Econometrics Test Exercise 4

Vishesh Gupta

Questions

A challenging and very relevant economic problem is the measurement of the returns to schooling. In this question we will use the following variables on 3010 US men:

- **logw**: log wage
- **educ**: number of years of schooling
- **age**: age of the individual in years
- **exper**: working experience in years
- **smsa**: dummy indicating whether the individual lived in a metropolitan area
- **south**: dummy indicating whether the individual lived in the south
- **nearc**: dummy indicating whether the individual lived near a 4-year college
- **daded**: education of the individual's father (in years)
- **momed**: education of the individual's mother (in years)

This data is a selection of the data used by D. Card (1995)

(a) Use OLS to estimate the parameters of the model

$$logw = \beta_1 + \beta_2 * educ + \beta_3 * exper + \beta_4 * exper^2 + \beta_5 * smsa + \beta_6 * south + \epsilon.$$

Give an interpretation to the estimated β_2 coefficient.

(b) OLS may be inconsistent in this case as $educ$ and $exper$ may be endogenous. Give a reason why this may be the case. Also indicate whether the estimate in part (a) is still useful.

(c) Give a motivation why age and age^2 can be used as instruments for $exper$ and $exper^2$.

(d) Run the first-stage regression for $educ$ for the two-stage least squares estimation of the parameters in the model above when age, age^2, $nearc$, $daded$, and $momed$ are used as additional instruments. What do you conclude about the suitability of these instruments for schooling?

(e) Estimate the parameters of the model for log wage using two-stage least squares where you correct for the endogeneity of education and experience. Compare your result to the estimate in part (a).

(f) Perform the Sargan test for validity of the instruments. What is your conclusion?

Exercise initialization

Loading data…

```
dat <- read.csv("../TestExer4_Wage-round1.txt")
#dat
dat$nbr <- 1:nrow(dat)
dat$exper2 <- dat$exper^2
dat$age2 <- dat$age^2
str(dat)
```

```
## 'data.frame':    3010 obs. of  12 variables:
##  $ logw  : num  6.31 6.18 6.58 5.52 6.59 ...
##  $ educ  : int  7 12 12 11 12 12 18 14 12 12 ...
##  $ age   : int  29 27 34 27 34 26 33 29 28 29 ...
##  $ exper : int  16 9 16 10 16 8 9 9 10 11 ...
##  $ smsa  : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ south : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ nearc : int  0 0 0 1 1 1 1 1 1 1 ...
##  $ daded : num  9.94 8 14 11 8 9 14 14 12 12 ...
##  $ momed : num  10.2 8 12 12 7 ...
##  $ nbr   : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ exper2: num  256 81 256 100 256 64 81 81 100 121 ...
##  $ age2  : num  841 729 1156 729 1156 ...
```

```
summary(dat)
```

```
##       logw            educ            age            exper       
##  Min.   :4.605   Min.   : 1.00   Min.   :24.00   Min.   : 0.000  
##  1st Qu.:5.977   1st Qu.:12.00   1st Qu.:25.00   1st Qu.: 6.000  
##  Median :6.287   Median :13.00   Median :28.00   Median : 8.000  
##  Mean   :6.262   Mean   :13.26   Mean   :28.12   Mean   : 8.856  
##  3rd Qu.:6.564   3rd Qu.:16.00   3rd Qu.:31.00   3rd Qu.:11.000  
##  Max.   :7.785   Max.   :18.00   Max.   :34.00   Max.   :23.000  
##       smsa           south            nearc            daded       
##  Min.   :0.000   Min.   :0.0000   Min.   :0.0000   Min.   : 0.000  
##  1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.: 8.000  
##  Median :1.000   Median :0.0000   Median :1.0000   Median : 9.940  
##  Mean   :0.713   Mean   :0.4037   Mean   :0.6821   Mean   : 9.989  
##  3rd Qu.:1.000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:12.000  
##  Max.   :1.000   Max.   :1.0000   Max.   :1.0000   Max.   :18.000  
##      momed            nbr             exper2            age2       
##  Min.   : 0.00   Min.   :   1.0   Min.   :  0.00   Min.   : 576.0  
##  1st Qu.: 9.00   1st Qu.: 753.2   1st Qu.: 36.00   1st Qu.: 625.0  
##  Median :11.00   Median :1505.5   Median : 64.00   Median : 784.0  
##  Mean   :10.34   Mean   :1505.5   Mean   : 95.58   Mean   : 800.5  
##  3rd Qu.:12.00   3rd Qu.:2257.8   3rd Qu.:121.00   3rd Qu.: 961.0  
##  Max.   :18.00   Max.   :3010.0   Max.   :529.00   Max.   :1156.0
```

