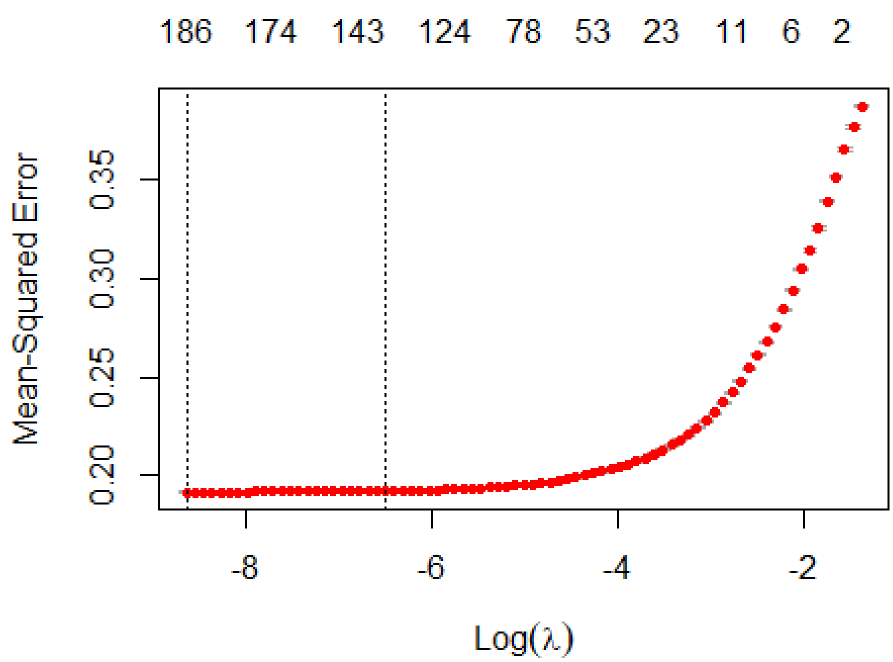
Double ML and Regression

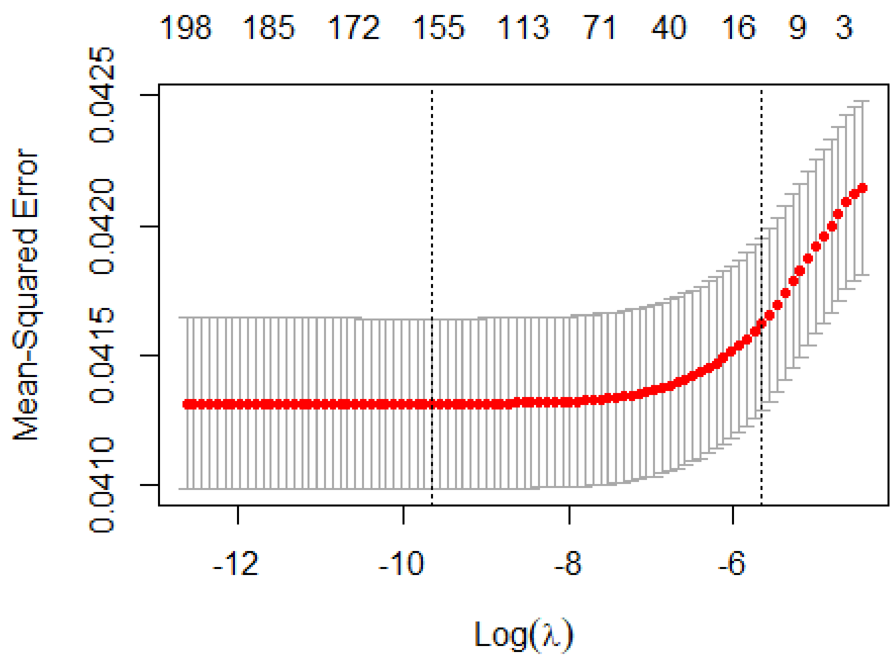
```r
## Initial Model 2: Double ML (Double LASSO) ----------------------------------------
temp <- dat
dat <- temp # recover original dataset

# DATA CLEANING FOR DOUBLE LASSO
nums <- unlist(lapply(dat, is.factor))
dattemp <- dat[,nums] # all the factors of dataset
# delete variables have >51 factor levels
get1 <- names(which(sapply(dattemp, function(x) length(unique(x))>51)))
delete <- which(names(dat) %in% get1[-16])
dat <- dat[,-c(delete)]
dat <- dat[,-c(9,43:52,82,90,108,95,100)] # delete CITWP,MIL~MLPK,HISP,POVPIP,SFR,RAC1P,RACNUM
dat <- dat[,-c(1,3,76,77)] # delete DIVISION,REGION,PERNP,PINCP
# delete NA rows for Income-Poverty ratio
dat <- dat[!is.na(dat$IncomePovertyRatio),]
dat <- dat[,-c(which(colnames(dat)=="JWRIP"),which(colnames(dat)=="YOEP"))]
# delete NA rows for JWMNP (travel time to work)
dat <- dat[!is.na(dat$JWMNP),]
# delete NA rows for MARHYP: for factor <2 error
dat <- dat[!is.na(dat$MARHYP),]
# delete NA rows for WKHP (usual hours worked per week)
dat <- dat[!is.na(dat$WKHP),]


# delete/add vars that should be deleted/added (from correlation/causal inference)
dat <- dat[, -which(names(dat) %in% c("INTP","OIP","PAP","RETP","SEMP","SSIP","SSP","WAGP"))]   # drop val
ues related to Income
dat <- dat[, -which(names(dat) %in% c("SCH","SCHG"))]   # drop weird educ vars
dat <- dat[, -which(names(dat) %in% c("ANC"))]  # drop ancestry
dat <- droplevels(dat)
#str(dat)
dat <- dat[, -which(names(dat) %in% c("ESR","ESP"))]  # drop meaningless labor vars
dat <- dat[, -which(names(dat) %in% c("HICOV","PRIVCOV","PUBCOV"))]  # drop redundant insurance vars
dat <- dat[, -which(names(dat) %in% c("OC","RC"))]  # drop child vars. Lack data
dat <- dat[, -which(names(dat) %in% c("SFN"))]  # drop "subfamily number"
dat <- dat[, -which(names(dat) %in% c("WRK"))]  # drop "worked last week" (we don't know when is "last wee
k")

dat <- cbind(dat, model.matrix(~(AGEP:HINS3), dat)[,-1])  # age*medicare
dat <- cbind(dat, model.matrix(~(SCIENGP:SCHL), dat)[,-1])  # stem degree*attained degree
dat <- cbind(dat, model.matrix(~(SCIENGRLP:SCHL), dat)[,-1])  # stem related degree*attained degree
dat$VETERAN <- ifelse((dat$DRATX %in% c("1","2")), 1, 0)  # veteran or not
dat <- dat[, -which(names(dat) %in% c("DRATX","VPS","DRAT"))]  # drop veteran related vars
dat <- cbind(dat, model.matrix(~(AGEP:VETERAN), dat)[,2])  # age*veteran or not
names(dat)[ncol(dat)] <- "AGEP_VETERAN"
dat <- cbind(dat, model.matrix(~(AGEP:GCL), dat)[,-1])  # age*grandparent living with grandchild
dat <- cbind(dat, model.matrix(~(AGEP:GCR), dat)[,-1])  # age*grandparent responsible grandchild


# logical dummy for ST==POWSP
dat$SameResidenceWorkplace <- (as.numeric(dat$ST)==as.numeric(dat$POWSP))
dat <- dat[,-which(names(dat) %in% c("ST","POWSP"))]  # delete ST,POWSP
# get which variables have <2 factor levels
get2 <- which(sapply(dat, function(x) length(unique(x)))<2)
dat <- dat[,-get2]
names(dat) <- str_replace(names(dat), ":", "_") # reformat interaction term names

# STEP 1: FIRST LASSO: LOG(IncPovRatio) on ALL POTENTIAL VARIATES (i.e. y on focals)
varnames <- paste(c(names(dat[,-c(which(names(dat) %in%
                                          c("IncomePovertyRatio","SameResidenceWorkplace",
                                            "JWMNP","JWTR")))])), collapse = "+")
# throw in everything and see what happens with this LASSO
formula <- paste(c("log(IncomePovertyRatio)",varnames), collapse = "~")

