Regression

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```
library(ISLR)
library(dplyr)
```

```
## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'pillar'
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(readr)
```

```
## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'hms'
```

```
library(broom)
```

```
## Warning: package 'broom' was built under R version 4.1.2
```

```
library(ggplot2)
library(splines)
library(tidymodels)
```

```
## Registered S3 method overwritten by 'tune':
##   method                   from
##   required_pkgs.model_spec parsnip
```

```
## -- Attaching packages -------------------------------------- tidymodels 0.1.4 --
```

```
## v dials        0.0.10     v tibble       3.1.6
## v infer        1.0.0      v tidyr        1.1.4
## v modeldata    0.1.1      v tune         0.1.6
## v parsnip      0.1.7      v workflows    0.2.4
## v purrr        0.3.4      v workflowsets 0.1.0
## v recipes      0.1.17     v yardstick    0.0.9
## v rsample      0.1.1

## -- Conflicts ----------------------------------------- tidymodels_conflicts() --
## x purrr::discard()  masks scales::discard()
## x dplyr::filter()   masks stats::filter()
## x dplyr::lag()      masks stats::lag()
## x yardstick::spec() masks readr::spec()
## x recipes::step()   masks stats::step()
## * Dig deeper into tidy modeling with R at https://www.tmwr.org
```

```
tidymodels_prefer()
```

```
COVID_State <- read.csv("COVID - State - Daily.csv", na.strings = ".")

Employment_State <- read.csv("Employment - State - Daily.csv", na.strings = ".")

Mobility_State <- read.csv("Google Mobility - State - Daily.csv", na.strings = ".")

Spending_State <- read.csv("Affinity - State - Daily.csv", na.strings = ".")
```

```
COVID_State$Date<-as.Date(with(COVID_State,paste(year,month,day,sep="-")),"%Y-%m-%d")

Employment_State$Date<-as.Date(with(Employment_State,paste(year,month,day,sep="-")),"%Y-%m-%d")

Mobility_State$Date<-as.Date(with(Mobility_State,paste(year,month,day,sep="-")),"%Y-%m-%d")

Spending_State$Date<-as.Date(with(Spending_State,paste(year,month,day,sep="-")),"%Y-%m-%d")

full_data <- merge(merge(merge(COVID_State, Employment_State, by=c("Date","statefips")), Mobility_State
```

```
## Warning in merge.data.frame(merge(merge(COVID_State, Employment_State, by =
## c("Date", : column names 'year.x', 'month.x', 'day.x', 'year.y', 'month.y',
## 'day.y' are duplicated in the result
```

```
head(full_data)
```

```
##         Date statefips year.x month.x day.x new_case_count new_death_count
## 1 2020-02-24         1   2020       2    24             NA              NA
## 2 2020-02-24        10   2020       2    24             NA              NA
## 3 2020-02-24        11   2020       2    24             NA              NA
## 4 2020-02-24        12   2020       2    24             NA              NA
## 5 2020-02-24        13   2020       2    24             NA              NA
## 6 2020-02-24        15   2020       2    24             NA              NA
##   case_count death_count vaccine_count fullvaccine_count booster_first_count
## 1         NA          NA            NA                NA                  NA
## 2         NA          NA            NA                NA                  NA
```

```
## 3        NA          NA           NA                NA                 NA
## 4        NA          NA           NA                NA                 NA
## 5        NA          NA           NA                NA                 NA
## 6        NA          NA           NA                NA                 NA
##   new_vaccine_count new_fullvaccine_count new_booster_first_count
## 1                NA                    NA                      NA
## 2                NA                    NA                      NA
## 3                NA                    NA                      NA
## 4                NA                    NA                      NA
## 5                NA                    NA                      NA
## 6                NA                    NA                      NA
##   new_test_count test_count hospitalized_count new_case_rate case_rate
## 1             NA         NA                 NA            NA        NA
## 2             NA         NA                 NA            NA        NA
## 3             NA         NA                 NA            NA        NA
## 4             NA         NA                 NA            NA        NA
## 5             NA         NA                 NA            NA        NA
## 6             NA         NA                  0            NA        NA
##   new_death_rate death_rate new_test_rate test_rate new_vaccine_rate
## 1             NA         NA            NA        NA               NA
## 2             NA         NA            NA        NA               NA
## 3             NA         NA            NA        NA               NA
## 4             NA         NA            NA        NA               NA
## 5             NA         NA            NA        NA               NA
## 6             NA         NA            NA        NA               NA
##   vaccine_rate new_fullvaccine_rate fullvaccine_rate new_booster_first_rate
## 1           NA                   NA               NA                     NA
## 2           NA                   NA               NA                     NA
## 3           NA                   NA               NA                     NA
## 4           NA                   NA               NA                     NA
## 5           NA                   NA               NA                     NA
## 6           NA                   NA               NA                     NA
##   booster_first_rate hospitalized_rate year.y month.y day.y      emp emp_incq1
## 1                 NA                NA   2020       2    24  0.01580   0.00751
## 2                 NA                NA   2020       2    24  0.00537  -0.02670
## 3                 NA                NA   2020       2    24       NA        NA
## 4                 NA                NA   2020       2    24  0.00448  -0.00263
## 5                 NA                NA   2020       2    24  0.00532  -0.00537
## 6                 NA                 0   2020       2    24 -0.03530  -0.07190
##   emp_incq2 emp_incq3 emp_incq4 emp_incmiddle emp_incbelowmed emp_incabovemed
## 1   0.02320   0.01680        NA       0.01960        0.013600          0.0183
## 2   0.00570   0.01680    0.0242       0.01170       -0.011400          0.0206
## 3        NA        NA        NA            NA              NA              NA
## 4  -0.00458   0.01070    0.0164       0.00324       -0.003550          0.0133
## 5   0.00520   0.00873    0.0140       0.00710       -0.000838          0.0114
## 6  -0.04920  -0.00520        NA      -0.02980       -0.058300         -0.0112
##    emp_ss40 emp_ss60 emp_ss65 emp_ss70 year.x month.x day.x
## 1  0.001540 -0.00399  0.05300 -0.01620   2020       2    24
## 2  0.015400  0.01340  0.01030 -0.05550   2020       2    24
## 3        NA       NA       NA       NA   2020       2    24
## 4 -0.002320  0.00134  0.00576  0.01620   2020       2    24
## 5 -0.000237  0.00168  0.00889  0.00964   2020       2    24
## 6  0.054800       NA       NA -0.01530   2020       2    24
##   gps_retail_and_recreation gps_grocery_and_pharmacy gps_parks
```

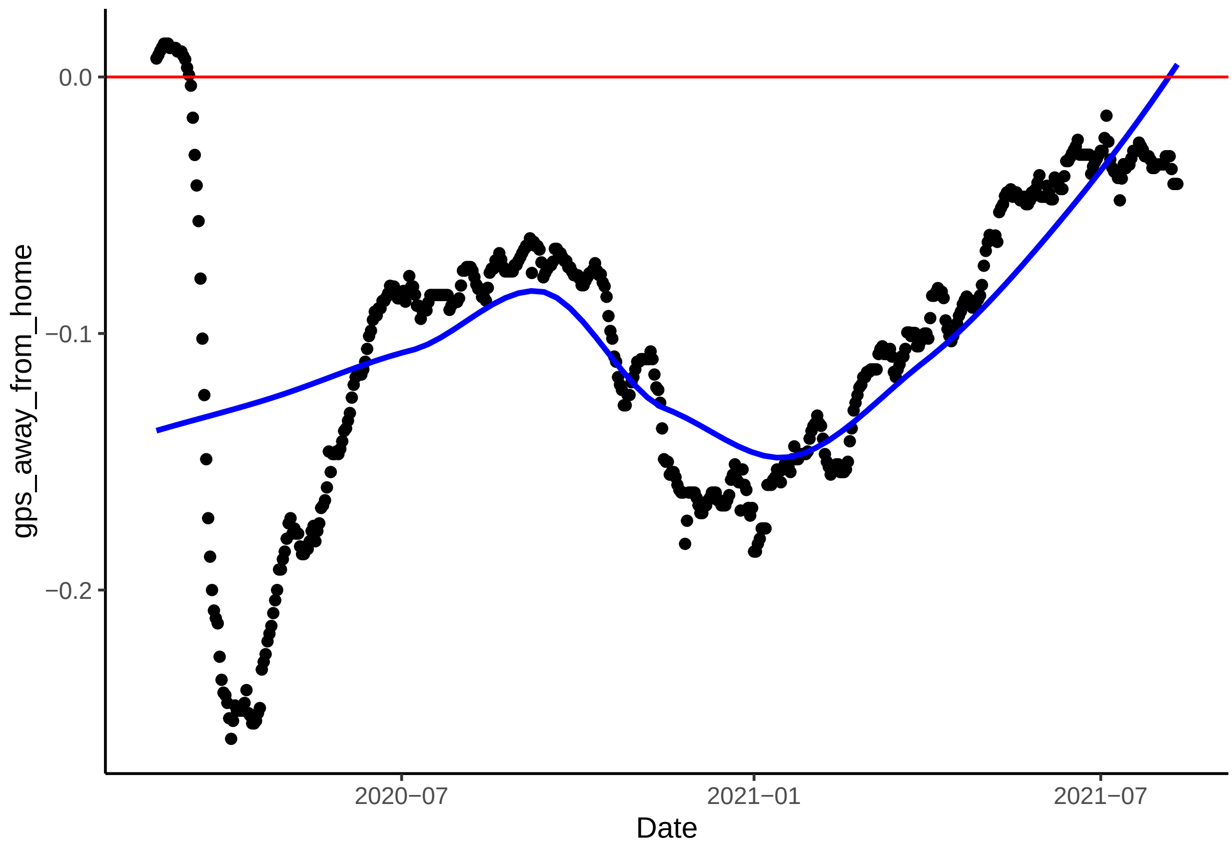
```
## 1                   0.00286                 -0.00714    0.0557
## 2                   0.03710                  0.01290    0.2340
## 3                  -0.01140                 -0.03290    0.1400
## 4                   0.02710                  0.00714    0.0943
## 5                  -0.00571                 -0.02290    0.0186
## 6                   0.01140                 -0.00571    0.0814
##   gps_transit_stations gps_workplaces gps_residential gps_away_from_home year.y
## 1              0.06000        0.01290         0.00857           -0.00798   2020
## 2              0.07000        0.02860        -0.00571            0.00850   2020
## 3              0.00571       -0.01430         0.00714           -0.00492   2020
## 4              0.03430        0.01000         0.00143           -0.00138   2020
## 5              0.01710       -0.01140         0.01000           -0.00781   2020
## 6              0.02570        0.00714         0.00143           -0.00049   2020
##   month.y day.y freq spend_all spend_aap spend_acf spend_aer spend_apg
## 1       2    24    d   -0.0198   -0.1320   -0.0220   -0.1000   -0.0810
## 2       2    24    d   -0.0461    0.1130   -0.0279   -0.6280    0.4140
## 3       2    24    d    0.0192   -0.1280   -0.0113    0.0740   -0.0855
## 4       2    24    d   -0.0452   -0.0847   -0.0493   -0.1020   -0.0675
## 5       2    24    d   -0.0163   -0.0321   -0.0334    0.0287   -0.0308
## 6       2    24    d   -0.0504   -0.1210   -0.0447   -0.1650   -0.0851
##   spend_durables spend_nondurables spend_grf spend_gen spend_hic spend_hcs
## 1        -0.0317          -0.04750   -0.0223  -0.01050  -0.06180  -0.07310
## 2         0.0208           0.13400   -0.0284   0.63600   0.13400  -0.01060
## 3         0.0311          -0.00364    0.0294   0.00856   0.59500   0.02630
## 4        -0.0492          -0.04720   -0.0468  -0.03810  -0.08320   0.00175
## 5        -0.0164          -0.02450   -0.0110  -0.03000  -0.00361  -0.02010
## 6        -0.0118          -0.04380   -0.0173  -0.04770   0.16600  -0.08730
##   spend_inpersonmisc spend_remoteservices spend_sgh spend_tws
## 1             0.0062              0.02110   -0.0453   -0.1020
## 2            -0.1380             -0.15500   -0.1540   -0.0929
## 3             0.2100             -0.03610   -0.1230   -0.1360
## 4            -0.0815             -0.04600   -0.0426   -0.1030
## 5            -0.0658             -0.00774    0.0940   -0.1060
## 6            -0.0645             -0.04000   -0.2270   -0.0909
##   spend_retail_w_grocery spend_retail_no_grocery spend_all_incmiddle
## 1               -0.03910                 -0.0459            -0.02970
## 2                0.10200                  0.1560            -0.06480
## 3               -0.00169                 -0.0124            -0.06430
## 4               -0.04390                 -0.0421            -0.03880
## 5               -0.01640                 -0.0176            -0.01870
## 6               -0.03610                 -0.0498             0.00268
##   spend_all_q1 spend_all_q2 spend_all_q3 spend_all_q4 provisional
## 1      -0.0158      -0.0717     0.036100     0.009840           0
## 2       0.2240      -0.0565    -0.068700    -0.016000           0
## 3      -0.0265      -0.5850    -0.047300     0.039400           0
## 4      -0.0677      -0.0420    -0.035100    -0.035700           0
## 5      -0.0386      -0.0234    -0.015600    -0.000937           0
## 6           NA       0.0134     0.000257    -0.076700           0
```