(a) OLS estimation

(a) Use OLS to estimate the parameters of the model

$$logw = \beta_1 + \beta_2 * educ + \beta_3 * exper + \beta_4 * exper^2 + \beta_5 * smsa + \beta_6 * south + \epsilon.$$

Give an interpretation to the estimated β_2 coefficient.

logw variable regression results (see also Appendix A).

Variable	Coefficient	Standard Error	t-statistic
(Constant)	4.611	0.0679	67.914

Variable	Coefficient	Standard Error	t-statistic
educ	0.082	0.0035	23.315
exper	0.084	0.0068	12.377
$exper^2$	-0.002	0.0003	-6.800
smsa	0.151	0.0158	9.523
south	-0.175	0.0146	-11.959
……	……	……	……
R^2	0.2632		

Conclusion:

OLS estimates the following model:

$$\begin{aligned} logw =& 4.611 \\ &+ 0.082 \cdot educ \\ &+ 0.084 \cdot exper \\ &- 0.002 \cdot exper^2 \\ &+ 0.151 \cdot smsa \\ &- 0.175 \cdot south \end{aligned}$$

Model characteristics: R^2 = 0.2632

Estimated β_2 coefficient interpretation:

The 0.082 $educ$ coefficient means that with each additional year of schooling, the log wage increases by about 0.082.

Therefore, with each additional year of schooling the wage increases by about exp(0.082), or by 1.085 or ~8.5%.

(b) Endogeneity insight

(b) OLS may be inconsistent in this case as $educ$ and $exper$ may be endogenous. Give a reason why this may be the case. Also indicate whether the estimate in part (a) is still useful.

It is possible the wage, experience and education variables to be affected by some other variable (i.e. ability, social class, family support, etc.) in a way, such as, a higher ability to lead to a higher wage, longer education and less experience (due to long education) and vice versa.

In this case, these variables would be endogenous and the OLS estimates would be biased and inconsistent, therefore not useful anymore.

(c) Instrument variables motivation

(c) Give a motivation why age and age^2 can be used as instruments for $exper$ and $exper^2$.

Age is obviously exogenous as it cannot be influenced by the people, and it is also obviously related to experience as younger people cannot have a very long experience.

So it’s a good instrument for the experience variable. And the same applies for their squared values.

(d) First-stage regression

(d) Run the first-stage regression for $educ$ for the two-stage least squares estimation of the parameters in the model above when age, age^2, $nearc$, $daded$, and $momed$ are used as additional instruments. What do you conclude about the suitability of these instruments for schooling?

educ variable regression results (see also Appendix B).

Variable	Coefficient	Standard Error	t-statistic
(Constant)	-5.652	3.976	-1.421
age	0.990	0.279	3.551
age^2	-0.017	0.005	-3.518
smsa	0.530	0.102	5.217
south	-0.425	0.091	-4.667
nearc	0.265	0.099	2.670
daded	0.190	0.016	12.199
momed	0.235	0.017	13.773
……	……	……	……
R^2	0.2466		

Conclusions:

First-stage regression is giving the following model:

$$\begin{aligned} educ = & - 5.652 \\ & + 0.990 \cdot age \\ & - 0.017 \cdot age^2 \\ & + 0.530 \cdot smsa \\ & - 0.425 \cdot south \\ & + 0.265 \cdot nearc \\ & + 0.190 \cdot daded \\ & + 0.235 \cdot momed \end{aligned}$$

Model characteristics: $R^2 = 0.2466$

The additional instruments (age, age^2, $nearc$, $daded$, and $momed$) are significantly correlated with the education. This is especially true about the later two ($daded$ and $momed$) due to their high t-statistics, which makes perfect sense as highly educated parents are more likely to support and promote their children education as well.

So, the instrument variables and the endogenous variable $educ$ are significantly related.

