COVID_day25_SL

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Load Libraries

Import case data and covariates

```
# Case data
day25 <- read_excel("Data/day25.xls")</pre>
day25$popland <- day25$Population/(day25$LandArea)</pre>
# Covariate Data
analytic data2020 <- read csv("Data/analytic data2020.csv")</pre>
colnames(analytic_data2020) [which(names(analytic_data2020) == "State Abbreviation")] <- "State"</pre>
eco_vars_of_int <- c("State",
                      "Name",
                      "Poor or fair health raw value",
                      "Adult smoking raw value",
                      "Food environment index raw value",
                      "Physical inactivity raw value",
                      "Excessive drinking raw value",
                      "Sexually transmitted infections raw value",
                      "Primary care physicians raw value",
                      "Flu vaccinations raw value",
                      "High school graduation raw value",
                      "Unemployment raw value",
                      "Air pollution - particulate matter raw value",
                      "Drinking water violations raw value",
                     "Diabetes prevalence raw value",
                      "HIV prevalence raw value",
                      "Food insecurity raw value",
                      "Drug overdose deaths raw value",
                      "Median household income raw value",
                      "% below 18 years of age raw value",
                      "% 65 and older raw value",
                      "% Hispanic raw value",
                      "% Females raw value", "% Rural raw value",
                      "Adult obesity raw value",
                      "Income inequality raw value",
                      "Uninsured adults raw value")
eco_health_covars <- names(analytic_data2020) %in% eco_vars_of_int
covars <- analytic_data2020[eco_health_covars]</pre>
```

```
# Merge case data with covarites
day25_covars <- merge(day25, covars, by = c("Name", "State"))</pre>
day25_covars$log_pop_dense <- log(day25_covars$Population/(day25_covars$LandArea))</pre>
Import Google mobility data
# Data 1
grocery_pharmacy <- read_csv("Data/Mobility/google-mobility-us-groceryAndPharmacy.csv")</pre>
df.1 <-
  grocery_pharmacy %>%
  gather(key = date, value = value, -State)
df.1$type <- "grocery_pharmacy"</pre>
# Data 2
parks <- read_csv("Data/Mobility/google-mobility-us-parks.csv")</pre>
df.2 <-
  parks %>%
  gather(key = date, value = value, -State)
df.2$type <- "parks"</pre>
# Data 3
residential <- read_csv("Data/Mobility/google-mobility-us-residential.csv")</pre>
df.3 <-
  residential %>%
  gather(key = date, value = value, -State)
df.3$type <- "residential"</pre>
# Data 4
retailAndRecreation <- read_csv("Data/Mobility/google-mobility-us-retailAndRecreation.csv")
df.4 <-
  retailAndRecreation %>%
  gather(key = date, value = value, -State)
df.4$type <- "retailAndRecreation"</pre>
# Data 5
transitStations <- read_csv("Data/Mobility/google-mobility-us-transitStations.csv")</pre>
df.5 <-
  transitStations %>%
  gather(key = date, value = value, -State)
df.5$type <- "transitStations"</pre>
# Data 6
workplaces <- read_csv("Data/Mobility/google-mobility-us-workplaces.csv")</pre>
```

```
df.6 <-
  workplaces %>%
  gather(key = date, value = value, -State)
df.6$type <- "workplaces"</pre>
mobility.data <-</pre>