```
full_data1 <- full_data %>%
  select(-year.x, -month.x, -day.x, - year.y, -month.y, -day.y, -year.x )

# Creating a Dummy Variable that is yes from entry 22 to 50, the period of dramatic change.
full_data1 <- mutate(full_data1, dummy_spend_fall = if_else(Date >= "2020-03-16" & Date <= "2020-04-13"
```

```
minnesota <- full_data1 %>%
  filter(statefips==27)
```

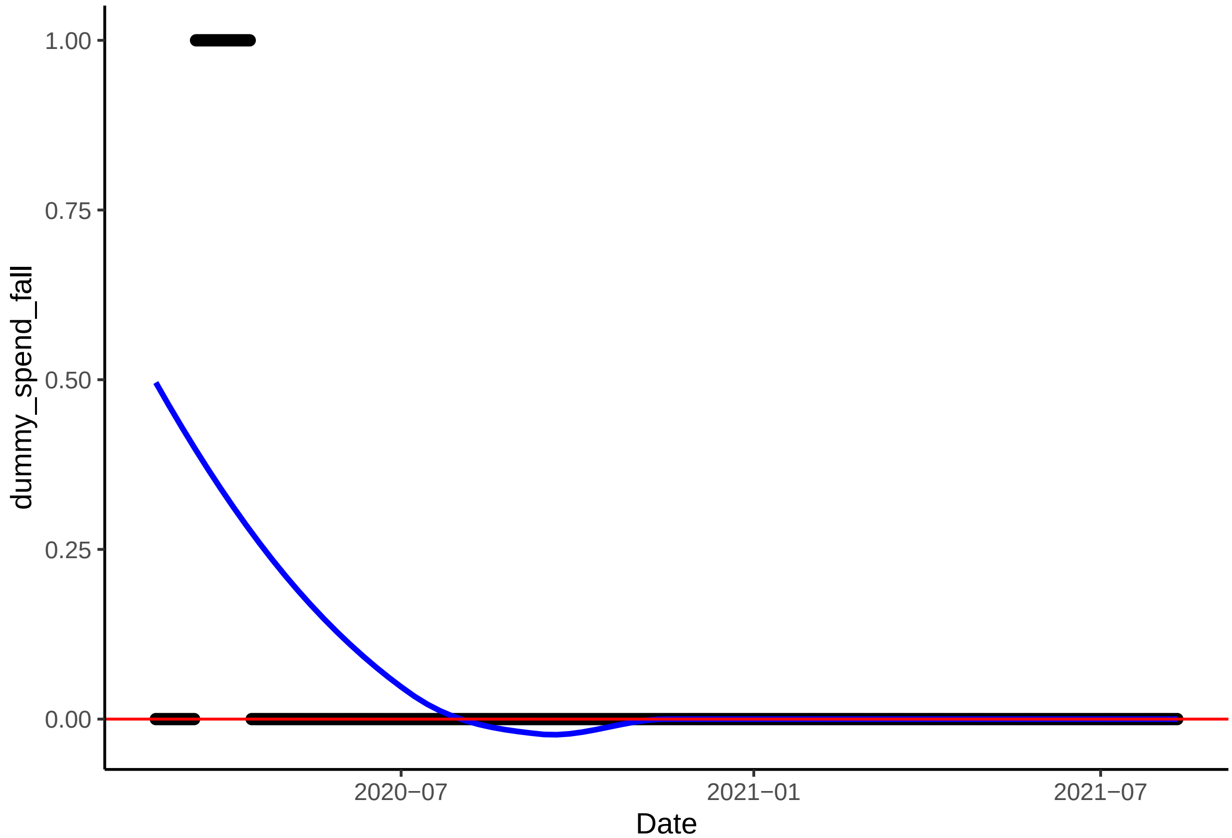
```
ggplot(minnesota, aes(y = gps_away_from_home, x = Date)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
ggplot(minnesota, aes(y = dummy_spend_fall, x = Date)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
#ggplot(mn_mod_output_lasso, aes(y = resid, x = Date)) +
#    geom_point() +
#    geom_smooth(color = "blue", se = FALSE) +
#    geom_hline(yintercept = 0, color = "red") +
#    theme_classic()
#
#tmp <- mn_mod_output_lasso
#tmp$resid
```

Here we can see the data combined. N/A slots represent cases were there was no value to enter or where data was missing.

```
#OLS
set.seed(123)

folded_mn <- vfold_cv(minnesota, v = 6)

lm_spec <-
  linear_reg() %>%
  set_engine(engine = 'lm') %>%
  set_mode('regression')

full_rec <- recipe(gps_away_from_home ~  fullvaccine_rate + case_rate + hospitalized_rate + emp_incq1 +
  step_normalize(all_numeric_predictors()) %>%
  step_dummy(all_nominal_predictors())%>%
```

```
  step_nzv(all_predictors())

full_rec_dummy <- recipe(gps_away_from_home ~  fullvaccine_rate + case_rate + hospitalized_rate + emp_in
  step_normalize(all_numeric_predictors()) %>%
  step_dummy(all_nominal_predictors())%>%
  step_nzv(all_predictors())

mn_model_wf <- workflow() %>%
  add_recipe(full_rec) %>%
  add_model(lm_spec)

mn_model_dumy_wf <- workflow() %>%
  add_recipe(full_rec_dummy) %>%
  add_model(lm_spec)

#CV is to see how well the model is doing
mnFullMod_cv <- fit_resamples(mn_model_wf,
  resamples = folded_mn,
  control = control_resamples(save_pred = TRUE),
  metrics = metric_set(rmse, rsq, mae))
```

```
## Warning: package 'rlang' was built under R version 4.1.2
```

```
mnFullMod_cv %>% collect_metrics(summarize=TRUE)
```

```
## # A tibble: 3 x 6
##   .metric .estimator    mean     n  std_err .config
##   <chr>   <chr>        <dbl> <int>    <dbl> <chr>
## 1 mae     standard   0.00463     6 0.000223 Preprocessor1_Model1
## 2 rmse    standard   0.00589     6 0.000310 Preprocessor1_Model1
## 3 rsq     standard   0.965       6 0.00447  Preprocessor1_Model1
```

```
mn_mod <- mn_model_wf %>% fit(data=minnesota)

#with Dummy fo dramatic drop in spending
mnFullMod_cv_dumy <- fit_resamples(mn_model_dumy_wf,
  resamples = folded_mn,
  control = control_resamples(save_pred = TRUE),
  metrics = metric_set(rmse, rsq, mae))
```

```
## ! Fold1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold6: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```r
mnFullMod_cv_dumy %>% collect_metrics(summarize=TRUE)
```

```
## # A tibble: 3 x 6
##   .metric .estimator    mean     n  std_err .config
##   <chr>   <chr>        <dbl> <int>    <dbl> <chr>
## 1 mae     standard   0.00463     6 0.000223 Preprocessor1_Model1
## 2 rmse    standard   0.00589     6 0.000310 Preprocessor1_Model1
## 3 rsq     standard   0.965       6 0.00447  Preprocessor1_Model1
```

```r
mn_mod_dummy <- mn_model_dumy_wf %>% fit(data=minnesota)
```

```r
mn_mod_output_OLS <- mn_mod %>%
  predict(new_data=minnesota) %>%
  bind_cols(minnesota)%>%
    mutate(resid = gps_away_from_home - .pred)

mn_mod_output_OLS <- mn_mod_dummy %>%
  predict(new_data=minnesota) %>%
  bind_cols(minnesota)%>%
    mutate(resid = gps_away_from_home - .pred)
```

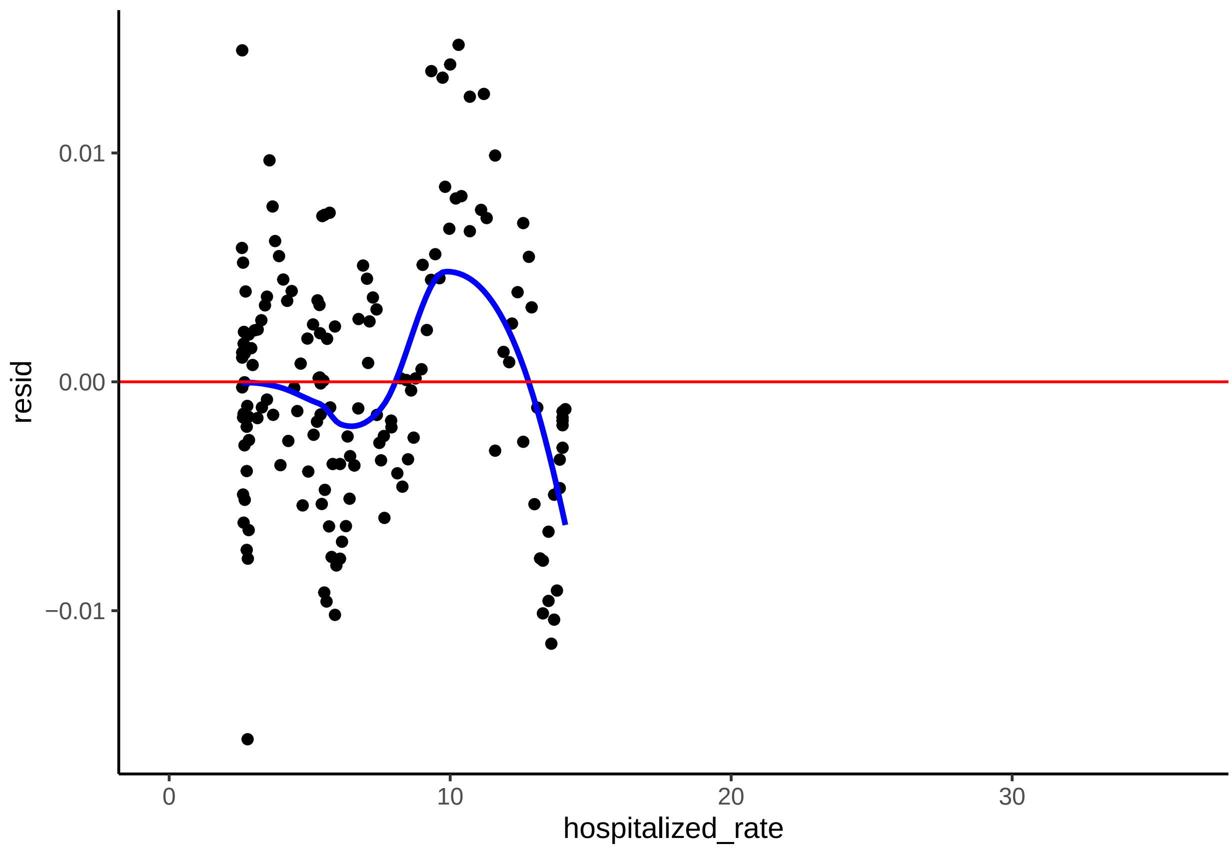
```
## Warning in predict.lm(object = object$fit, newdata = new_data, type =
## "response"): prediction from a rank-deficient fit may be misleading
```

```r
ggplot(mn_mod_output_OLS, aes(y = resid, x = hospitalized_rate)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