# Split data into train and test for K-fold CV
set.seed(497)
```

```
train <- sample(1:nrow(dat), nrow(dat)*0.8)  # 80% for training

# get which variables have <2 factor levels AFTER SUBSETTING
get <- which(sapply(dat[train,], function(x) length(unique(x))<2))

# get train and test datasets
# takeout intercept
xtrain <- model.matrix(as.formula(formula), data = dat[train,])[,-1]
ytrain <- log(dat[train,]$IncomePovertyRatio)

# cross validation then fit LASSO
cv.lasso.1 <- cv.glmnet(xtrain, ytrain, alpha = 1)  # 1 for lasso
cv.lambda.1 <- cv.lasso.1$lambda.min  # get smallest tuning parameter
cv.lambda.1

## [1] 0.0001775132


plot(cv.lasso.1)
```

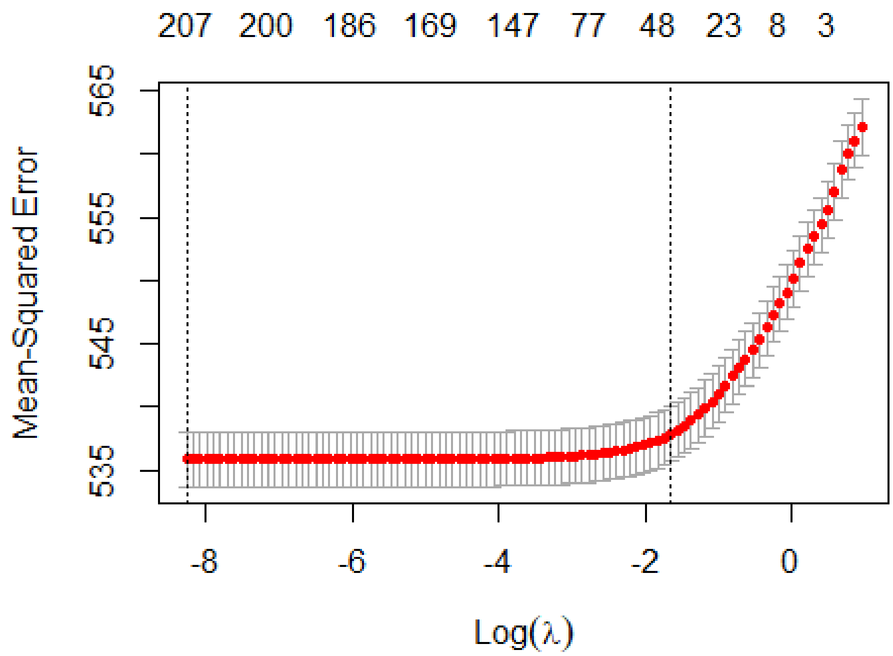



```
# run lasso and get the necessary focal variables
dlasso.1 <- rlasso(formula, data = dat[train,],
                   lambda.start = cv.lambda.1, post = F)
#summary(lasso.2, all = F)
control <- which(coef(dlasso.1)[-1]!=0)
length(control)

## [1] 157

# STEP 2: SECOND LASSO: Core vars on ALL POTENTIAL VARIATES (i.e. controls on focals)
formula2.1 <- paste(c("SameResidenceWorkplace",varnames), collapse = "~")
# k-fold cv
xtrain <- model.matrix(as.formula(formula2.1), data = dat[train,])[,-1]
ytrain <- dat[train,]$SameResidenceWorkplace
cv.lasso.2.1 <- cv.glmnet(xtrain, ytrain, alpha = 1)  # 1 for lasso
```

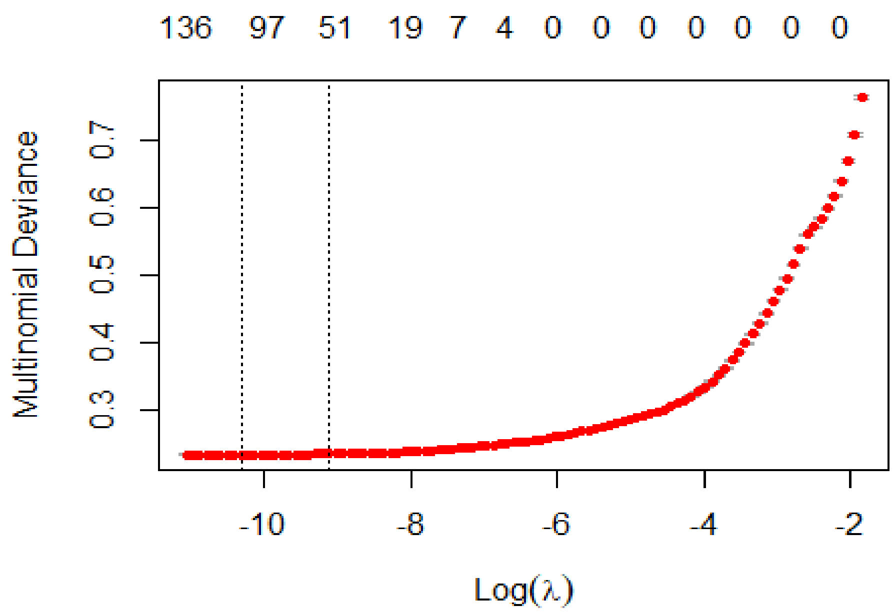
```r
cv.lambda.2.1 <- cv.lasso.2.1$lambda.min  # get smallest tuning parameter
cv.lambda.2.1

## [1] 6.405355e-05

plot(cv.lasso.2.1)
```




```r
# lasso
dlasso.2.1 <- rlasso(formula2.1, data = dat[train,],
                     lambda.start = cv.lambda.2.1, post = F)
#summary(dlasso.2.1, all = F)
focal1 <- which(coef(dlasso.2.1)[-1]!=0)
length(focal1)

## [1] 74

# travel time
formula2.2 <- paste(c("JWMNP",varnames), collapse = "~")
# k-fold cv
xtrain <- model.matrix(as.formula(formula2.2), data = dat[train,])[,-1]
ytrain <- dat[train,]$JWMNP
cv.lasso.2.2 <- cv.glmnet(xtrain, ytrain, alpha = 1)  # 1 for lasso
cv.lambda.2.2 <- cv.lasso.2.2$lambda.min  # get smallest tuning parameter
cv.lambda.2.2

## [1] 0.0002590354

plot(cv.lasso.2.2)
```




```
# lasso
dlasso.2.2 <- rlasso(formula2.2, data = dat[train,],
                     lambda.start = cv.lambda.2.2, post = F)
#summary(dlasso.2.2, all = F)
focal2 <- which(coef(dlasso.2.2)[-1]!=0)
length(focal2)

## [1] 81

formula2.4 <- paste(c("JWTR",varnames), collapse = "~")
# k-fold cv
xtrain <- model.matrix(as.formula(formula2.4), data = dat[train,])[,-1]
ytrain <- drop.levels(dat[train,]$JWTR) # factor level "11" has 0 observations, use drop.levels()
cv.lasso.2.4 <- cv.glmnet(xtrain, ytrain, alpha = 1, family = "multinomial", nfolds = 3) # 1 for lasso
cv.lambda.2.4 <- cv.lasso.2.4$lambda.min  # get smallest tuning parameter
cv.lambda.2.4

## [1] 3.31276e-05

plot(cv.lasso.2.4)
```




```
# Lasso
tempdat2 <- fastDummies::dummy_cols(dat)
focal4 <- c()
for (ii in 1:11) {
  if (ii<10) {
    formula2.4.n <- paste(c(paste("JWTR_0",ii,sep=""),varnames), collapse = "~")
    dlasso.2.4.n <- rlasso(formula2.4.n, data = tempdat2[train,],
                           lambda.start = cv.lambda.2.4, post = F)
    focal4.n <- which(coef(dlasso.2.4.n)[-1]!=0)
    focal4 <- unique(c(focal4, names(focal4.n)))
  } else if (ii==10) {
    formula2.4.n <- paste(c("JWTR_10",varnames), collapse = "~")
    dlasso.2.4.n <- rlasso(formula2.4.n, data = tempdat2[train,],
                           lambda.start = cv.lambda.2.4, post = F)
    focal4.n <- which(coef(dlasso.2.4.n)[-1]!=0)