  left join(df.1, df.2, by = c("State", "date", "value", "type")) %>%
  left join(df.3) %>%
  left_join(df.4) %>%
  left_join(df.5) %>%
  left_join(df.6)
mobility_data_long <- rbind(df.1, df.2,df.3,df.4,df.5,df.6)</pre>
mobility_data_wide <- spread(mobility_data_long, date, value)</pre>
Run Simple Triple Interaction Model and get Marginal Effects for Transportation
## set up bootstrap CI function
 bootstrapCI <- function(model, perc, boot_pred_data, type) {</pre>
  nr <- nrow(model$data)</pre>
  data <- model$data</pre>
  new_data <- data[sample(1:nr, size = nr, replace = TRUE), ]</pre>
  up <- update(model, data = new data)
  #norm <- sum(predict(up, newdata = new_data, type = 'response'), na.rm = TRUE)</pre>
  boot_pred_data[,"log_Pub_Trans"] <- boot_pred_data$log_Pub_Trans - (boot_pred_data$log_Pub_Trans*perc
  if (type == 'count') {
      perc_red <- sum(predict(up, newdata = boot_pred_data, type = 'response'), na.rm=TRUE)</pre>
  } else {
    perc_red <- mean(predict(up, newdata = boot_pred_data, type = 'response'), na.rm=TRUE)</pre>
 return(perc_red)
 }
#set up percentiles for trans reduction
percents \leftarrow c(0.0, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90)
#log transformation because the data is skewed forday 25 only
day25$log_pop_dense <- log(day25$popland+1)</pre>
day25$log_GDP <- log(day25$GDP+1)
day25$log_Pub_Trans <- log(day25$CommutingByPublicTransportation + 1)</pre>
#log transformation because the data is skewed forday 25 covars - 8 regions reduced compared to day25 d
day25_covars$log_pop_dense <- log(day25_covars$popland+1)</pre>
```

day25_covars\$log_Pub_Trans <- log(day25_covars\$CommutingByPublicTransportation + 1)</pre>

day25_covars\$log_GDP <- log(day25_covars\$GDP+1)</pre>

#models

```
est_day25_pois_model <- glm(ConfirmedCasesDay25~ log_pop_dense+log_GDP+log_Pub_Trans +
                        log(Population) +
                        `% Females raw value` +
                        '% 65 and older raw value' +
                        `Adult obesity raw value`+
                        `Physical inactivity raw value` +
                        `Unemployment raw value` +
                        `Income inequality raw value` +
                        `Poor or fair health raw value`+
                        `Uninsured adults raw value` +
                       `Adult smoking raw value`,
                       family = "poisson",
                       data = day25_covars,
                       offset(log(Population)))
est_day_snc_t1_pois_model <- glm(DayOfFirstCases~ log_pop_dense+log_GDP+log_Pub_Trans +
                        log(Population) +
                        `% Females raw value` +
                        `% 65 and older raw value` +
                        `Adult obesity raw value`+
                        `Physical inactivity raw value` +
                        `Unemployment raw value` +
                       `Income inequality raw value` +
                       `Poor or fair health raw value`+
                        `Uninsured adults raw value` +
                       `Adult smoking raw value`,
                       family = "gaussian",
                       data = day25_covars)
summary(est_day25_pois_model)
##
## glm(formula = ConfirmedCasesDay25 ~ log_pop_dense + log_GDP +
       log_Pub_Trans + log(Population) + `% Females raw value` +