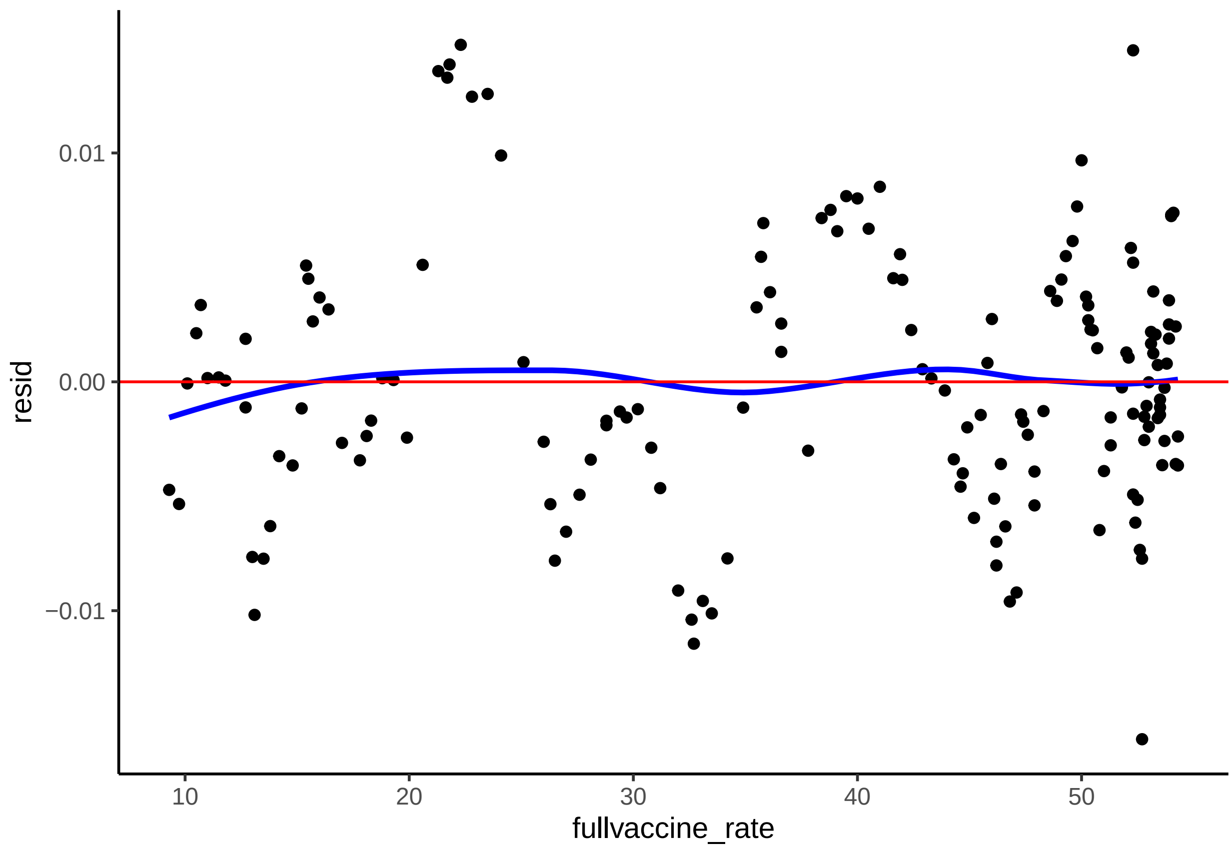
```
## Warning: Removed 375 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 375 rows containing missing values (geom_point).
```




```
ggplot(mn_mod_output_OLS, aes(y = resid, x = fullvaccine_rate)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 375 rows containing non-finite values (stat_smooth).

## Warning: Removed 375 rows containing missing values (geom_point).
```

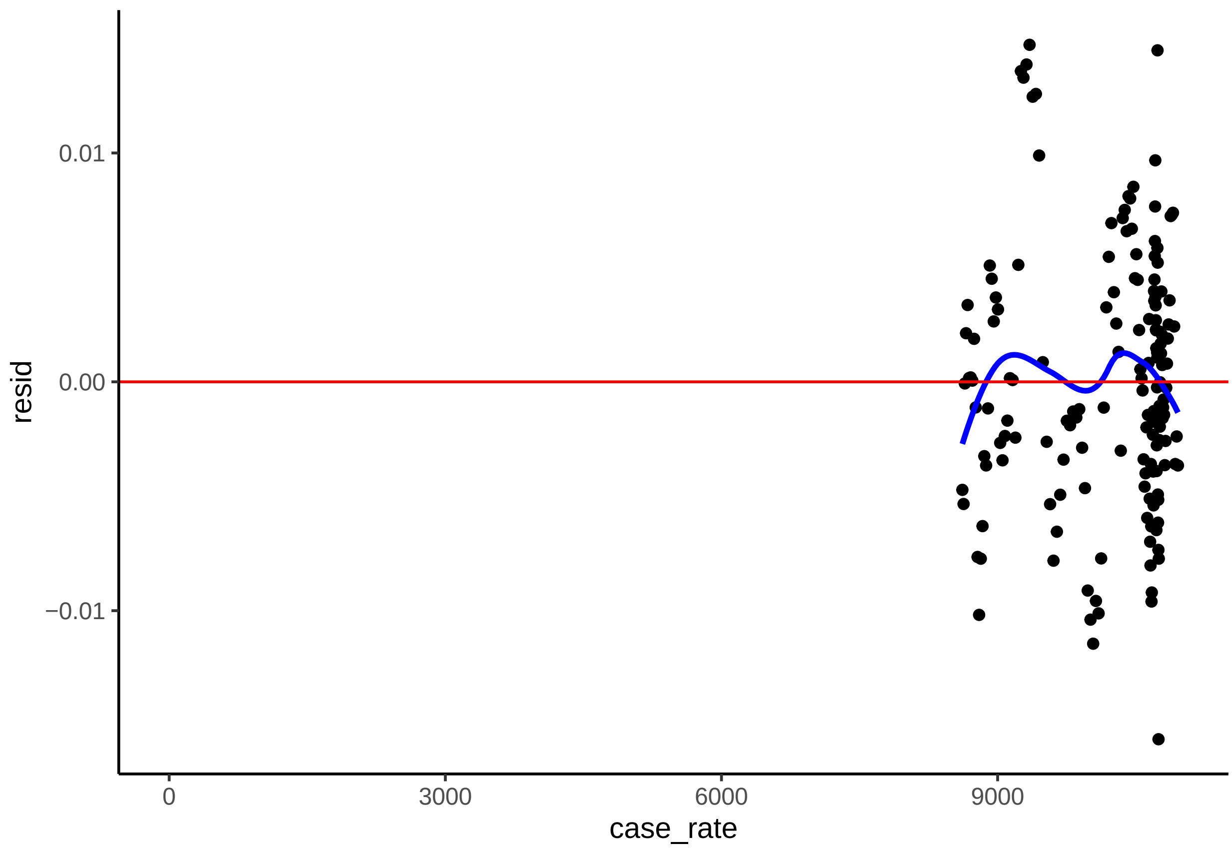



```
ggplot(mn_mod_output_OLS, aes(y = resid, x = case_rate)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

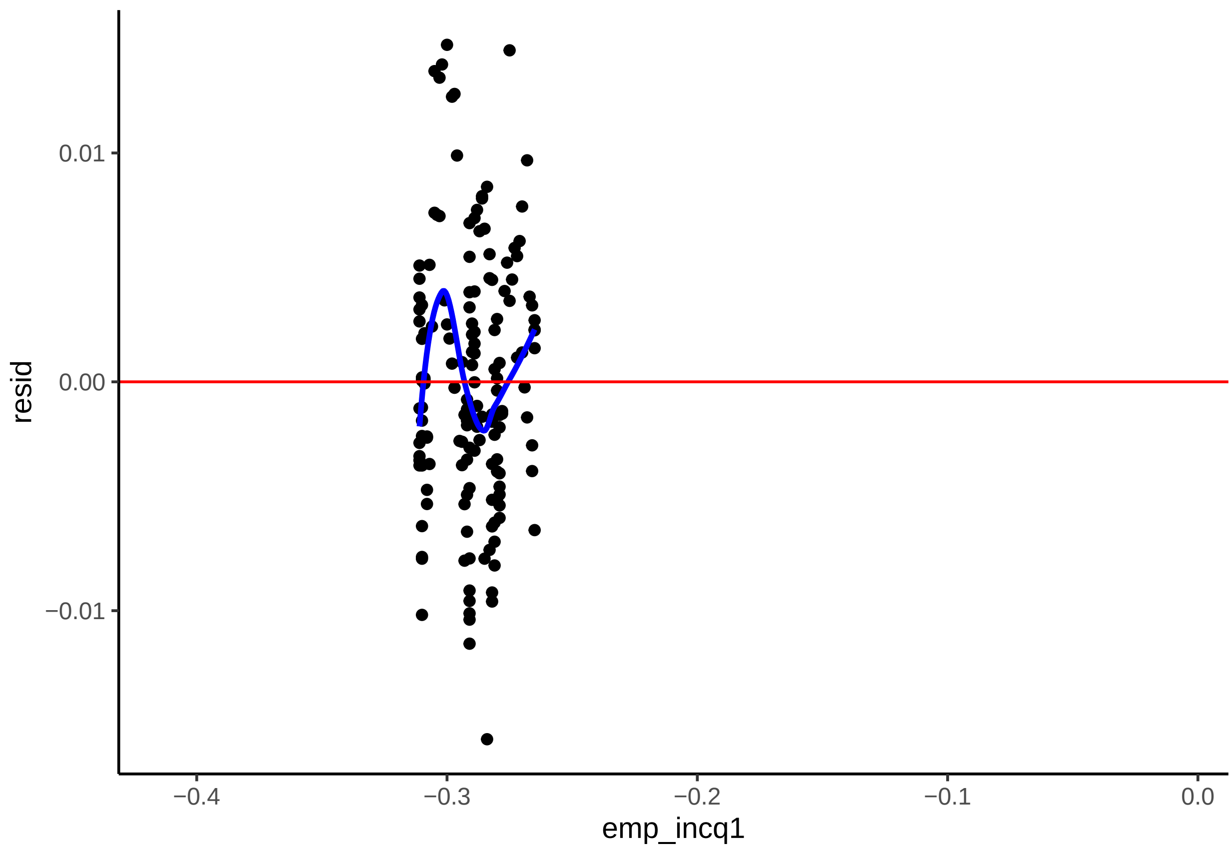
```
## Warning: Removed 375 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 375 rows containing missing values (geom_point).
```



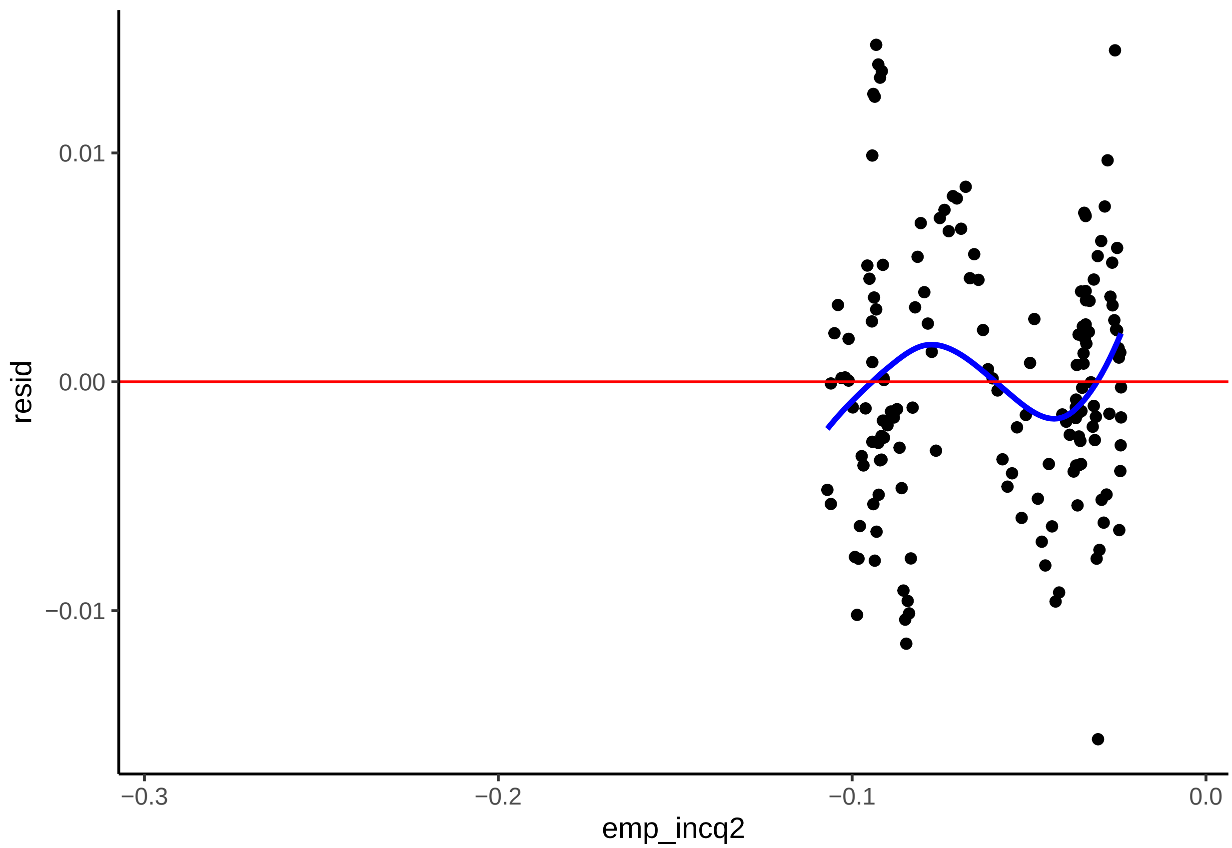

```
ggplot(mn_mod_output_OLS, aes(y = resid, x = emp_incq1)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 375 rows containing non-finite values (stat_smooth).