    focal4 <- unique(c(focal4, names(focal4.n)))
  } else if (ii==11) {
    formula2.4.n <- paste(c("JWTR_12",varnames), collapse = "~")
    dlasso.2.4.n <- rlasso(formula2.4.n, data = tempdat2[train,],
                           lambda.start = cv.lambda.2.4, post = F)
    focal4.n <- which(coef(dlasso.2.4.n)[-1]!=0)
    focal4 <- unique(c(focal4, names(focal4.n)))
  }
}
length(focal4)

## [1] 213

# STEP 3: Take union of all remainder potential variates
union <- c(names(control), names(focal1), names(focal2), focal4)
if (any(duplicated(union))==T) {
  union <- unique(union)
}

# Total number of feature variables kept from Double Lasso
length(union)

## [1] 219
```

```r
# STEP 3 Continued: do OLS of y on focals and kept potential variates
unionf <- paste(c("SameResidenceWorkplace*JWMNP+JWTR*JWMNP",union), collapse = "+")
formula <- paste(c("log(IncomePovertyRatio)", unionf), collapse = "~")

# name all extra variables created from doing LASSO
dattemp <- dat
for (i in 1:500) { # look at formula and count how many new vars need to be made
  error <- myTryCatch(olsDLasso1<- lm(formula, data = dattemp)) # CAUTION
  newvars <- substr(error[[1]], 45, str_length(error[[1]])-12)
  existingvars <- names(dattemp)[which(str_detect(newvars, names(dattemp)))]
  existingchars <- sub(existingvars, "", newvars)
  dattemp[,newvars] <- dattemp[,which(names(dattemp)==existingvars)]==existingchars
}

# start with declaring the new vars
which(colSums(is.na(dattemp))==nrow(dattemp))

## SCIENGRLP1 SCIENGRLP2
##        238        239

dattemp$SCIENGRLP1 <- dattemp$SCIENGRLP == "1"
dattemp$SCIENGRLP2 <- dattemp$SCIENGRLP == "2"

which(lapply(dattemp, class)=="matrix")

## MARHD2 MARHT2 MARHT3 MARHD8
##    160    162    163    244

dattemp$MARHT3 <- dattemp$MARHT == "3"
dattemp$MARHD2 <- dattemp$MARHD == "2"
dattemp$MARHD8 <- dattemp$MARHD == "8"
dattemp$MARHT2 <- dattemp$MARHT == "2"

# multicolinearity: get which variables have <2 unique values
multicol <- names(which(sapply(dattemp[train,], function(x) length(unique(x))<2)))
# manually delete some of the rest (NA values in summary of lm, multicollinearity)
multicol <- c(multicol,
              "MSP3","MSP4","MSP5","ENG1","SCHL21","DRIVESP6",
              "NATIVITY2","SCHL18","DECADE6","WAOB4")
union <- union[-which(union %in% multicol)] # delete them from formula
aliased <- which(summary(lm(formula, data = dattemp[train,]))$aliased)
union <- union[-which(union %in% names(aliased))]

# rewrite formula for OLS
unionf <- paste(c("SameResidenceWorkplace*JWMNP+JWTR*JWMNP",union), collapse = "+")
formula <- paste(c("log(IncomePovertyRatio)", unionf), collapse = "~")

# Training OLS regression post double LASSO
olsDLasso1 <- lm(formula, data = dattemp[train,])
DMLresult <- summary(olsDLasso1)
DMLresult

##
## Call:
## lm(formula = formula, data = dattemp[train, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0233 -0.2576 -0.0282  0.2212  3.5316
##
## Coefficients:
##                                   Estimate Std. Error  t value Pr(>|t|)
## (Intercept)                      1.918e+00  1.461e-01   13.124  < 2e-16 ***
## SameResidenceWorkplaceTRUE      -8.169e-02  4.054e-03  -20.149  < 2e-16 ***
## JWMNP                            1.431e-03  7.106e-05   20.141  < 2e-16 ***
## JWTR02                           1.093e-02  1.481e-02    0.737 0.460822
## JWTR03                           3.399e-02  4.974e-02    0.683 0.494321
## JWTR04                           2.488e-01  1.612e-02   15.434  < 2e-16 ***
```