We can use the model estimated in order to compute its fitted values for education, like this:

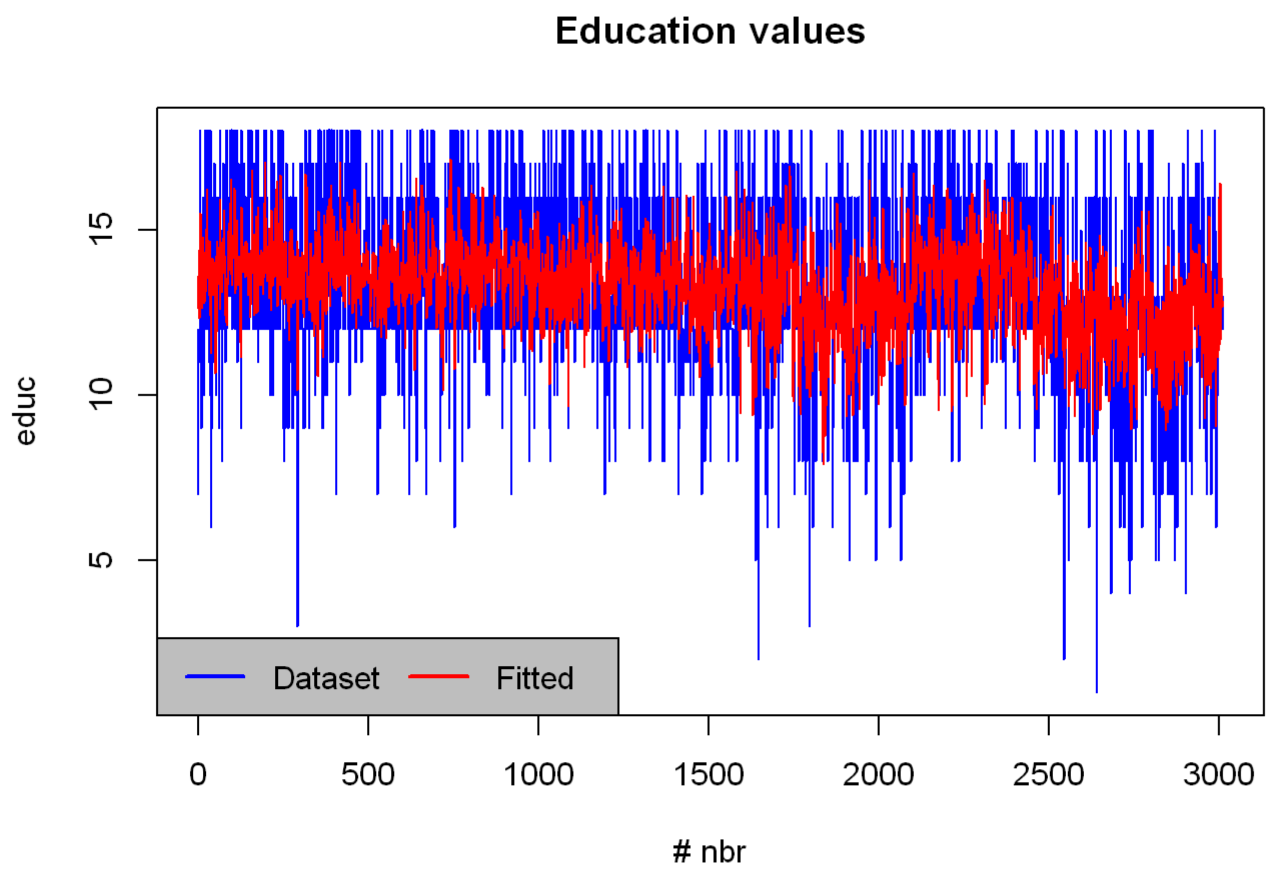
```
dat$educFIT <- -5.652 + 0.990 * dat$age - 0.017 * dat$age2 + 0.530 * dat$smsa -
                0.425 * dat$south + 0.265 * dat$nearc + 0.190 * dat$daded + 0.235 * dat$momed
summary(dat$educ)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00   12.00   13.00   13.26   16.00   18.00
```

```
summary(dat$educFIT)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   7.891  12.560  13.410  13.290  14.170  17.130
```

```
with(dat, plot(nbr, educ,      type='l', col='blue', main="Education values", xlab='# nbr'))
with(dat, points(nbr, educFIT, type='l', col='red'))
legend("bottomleft", c("Dataset","Fitted"), horiz=TRUE,
       lty=c(1,1), lwd=c(2,2), col=c("blue","red"), bg="grey")
```



(e) Two-stage least squares correction

(e) Estimate the parameters of the model for log wage using two-stage least squares where you correct for the endogeneity of education and experience. Compare your result to the estimate in part (a).