## Warning: Removed 375 rows containing missing values (geom_point).
```



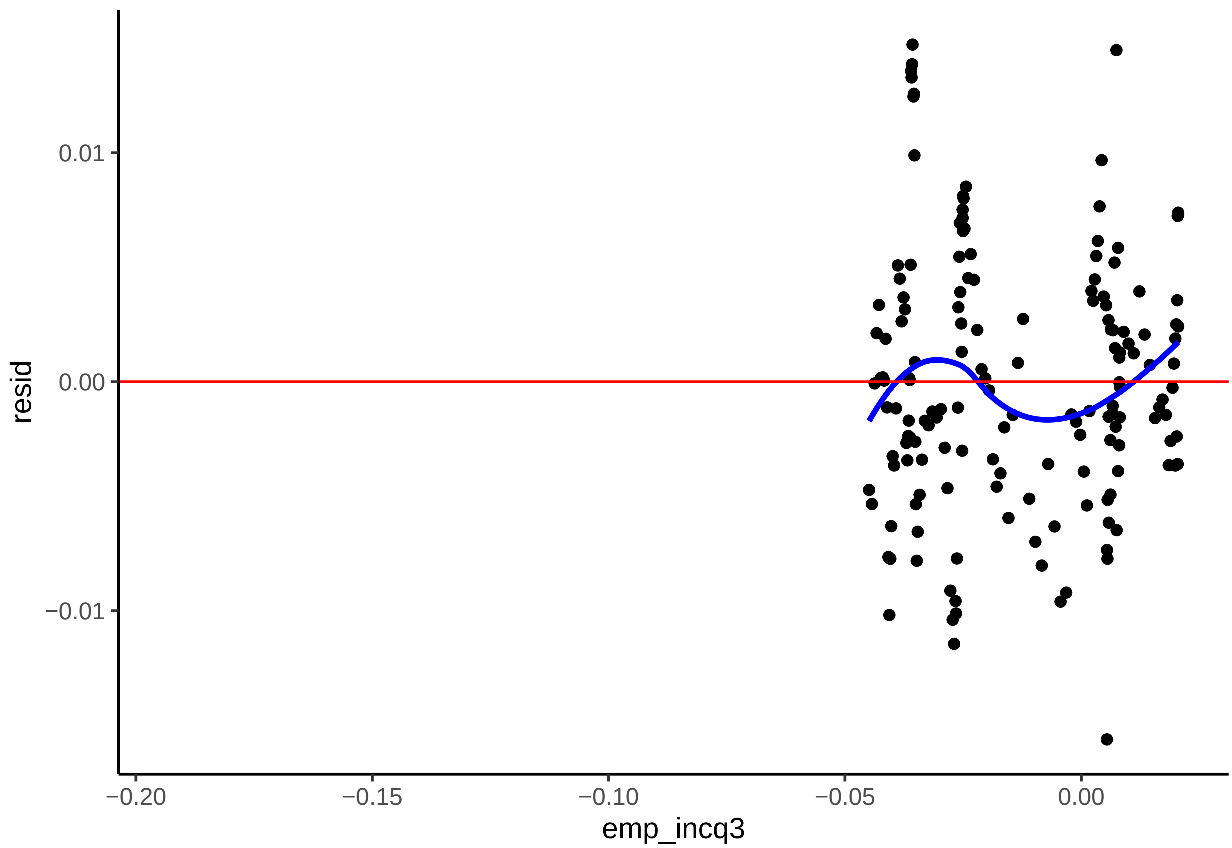

```
ggplot(mn_mod_output_OLS, aes(y = resid, x = emp_incq2)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 375 rows containing non-finite values (stat_smooth).

## Warning: Removed 375 rows containing missing values (geom_point).
```




```r
ggplot(mn_mod_output_OLS, aes(y = resid, x = emp_incq3)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 375 rows containing non-finite values (stat_smooth).

## Warning: Removed 375 rows containing missing values (geom_point).
```

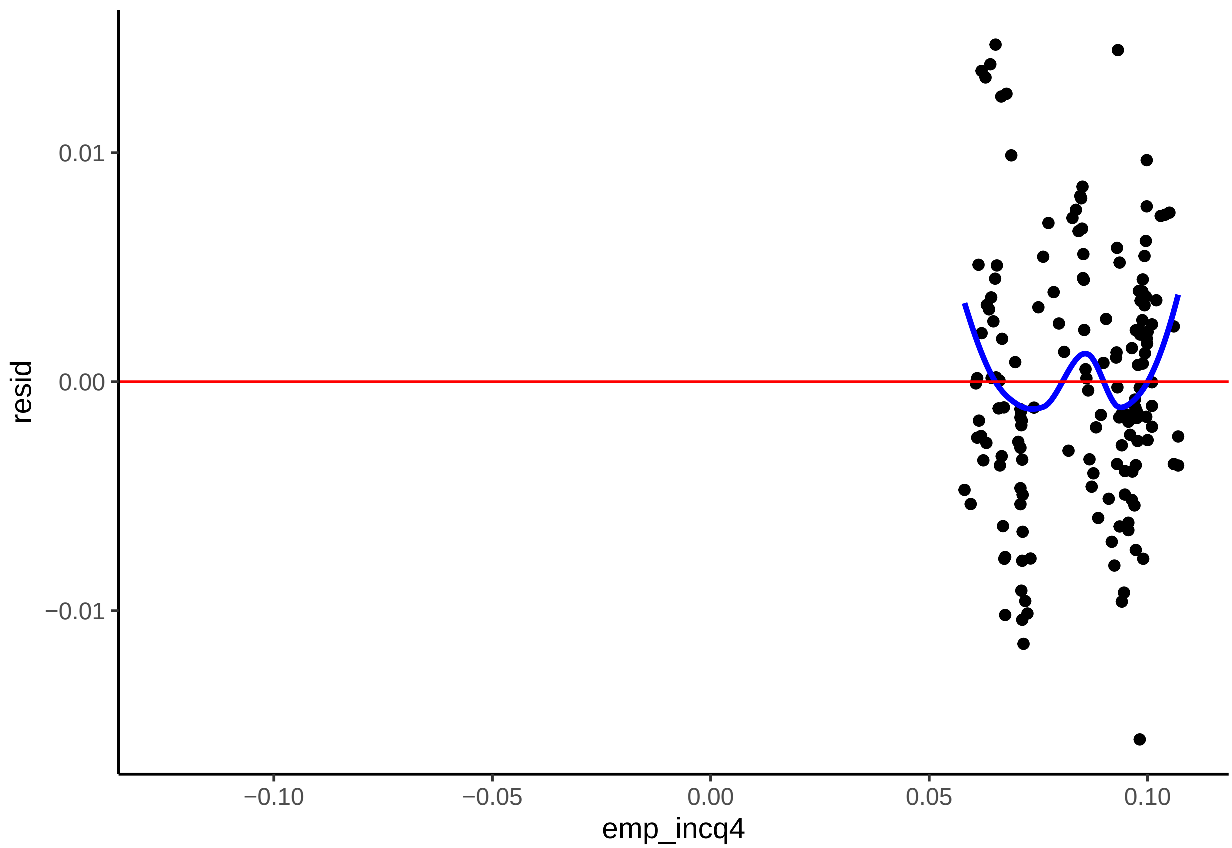



```
ggplot(mn_mod_output_OLS, aes(y = resid, x = emp_incq4)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

```
## Warning: Removed 375 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 375 rows containing missing values (geom_point).
```

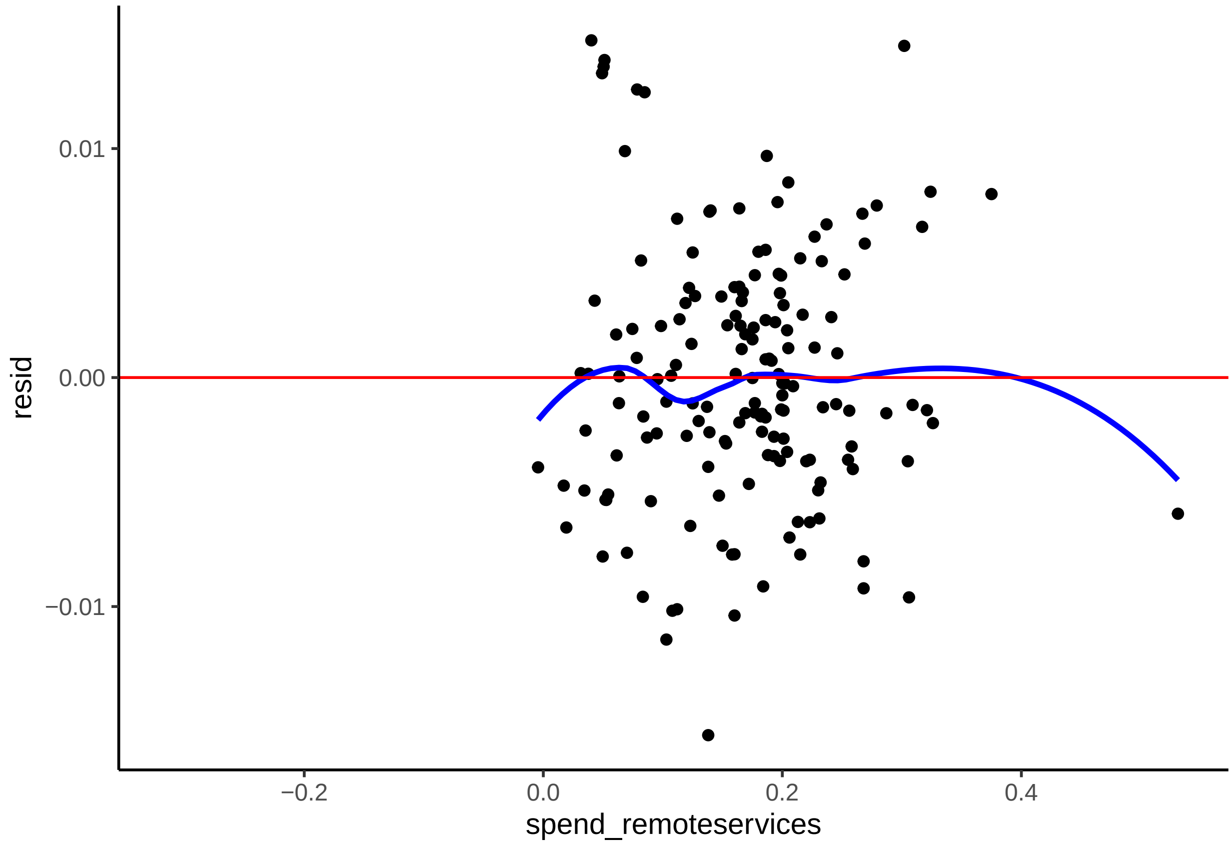



```
ggplot(mn_mod_output_OLS, aes(y = resid, x = spend_remoteservices)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