```
## JWTR05                             3.626e-01  1.985e-02   18.263  < 2e-16 ***
## JWTR06                             3.288e-01  4.727e-02    6.955 3.53e-12 ***
## JWTR07                             8.782e-02  2.524e-02    3.479 0.000503 ***
## JWTR08                            -2.325e-02  2.305e-02   -1.009 0.313043
## JWTR09                            -5.182e-02  1.791e-02   -2.894 0.003805 **
## JWTR10                            -6.349e-02  1.350e-02   -4.705 2.54e-06 ***
## JWTR12                             9.491e-03  1.469e-02    0.646 0.518130
## SPORDER                           -6.923e-02  1.313e-03  -52.723  < 2e-16 ***
## PWGTP                              4.407e-05  6.578e-06    6.700 2.09e-11 ***
## AGEP                               4.456e-03  4.849e-04    9.191  < 2e-16 ***
## CIT3TRUE                          -3.097e-02  6.628e-03   -4.672 2.98e-06 ***
## CIT4TRUE                           9.808e-03  4.480e-03    2.189 0.028572 *
## CIT5TRUE                          -1.488e-02  4.987e-03   -2.983 0.002857 **
## COW2TRUE                          -8.112e-02  1.805e-03  -44.949  < 2e-16 ***
## COW3TRUE                          -8.743e-02  1.869e-03  -46.793  < 2e-16 ***
## COW4TRUE                          -1.141e-01  2.277e-03  -50.089  < 2e-16 ***
## COW5TRUE                           6.980e-02  2.941e-03   23.732  < 2e-16 ***
## COW6TRUE                          -1.073e-01  2.194e-03  -48.883  < 2e-16 ***
## COW7TRUE                           9.960e-02  2.500e-03   39.844  < 2e-16 ***
## COW8TRUE                          -1.725e-01  1.103e-02  -15.645  < 2e-16 ***
## DDRS2TRUE                         -2.697e-02  8.954e-03   -3.012 0.002594 **
## DEYE2TRUE                          2.110e-02  5.392e-03    3.913 9.13e-05 ***
## DPHY2TRUE                          2.578e-02  5.036e-03    5.119 3.07e-07 ***
## DREM2TRUE                          3.432e-02  5.451e-03    6.296 3.06e-10 ***
## ENG2TRUE                          -9.786e-02  2.844e-03  -34.408  < 2e-16 ***
## ENG3TRUE                          -1.272e-01  3.656e-03  -34.784  < 2e-16 ***
## ENG4TRUE                          -1.138e-01  6.350e-03  -17.920  < 2e-16 ***
## FER1TRUE                           4.442e-02  5.013e-03    8.861  < 2e-16 ***
## FER2TRUE                           2.342e-02  2.036e-03   11.503  < 2e-16 ***
## GCL2TRUE                           2.570e-01  2.083e-02   12.342  < 2e-16 ***
## GCR2TRUE                           8.356e-02  4.472e-02    1.869 0.061677 .
## HINS12TRUE                        -1.520e-01  1.500e-03 -101.372  < 2e-16 ***
## HINS22TRUE                        -1.308e-02  1.728e-03   -7.569 3.76e-14 ***
## HINS42TRUE                         9.252e-02  2.248e-03   41.164  < 2e-16 ***
## HINS52TRUE                        -2.228e-02  3.320e-03   -6.711 1.94e-11 ***
## HINS62TRUE                         5.436e-02  3.758e-03   14.465  < 2e-16 ***
## HINS72TRUE                         3.229e-03  8.499e-03    0.380 0.703987
## LANX2TRUE                          1.159e-02  2.012e-03    5.758 8.50e-09 ***
## MAR2TRUE                          -2.623e-02  3.210e-03   -8.173 3.02e-16 ***
## MAR3TRUE                          -4.197e-02  1.670e-03  -25.131  < 2e-16 ***
## MAR4TRUE                          -4.869e-02  3.359e-03  -14.493  < 2e-16 ***
## MARHD2TRUE                        -2.075e-02  4.490e-03   -4.621 3.81e-06 ***
## MARHT2TRUE                        -5.534e-03  1.472e-03   -3.758 0.000171 ***
## MARHT3TRUE                        -2.639e-02  2.677e-03   -9.860  < 2e-16 ***
## MARHYP                            -3.978e-04  6.967e-05   -5.710 1.13e-08 ***
## MIG2TRUE                          -5.720e-02  8.815e-03   -6.489 8.64e-11 ***
## MIG3TRUE                          -1.420e-02  1.707e-03   -8.323  < 2e-16 ***
## NWAB2TRUE                         -2.978e-02  9.740e-03   -3.057 0.002234 **
## NWAV5TRUE                          7.657e-03  5.268e-03    1.454 0.146062
## NWLA3TRUE                          3.213e-03  1.069e-02    0.301 0.763636
## NWLK3TRUE                          8.442e-02  7.974e-03   10.586  < 2e-16 ***
## NWRE2TRUE                          6.009e-02  1.167e-02    5.149 2.62e-07 ***
## RELP01TRUE                        -1.579e-01  1.740e-03  -90.721  < 2e-16 ***
## RELP02TRUE                        -2.422e-01  4.139e-03  -58.517  < 2e-16 ***
## RELP03TRUE                        -2.222e-01  2.175e-02  -10.218  < 2e-16 ***
## RELP04TRUE                        -2.501e-01  1.523e-02  -16.422  < 2e-16 ***
## RELP05TRUE                        -2.344e-01  7.721e-03  -30.357  < 2e-16 ***
## RELP06TRUE                        -2.428e-01  7.102e-03  -34.192  < 2e-16 ***
## RELP07TRUE                        -2.017e-01  1.581e-02  -12.757  < 2e-16 ***
## RELP08TRUE                        -3.037e-01  1.467e-02  -20.705  < 2e-16 ***
## RELP09TRUE                        -2.874e-01  7.891e-03  -36.425  < 2e-16 ***
## RELP10TRUE                        -2.442e-01  8.130e-03  -30.035  < 2e-16 ***
## RELP11TRUE                        -2.412e-01  1.051e-02  -22.950  < 2e-16 ***
## RELP12TRUE                        -2.277e-01  7.150e-03  -31.849  < 2e-16 ***
## RELP13TRUE                        -2.062e-01  4.674e-03  -44.118  < 2e-16 ***
## RELP15TRUE                        -2.442e-01  7.903e-03  -30.895  < 2e-16 ***
## RELP17TRUE                        -2.786e-01  1.332e-02  -20.911  < 2e-16 ***
## SCHL04TRUE                        -1.043e-01  3.053e-02   -3.416 0.000635 ***
## SCHL05TRUE                        -1.342e-01  2.178e-02   -6.160 7.27e-10 ***
```

```