##
       `% 65 and older raw value` + `Adult obesity raw value` +
##
       `Physical inactivity raw value` + `Unemployment raw value` +
##
##
       `Income inequality raw value` + `Poor or fair health raw value` +
##
       'Uninsured adults raw value' + 'Adult smoking raw value',
       family = "poisson", data = day25_covars, weights = offset(log(Population)))
##
##
## Deviance Residuals:
##
      Min
              1Q Median
                                  30
                                          Max
## -745.51 -94.18 -34.04
                                       878.19
                               25.02
##
## Coefficients:
                                    Estimate Std. Error z value Pr(>|z|)
##
## (Intercept)
                                  -6.324e+00 1.751e-02 -361.12 <2e-16 ***
                                  -2.770e+01 8.210e-02 -337.41 <2e-16 ***
## log_pop_dense
## log_GDP
                                  -1.221e-01 7.437e-04 -164.18 <2e-16 ***
                                   3.668e-01 3.064e-04 1197.13 <2e-16 ***
## log_Pub_Trans
## log(Population)
                                   3.866e-01 9.184e-04 420.96
                                                                   <2e-16 ***
## `% Females raw value`
                                  1.516e+01 3.665e-02 413.57
                                                                   <2e-16 ***
                                 -1.870e+00 9.375e-03 -199.43
## `% 65 and older raw value`
                                                                   <2e-16 ***
```

```
## `Adult obesity raw value`
                                   -1.053e+01 1.128e-02 -933.33
                                                                   <2e-16 ***
## `Physical inactivity raw value` 1.828e+01 9.862e-03 1853.18
                                                                   <2e-16 ***
## `Unemployment raw value`
                                    7.787e+00 3.085e-02 252.38
                                                                   <2e-16 ***
## `Income inequality raw value`
                                    1.274e-02 4.721e-04
                                                                   <2e-16 ***
                                                           26.99
## `Poor or fair health raw value` -4.566e+00
                                               1.459e-02 -312.89
                                                                   <2e-16 ***
## `Uninsured adults raw value`
                                   -5.089e+00 7.402e-03 -687.50
                                                                   <2e-16 ***
## `Adult smoking raw value`
                                    3.363e+00 1.345e-02 250.03
                                                                   <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
  (Dispersion parameter for poisson family taken to be 1)
##
##
       Null deviance: 48739096 on 445 degrees of freedom
## Residual deviance: 13412779 on 432 degrees of freedom
     (6 observations deleted due to missingness)
## AIC: 13459324
##
## Number of Fisher Scoring iterations: 6
summary(est_day_snc_t1_pois_model)
##
## Call:
  glm(formula = DayOfFirstCases ~ log_pop_dense + log_GDP + log_Pub_Trans +
##
       log(Population) + `% Females raw value` + `% 65 and older raw value` +
       `Adult obesity raw value` + `Physical inactivity raw value` +