```
## Warning: Removed 375 rows containing non-finite values (stat_smooth).
```

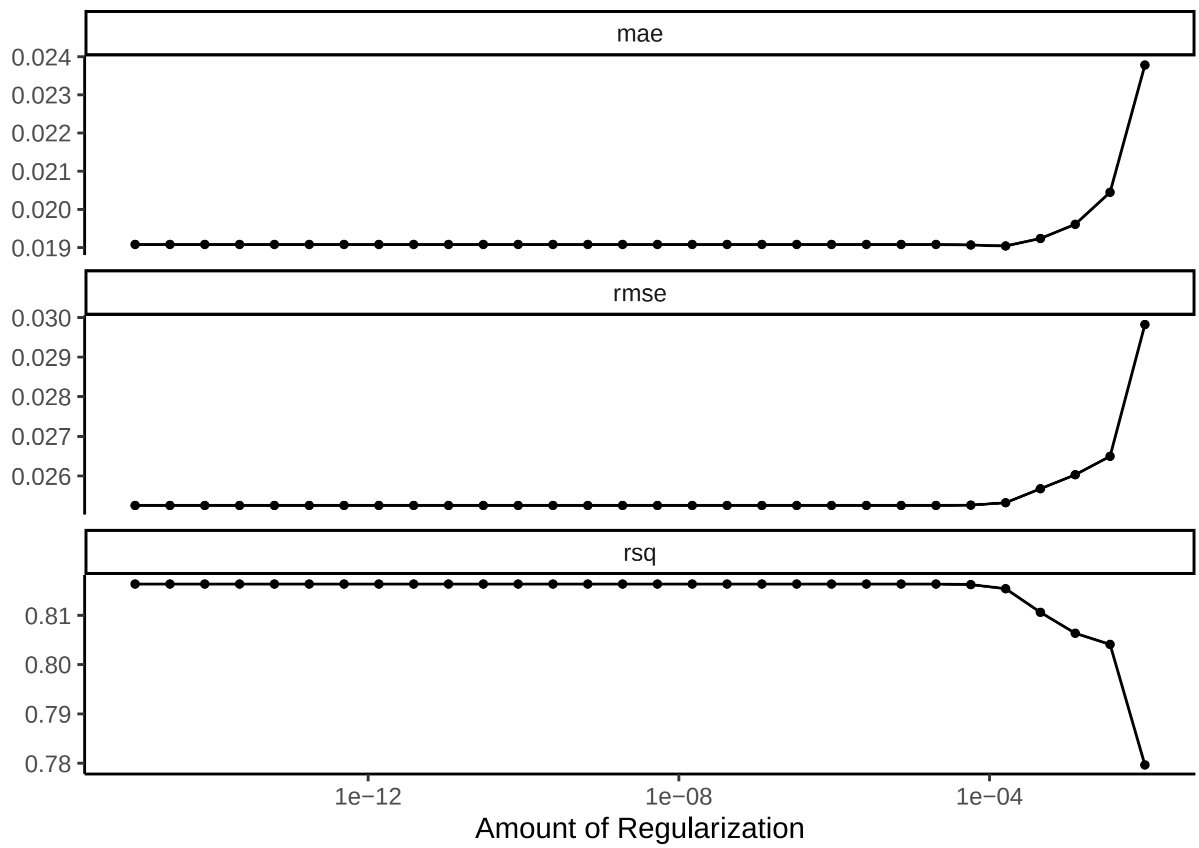
```
## Warning: Removed 375 rows containing missing values (geom_point).
```



Here we have the summery data for our basic best fit model. We can see that the standard error is about three hundredths of a percent; this is very low for predicting in a range of up to 10 % change but is more significant for most days when there is very little change in average movement.

```
#LASSO
set.seed(123)

folded_mn <- vfold_cv(minnesota, v = 6)

lm_lasso_spec <-
  linear_reg() %>%
  set_args(mixture = 1, penalty = tune()) %>% ## mixture = 1 indicates Lasso, we'll choose penalty later
  set_engine(engine = 'glmnet') %>%
  set_mode('regression')

full_lasso_rec <- recipe(gps_away_from_home ~  fullvaccine_rate + case_rate + hospitalized_rate  + emp_
  step_normalize(all_numeric_predictors()) %>%
  step_dummy(all_nominal_predictors())%>%
  step_nzv(all_predictors())

mn_lasso_wf_tune <- workflow() %>%
  add_recipe(full_lasso_rec) %>%
  add_model(lm_lasso_spec)

# Tune Model (trying a variety of values of Lambda penalty)
penalty_grid <- grid_regular(
```

```r
  penalty(range = c(-15, -2)), #log10 transformed 10^-5 to 10^3
  levels = 30)

tune_res <- tune_grid( # new function for tuning parameters
  mn_lasso_wf_tune, # workflow
  resamples = folded_mn, # cv folds
  metrics = metric_set(rmse, rsq, mae),
  grid = penalty_grid # penalty grid defined above
)

# Visualize Model Evaluation Metrics from Tuning
autoplot(tune_res) + theme_classic()
```




```r
# Summarize Model Evaluation Metrics (CV)
collect_metrics(tune_res) %>%
  filter(.metric == 'rmse') %>% # or choose mae
  select(penalty, rmse = mean)
```

```
## # A tibble: 30 x 2
##     penalty   rmse
##       <dbl>  <dbl>
##  1 1    e-15 0.0253
##  2 2.81e-15 0.0253
##  3 7.88e-15 0.0253
##  4 2.21e-14 0.0253
```

```
##  5 6.21e-14 0.0253
##  6 1.74e-13 0.0253
##  7 4.89e-13 0.0253
##  8 1.37e-12 0.0253
##  9 3.86e-12 0.0253
## 10 1.08e-11 0.0253
## # ... with 20 more rows
```

```
best_penalty <- select_best(tune_res, metric = 'rmse') # choose penalty value based on lowest mae or rm
```

```
# Fit Final Model
final_wf <- finalize_workflow(mn_lasso_wf_tune, best_penalty) # incorporates penalty value to workflow

final_fit <- fit(final_wf, data = minnesota)

tidy(final_fit)
```

```
## # A tibble: 9 x 3
##   term                 estimate penalty
##   <chr>                   <dbl>   <dbl>
## 1 (Intercept)          -0.105     1e-15
## 2 fullvaccine_rate      0         1e-15
## 3 case_rate             0         1e-15
## 4 hospitalized_rate     0.00224   1e-15
## 5 emp_incq1             0.0290    1e-15
## 6 emp_incq2            -0.0268    1e-15
## 7 emp_incq3             0.0459    1e-15
## 8 emp_incq4             0.00832   1e-15
## 9 spend_remoteservices  0.0144    1e-15
```

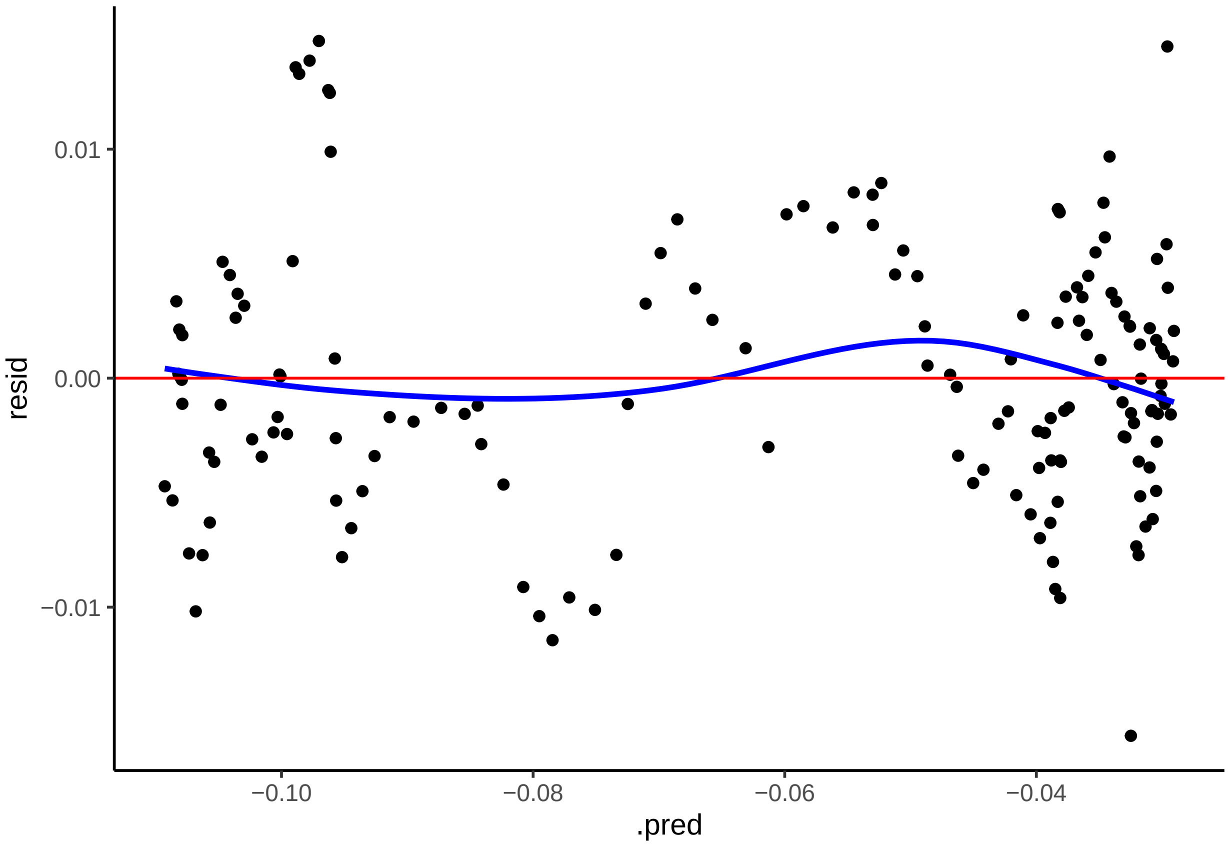
Here we can see that the Penalty for the lasso model has very little effect on the RMSE until it gets quite high. This is probably because some predictors are quickly eliminated and the more important ones are not removed until much later.

```
#Residual Plots
#OLS
mn_mod_output <- mn_mod %>%
    predict(new_data = minnesota) %>%
    bind_cols(minnesota)%>%
    mutate(resid = gps_away_from_home - .pred)

ggplot(mn_mod_output, aes(y = resid, x = .pred)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

```
## Warning: Removed 375 rows containing non-finite values (stat_smooth).
```

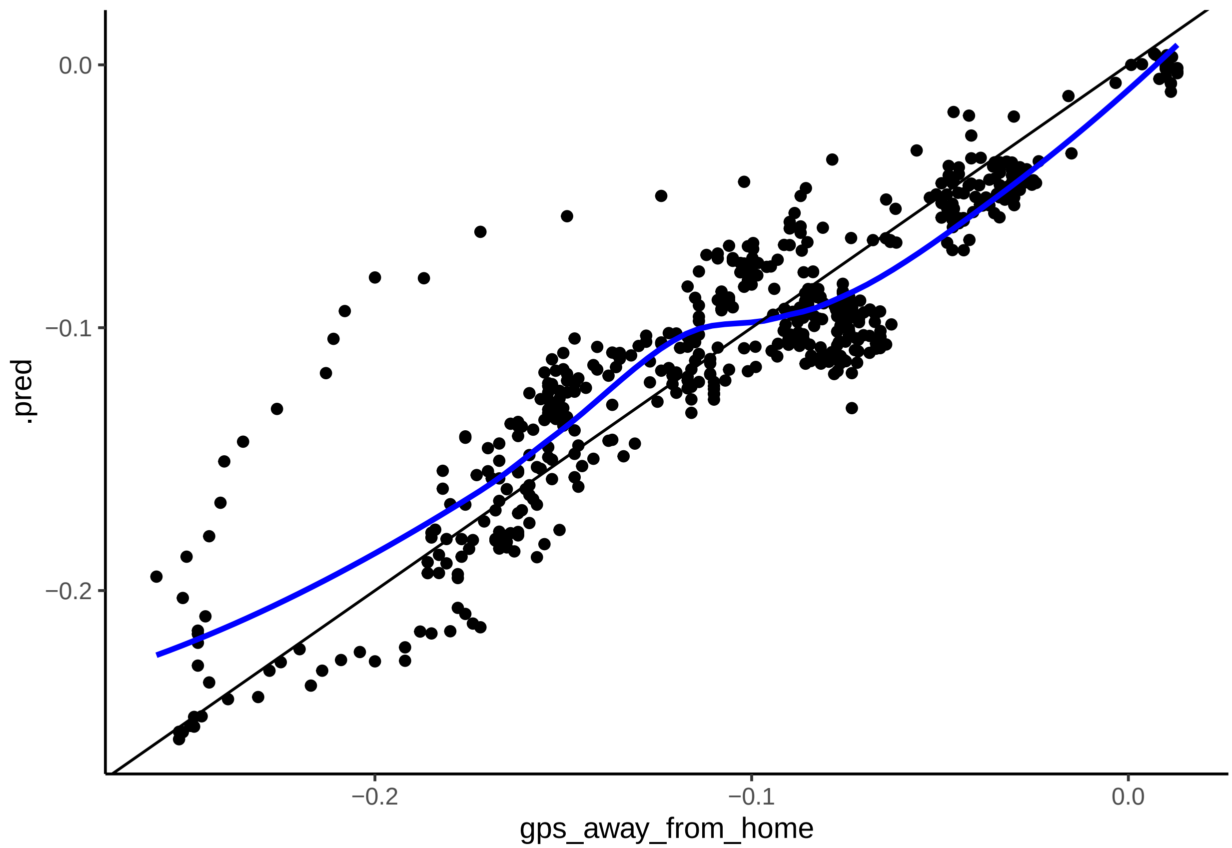
```
## Warning: Removed 375 rows containing missing values (geom_point).
```



Our model seems to be fairly randomly distributed around the middle line. There is, however, a concerning lack of predictions in the area above the 0 line around -0.09 and below the 0 line around -0.045.

