Regression Without Potential Endogeneity

```
## Model 2 Post-Double ML OLs with exogenous variable selection ---------------------
# manually delete potentially endogenous variables
# Can X affect or cause Income or Poverty of Both?
endog <- c("SPORDER",    # household size
           "CIT3","CIT4","CIT5",     # citizenship status
           "COW2","COW3","COW4","COW5","COW6","COW7","COW8",   # class of worker
           "DDRS2","DEYE2","DPHY2","DREM2",     # disability
           "ENG2","ENG3","ENG4","FER1","FER2",     # level of english and child birth
           "GCL2","GCR2",     # grandparents with grandchildren
           "HINS12","HINS22","HINS42","HINS52","HINS62","HINS72",    # insurance
           "MAR2","MAR3","MAR4","MARHD2","MARHT2","MARHT3",   # marriage
           "MIG2","MIG3",    # migration
           "NWAB2","NWAV5","NWLA3","NWLK3","NWRE2",   # current work status
           "RELP01","RELP02","RELP03","RELP04","RELP05","RELP06","RELP07",    # relationship in household
           "RELP08","RELP09","RELP10","RELP11","RELP12","RELP13","RELP15","RELP17"
           )
endog2 <- c(61:79,80,81:86,    # degree, sex, work
            91,92:96,97,    # disability, num cars per ppl, marriage status,
            102:106,107:108,    # race, stem degree
            116:122,123:124,125,    # stem*degree, age*stuff, disability
            126:134,    # marriage, work, race, age*stuff, citizenship, disability, work
            136:140,    # school, veteran, grandparents with grandchild
            142:144,    # insurance, work, school
            148:152    # age*stuff, grandparents with grandchild, work
            )

union <- union[-endog2]
union <- union[-which(union %in% endog)] # delete them from formula

# rewrite formula for OLS
exogunionf <- paste(union, collapse = "+")
exogformula <- paste(c("log(IncomePovertyRatio)", exogunionf), collapse = "~")

# Training OLS regression post LASSO
olsDLasso2 <- lm(exogformula, data = dattemp[train,])
DMLresult2 <- summary(olsDLasso2)
# Post-Double LASSO OLS only on Exogeneous vars Result
DMLresult2
```

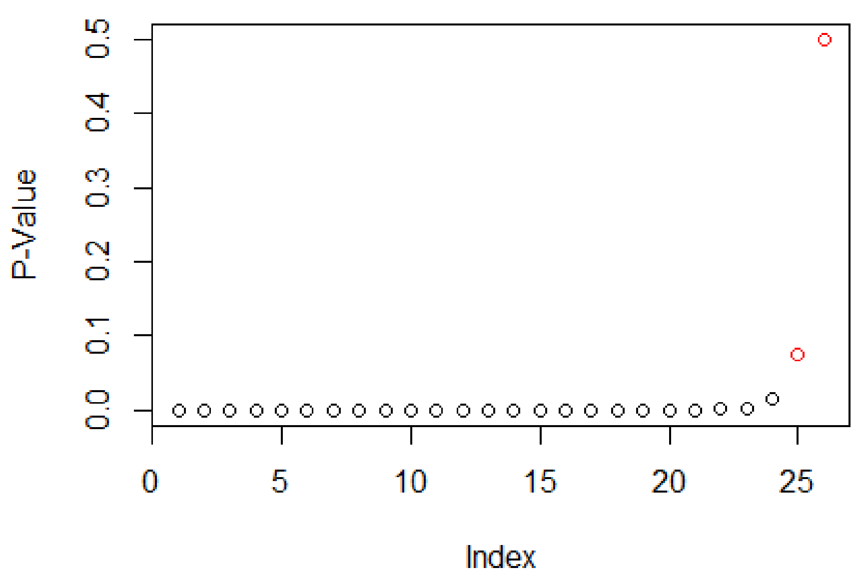
```
##
## Call:
## lm(formula = exogformula, data = dattemp[train, ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.34876 -0.39110 -0.04425  0.33410  3.11596
##
## Coefficients:
##               Estimate Std. Error  t value Pr(>|t|)
## (Intercept) -1.428e+00  1.631e-01   -8.758  < 2e-16 ***
## PWGTP       -1.671e-04  8.701e-06  -19.200  < 2e-16 ***
## AGEP         8.362e-03  9.287e-05   90.045  < 2e-16 ***
## LANX2TRUE    5.025e-02  2.234e-03   22.496  < 2e-16 ***
## MARHYP       1.625e-03  7.909e-05   20.547  < 2e-16 ***
## DECADE3TRUE  1.416e-01  7.867e-03   18.003  < 2e-16 ***
## DECADE4TRUE  1.505e-01  5.346e-03   28.160  < 2e-16 ***
## DECADE7TRUE  2.341e-02  3.879e-03    6.034  1.6e-09 ***
## DECADE8TRUE -5.670e-02  4.600e-03  -12.326  < 2e-16 ***
## PAOC1TRUE   -1.810e-01  3.869e-03  -46.789  < 2e-16 ***
## PAOC2TRUE   -2.695e-01  2.217e-03 -121.533  < 2e-16 ***
## PAOC4TRUE   -3.561e-01  1.553e-03 -229.339  < 2e-16 ***
## QTRBIR3TRUE  4.710e-03  1.610e-03    2.926  0.00344 **
## WAOB2TRUE   -1.658e-01  9.589e-03  -17.294  < 2e-16 ***
## WAOB3TRUE   -3.119e-01  3.194e-03  -97.644  < 2e-16 ***
## WAOB5TRUE    8.521e-02  4.784e-03   17.810  < 2e-16 ***
## WAOB6TRUE   -1.018e-01  7.735e-03  -13.166  < 2e-16 ***
```

