model.byregion.cases.urban, dv.labels = "Cases (Urban)", robust = T,
    digits = 3)
tab_model(model.byregion.deaths.urban, dv.labels = "Deaths (Urban)", robust = T,
    digits = 3)
tab_model(model.byregion.cases.rural, dv.labels = "Cases (Rural)", robust = T,
    digits = 3)
tab_model(model.byregion.deaths.rural, dv.labels = "Deaths (Rural)", robust = T,
    digits = 3)
```

Manually Calculate Confidence Intervals

```
for (i in c(2, 3, 4)) {
    print(exp(summary(model.byregion.cases)$coefficients[i, 1]))
    print(c(exp(summary(model.byregion.cases)$coefficients[i, 1] - 1.9599 *
        (summary(model.byregion.cases)$coefficients[i, 4])), exp(summary(model.byregion.cases)$coeffici
        1] + 1.9599 * (summary(model.byregion.cases)$coefficients[i, 4]))))
}
```

```
## [1] 1.225652
## [1] 1.077416 1.394284
## [1] 0.8931389
## [1] 0.8054937 0.9903208
## [1] 0.9507256
## [1] 0.7895248 1.1448395
```

```
for (i in c(2, 3, 4)) {
    print(exp(summary(model.byregion.deaths)$coefficients[i, 1]))
    print(c(exp(summary(model.byregion.deaths)$coefficients[i, 1] - 1.9599 *
        (summary(model.byregion.deaths)$coefficients[i, 4])), exp(summary(model.byregion.deaths)$coeffi
        1] + 1.9599 * (summary(model.byregion.deaths)$coefficients[i, 4]))))
}
```

```
## [1] 1.220537
## [1] 1.062857 1.401610
## [1] 0.9302774
## [1] 0.8334171 1.0383949
## [1] 0.8455218
## [1] 0.6983919 1.0236475
```

```
for (i in c(2, 3, 4)) {
    print(exp(summary(model.byregion.cases.rural)$coefficients[i, 1]))
    print(c(exp(summary(model.byregion.cases.rural)$coefficients[i, 1] -
        1.9599 * (summary(model.byregion.cases.rural)$coefficients[i, 4])),
        exp(summary(model.byregion.cases.rural)$coefficients[i, 1] + 1.9599 *
            (summary(model.byregion.cases.rural)$coefficients[i, 4]))))
}
```

```
## [1] 1.227977
## [1] 1.078066 1.398733
## [1] 0.9764758
## [1] 0.8807504 1.0826054
## [1] 0.8278683
## [1] 0.6464376 1.0602198
```

```
for (i in c(2, 3, 4)) {
    print(exp(summary(model.byregion.deaths.rural)$coefficients[i, 1]))
    print(c(exp(summary(model.byregion.deaths.rural)$coefficients[i, 1] -
        1.9599 * (summary(model.byregion.deaths.rural)$coefficients[i,
            4])), exp(summary(model.byregion.deaths.rural)$coefficients[i,
        1] + 1.9599 * (summary(model.byregion.deaths.rural)$coefficients[i,
        4]))))
}
```

```
## [1] 1.198455
## [1] 1.050721 1.366961
## [1] 1.03978
## [1] 0.8558905 1.2631786
## [1] 0.7141539
## [1] 0.5964994 0.8550147
```