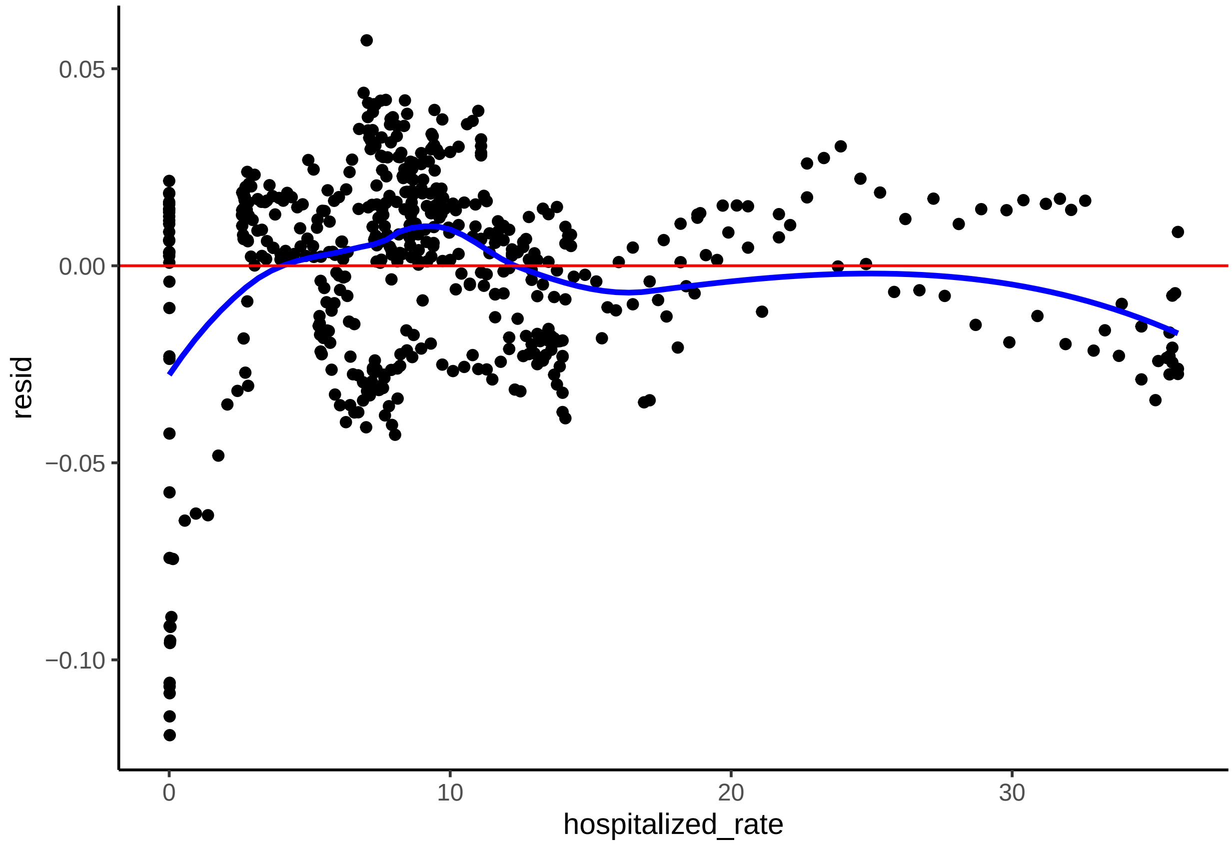
```
#LASSO residual plots
mn_mod_output_lasso <- final_fit %>%
  predict(new_data=minnesota) %>%
  bind_cols(minnesota)%>%
    mutate(resid = gps_away_from_home - .pred)

ggplot(mn_mod_output_lasso, aes(y = .pred, x = gps_away_from_home)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_abline(intercept = 0, slope = 1) +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
ggplot(mn_mod_output_lasso, aes(y = resid, x = hospitalized_rate)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

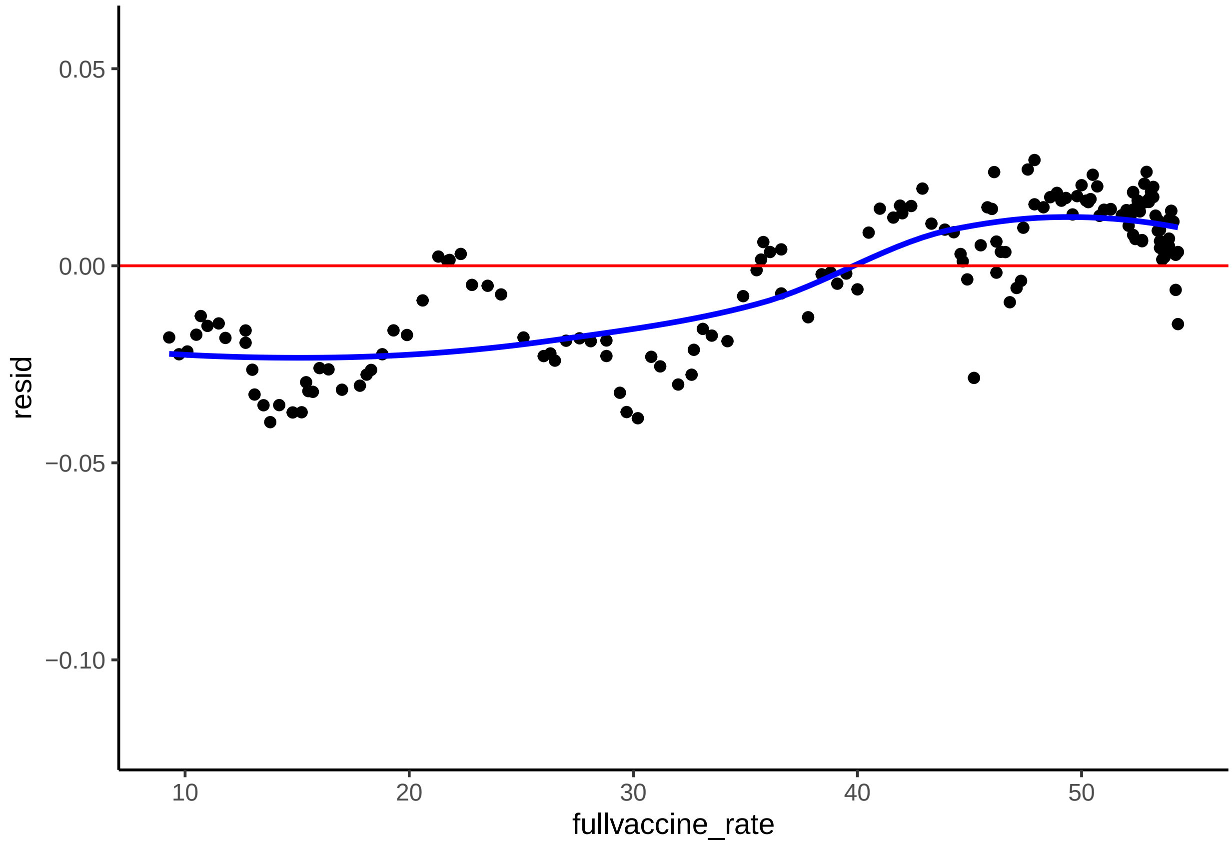



```
ggplot(mn_mod_output_lasso, aes(y = resid, x = fullvaccine_rate)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

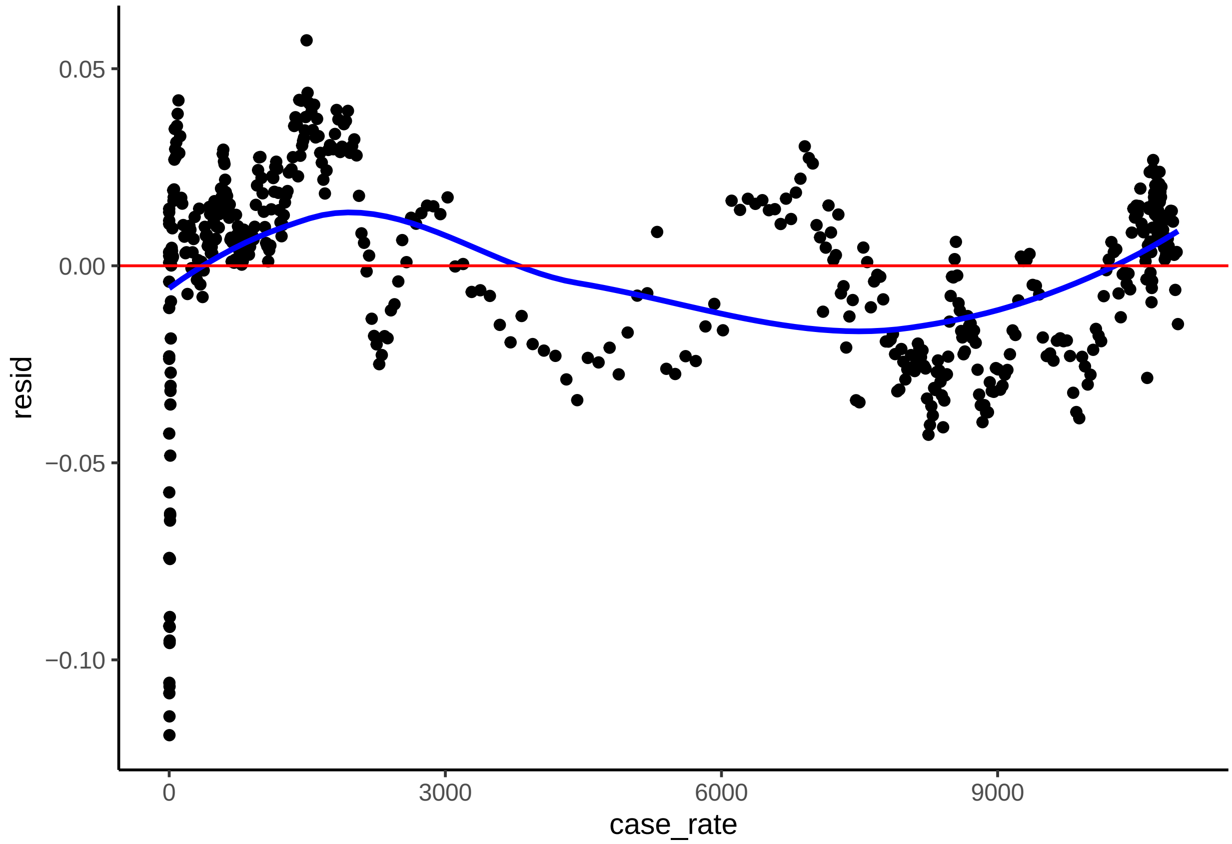
```
## Warning: Removed 375 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 375 rows containing missing values (geom_point).
```