##
##
       `Unemployment raw value` + `Income inequality raw value` +
##
       `Poor or fair health raw value` + `Uninsured adults raw value` +
       `Adult smoking raw value`, family = "gaussian", data = day25_covars)
##
##
## Deviance Residuals:
##
                      Median
                                   30
                                           Max
       Min
                 10
                       0.703
##
  -44.831
             -1.552
                                2.989
                                        12.243
## Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                                                12.2717
                                                          2.634
                                                                0.00875 **
                                     32.3189
## log_pop_dense
                                   -147.9050
                                               213.4755
                                                         -0.693
                                                                 0.48878
## log_GDP
                                     -1.0485
                                                 1.0050
                                                         -1.043 0.29739
## log_Pub_Trans
                                     0.5332
                                                 0.3133
                                                          1.702 0.08946
## log(Population)
                                     -1.2398
                                                 1.0829
                                                         -1.145
                                                                0.25290
## `% Females raw value`
                                     84.3859
                                                26.1392
                                                          3.228 0.00134 **
## `% 65 and older raw value`
                                     -6.6039
                                                 7.5673
                                                         -0.873 0.38332
## `Adult obesity raw value`
                                     -1.5171
                                                 9.4960
                                                         -0.160 0.87314
## `Physical inactivity raw value`
                                      4.4885
                                                10.2056
                                                          0.440
                                                                 0.66030
## `Unemployment raw value`
                                     57.8106
                                                34.4287
                                                          1.679 0.09385
## `Income inequality raw value`
                                     -0.9204
                                                 0.6006
                                                         -1.533 0.12611
## `Poor or fair health raw value`
                                    -38.8263
                                                19.1354
                                                         -2.029 0.04307 *
## `Uninsured adults raw value`
                                      6.6476
                                                 8.2232
