Pol Sci 630: Problem Set 10 Solutions: 2SLS, Matching, Outlier, Heckman

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1 2SLS

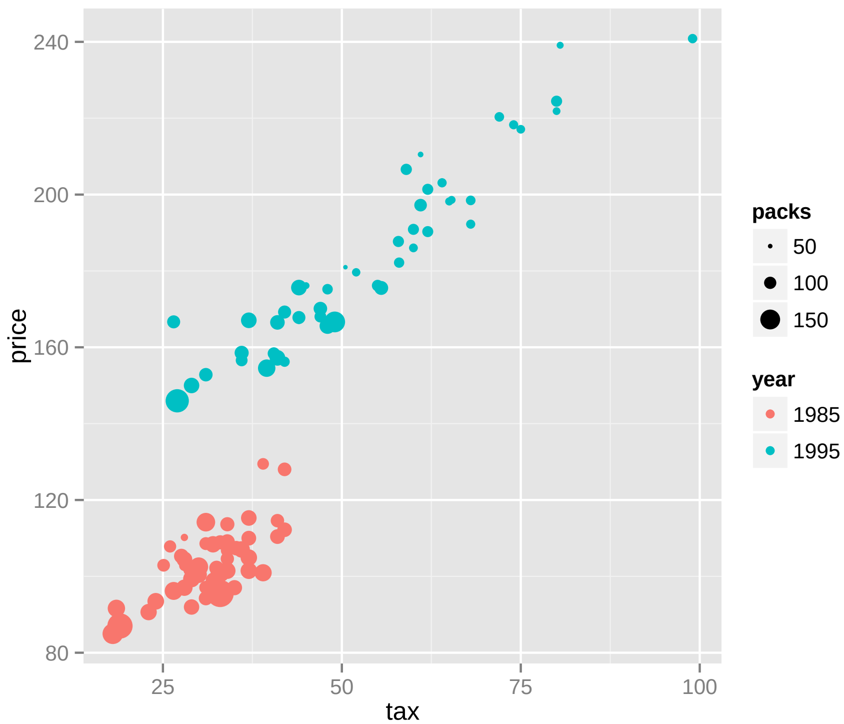
Insert your comments on the assignment that you are grading above the solution in bold and red text. For example write: "GRADER COMMENT: everything is correct! - 8/8 Points" Also briefly point out which, if any, problems were not solved correctly and what the mistake was. See below for more examples.

1.1 Load dataset CigarettesSW from package AER

```
library(AER)
data("CigarettesSW")
```

1.2 Plot the following

What can we say about the relationship between tax, price, and packs? Note: This is a good way to show the relationship between 3 variables with a 2D plot.



Solution

Tax and price are positively correlated. This gives a hint that tax can be a good instrument for price.

Tax and price are negatively correlated with the number of cigarette packs consumed per capita.

1.3 Divide variable income by 1000 (for interpretability)

```
CigarettesSW$income <- CigarettesSW$income / 1000
```

1.4 Run 2SLS

Run 2SLS with `ivreg`. Outcome: packs. Exogenous var: income. Endogenous var: price, whose instrument is tax. Interpret the coefficient of `income` and `price`.

Solution

```
library(stargazer)
m11 <- ivreg(packs ~ income + price | income + tax, data = CigarettesSW)
stargazer(m11)
```

Table 1:

	Dependent variable:
	packs
income	-0.00002
	(0.00002)
price	-0.398^{***}
	(0.055)
Constant	168.488^{***}
	(7.673)
Observations	96
R^2	0.436
Adjusted R^2	0.424
Residual Std. Error	19.637 (df = 93)
Note:	*p<0.1; **p<0.05; ***p<0.01

1000 dollar increase in income leads to $-2.2311969 \times 10^{-5}$ change in number of packs per capita, but the effect is not significant.

1 dollar increase in price leads to -0.3978933 change in number of packs per capita, holding other constants. The coefficient is statistically significant.