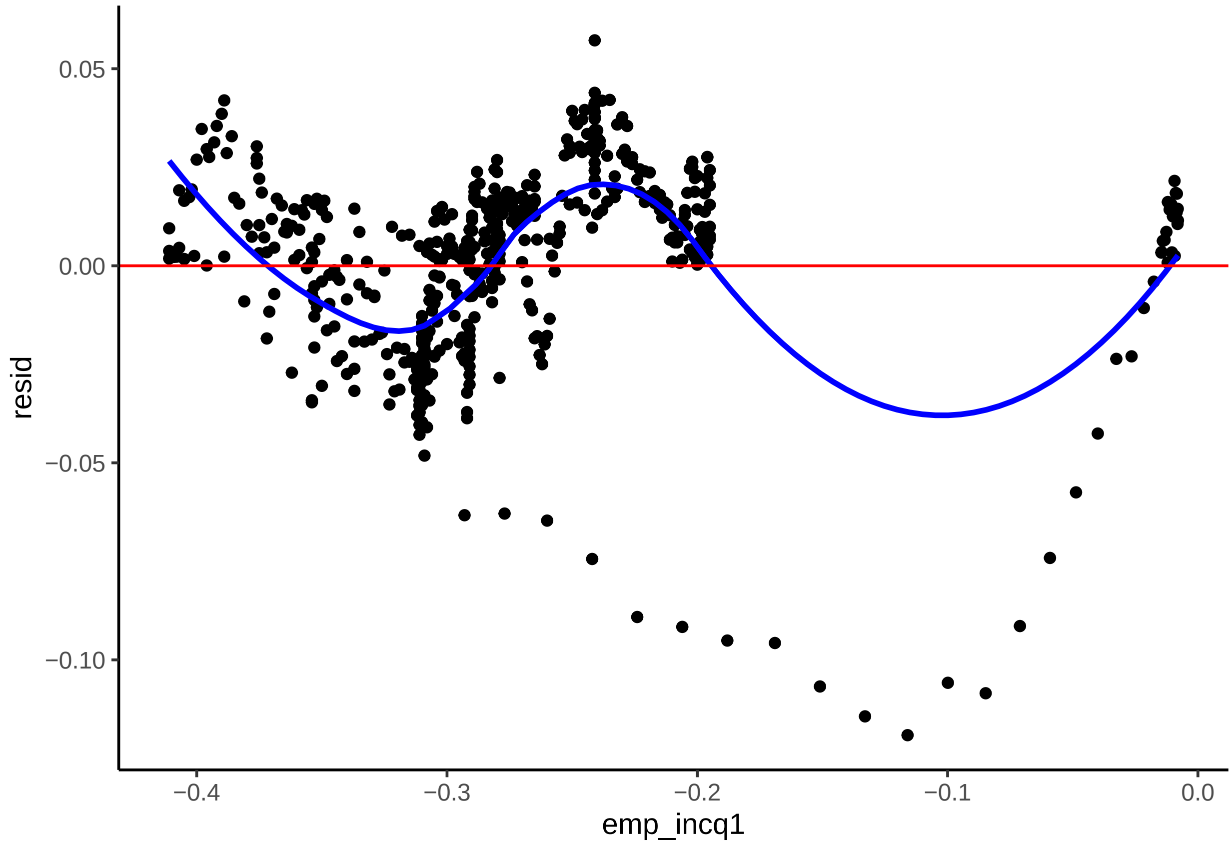

```
ggplot(mn_mod_output_lasso, aes(y = resid, x = case_rate)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 11 rows containing non-finite values (stat_smooth).

## Warning: Removed 11 rows containing missing values (geom_point).
```



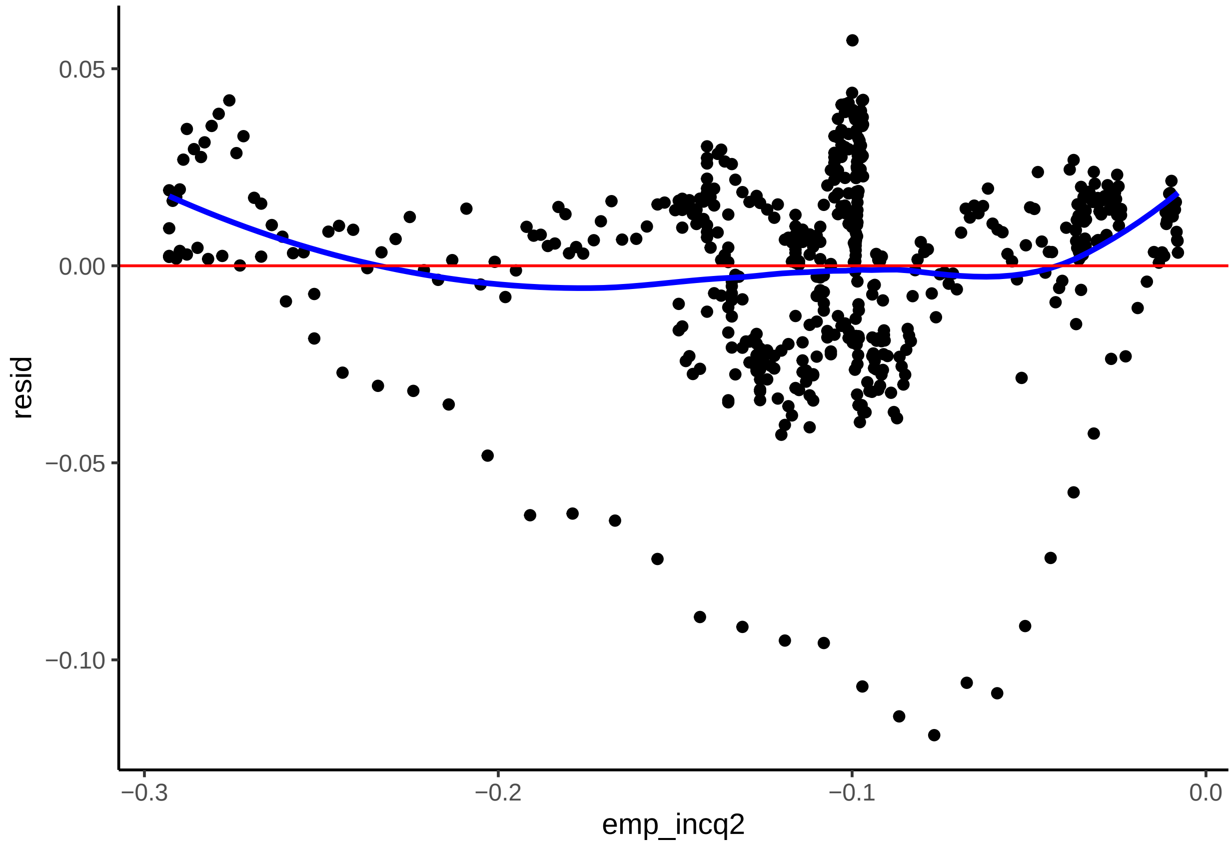

```
ggplot(mn_mod_output_lasso, aes(y = resid, x = emp_incq1)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



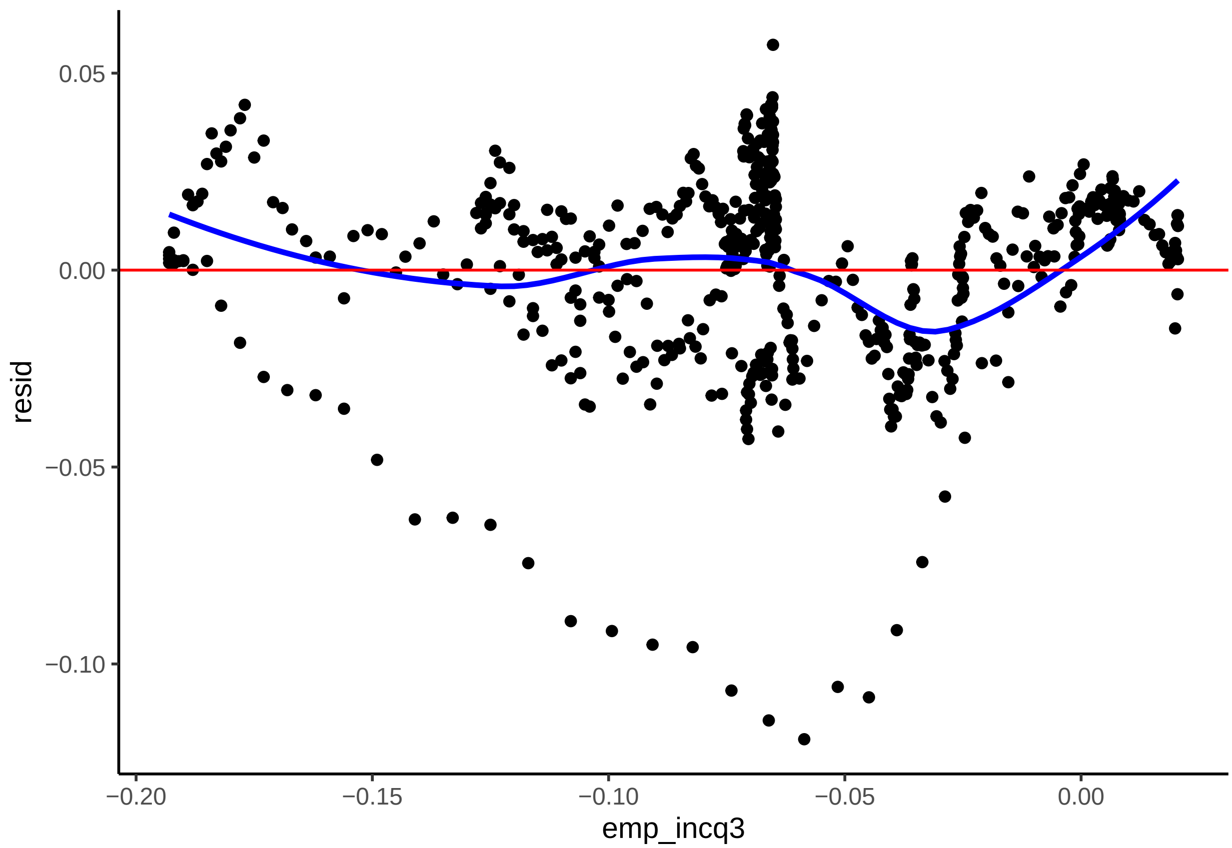

```
ggplot(mn_mod_output_lasso, aes(y = resid, x = emp_incq2)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