## SCHL06TRUE                         -1.007e-01  1.467e-02   -6.863 6.73e-12 ***
## SCHL07TRUE                         -1.055e-01  1.708e-02   -6.175 6.61e-10 ***
## SCHL08TRUE                         -1.064e-01  1.370e-02   -7.771 7.82e-15 ***
## SCHL09TRUE                         -1.012e-01  6.870e-03  -14.725  < 2e-16 ***
## SCHL10TRUE                         -1.151e-01  1.224e-02   -9.400  < 2e-16 ***
## SCHL11TRUE                         -8.077e-02  7.093e-03  -11.386  < 2e-16 ***
## SCHL12TRUE                         -1.061e-01  5.992e-03  -17.709  < 2e-16 ***
## SCHL13TRUE                         -1.301e-01  5.561e-03  -23.397  < 2e-16 ***
## SCHL14TRUE                         -1.185e-01  5.176e-03  -22.892  < 2e-16 ***
## SCHL15TRUE                         -9.016e-02  4.420e-03  -20.397  < 2e-16 ***
## SCHL16TRUE                         -6.246e-02  2.171e-03  -28.772  < 2e-16 ***
## SCHL17TRUE                         -8.702e-02  3.278e-03  -26.545  < 2e-16 ***
## SCHL19TRUE                          3.397e-02  2.304e-03   14.741  < 2e-16 ***
## SCHL20TRUE                          6.445e-02  2.424e-03   26.591  < 2e-16 ***
## SCHL22TRUE                          1.233e-01  2.478e-03   49.751  < 2e-16 ***
## SCHL23TRUE                          3.437e-01  8.596e-03   39.985  < 2e-16 ***
## SCHL24TRUE                          2.175e-01  6.802e-03   31.977  < 2e-16 ***
## SEX2TRUE                           -7.976e-02  2.289e-02   -3.484 0.000493 ***
## WKHP                                1.365e-02  4.765e-05  286.546  < 2e-16 ***
## WKW2TRUE                           -7.342e-02  3.505e-03  -20.948  < 2e-16 ***
## WKW3TRUE                           -1.582e-01  2.339e-03  -67.629  < 2e-16 ***
## WKW4TRUE                           -2.789e-01  2.820e-03  -98.897  < 2e-16 ***
## WKW5TRUE                           -4.105e-01  3.867e-03 -106.155  < 2e-16 ***
## WKW6TRUE                           -5.210e-01  3.940e-03 -132.240  < 2e-16 ***
## DECADE3TRUE                         3.593e-02  6.193e-03    5.801 6.58e-09 ***
## DECADE4TRUE                         2.350e-02  4.386e-03    5.359 8.37e-08 ***
## DECADE7TRUE                        -2.040e-02  3.331e-03   -6.125 9.10e-10 ***
## DECADE8TRUE                        -5.498e-02  4.133e-03  -13.302  < 2e-16 ***
## DIS2TRUE                            4.190e-02  4.841e-03    8.655  < 2e-16 ***
## DRIVESP1TRUE                       -1.330e-02  1.269e-02   -1.049 0.294402
## DRIVESP2TRUE                       -6.237e-02  1.281e-02   -4.870 1.12e-06 ***
## DRIVESP3TRUE                       -5.937e-02  1.334e-02   -4.451 8.55e-06 ***
## DRIVESP4TRUE                       -5.789e-02  1.438e-02   -4.025 5.70e-05 ***
## DRIVESP5TRUE                       -3.096e-02  1.578e-02   -1.962 0.049801 *
## MSP2TRUE                           -1.459e-02  3.143e-03   -4.642 3.45e-06 ***
## PAOC1TRUE                          -9.965e-02  2.304e-02   -4.324 1.53e-05 ***
## PAOC2TRUE                          -1.329e-01  2.291e-02   -5.803 6.53e-09 ***
## PAOC4TRUE                          -1.321e-01  2.288e-02   -5.773 7.80e-09 ***
## QTRBIR3TRUE                         3.229e-03  1.189e-03    2.715 0.006626 **
## RACAIAN1TRUE                       -2.852e-02  5.081e-03   -5.612 2.00e-08 ***
## RACASN1TRUE                         6.301e-02  4.437e-03   14.203  < 2e-16 ***
## RACBLK1TRUE                        -6.564e-02  4.108e-03  -15.980  < 2e-16 ***
## RACPI1TRUE                         -2.557e-02  1.224e-02   -2.088 0.036787 *
## RACWHT1TRUE                         2.257e-02  3.879e-03    5.817 6.00e-09 ***
## SCIENGRLP1TRUE                      3.276e-01  3.554e-03   92.186  < 2e-16 ***
## SCIENGRLP2TRUE                      2.506e-01  2.330e-03  107.536  < 2e-16 ***
## WAOB2TRUE                           1.641e-02  5.217e-02    0.315 0.753068
## WAOB3TRUE                          -1.879e-02  4.167e-03   -4.508 6.54e-06 ***
## WAOB5TRUE                           6.072e-02  4.846e-03   12.528  < 2e-16 ***
## WAOB6TRUE                          -2.510e-02  6.657e-03   -3.771 0.000163 ***
## WAOB7TRUE                           1.233e-01  8.684e-03   14.196  < 2e-16 ***
## WAOB8TRUE                           1.105e-01  1.535e-02    7.198 6.13e-13 ***
## AGEP_HINS31                         1.562e-03  2.448e-04    6.382 1.75e-10 ***
## SCIENGP_SCHL01                     -9.545e-02  5.379e-03  -17.745  < 2e-16 ***
## SCIENGP1_SCHL22                     1.123e-01  3.115e-03   36.039  < 2e-16 ***
## SCIENGP1_SCHL23                     2.355e-01  5.968e-03   39.456  < 2e-16 ***
## SCIENGP1_SCHL24                     1.742e-01  7.863e-03   22.154  < 2e-16 ***
## SCIENGRLP1_SCHL22                   7.894e-03  5.833e-03    1.353 0.175985
## SCIENGRLP2_SCHL23                   1.390e-02  9.687e-03    1.435 0.151276
## SCIENGRLP1_SCHL24                   7.851e-02  1.269e-02    6.188 6.08e-10 ***
## AGEP_VETERAN                        5.122e-04  1.336e-04    3.834 0.000126 ***
## AGEP_GCL                            6.289e-03  9.141e-04    6.880 5.99e-12 ***
## DOUT2TRUE                          -7.836e-03  6.693e-03   -1.171 0.241662
## MARHD8TRUE                         -5.994e-03  1.348e-02   -0.445 0.656588
## NWAB3TRUE                           8.029e-04  1.048e-02    0.077 0.938949
## RACNH1TRUE                         -1.854e-03  1.226e-02   -0.151 0.879789
## RACSOR1TRUE                         8.821e-03  4.479e-03    1.969 0.048897 *
## AGEP_GCL2                           6.915e-04  4.779e-04    1.447 0.147896
## CIT2TRUE                           -4.371e-02  5.260e-02   -0.831 0.406013
```