1.5 2SLS diagnostics: use F-test to check for weak instrument

Solution

```
summary(m11, diagnostics = TRUE)

##
## Call:
## ivreg(formula = packs ~ income + price | income + tax, data = CigarettesSW)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -56.16120 -10.40243   0.07866   6.87649  67.85671
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.685e+02  7.673e+00  21.957  < 2e-16 ***
## income      -2.231e-05  1.803e-05  -1.238    0.219
```

```
## price       -3.979e-01  5.502e-02  -7.232 1.31e-10 ***
##
## Diagnostic tests:
##                  df1 df2 statistic p-value
## Weak instruments   1  93   341.145  <2e-16 ***
## Wu-Hausman         1  92     2.312   0.132
## Sargan             0  NA        NA      NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.64 on 93 degrees of freedom
## Multiple R-Squared: 0.436,Adjusted R-squared: 0.4239
## Wald test: 35.23 on 2 and 93 DF,  p-value: 4.081e-12
```

The weak instrument test (i.e. F-test) rejects the null hypothesis that the instrument is not correlated with the endogenous variable (p-value $= 7.1137017 \times 10^{-33}$). So our instruments are not weak.

1.6 2SLS by hand

Run the 2SLS by hand, i.e. not using `ivreg`, but run 2 stages of `lm`. Do you get the same estimate from `ivreg`?

Solution

```
m_stage1 <- lm(price ~ tax + income, data = CigarettesSW)
CigarettesSW$price_hat <- predict(m_stage1)

m_stage2 <- lm(packs ~ income + price_hat, data = CigarettesSW)
stargazer(m_stage2)
```

The coefficients are exactly the same (by hand: -0.3978933, by ivreg: -0.3978933)

2 Matching

2.1 Load dataset lalonde from MatchIt, show covariate imbalance

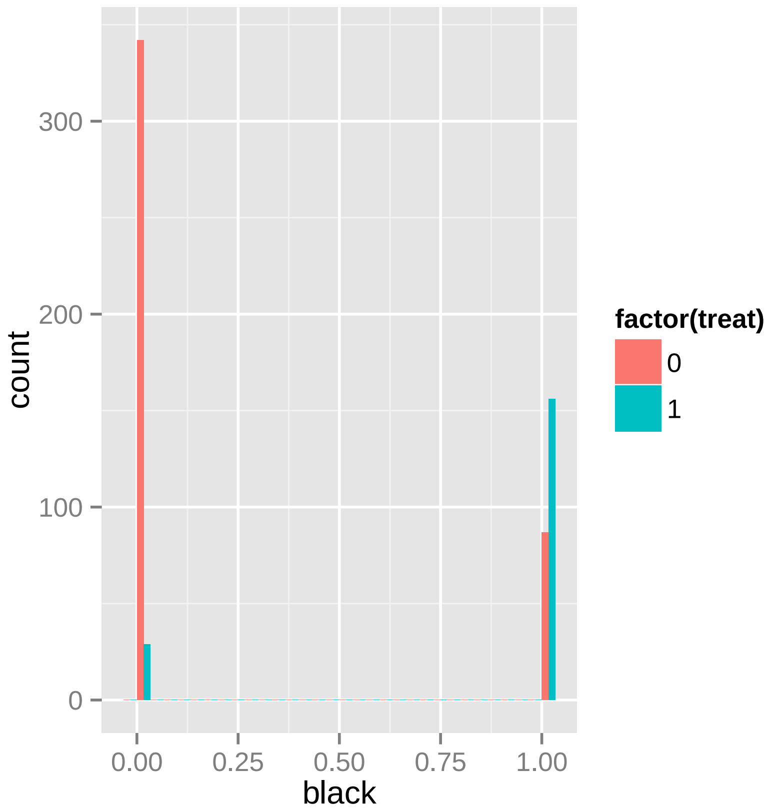
Plot the following. Hint: Look up `position="dodge"` for ggplot2

```
library(MatchIt)

## Loading required package:  MASS

data("lalonde")
ggplot(data = lalonde) +
  geom_histogram(aes(x = black, fill = factor(treat)),
                 position = "dodge")
```