                                                          0.808 0.41931
                                                          4.059 5.86e-05 ***
## `Adult smoking raw value`
                                     66.8955
                                                16.4819
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for gaussian family taken to be 41.9019)
##
```

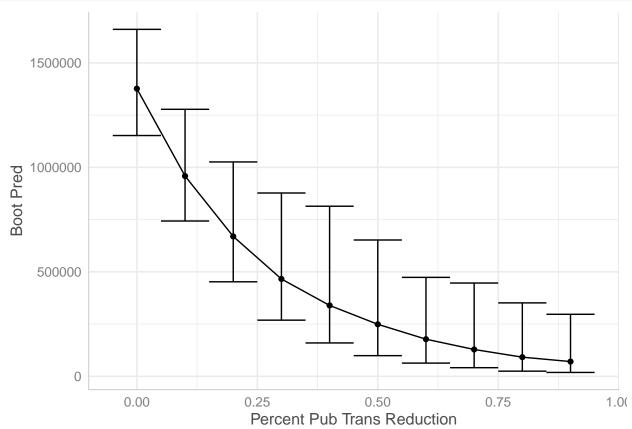
```
Null deviance: 22527 on 445 degrees of freedom
## Residual deviance: 18102 on 432 degrees of freedom
     (6 observations deleted due to missingness)
## AIC: 2947.4
## Number of Fisher Scoring iterations: 2
model_day25 <- est_day25_pois_model</pre>
model_snc_t1 <- est_day_snc_t1_pois_model</pre>
results_day25 <- as.data.frame(matrix(nrow = length(percents), ncol = 5))
colnames(results_day25) <- c('Percent Pub Trans Reduction',</pre>
                               'Boot Pred',
                               'Boot Low',
                               'Boot High',
                               'Init. Model Pred')
results_day_first <- as.data.frame(matrix(nrow = length(percents), ncol = 5))
colnames(results_day_first) <- c('Percent Pub Trans Reduction',</pre>
                                   'Boot Pred',
                                   'Boot Low',
                                   'Boot High',
                                   'Init. Model Pred')
for (i in 1:length(percents)) {
 perc <- percents[i]</pre>
 data_temp <- day25_covars
  data_temp$log_Pub_Trans <- day25_covars$log_Pub_Trans - (day25_covars$log_Pub_Trans*perc)
  pred_perc_red <- predict(model_day25, newdata = data_temp, type = 'response')</pre>
  pred_day_red <- predict(model_snc_t1, newdata = data_temp, type = 'response')</pre>
  sum_perc_red <- sum(pred_perc_red, na.rm = TRUE)</pre>
  mean_first_day <- mean(pred_day_red, na.rm = TRUE)</pre>
  boot_day25 <- replicate(1000, bootstrapCI(model = model_day25,</pre>
                                        perc = perc,
                                        boot_pred_data = day25_covars,
                                        type = 'count'))
  boot_day1 <- replicate(1000, bootstrapCI(model = model_snc_t1,</pre>
                                        perc = perc,
                                        boot_pred_data = day25_covars,
                                        type = 'day'))
  #mean_boot_diff <- mean(boot, na.rm = TRUE)</pre>
  CI_{boot_day25} \leftarrow quantile(boot_day25, probs = c(0.025, 0.50, 0.975), na.rm = TRUE)
  CI_boot_day1 <- quantile(boot_day1, probs = c(0.025,0.50, 0.975), na.rm = TRUE)
```

```
results_day25[i,1] <- perc
results_day25[i,2] <- CI_boot_day25[[2]]
results_day25[i,3] <- CI_boot_day25[[1]]
results_day25[i,4] <- CI_boot_day25[[3]]
results_day25[i,5] <- sum_perc_red

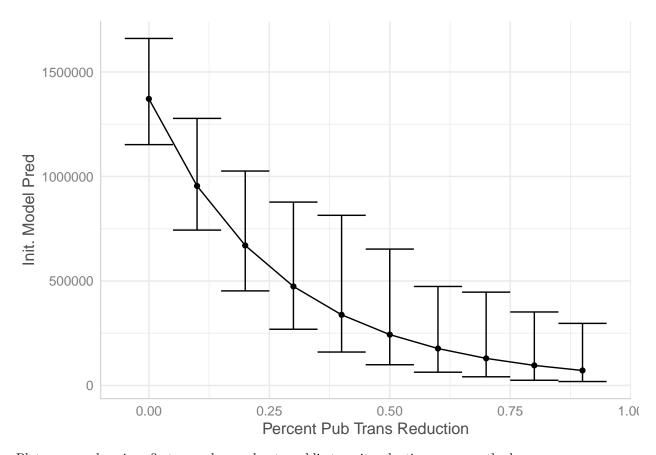
results_day_first[i,1] <- perc
results_day_first[i,2] <- CI_boot_day1[[2]]
results_day_first[i,3] <- CI_boot_day1[[1]]
results_day_first[i,4] <- CI_boot_day1[[3]]
results_day_first[i,5] <- mean_first_day
}</pre>
```

Plot cases over time marginally attributed to each reduction level - comparing bootstrap 50% percentile to initial model predictions as a sanity check of the bootstrap CI estimates:

```
ggplot(results_day25, aes(x=`Percent Pub Trans Reduction`, y=`Boot Pred`)) +
   geom_errorbar(aes(ymin=`Boot Low`, ymax=`Boot High`), width=.1) +
   geom_line() +