```
## DEAR2TRUE                          1.772e-03  5.003e-03    0.354 0.723115
## GCL1TRUE                           1.786e-01  4.101e-02    4.355 1.33e-05 ***
## NWLA2TRUE                         -1.020e-02  1.103e-02   -0.925 0.354919
## DECADE5TRUE                        1.040e-03  3.506e-03    0.297 0.766786
## SCIENGP1_SCHL21                    7.754e-02  2.292e-03   33.827  < 2e-16 ***
## VETERAN                           -1.758e-02  7.315e-03   -2.404 0.016228 *
## GCM1TRUE                           1.106e-02  1.711e-02    0.646 0.518256
## GCM2TRUE                          -6.377e-03  1.695e-02   -0.376 0.706680
## GCM4TRUE                           2.230e-02  1.348e-02    1.654 0.098059 .
## HINS32TRUE                         4.964e-02  1.664e-02    2.983 0.002857 **
## NWAV3TRUE                         -2.263e-02  8.308e-03   -2.723 0.006466 **
## SCHL02TRUE                        -3.983e-02  3.363e-02   -1.184 0.236227
## SCHL03TRUE                        -6.848e-02  3.793e-02   -1.805 0.071006 .
## DECADE1TRUE                        1.600e-02  3.138e-02    0.510 0.610265
## DECADE2TRUE                        5.866e-03  1.042e-02    0.563 0.573573
## PAOC3TRUE                         -1.105e-01  2.305e-02   -4.795 1.63e-06 ***
## AGEP_GCR1                          1.164e-03  7.613e-04    1.529 0.126288
## GCM3TRUE                           2.665e-03  1.223e-02    0.218 0.827452
## NWAV2TRUE                         -8.294e-03  1.418e-02   -0.585 0.558620
## NWLK2TRUE                          7.811e-02  7.118e-03   10.973  < 2e-16 ***
## NWRE3TRUE                          3.179e-02  1.178e-02    2.698 0.006973 **
## QTRBIR2TRUE                        2.164e-03  1.219e-03    1.776 0.075757 .
## SameResidenceWorkplaceTRUE:JWMNP  4.053e-06  7.287e-05    0.056 0.955644
## JWMNP:JWTR02                      -4.712e-04  1.278e-04   -3.688 0.000226 ***
## JWMNP:JWTR03                      -4.075e-04  1.036e-03   -0.393 0.693954
## JWMNP:JWTR04                      -3.007e-03  1.743e-04  -17.252  < 2e-16 ***
## JWMNP:JWTR05                      -1.646e-03  1.913e-04   -8.605  < 2e-16 ***
## JWMNP:JWTR06                      -1.650e-03  6.101e-04   -2.704 0.006852 **
## JWMNP:JWTR07                      -1.013e-03  7.045e-04   -1.439 0.150256
## JWMNP:JWTR08                       3.503e-04  6.298e-04    0.556 0.578017
## JWMNP:JWTR09                       1.478e-03  4.447e-04    3.325 0.000885 ***
## JWMNP:JWTR10                       4.182e-04  2.490e-04    1.680 0.093044 .
## JWMNP:JWTR12                      -4.323e-05  1.213e-04   -0.356 0.721470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.435 on 781192 degrees of freedom
## Multiple R-squared:  0.5123, Adjusted R-squared:  0.5122
## F-statistic:  4662 on 176 and 781192 DF,  p-value: < 2.2e-16
```

```r
# Test Prediction
pred.olsDLasso.1 <- predict(olsDLasso1, newdata = dattemp[-train,])
summary(pred.olsDLasso.1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.3127  1.9878  2.2644  2.2562  2.5408  4.2571
```

```r
length(na.omit(pred.olsDLasso.1)) # count remaining observations
```

```
## [1] 195343
```

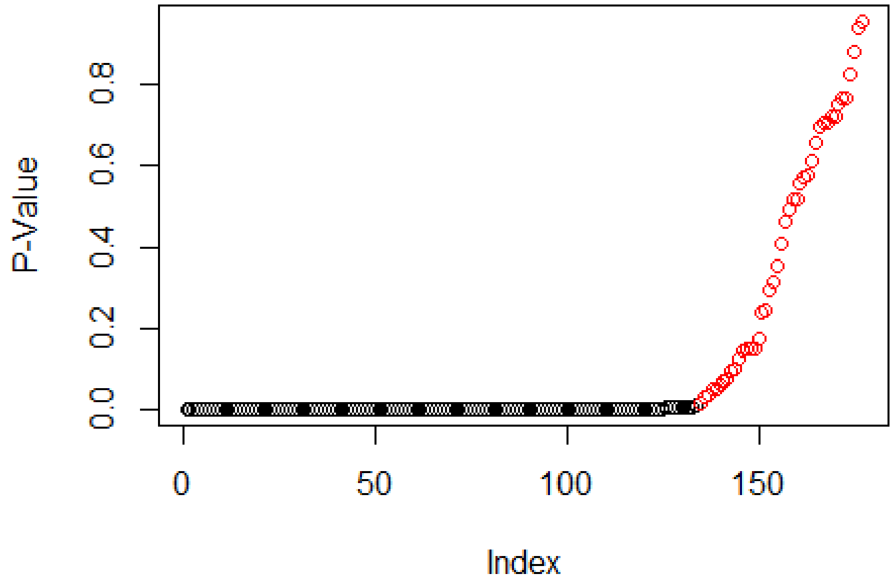
```r
# test error
mse.1 <- mean((pred.olsDLasso.1-log(dattemp[-train,]$IncomePovertyRatio))^2, na.rm=T)
mse.1
```

```
## [1] 0.1894029
```

Result 1: Analysis & Hypothesis Testing

```r
# 3 Ways of getting Test R2
y <- log(dattemp[-train,]$IncomePovertyRatio)-mean(log(dattemp[-train,]$IncomePovertyRatio))
yhat <- pred.olsDLasso.1-mean(pred.olsDLasso.1)
u <- y - yhat
# 1:
# R2 = yhat*yhat/yTy
r2_1 <- (yhat %*% yhat)/(y %*% y)
r2_1
```

```
##           [,1]
## [1,] 0.5125579

# 2:
# R2 = 1- SSR/SST = 1- uTu/yTy
r2_2 <- 1 - (u %*% u)/(y %*% y)
r2_2

##           [,1]
## [1,] 0.5089613

# 3:
# R2 = corr(y, yhat)^2, "fair r-squared"
r2_3 <- cor.test(y, yhat, use = "complete.obs")
# now, square the correlation coefficient
r2_3

##
##  Pearson's product-moment correlation
##
## data:  y and yhat
## t = 449.97, df = 195341, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.7112352 0.7155903
## sample estimates:
##       cor
## 0.7134197

r2_3$estimate^2

##       cor
## 0.5089676

# False Discovery Rate control
p <- as.data.frame(DMLresult$coefficients[,4])
sigcode <- cut(p[,1], breaks = c(-Inf, 0.001, 0.01, 0.05, 0.1, 1),
               labels = c("***", "**", "*", ".", " "))
p$"" <- sigcode

# sort by increasing p-value
p <- p[order(p$`DMLresult$coefficients[, 4]`),]
p$BY <- 0
m <- nrow(p)
Q = 0.10  # 10%
cm=0
for (ii in 1:m) {
  cm = cm + 1/ii
  p[ii,3] <- ii/m/cm*Q
}
noreject <- (!(p[,1] < p[,3]))
plot(p$`DMLresult$coefficients[, 4]`,ylab="P-Value", col = ifelse(noreject,'red','black'))
```




```
noreject <- which(noreject)
p <- p[noreject,]   # these one's we cannot reject the null
names(p) <- c("p-value","Sig. Level","BY Stat")
p

##                                 p-value Sig. Level    BY Stat
## VETERAN                      0.01622773          * 0.01390240
## CIT4TRUE                     0.02857226          * 0.01398663
## RACPI1TRUE                   0.03678683          * 0.01407078
## RACSOR1TRUE                  0.04889671          * 0.01415484
## DRIVESP5TRUE                 0.04980121          * 0.01423881
## GCR2TRUE                     0.06167725          . 0.01432270
## SCHL03TRUE                   0.07100579          . 0.01440650
## QTRBIR2TRUE                  0.07575731          . 0.01449022
## JWMNP:JWTR10                 0.09304410          . 0.01457386
## GCM4TRUE                     0.09805948          . 0.01465741
## AGEP_GCR1                    0.12628818            0.01474089
## NWAV5TRUE                    0.14606246            0.01482428
## AGEP_GCL2                    0.14789649            0.01490759
## JWMNP:JWTR07                 0.15025585            0.01499082
## SCIENGRLP2_SCHL23            0.15127602            0.01507397
## SCIENGRLP1_SCHL22            0.17598520            0.01515704
## SCHL02TRUE                   0.23622737            0.01524004
## DOUT2TRUE                    0.24166238            0.01532296
## DRIVESP1TRUE                 0.29440172            0.01540580
## JWTR08                       0.31304290            0.01548857
## NWLA2TRUE                    0.35491891            0.01557126
## CIT2TRUE                     0.40601337            0.01565387
## JWTR02                       0.46082218            0.01573642
## JWTR03                       0.49432147            0.01581889
## JWTR12                       0.51813036            0.01590128
## GCM1TRUE                     0.51825607            0.01598361
## NWAV2TRUE                    0.55862008            0.01606586
## DECADE2TRUE                  0.57357341            0.01614804
## JWMNP:JWTR08                 0.57801715            0.01623016
## DECADE1TRUE                  0.61026469            0.01631220
## MARHD8TRUE                   0.65658784            0.01639417
```