Table 2:

	Dependent variable:
	packs
income	−0.00002
	(0.00002)
price_hat	-0.398^{***}
	(0.055)
Constant	168.488^{***}
	(7.733)
Observations	96
R^2	0.427
Adjusted R^2	0.415
Residual Std. Error	19.788 (df = 93)
F Statistic	34.693^{***} (df = 2; 93)
Note:	*p<0.1; **p<0.05; ***p<0.01

```
## stat_bin:  binwidth defaulted to range/30.  Use 'binwidth = x' to
adjust this.
```



2.2 See the effect of omitting an important variable

Regress re78 against 1) treat, age, educ; 2) treat, age, educ, black. Do the treatment effect differ a lot? Why?

Solution

```
lm(re78 ~ treat + age + educ, data = lalonde)

##
## Call:
## lm(formula = re78 ~ treat + age + educ, data = lalonde)
##
## Coefficients:
## (Intercept)        treat          age         educ
##     -851.74      -480.73        94.93       505.61

lm(re78 ~ treat + age + educ + black, data = lalonde)
```

```
##
## Call:
## lm(formula = re78 ~ treat + age + educ + black, data = lalonde)
##
## Coefficients:
## (Intercept)        treat          age         educ        black
##     -156.53       853.13        89.41       494.39     -2099.82
```

If we do not control for `black`, we would wrongly conclude that the treatment effect is negative. This is because we have a lot of blacks in the treatment group, and blacks tend to have poorer outcomes.

2.3 Running CEM: Matching and check balance

Match the treatment and the control group based on age, educ, and black. Check the balance

Solution

```
m.out <- matchit(treat ~ age + educ + black, data = lalonde,
                 method = "cem")

## Loading required package:  cem
## Loading required package:  tcltk
## Loading required package:  lattice
##
## How to use CEM? Type vignette("cem")

##
## Using 'treat'='1' as baseline group

summary(m.out) # to check balance

##
## Call:
## matchit(formula = treat ~ age + educ + black, data = lalonde,
##     method = "cem")
##
## Summary of balance for all data:
##          Means Treated Means Control SD Control Mean Diff eQQ Med eQQ Mean
## distance        0.5548        0.1920     0.2275    0.3628  0.5435   0.3640
## age            25.8162       28.0303    10.7867   -2.2141  1.0000   3.2649
## educ           10.3459       10.2354     2.8552    0.1105  1.0000   0.7027
## black           0.8432        0.2028     0.4026    0.6404  1.0000   0.6432
##          eQQ Max
## distance  0.5683
## age      10.0000
## educ      4.0000
```

```
## black     1.0000
##
##
## Summary of balance for matched data:
##          Means Treated Means Control SD Control Mean Diff eQQ Med eQQ Mean
## distance        0.5434        0.5458     0.2232   -0.0024   0.524   0.3040
## age            24.6731       24.2833     6.7293    0.3898   2.000   1.6090
## educ           10.5641       10.7771     1.7526   -0.2130   0.000   0.1987
## black           0.8141        0.8141     0.3898    0.0000   1.000   0.5385
##          eQQ Max
## distance  0.5673
## age       4.0000
## educ      1.0000
## black     1.0000
##
## Percent Balance Improvement:
##          Mean Diff.   eQQ Med eQQ Mean eQQ Max
## distance    99.3301    3.5914  16.4991  0.1884
## age         82.3941 -100.0000  50.7185 60.0000
## educ       -92.7588  100.0000  71.7209 75.0000
## black      100.0000    0.0000  16.2896  0.0000
##
## Sample sizes:
##           Control Treated
## All           429     185
## Matched       266     156
## Unmatched     163      29
## Discarded       0       0
```

We get exact balance after running CEM.