```
## WAOB7TRUE    2.027e-01  1.084e-02   18.696  < 2e-16 ***
## WAOB8TRUE    4.730e-02  1.933e-02    2.448  0.01439 *
## AGEP_HINS31 -2.175e-04  3.219e-04   -0.676  0.49922
## DECADE5TRUE  9.779e-02  4.130e-03   23.680  < 2e-16 ***
## HINS32TRUE   1.916e-01  2.207e-02    8.682  < 2e-16 ***
## DECADE1TRUE  7.548e-02  4.239e-02    1.781  0.07499 .
## DECADE2TRUE  7.733e-02  1.371e-02    5.640  1.7e-08 ***
## PAOC3TRUE   -2.705e-01  4.101e-03  -65.946  < 2e-16 ***
## QTRBIR2TRUE  5.347e-03  1.649e-03    3.241  0.00119 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5889 on 781343 degrees of freedom
## Multiple R-squared:  0.106,  Adjusted R-squared:  0.106
## F-statistic:  3708 on 25 and 781343 DF,  p-value: < 2.2e-16

# Test Prediction
pred.olsDLasso.2 <- predict(olsDLasso2, newdata = dattemp[-train,])
summary(pred.olsDLasso.2)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.402   2.113   2.234   2.258   2.431   2.950

length(na.omit(pred.olsDLasso.2)) # count remaining observations

## [1] 195343

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

## [1] 0.34607
```

Result 2: Analysis & Hypothesis Testing

```
# 3 Ways of getting Test R2
y2 <- log(dattemp[-train,]$IncomePovertyRatio)-mean(log(dattemp[-train,]$IncomePovertyRatio))
yhat2 <- pred.olsDLasso.2-mean(pred.olsDLasso.2)
u2 <- y2 - yhat2
# 1:
# R2 = yhat*y/yTy
r2_1_2 <- (yhat2 %*% yhat2)/(y2 %*% y2)
r2_1_2

##           [,1]
## [1,] 0.1064778

# 2:
# R2 = 1- SSR/SST = 1- uTu/yTy
r2_2_2 <- 1 - (u2 %*% u2)/(y2 %*% y2)
r2_2_2

##           [,1]
## [1,] 0.1028011

# 3:
# R2 = corr(y, yhat)^2, "fair r-squared"
r2_3_2 <- cor.test(y2, yhat2, use = "complete.obs")
# now, square the correlation coefficient
r2_3_2

##
##  Pearson's product-moment correlation
##
## data:  y2 and yhat2
## t = 149.63, df = 195341, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
```

```
##  0.3166914 0.3246485
## sample estimates:
##       cor
## 0.3206756

r2_3_2$estimate^2

##       cor
## 0.1028329

# BP test for heteroskedasticity
bpres2 <- bptest(olsDLasso2, data = dattemp[-train,]) #reject homoskedasticity if p-value is small
bpres2

##
##  studentized Breusch-Pagan test
##
## data:  olsDLasso2
## BP = 13044, df = 25, p-value < 2.2e-16

# False Discovery Rate control
p2 <- as.data.frame(DMLresult2$coefficients[,4])
sigcode2 <- cut(p2[,1], breaks = c(-Inf, 0.001, 0.01, 0.05, 0.1, 1),
               labels = c("***", "**", "*", ".", " "))
p2$"" <- sigcode2

# sort by increasing p-value
p2 <- p2[order(p2$`DMLresult2$coefficients[, 4]`),]
p2$BY <- 0
m2 <- nrow(p2)
Q = 0.10  # 10%
cm=0
for (ii in 1:m2) {
  cm = cm + 1/ii
  p2[ii,3] <- ii/m2/cm*Q
}
noreject2 <- (!(p2[,1] < p2[,3]))
plot(p2$`DMLresult2$coefficients[, 4]`,ylab="P-Value", col = ifelse(noreject2,'red','black'))
```



```r
noreject2 <- which(noreject2)
p2 <- p2[noreject2,]   # these one's we cannot reject the null
names(p2) <- c("p-value","Sig. Level","BY Stat")
p2

##                p-value Sig. Level    BY Stat
## DECADE1TRUE 0.07498765          . 0.02519782
## AGEP_HINS31 0.49921838            0.02594424

# get BY-adjusted p-values
pBY2 <- as.data.frame(p.adjust(p2[,1], method = "BY"))   #Benjamini-Yekutieli
rownames(pBY2) <- rownames(p2)
adjsigcode <- cut(pBY2[,1], breaks = c(-Inf, 0.001, 0.01, 0.05, 0.1, 1),
                  labels = c("***", "**", "*", ".", " "))
pBY2$"" <- adjsigcode

# compare p-values for non-rejected
fdr2 <- cbind.data.frame(p2[,c(1,2)], pBY2)
colnames(fdr2) <- c("Original","Sig. Level", "FDR Adj.","Sig. Level")
fdr2

##               Original Sig. Level  FDR Adj. Sig. Level
## DECADE1TRUE 0.07498765          . 0.2249630
## AGEP_HINS31 0.49921838            0.7488276
```