We already run the first-stage regression and estimated fitted values for the $educ$ variable, in (d). We can repeat that process for the $exper$ and $exper^2$ variables:

exper and **exper^2** variables regressions results (see also Appendix C).

Variable	exper Coefficient	Std.Error	t-stat	exper^2 Coefficient	Std.Error	t-stat
(Constant)	-0.348	3.976	-0.087	681.383	84.845	8.031
age	0.010	0.279	0.037	-54.065	5.947	-9.091
age^2	0.017	0.005	3.518	1.280	0.103	12.399
smsa	-0.530	0.102	-5.217	-11.803	2.166	-5.450
south	0.425	0.091	4.667	10.615	1.943	5.464
nearc	-0.265	0.099	-2.670	-5.780	2.114	-2.734
daded	-0.190	0.016	-12.199	-3.314	0.333	-9.949
momed	-0.235	0.017	-13.773	-4.733	0.3633	-13.028

Variable	exper Coefficient	Std.Error	t-stat	exper Coefficient	Std.Error	t-stat
……	……	……	……	……	……	……
R^2	0.6853	.	.	0.6567	.	.

Conclusions:

> First-stage regressions are giving the following models:
>
> $$\begin{aligned} exper = &- 0.348 \\ &+ 0.010 \cdot age \\ &+ 0.017 \cdot age^2 \\ &- 0.530 \cdot smsa \\ &+ 0.425 \cdot south \\ &- 0.265 \cdot nearc \\ &- 0.190 \cdot daded \\ &- 0.235 \cdot momed \end{aligned}$$
>
> $$\begin{aligned} exper^2 = &681.383 \\ &- 54.065 \cdot age \\ &+ 1.280 \cdot age^2 \\ &- 11.803 \cdot smsa \\ &+ 10.615 \cdot south \\ &- 5.780 \cdot nearc \\ &- 3.314 \cdot daded \\ &- 4.733 \cdot momed \end{aligned}$$

We can use these models estimated in order to compute their fitted values for $exper$ and $exper^2$, like this:

```
dat$experFIT <- -0.348 + 0.010 * dat$age + 0.017 * dat$age2 - 0.530 * dat$smsa +
                 0.425 * dat$south - 0.265 * dat$nearc - 0.190 * dat$daded - 0.235 * dat$mome
d
summary(dat$exper)
```