2.4 Running CEM: Analysis after matching

Run a weighted regression of re78 against 1) treat, age, educ, 2) treat, age, educ, and black. Do the treatment effect differ? Compare this result with part 2.

Solution

```
# Get the matched data
lalonde_matched <- match.data(m.out)

# Run weighted regression to get the causal treatment effect
lm(re78 ~ treat + age + educ,
   data = lalonde_matched, weights = lalonde_matched$weights)

##
## Call:
```

```
## lm(formula = re78 ~ treat + age + educ, data = lalonde_matched,
##     weights = lalonde_matched$weights)
##
## Coefficients:
## (Intercept)        treat          age         educ
##     -2158.1       1290.1         53.5        543.8
```

```
lm(re78 ~ treat + age + educ + black,
   data = lalonde_matched, weights = lalonde_matched$weights)
```

```
##
## Call:
## lm(formula = re78 ~ treat + age + educ + black, data = lalonde_matched,
##     weights = lalonde_matched$weights)
##
## Coefficients:
## (Intercept)        treat          age         educ        black
##     -622.46      1297.18        52.07       574.55     -2250.82
```

The treatment effect doen't differ by a lot across the two regressions. It's because in the matched data, we have equal number of blacks in the control and the treatment group.

3 Heckman

3.1 Load Mroz87 data from package sampleSelection

```
library(sampleSelection)
data(Mroz87)
```

3.2 Run a Heckman model

The selection variable is lfp. Run a heckman model with huswage, kid5, educ, city explaning the selection, and educ and city explaning the outcome variable log(wage). Interpret the result for the outcome model

Solution

```
a <- heckit(lfp ~ huswage + kids5 + educ + city, log(wage) ~ educ + city, data=Mroz87)
summary(a)
```

```
## --------------------------------------------
## Tobit 2 model (sample selection model)
## 2-step Heckman / heckit estimation
## 753 observations (325 censored and 428 observed)
```

```
## 11 free parameters (df = 743)
## Probit selection equation:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.22827    0.26978  -4.553 6.18e-06 ***
## huswage     -0.04370    0.01295  -3.375 0.000777 ***
## kids5       -0.63490    0.09819  -6.466 1.83e-10 ***
## educ         0.15536    0.02322   6.691 4.35e-11 ***
## city        -0.03468    0.10593  -0.327 0.743469
## Outcome equation:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.02817    0.34074  -0.083    0.934
## educ         0.09843    0.01979   4.973 8.19e-07 ***
## city         0.07437    0.07088   1.049    0.294
## Multiple R-Squared:0.1205,Adjusted R-Squared:0.1143
## Error terms:
##               Estimate Std. Error t value Pr(>|t|)
## invMillsRatio  -0.1195     0.1991    -0.6    0.549
## sigma           0.6833         NA      NA       NA
## rho            -0.1749         NA      NA       NA
## --------------------------------------------
```

1 more year of education leads to 0.0984295 change in log wage (the effect is also significant). Being in a city leads to 0.0743715 change in the log wage but the effect is not significant.

3.3 Outlier

Load the anscombe dataset (the famous Anscombe quartet). Run a regression of y3 against x3, and find the outlier using any tools that we have discussed (DFbeta, cook distance, etc.)

Brownie point: Fit a linear model for y1 agains x1, y2 against x2, etc. What spooky thing did you notice?