```
## JWMNP:JWTR03                     0.69395359          0.01647607
## HINS72TRUE                       0.70398697          0.01655791
## GCM2TRUE                         0.70667974          0.01663968
## JWMNP:JWTR12                     0.72146983          0.01672138
## DEAR2TRUE                        0.72311468          0.01680301
## WAOB2TRUE                        0.75306776          0.01688458
## NWLA3TRUE                        0.76363569          0.01696608
## DECADE5TRUE                      0.76678592          0.01704751
## GCM3TRUE                         0.82745213          0.01712888
## RACNH1TRUE                       0.87978946          0.01721019
## NWAB3TRUE                        0.93894933          0.01729143
## SameResidenceWorkplaceTRUE:JWMNP 0.95564425          0.01737261

# get BY-adjusted p-values
pBY <- as.data.frame(p.adjust(p[,1], method = "BY"))   #Benjamini-Yekutieli
rownames(pBY) <- rownames(p)
adjsigcode <- cut(pBY[,1], breaks = c(-Inf, 0.001, 0.01, 0.05, 0.1, 1),
               labels = c("***", "**", "*", ".", " "))
pBY$"" <- adjsigcode

# compare p-values for non-rejected
fdr <- cbind.data.frame(p[,c(1,2)], pBY)
colnames(fdr) <- c("Original","Sig. Level", "FDR Adj.","Sig. Level")
fdr

##                                    Original Sig. Level FDR Adj. Sig. Level
## VETERAN                          0.01622773          *        1
## CIT4TRUE                         0.02857226          *        1
## RACPI1TRUE                       0.03678683          *        1
## RACSOR1TRUE                      0.04889671          *        1
## DRIVESP5TRUE                     0.04980121          *        1
## GCR2TRUE                         0.06167725          .        1
## SCHL03TRUE                       0.07100579          .        1
## QTRBIR2TRUE                      0.07575731          .        1
## JWMNP:JWTR10                     0.09304410          .        1
## GCM4TRUE                         0.09805948          .        1
## AGEP_GCR1                        0.12628818                   1
## NWAV5TRUE                        0.14606246                   1
## AGEP_GCL2                        0.14789649                   1
## JWMNP:JWTR07                     0.15025585                   1
## SCIENGRLP2_SCHL23                0.15127602                   1
## SCIENGRLP1_SCHL22                0.17598520                   1
## SCHL02TRUE                       0.23622737                   1
## DOUT2TRUE                        0.24166238                   1
## DRIVESP1TRUE                     0.29440172                   1
## JWTR08                           0.31304290                   1
## NWLA2TRUE                        0.35491891                   1
## CIT2TRUE                         0.40601337                   1
## JWTR02                           0.46082218                   1
## JWTR03                           0.49432147                   1
## JWTR12                           0.51813036                   1
## GCM1TRUE                         0.51825607                   1
## NWAV2TRUE                        0.55862008                   1
## DECADE2TRUE                      0.57357341                   1
## JWMNP:JWTR08                     0.57801715                   1
## DECADE1TRUE                      0.61026469                   1
## MARHD8TRUE                       0.65658784                   1
## JWMNP:JWTR03                     0.69395359                   1
## HINS72TRUE                       0.70398697                   1
## GCM2TRUE                         0.70667974                   1
## JWMNP:JWTR12                     0.72146983                   1
## DEAR2TRUE                        0.72311468                   1
## WAOB2TRUE                        0.75306776                   1
## NWLA3TRUE                        0.76363569                   1
## DECADE5TRUE                      0.76678592                   1
## GCM3TRUE                         0.82745213                   1
## RACNH1TRUE                       0.87978946                   1
## NWAB3TRUE                        0.93894933                   1
## SameResidenceWorkplaceTRUE:JWMNP 0.95564425                   1
```

```r
# BP test for heteroskedasticity
bpres1 <- bptest(olsDLasso1, data = dattemp[-train,]) #reject homoskedasticity if p-value is small
bpres1

##
##  studentized Breusch-Pagan test
##
## data:  olsDLasso1
## BP = 58372, df = 176, p-value < 2.2e-16

# F-test
null = c("SameResidenceWorkplaceTRUE","JWMNP",
         "JWTR02","JWTR03","JWTR04","JWTR05","JWTR06","JWTR07","JWTR08",
         "JWTR09","JWTR10","JWTR12")
if (bpres1$p.value >= 0.001) {   # homoskedastic
  linearHypothesis(olsDLasso1, null, vcov = hccm(olsDLasso1, type = "hc0")) # classical White VCOV
} else {
  linearHypothesis(olsDLasso1, null) # default homoskedastic error
}


## Hypothesis:
## SameResidenceWorkplaceTRUE = 0
## JWMNP = 0
## JWTR02 = 0
## JWTR03 = 0
## JWTR04 = 0
## JWTR05 = 0
## JWTR06 = 0
## JWTR07 = 0
## JWTR08 = 0
## JWTR09 = 0
## JWTR10 = 0
## JWTR12 = 0
##
## Model 1: restricted model
## Model 2: log(IncomePovertyRatio) ~ SameResidenceWorkplace * JWMNP + JWTR *
##     JWMNP + SPORDER + PWGTP + AGEP + CIT3 + CIT4 + CIT5 + COW2 +
##     COW3 + COW4 + COW5 + COW6 + COW7 + COW8 + DDRS2 + DEYE2 +
##     DPHY2 + DREM2 + ENG2 + ENG3 + ENG4 + FER1 + FER2 + GCL2 +
##     GCR2 + HINS12 + HINS22 + HINS42 + HINS52 + HINS62 + HINS72 +
##     LANX2 + MAR2 + MAR3 + MAR4 + MARHD2 + MARHT2 + MARHT3 + MARHYP +
##     MIG2 + MIG3 + NWAB2 + NWAV5 + NWLA3 + NWLK3 + NWRE2 + RELP01 +
##     RELP02 + RELP03 + RELP04 + RELP05 + RELP06 + RELP07 + RELP08 +
##     RELP09 + RELP10 + RELP11 + RELP12 + RELP13 + RELP15 + RELP17 +
##     SCHL04 + SCHL05 + SCHL06 + SCHL07 + SCHL08 + SCHL09 + SCHL10 +
##     SCHL11 + SCHL12 + SCHL13 + SCHL14 + SCHL15 + SCHL16 + SCHL17 +
##     SCHL19 + SCHL20 + SCHL22 + SCHL23 + SCHL24 + SEX2 + WKHP +
##     WKW2 + WKW3 + WKW4 + WKW5 + WKW6 + DECADE3 + DECADE4 + DECADE7 +
##     DECADE8 + DIS2 + DRIVESP1 + DRIVESP2 + DRIVESP3 + DRIVESP4 +
##     DRIVESP5 + MSP2 + PAOC1 + PAOC2 + PAOC4 + QTRBIR3 + RACAIAN1 +
##     RACASN1 + RACBLK1 + RACPI1 + RACWHT1 + SCIENGRLP1 + SCIENGRLP2 +
##     WAOB2 + WAOB3 + WAOB5 + WAOB6 + WAOB7 + WAOB8 + AGEP_HINS31 +
##     SCIENGP_SCHL01 + SCIENGP1_SCHL22 + SCIENGP1_SCHL23 + SCIENGP1_SCHL24 +
##     SCIENGRLP1_SCHL22 + SCIENGRLP2_SCHL23 + SCIENGRLP1_SCHL24 +
##     AGEP_VETERAN + AGEP_GCL + DOUT2 + MARHD8 + NWAB3 + RACNH1 +
##     RACSOR1 + AGEP_GCL2 + CIT2 + DEAR2 + GCL1 + NWLA2 + DECADE5 +
##     SCIENGP1_SCHL21 + VETERAN + GCM1 + GCM2 + GCM4 + HINS32 +
##     NWAV3 + SCHL02 + SCHL03 + DECADE1 + DECADE2 + PAOC3 + AGEP_GCR1 +
##     GCM3 + NWAV2 + NWLK2 + NWRE3 + QTRBIR2
##
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1 781204 148776
