

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)
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
# 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
```

```
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
```

```
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	

```
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
```

```
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
```

```
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, robust = T, digits = 3)
tab_model(model.byregion.deaths, robust = T, digits = 3)
tab_model(model.byregion.cases.urban, robust = T, digits = 3)
tab_model(model.byregion.deaths.urban, robust = T, digits = 3)
tab_model(model.byregion.cases.rural, robust = T, digits = 3)
tab_model(model.byregion.deaths.rural, robust = T, digits = 3)
```

Manually Calculate Confidence Intervals

```
for (i in c(2, 5, 9)) {
  print(exp(summary(model.byregion.cases)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.cases)$coefficients[i, 1] - 1.96 *
    (summary(model.byregion.cases)$coefficients[i, 4])), exp(summary(model.byregion.cases)$coefficients[i, 1] + 1.96 *
    (summary(model.byregion.cases)$coefficients[i, 4]))))
}
```

```
## [1] 1.225652
## [1] 1.077408 1.394293
## [1] 1.001681
## [1] 0.9820578 1.0216961
## [1] 1.154833
## [1] 1.064331 1.253030
```

```
for (i in c(2, 5, 9)) {
  print(exp(summary(model.byregion.deaths)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.deaths)$coefficients[i, 1] - 1.96 *
    (summary(model.byregion.deaths)$coefficients[i, 4])), exp(summary(model.byregion.deaths)$coefficients[i, 1] + 1.96 *
    (summary(model.byregion.deaths)$coefficients[i, 4]))))
}
```

```
## [1] 1.220537
## [1] 1.062849 1.401619
## [1] 1.016987
## [1] 0.9710198 1.0651298
## [1] 1.122003
## [1] 1.019645 1.234636
```

```
for (i in c(2, 5, 9)) {
  print(exp(summary(model.byregion.cases.rural)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.cases.rural)$coefficients[i, 1] -
    1.96 * (summary(model.byregion.cases.rural)$coefficients[i, 4])),
    exp(summary(model.byregion.cases.rural)$coefficients[i, 1] + 1.96 *
      (summary(model.byregion.cases.rural)$coefficients[i, 4]))))
}
```

```
## [1] 1.227977
## [1] 1.078059 1.398742
## [1] 1.045535
## [1] 1.001175 1.091861
## [1] 1.187882
## [1] 1.114798 1.265756
```

```
for (i in c(2, 5, 9)) {
  print(exp(summary(model.byregion.deaths.rural)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.deaths.rural)$coefficients[i, 1] -
    1.96 * (summary(model.byregion.deaths.rural)$coefficients[i, 4])),
    exp(summary(model.byregion.deaths.rural)$coefficients[i, 1] + 1.96 *
      (summary(model.byregion.deaths.rural)$coefficients[i, 4]))))
}
```

```
## [1] 1.198455
## [1] 1.050714 1.366970
## [1] 1.035503
## [1] 0.9875052 1.0858329
## [1] 1.175846
## [1] 1.083822 1.275684
```