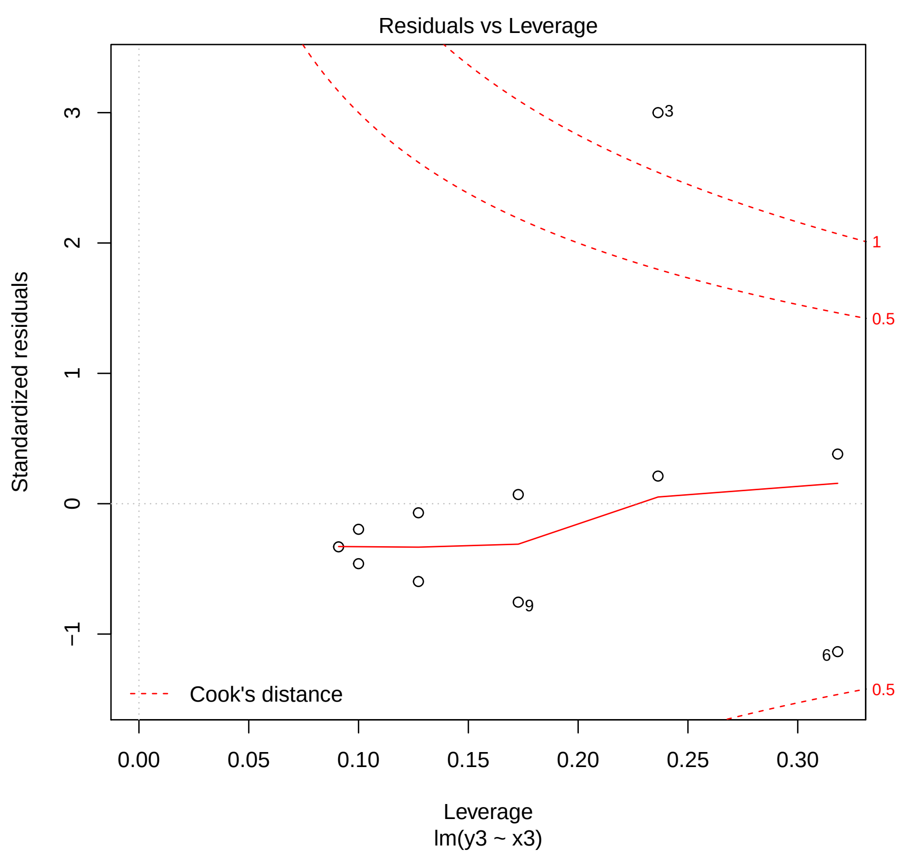
Solution

```
data("anscombe")

# DFBetas
m3 <- lm(y3 ~ x3, data = anscombe)
influence.measures(m3)

## Influence measures of
##   lm(formula = y3 ~ x3, data = anscombe) :
##
##       dfb.1_    dfb.x3    dffit    cov.r   cook.d    hat inf
## 1  -4.63e-03 -4.41e-02  -0.1464 1.34e+00 0.011765 0.1000
## 2  -3.71e-02  1.86e-02  -0.0618 1.39e+00 0.002141 0.1000
```

```
## 3  -3.58e+02  5.25e+02 669.5875 5.06e-11 1.392849 0.2364   *
## 4  -3.29e-02 -2.66e-18  -0.0992 1.36e+00 0.005473 0.0909
## 5   4.92e-02 -1.17e-01  -0.2193 1.34e+00 0.025984 0.1273
## 6   4.90e-01 -6.67e-01  -0.7897 1.36e+00 0.300571 0.3182
## 7   2.70e-02 -2.09e-02   0.0303 1.53e+00 0.000518 0.1727
## 8   2.41e-01 -2.09e-01   0.2472 1.80e+00 0.033817 0.3182   *
## 9   1.37e-01 -2.31e-01  -0.3362 1.34e+00 0.059536 0.1727
## 10 -1.97e-02  1.34e-02  -0.0251 1.45e+00 0.000355 0.1273
## 11  1.05e-01 -8.74e-02   0.1114 1.64e+00 0.006948 0.2364
```

The third observation has a very large DFbetas, thus likely an outlier.

```r
plot(m3, which = 5)
```



The Cook's D plot confirms that the third observation is an outlier, as it goes out of bound of the red lines denoting Cook's D = 1