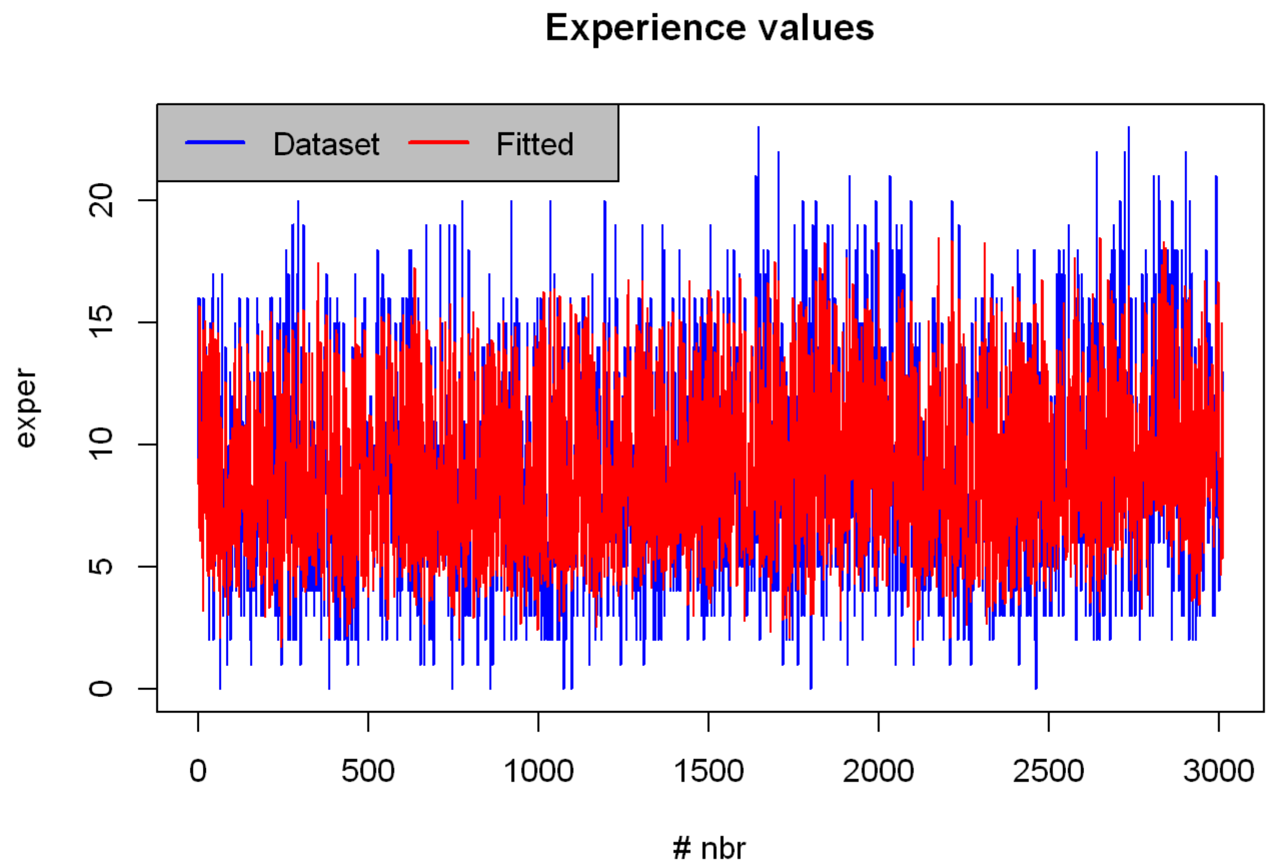
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   6.000   8.000   8.856  11.000  23.000
```

```
summary(dat$experFIT)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.709   6.098   8.260   8.828  11.360  18.470
```

```
dat$exper2FIT <- 681.383 - 54.065 * dat$age + 1.280 * dat$age^2 - 11.803 * dat$smsa +
                  10.615 * dat$south - 5.780 * dat$nearc - 3.314 * dat$daded - 4.733 * dat$mo
med

with(dat, plot(nbr, exper,      type='l', col='blue', main="Experience values", xlab='# nbr')
)
with(dat, points(nbr, experFIT, type='l', col='red'))
legend("topleft", c("Dataset","Fitted"), horiz=TRUE, lty=c(1,1),
       lwd=c(2,2), col=c("blue","red"), bg="grey")
```



Then we can perform **the second stage regression**, by replacing the dataset with the fitted values for the variables $\hat{educ}$, $\hat{exper}$ and $\hat{exper^2}$ (denoted by the hat symbol):

logw second stage regression results (see also Appendix C).

Variable	Coefficient	Standard Error	t-statistic
(Constant)	4.417	0.1179	37.460
$\hat{educ}$	0.100	0.0067	14.894
$\hat{exper}$	0.073	0.0171	4.255
$\hat{exper^2}$	-0.002	0.0009	-1.910
smsa	0.135	0.0171	7.879
south	-0.159	0.0160	-9.925
……	……	……	……

Variable	Coefficient	Standard Error	t-statistic
R^2	0.2192		

Conclusion:

> 2SLS with endogeneity correction for the education and experience, estimates the following model:
>
> $$\begin{aligned} logw = & 4.417 \\ & + 0.100 \cdot educ \\ & + 0.073 \cdot exper \\ & - 0.002 \cdot exper^2 \\ & + 0.135 \cdot smsa \\ & - 0.159 \cdot south \end{aligned}$$
>
> Model characteristics: R^2 = 0.2192

Comparison with part (a) OLS model:

Part (a) OLS model was:

> $$\begin{aligned} logw = & 4.611 \\ & + 0.082 \cdot educ \\ & + 0.084 \cdot exper \\ & - 0.002 \cdot exper^2 \\ & + 0.151 \cdot smsa \\ & - 0.175 \cdot south \end{aligned}$$

We can see that both models look a bit similar, and that both education and experience still have a positive effect while the squared experience still has a negative effect to $logw$.

The 2SLS education estimated effect size of about 10% is a bit larger than the OLS estimation of about 8.2%, while the 2SLS experience estimated effect size of about 7.3% is a bit smaller than the OLS estimation of about 8.4%. And both 2SLS and OLS estimated a (small) negative 0.2% effect size for the squared experience variable.

(f) Sargan validity testing

(f) Perform the Sargan test for validity of the instruments. What is your conclusion?

In order to perform the Sargan test, we need to calculate the 2SLS residuals using the original dataset values (not the fitted ones).