## 2 781192 147823 12    953.35 419.85 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
null = c("JWMNP",
         "JWTR02","JWTR03","JWTR04","JWTR05","JWTR06","JWTR07","JWTR08",
         "JWTR09","JWTR10","JWTR12",
         "JWMNP:JWTR02","JWMNP:JWTR03","JWMNP:JWTR04","JWMNP:JWTR05","JWMNP:JWTR06",
         "JWMNP:JWTR07","JWMNP:JWTR08","JWMNP:JWTR09","JWMNP:JWTR10","JWMNP:JWTR12")
if (bpres1$p.value >= 0.001) {   # homoskedastic
  linearHypothesis(olsDLasso1, null, vcov = hccm(olsDLasso1, type = "hc0")) # classical White VCOV
} else {
  linearHypothesis(olsDLasso1, null)
}
```

```
## Hypothesis:
## JWMNP = 0
## JWTR02 = 0
## JWTR03 = 0
## JWTR04 = 0
## JWTR05 = 0
## JWTR06 = 0
## JWTR07 = 0
## JWTR08 = 0
## JWTR09 = 0
## JWTR10 = 0
## JWTR12 = 0
## JWMNP:JWTR02 = 0
## JWMNP:JWTR03 = 0
## JWMNP:JWTR04 = 0
## JWMNP:JWTR05 = 0
## JWMNP:JWTR06 = 0
## JWMNP:JWTR07 = 0
## JWMNP:JWTR08 = 0
## JWMNP:JWTR09 = 0
## JWMNP:JWTR10 = 0
## JWMNP:JWTR12 = 0
##
## Model 1: restricted model
## Model 2: log(IncomePovertyRatio) ~ SameResidenceWorkplace * JWMNP + JWTR *
##     JWMNP + SPORDER + PWGTP + AGEP + CIT3 + CIT4 + CIT5 + COW2 +
##     COW3 + COW4 + COW5 + COW6 + COW7 + COW8 + DDRS2 + DEYE2 +
##     DPHY2 + DREM2 + ENG2 + ENG3 + ENG4 + FER1 + FER2 + GCL2 +
##     GCR2 + HINS12 + HINS22 + HINS42 + HINS52 + HINS62 + HINS72 +
##     LANX2 + MAR2 + MAR3 + MAR4 + MARHD2 + MARHT2 + MARHT3 + MARHYP +
##     MIG2 + MIG3 + NWAB2 + NWAV5 + NWLA3 + NWLK3 + NWRE2 + RELP01 +
##     RELP02 + RELP03 + RELP04 + RELP05 + RELP06 + RELP07 + RELP08 +
##     RELP09 + RELP10 + RELP11 + RELP12 + RELP13 + RELP15 + RELP17 +
##     SCHL04 + SCHL05 + SCHL06 + SCHL07 + SCHL08 + SCHL09 + SCHL10 +
##     SCHL11 + SCHL12 + SCHL13 + SCHL14 + SCHL15 + SCHL16 + SCHL17 +
##     SCHL19 + SCHL20 + SCHL22 + SCHL23 + SCHL24 + SEX2 + WKHP +
##     WKW2 + WKW3 + WKW4 + WKW5 + WKW6 + DECADE3 + DECADE4 + DECADE7 +
##     DECADE8 + DIS2 + DRIVESP1 + DRIVESP2 + DRIVESP3 + DRIVESP4 +
##     DRIVESP5 + MSP2 + PAOC1 + PAOC2 + PAOC4 + QTRBIR3 + RACAIAN1 +
##     RACASN1 + RACBLK1 + RACPI1 + RACWHT1 + SCIENGRLP1 + SCIENGRLP2 +
##     WAOB2 + WAOB3 + WAOB5 + WAOB6 + WAOB7 + WAOB8 + AGEP_HINS31 +
##     SCIENGP_SCHL01 + SCIENGP1_SCHL22 + SCIENGP1_SCHL23 + SCIENGP1_SCHL24 +
##     SCIENGRLP1_SCHL22 + SCIENGRLP2_SCHL23 + SCIENGRLP1_SCHL24 +
##     AGEP_VETERAN + AGEP_GCL + DOUT2 + MARHD8 + NWAB3 + RACNH1 +
##     RACSOR1 + AGEP_GCL2 + CIT2 + DEAR2 + GCL1 + NWLA2 + DECADE5 +
##     SCIENGP1_SCHL21 + VETERAN + GCM1 + GCM2 + GCM4 + HINS32 +
##     NWAV3 + SCHL02 + SCHL03 + DECADE1 + DECADE2 + PAOC3 + AGEP_GCR1 +
##     GCM3 + NWAV2 + NWLK2 + NWRE3 + QTRBIR2
##
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1 781213 148435
## 2 781192 147823 21    612.12 154.04 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
null = c("SameResidenceWorkplaceTRUE","JWMNP",
         "JWTR02","JWTR03","JWTR04","JWTR05","JWTR06","JWTR07","JWTR08",
```

```r
         "JWTR09","JWTR10","JWTR12",
         "SameResidenceWorkplaceTRUE:JWMNP",
         "JWMNP:JWTR02","JWMNP:JWTR03","JWMNP:JWTR04","JWMNP:JWTR05","JWMNP:JWTR06",
         "JWMNP:JWTR07","JWMNP:JWTR08","JWMNP:JWTR09","JWMNP:JWTR10","JWMNP:JWTR12")
if (bpres1$p.value >= 0.001) {   # homoskedastic
  linearHypothesis(olsDLasso1, null, vcov = hccm(olsDLasso1, type = "hc0")) # classical White VCOV
} else {
  linearHypothesis(olsDLasso1, null)
}
```

```
## Hypothesis:
## SameResidenceWorkplaceTRUE = 0
## JWMNP = 0
## JWTR02 = 0
## JWTR03 = 0
## JWTR04 = 0
## JWTR05 = 0
## JWTR06 = 0
## JWTR07 = 0
## JWTR08 = 0
## JWTR09 = 0
## JWTR10 = 0
## JWTR12 = 0
## SameResidenceWorkplaceTRUE:JWMNP = 0
## JWMNP:JWTR02 = 0
## JWMNP:JWTR03 = 0
## JWMNP:JWTR04 = 0
## JWMNP:JWTR05 = 0
## JWMNP:JWTR06 = 0
## JWMNP:JWTR07 = 0
## JWMNP:JWTR08 = 0
## JWMNP:JWTR09 = 0
## JWMNP:JWTR10 = 0
## JWMNP:JWTR12 = 0
##
## Model 1: restricted model
## Model 2: log(IncomePovertyRatio) ~ SameResidenceWorkplace * JWMNP + JWTR *
##     JWMNP + SPORDER + PWGTP + AGEP + CIT3 + CIT4 + CIT5 + COW2 +
##     COW3 + COW4 + COW5 + COW6 + COW7 + COW8 + DDRS2 + DEYE2 +
##     DPHY2 + DREM2 + ENG2 + ENG3 + ENG4 + FER1 + FER2 + GCL2 +
##     GCR2 + HINS12 + HINS22 + HINS42 + HINS52 + HINS62 + HINS72 +
##     LANX2 + MAR2 + MAR3 + MAR4 + MARHD2 + MARHT2 + MARHT3 + MARHYP +
##     MIG2 + MIG3 + NWAB2 + NWAV5 + NWLA3 + NWLK3 + NWRE2 + RELP01 +
##     RELP02 + RELP03 + RELP04 + RELP05 + RELP06 + RELP07 + RELP08 +
##     RELP09 + RELP10 + RELP11 + RELP12 + RELP13 + RELP15 + RELP17 +
##     SCHL04 + SCHL05 + SCHL06 + SCHL07 + SCHL08 + SCHL09 + SCHL10 +
##     SCHL11 + SCHL12 + SCHL13 + SCHL14 + SCHL15 + SCHL16 + SCHL17 +
##     SCHL19 + SCHL20 + SCHL22 + SCHL23 + SCHL24 + SEX2 + WKHP +
##     WKW2 + WKW3 + WKW4 + WKW5 + WKW6 + DECADE3 + DECADE4 + DECADE7 +
##     DECADE8 + DIS2 + DRIVESP1 + DRIVESP2 + DRIVESP3 + DRIVESP4 +
##     DRIVESP5 + MSP2 + PAOC1 + PAOC2 + PAOC4 + QTRBIR3 + RACAIAN1 +
##     RACASN1 + RACBLK1 + RACPI1 + RACWHT1 + SCIENGRLP1 + SCIENGRLP2 +
##     WAOB2 + WAOB3 + WAOB5 + WAOB6 + WAOB7 + WAOB8 + AGEP_HINS31 +
##     SCIENGP_SCHL01 + SCIENGP1_SCHL22 + SCIENGP1_SCHL23 + SCIENGP1_SCHL24 +
##     SCIENGRLP1_SCHL22 + SCIENGRLP2_SCHL23 + SCIENGRLP1_SCHL24 +
##     AGEP_VETERAN + AGEP_GCL + DOUT2 + MARHD8 + NWAB3 + RACNH1 +
##     RACSOR1 + AGEP_GCL2 + CIT2 + DEAR2 + GCL1 + NWLA2 + DECADE5 +
##     SCIENGP1_SCHL21 + VETERAN + GCM1 + GCM2 + GCM4 + HINS32 +
##     NWAV3 + SCHL02 + SCHL03 + DECADE1 + DECADE2 + PAOC3 + AGEP_GCR1 +
##     GCM3 + NWAV2 + NWLK2 + NWRE3 + QTRBIR2
##
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1 781215 149713
## 2 781192 147823 23    1890.1 434.27 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```