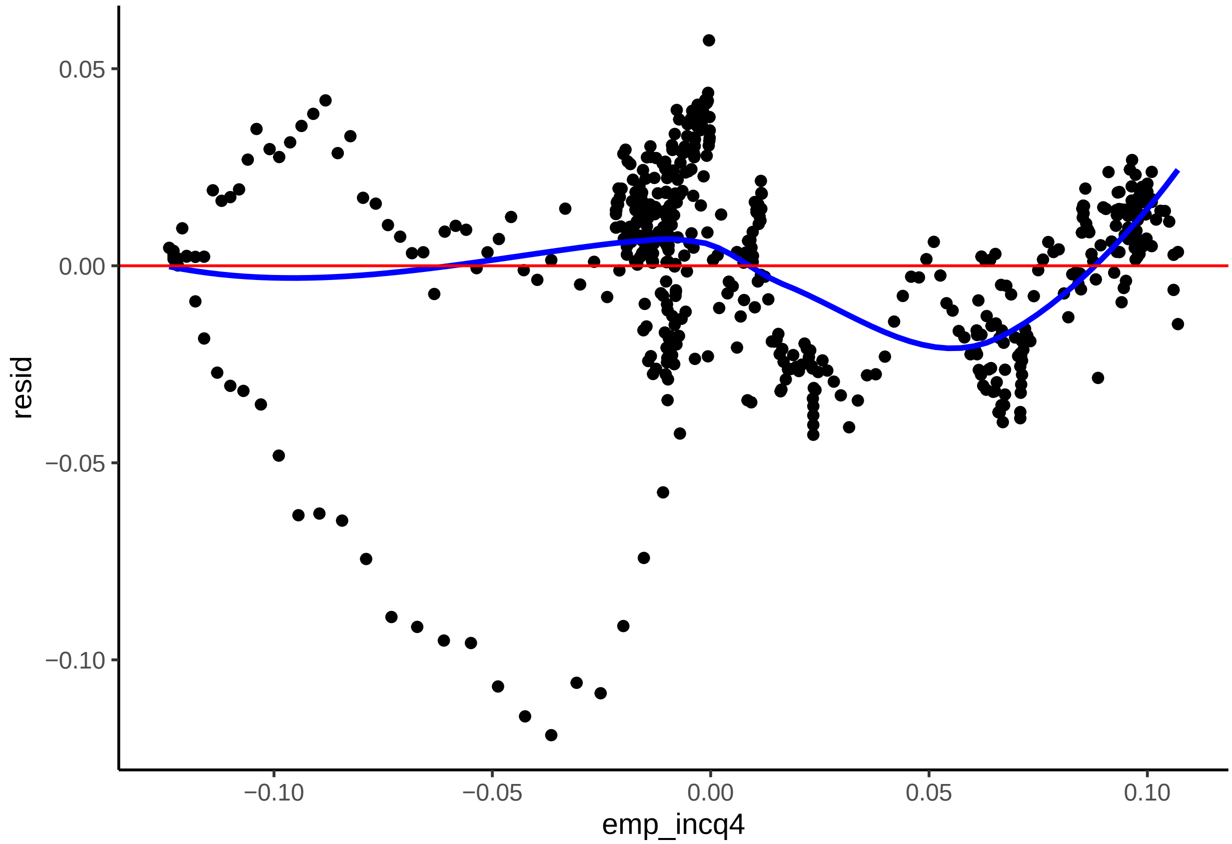

```
ggplot(mn_mod_output_lasso, aes(y = resid, x = emp_incq3)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



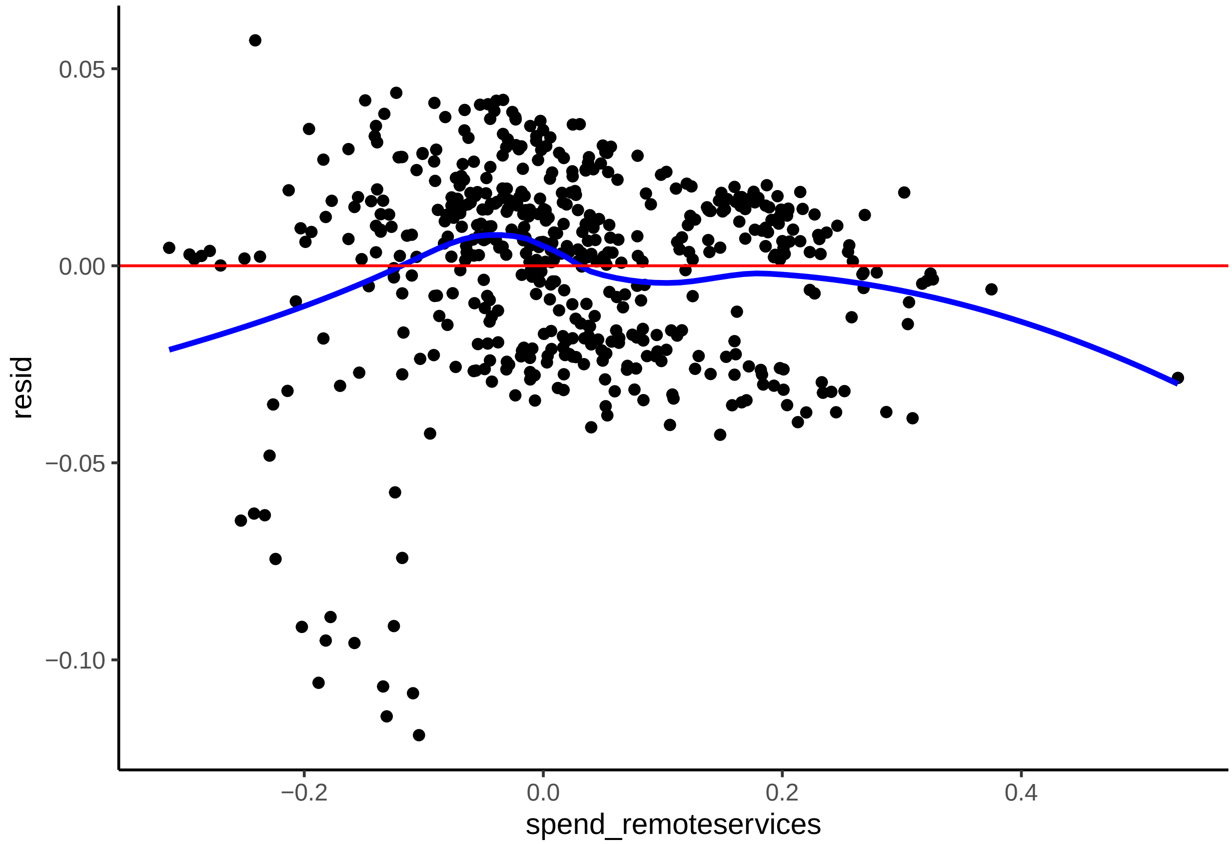

```
ggplot(mn_mod_output_lasso, aes(y = resid, x = emp_incq4)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
ggplot(mn_mod_output_lasso, aes(y = resid, x = spend_remoteservices)) +
    geom_point() +
    geom_smooth(color = "blue", se = FALSE) +
    geom_hline(yintercept = 0, color = "red") +
    theme_classic()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Overall our residuals are presenting some strange trends. Some of our predictions are taking weird paths into some kind of very negative ark. Many of our predictors have strong curves that look like some kind of spline. Since some of them are eliminated very quickly by our LASSO method I would not worry about several of these but emp_incq3 seems to have some strange patterns in it we should probably investigate.

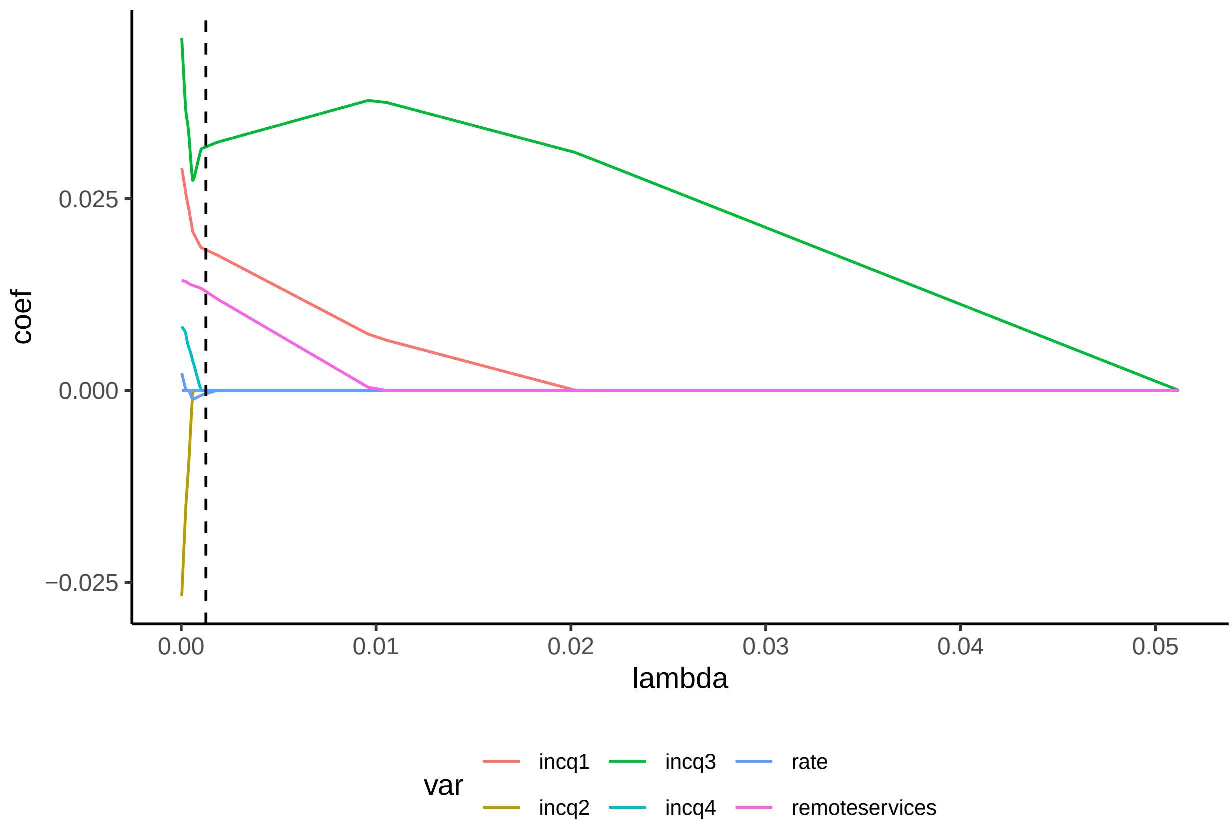
```
best_penalty <- select_best(tune_res, metric = 'mae') # choose penalty value based on lowest cv mae
best_penalty
```

```
## # A tibble: 1 x 2
##    penalty .config
##      <dbl> <chr>
## 1 0.000161 Preprocessor1_Model26
```

```
best_se_penalty <- select_by_one_std_err(tune_res, metric = 'mae', desc(penalty))
```

```
glmnet_output <- final_fit %>% extract_fit_parsnip() %>% pluck('fit') # get the original glmnet output

lambdas <- glmnet_output$lambda
coefs_lambdas <-
  coefficients(glmnet_output, s = lambdas )  %>%
  as.matrix() %>%
  t() %>%
  as.data.frame() %>%
  mutate(lambda = lambdas ) %>%
  select(lambda, everything(), -`(Intercept)`) %>%
```

```
  pivot_longer(cols = -lambda,
               names_to = "term",
               values_to = "coef") %>%
  mutate(var = purrr::map_chr(stringr::str_split(term,"_"),~.[2]))

coefs_lambdas %>%
  ggplot(aes(x = lambda, y = coef, group = term, color = var)) +
  geom_line() +
  geom_vline(xintercept = best_se_penalty %>% pull(penalty), linetype = 'dashed') +
  theme_classic() +
  theme(legend.position = "bottom", legend.text=element_text(size=8))
```




```
best_se_penalty
```

```
## # A tibble: 1 x 9
##   penalty .metric .estimator   mean     n  std_err .config          .best .bound
##     <dbl> <chr>   <chr>       <dbl> <int>    <dbl> <chr>            <dbl>  <dbl>
## 1 0.00127 mae     standard   0.0196     6 0.000918 Preprocessor1_~ 0.0190 0.0201
```

```
final_fit %>% tidy() %>% filter(estimate != 0)
```

```
## # A tibble: 7 x 3
##   term                    estimate penalty
##   <chr>                      <dbl>   <dbl>
```

```
## 1 (Intercept)          -0.105     1e-15
## 2 hospitalized_rate     0.00224   1e-15
## 3 emp_incq1             0.0290    1e-15
## 4 emp_incq2            -0.0268    1e-15
## 5 emp_incq3             0.0459    1e-15
## 6 emp_incq4             0.00832   1e-15
## 7 spend_remoteservices  0.0144    1e-15
```

```r
mnFullMod_cv_dumy2 <- fit_resamples(final_fit,
  resamples = folded_mn,
  control = control_resamples(save_pred = TRUE),
  metrics = metric_set(rmse, rsq, mae))

mnFullMod_cv_dumy <- fit_resamples(mn_model_dumy_wf,
  resamples = folded_mn,
  control = control_resamples(save_pred = TRUE),
  metrics = metric_set(rmse, rsq, mae))
```

```
## ! Fold1: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold4: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold5: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...

## ! Fold6: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-defici...
```

```r
mnFullMod_cv_dumy2 %>% collect_metrics(summarize=TRUE)
```

```
## # A tibble: 3 x 6
##   .metric .estimator   mean     n std_err .config
##   <chr>   <chr>       <dbl> <int>   <dbl> <chr>
## 1 mae     standard   0.0191     6 0.00107 Preprocessor1_Model1
## 2 rmse    standard   0.0253     6 0.00126 Preprocessor1_Model1
## 3 rsq     standard   0.816      6 0.0209  Preprocessor1_Model1
```

The predictor with the highest estimate (seen both in our tidy output and in the coefficient path visualization) is emp_incq3, which is the employment level for workers in the third quartile of the income distribution. However, this is part of a categorical variable, so we will consider employment level as the most important predictor. This makes contextual sense, as employment levels greatly influence how much time outside the house an individual can have. We arrived at the same outcome in LASSO as we did in OLS.