```
#model <- lm(formula = logw ~ educ + exper + exper2 + smsa + south, data = dat)
#dat$res2SLS = model$residuals
dat$logw2SLS = 4.417 + 0.100 * dat$educ + 0.073 * dat$exper - 0.002 * dat$exper2 + 0.135 * da
t$smsa - 0.159 * dat$south
dat$res2SLS = dat$logw - dat$logw2SLS
summary(dat$res2SLS)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -1.68300 -0.20390  0.05577  0.03108  0.28010  1.35000
```

```
# Store the model coefficients for later usage
model <- lm(formula = logw ~ educFIT + experFIT + exper2FIT + smsa + south, data = dat)
coefs2SLS <- matrix(summary(model)$coefficients[,1])

X = cbind(1, dat$educ, dat$exper, dat$exper2, dat$smsa, dat$south)
colnames(X) <- c('(Intersept)', 'educ', 'exper', 'exper2', 'smsa', 'south')
dat$logw2SLS <- X %*% coefs2SLS
dat$res2SLS = dat$logw - dat$logw2SLS
summary(dat$res2SLS)
```

```
##        V1
##  Min.   :-1.7486969
##  1st Qu.:-0.2357908
##  Median : 0.0270949
##  Mean   : 0.0005503
##  3rd Qu.: 0.2502512
##  Max.   : 1.3471109
```

2SLS residuals regression results (see also Appendix D).

Variable	Coefficient	Standard Error	t-statistic
(Constant)	0.1218	0.6568	0.185
smsa	-0.0033	0.0168	-0.199
south	0.0022	0.0150	0.147
age	-0.0090	0.0460	-0.196
age^2	0.0002	0.0008	0.193
nearc	0.0135	0.0164	0.825
daded	-0.0041	0.0026	-1.594
momed	0.0041	0.0028	1.461
……	……	……	……
R^2	0.00123		

Then, the Sargan test statistic is calculated by multiplying the size of the dataset with the 2SLS residuals regression's R^2:

```
model <- lm(formula = res2SLS ~ smsa + south + age + age2 + nearc + daded + momed, data = dat
)
sargan.tstat = nrow(dat) * summary(model)$r.squared
sargan.tstat
```

```
## [1] 3.70242
```

Appendix A

(a) OLS estimation

logw variable regression results:

```
model <- lm(formula = logw ~ educ + exper + exper2 + smsa + south, data = dat)
summary(model)
```

```
##
## Call:
## lm(formula = logw ~ educ + exper + exper2 + smsa + south, data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.71487 -0.22987  0.02268  0.24898  1.38552
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.6110144  0.0678950  67.914  < 2e-16 ***
## educ         0.0815797  0.0034990  23.315  < 2e-16 ***
## exper        0.0838357  0.0067735  12.377  < 2e-16 ***
## exper2      -0.0022021  0.0003238  -6.800 1.26e-11 ***
## smsa         0.1508006  0.0158360   9.523  < 2e-16 ***
## south       -0.1751761  0.0146486 -11.959  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3813 on 3004 degrees of freedom
## Multiple R-squared:  0.2632, Adjusted R-squared:  0.2619
## F-statistic: 214.6 on 5 and 3004 DF,  p-value: < 2.2e-16
```

Appendix B

(d) First-stage regression

educ variable regression results:

```
model <- lm(formula = educ ~ age + age2 + smsa + south + nearc + daded + momed, data = dat)
summary(model)
```