   geom_point()
```

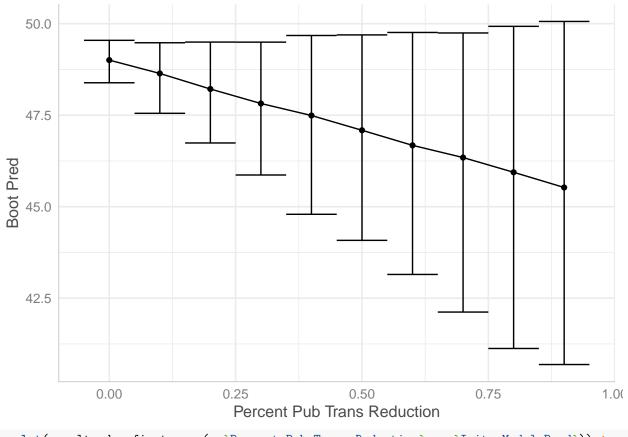


```
ggplot(results_day25, aes(x=`Percent Pub Trans Reduction`, y=`Init. Model Pred`)) +
   geom_errorbar(aes(ymin=`Boot Low`, ymax=`Boot High`), width=.1) +
   geom_line() +
   geom_point()
```

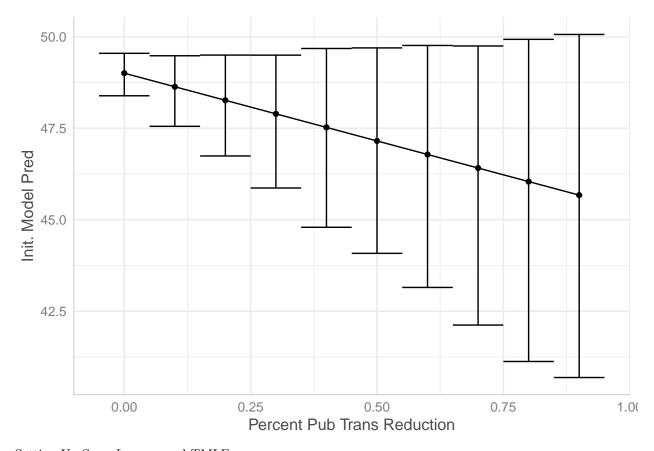


Plot average day since first case change due to public transit reduction, same method:

```
ggplot(results_day_first, aes(x=`Percent Pub Trans Reduction`, y=`Boot Pred`)) +
   geom_errorbar(aes(ymin=`Boot Low`, ymax=`Boot High`), width=.1) +
   geom_line() +
   geom_point()
```



```
ggplot(results_day_first, aes(x=`Percent Pub Trans Reduction`, y=`Init. Model Pred`)) +
   geom_errorbar(aes(ymin=`Boot Low`, ymax=`Boot High`), width=.1) +
   geom_line() +
   geom_point()
```



Setting Up SuperLearner and TMLE

Can include more covariates and not assuming linearity of the model - sanity check to make sure parametric model is sound:

```
##set up node list
node list <- list(</pre>
  W = c('popland', 'GDP',eco_vars_of_int[-c(1,2)]),
  A = "pub_trans_quantile",
  Y = "ConfirmedCasesDay25"
#process missing
processed <- process_missing(day25_covars, node_list)</pre>
COVID_data <- processed$data
node_list <- processed$node_list</pre>
ate_spec <- tmle_ATE(</pre>
  treatment_level = 10,
  control_level = 1
)
sl3_list_learners("continuous")
sl3_list_learners("binomial")
sl3_list_learners("categorical")
# choose y learners
```

```
lrnr_mean <- make_learner(Lrnr_mean)</pre>
lrnr_xgboost <- make_learner(Lrnr_xgboost)</pre>
Lrnr_glm <- make_learner(Lrnr_glm)</pre>
Lrnr_hal9001 <- make_learner(Lrnr_hal9001)</pre>
# choose a learners
Lrnr_grf <- make_learner(Lrnr_grf)</pre>
#Lrnr multivariate <- make learner(Lrnr multivariate)
# define metalearners appropriate to data types
ls_metalearner <- make_learner(Lrnr_nnls)</pre>
#mn_metalearner <- make_learner(Lrnr_solnp, metalearner_linear_multinomial,</pre>
                                 #loss_loglik_multinomial)
sl_Y <- Lrnr_sl$new(learners = list(lrnr_mean, lrnr_xgboost, Lrnr_glm, Lrnr_hal9001),</pre>
                     metalearner = ls_metalearner)
sl_A <- Lrnr_sl$new(learners = list(Lrnr_grf))</pre>
learner_list <- list(A = sl_A, Y = sl_Y)</pre>
tmle_fit <- tmle3(ate_spec, COVID_data, node_list, learner_list)</pre>
tmle_fit
estimates <- tmle_fit$summary$psi_transformed
estimates
Initial cross validated predictions: not used now
States <- unique(day25$State)</pre>
CV.risk <- matrix(NA, nrow=length(States), ncol=6)
#estimates<- matrix(NA, nrow=500, ncol=4)</pre>
ObsData <- day25
for(i in States){
idx <- match(i,States)</pre>
validation data <- ObsData %>% filter(State == i)
training_data <- ObsData %>% filter(State != i)
est1.model <- glm(ConfirmedCasesDay25 ~ popland + GDP + CommutingByPublicTransportation, family = "gaus
est2.model <- glm(ConfirmedCasesDay25 ~ popland + GDP + CommutingByPublicTransportation, family = "pois
est3.model <- glm(ConfirmedCasesDay25 ~ popland *GDP * CommutingByPublicTransportation, family = "gauss
est4.model <- glm(ConfirmedCasesDay25 ~ popland *GDP * CommutingByPublicTransportation, family = "poiss
est5.model <- glm(ConfirmedCasesDay25 ~ popland + GDP , family = "gaussian", data = training_data)
est6.model <- glm(ConfirmedCasesDay25 ~ popland + GDP, family = "poisson", data = training_data)
```

```
predict.est1 <- predict(est1.model, newdata = validation_data)</pre>
predict.est2 <- predict(est2.model, newdata = validation_data)</pre>
predict.est3 <- predict(est3.model, newdata = validation_data)</pre>
predict.est4 <- predict(est4.model, newdata = validation data)</pre>
predict.est5 <- predict(est5.model, newdata = validation_data)</pre>
predict.est6 <- predict(est6.model, newdata = validation_data)</pre>
#predict.est7 <- predict(est7.model, newdata = validation_data)</pre>
12.hat1 <- mean((validation data$ConfirmedCasesDay25 - predict.est1)^2)
12.hat2 <- mean((validation_data$ConfirmedCasesDay25 - predict.est2)^2)
12.hat3 <- mean((validation_data$ConfirmedCasesDay25 - predict.est3)^2)
12.hat4 <- mean((validation_data$ConfirmedCasesDay25 - predict.est4)^2)
12.hat5 <- mean((validation_data$ConfirmedCasesDay25 - predict.est5)^2)
12.hat6 <- mean((validation_data$ConfirmedCasesDay25 - predict.est6)^2)
#12.hat7 <- mean((validation_data$ConfirmedCasesDay25 - predict.est7)^2)
CV.risk[idx,] <- c(12.hat1, 12.hat2, 12.hat3, 12.hat4,12.hat5,12.hat6)
colnames(CV.risk) <- c("12.est1", "12.est2", "12.est3", "12.est4", "12.est5", "12.est6")</pre>
CV.risk <- as.data.frame(CV.risk)</pre>
CV.risk
mses <- colMeans(CV.risk, na.rm = TRUE)</pre>
match(mses, min(mses))
Y <- day25 ConfirmedCasesDay25
X <- subset(day25, select= -ConfirmedCasesDay25)</pre>
X <- as.data.frame(X)</pre>
Q_lib <- c("SL.mean", "SL.glmnet", "SL.ranger", "SL.rpartPrune", "SL.bayesglm")
g_lib <- c("SL.mean", "SL.glmnet")</pre>
vim <- varimpact(Y = Y, data = X, Q.library = Q_lib, g.library = g_lib, family="gaussian" )</pre>
vim$results all
plot_var("Population", vim)
Junk Drawer
boot_log <- replicate(1000, bootstrapCI(model = est1.log_model, newdata = newdata))</pre>
day25$uci_log <- apply(boot_log, MARGIN = 1, FUN = quantile, probs = 0.925, na.rm=TRUE)
day25$lci_log <- apply(boot_log, MARGIN = 1, FUN = quantile, probs = 0.025, na.rm=TRUE)
day25\fit_log <- apply(boot_log, MARGIN = 1, FUN = quantile, probs = 0.5, na.rm=TRUE)
day25$uci <- apply(boot, MARGIN = 1, FUN = quantile, probs = 0.925, na.rm=TRUE)
day25$lci <- apply(boot, MARGIN = 1, FUN = quantile, probs = 0.025, na.rm=TRUE)
day25\fit <- apply(boot, MARGIN = 1, FUN = quantile, probs = 0.5, na.rm=TRUE)
```

```
g3_log <- ggplot(day25, aes(x = day25$CommutingByPublicTransportation, y = ConfirmedCasesDay25)) +
  theme_bw() +
  geom_point() +
  geom_line(aes(y = fit)) +
  geom_ribbon(aes(ymin = lci, ymax = uci), alpha = 0.3)
g3_log
g3 <- ggplot(day25, aes(x = day25$CommutingByPublicTransportation, y = ConfirmedCasesDay25)) +
  theme bw() +
  geom_point() +
  geom_line(aes(y = fit_log)) +
  geom_ribbon(aes(ymin = lci_log, ymax = uci_log), alpha = 0.3)
g3
*predictions for 10 and 90 quantiles log model
predict.log_est_10 <- predict(est1.log_model, newdata = marginal_data_10, type='response')</pre>
predict.log_est_90 <- predict(est1.log_model, newdata = marginal_data_90, type='response')</pre>
#predictions for 10 and 90 quantiles
predict.est_10 <- predict(est1.model, newdata = marginal_data_10, type='response')</pre>
predict.est_90 <- predict(est1.model, newdata = marginal_data_90, type='response')</pre>
log_marg_10_90_diff <- mean(predict.log_est_90 - predict.log_est_10, na.rm = TRUE)</pre>
marg_10_90_diff <- mean(predict.est_90 - predict.est_10, na.rm = TRUE)</pre>
The marginal differences for public transportation at 90 vs. 10 percentile
marg_10_90_diff
log_marg_10_90_diff
```