```
##
## Call:
## lm(formula = educ ~ age + age2 + smsa + south + nearc + daded +
##     momed, data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.2777  -1.5450  -0.2224   1.6957   7.2250
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.652354   3.976343  -1.421 0.155277
## age          0.989610   0.278714   3.551 0.000390 ***
## age2        -0.017019   0.004838  -3.518 0.000441 ***
## smsa         0.529566   0.101504   5.217 1.94e-07 ***
## south       -0.424851   0.091037  -4.667 3.19e-06 ***
## nearc        0.264554   0.099085   2.670 0.007626 **
## daded        0.190443   0.015611  12.199  < 2e-16 ***
## momed        0.234515   0.017028  13.773  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.326 on 3002 degrees of freedom
## Multiple R-squared:  0.2466, Adjusted R-squared:  0.2448
## F-statistic: 140.4 on 7 and 3002 DF,  p-value: < 2.2e-16
```

Appendix C

(e) Two-stage least squares correction

exper variable regression results:

```
model <- lm(formula = exper ~ age + age2 + smsa + south + nearc + daded + momed, data = dat)
summary(model)
```

```
##
## Call:
## lm(formula = exper ~ age + age2 + smsa + south + nearc + daded +
##     momed, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.2250 -1.6957  0.2224  1.5450 11.2777
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.347646   3.976343  -0.087 0.930337
## age          0.010390   0.278714   0.037 0.970266
## age2         0.017019   0.004838   3.518 0.000441 ***
## smsa        -0.529566   0.101504  -5.217 1.94e-07 ***
## south        0.424851   0.091037   4.667 3.19e-06 ***
## nearc       -0.264554   0.099085  -2.670 0.007626 **
## daded       -0.190443   0.015611 -12.199  < 2e-16 ***
## momed       -0.234515   0.017028 -13.773  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.326 on 3002 degrees of freedom
## Multiple R-squared:  0.6853, Adjusted R-squared:  0.6845
## F-statistic: 933.7 on 7 and 3002 DF,  p-value: < 2.2e-16
```

exper^2 variable regression results:

```
model <- lm(formula = exper2 ~ age + age2 + smsa + south + nearc + daded + momed, data = dat)
summary(model)
```

```
##
## Call:
## lm(formula = exper2 ~ age + age2 + smsa + south + nearc + daded +
##     momed, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -164.28  -27.39   -0.20   23.05  380.94
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 681.3828    84.8457   8.031 1.38e-15 ***
## age         -54.0654     5.9471  -9.091  < 2e-16 ***
## age2          1.2799     0.1032  12.399  < 2e-16 ***
## smsa        -11.8031     2.1659  -5.450 5.46e-08 ***
## south        10.6147     1.9425   5.464 5.02e-08 ***
## nearc        -5.7804     2.1142  -2.734  0.00629 **
## daded        -3.3142     0.3331  -9.949  < 2e-16 ***
## momed        -4.7333     0.3633 -13.028  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 49.64 on 3002 degrees of freedom
## Multiple R-squared:  0.6567, Adjusted R-squared:  0.6559
## F-statistic: 820.4 on 7 and 3002 DF,  p-value: < 2.2e-16
```

logw second stage regression results:

```
model <- lm(formula = logw ~ educFIT + experFIT + exper2FIT + smsa + south, data = dat)
summary(model)
```

```
##
## Call:
## lm(formula = logw ~ educFIT + experFIT + exper2FIT + smsa + south,
##     data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.67803 -0.23815  0.01704  0.26700  1.46758
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.4171884  0.1179164  37.460  < 2e-16 ***
## educFIT      0.0998308  0.0067029  14.894  < 2e-16 ***
## experFIT     0.0727341  0.0170952   4.255 2.16e-05 ***
## exper2FIT   -0.0016340  0.0008557  -1.910   0.0563 .
## smsa         0.1349183  0.0171244   7.879 4.59e-15 ***
## south       -0.1589739  0.0160172  -9.925  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3925 on 3004 degrees of freedom
## Multiple R-squared:  0.2192, Adjusted R-squared:  0.2179
## F-statistic: 168.7 on 5 and 3004 DF,  p-value: < 2.2e-16
```

```
# Store the model coefficients for later usage
coefs2SLS <- matrix(summary(model)$coefficients[,1])
```

Appendix D

(f) Sargan validity testing

2SLS residuals regression results:

```
model <- lm(formula = res2SLS ~ smsa + south + age + age2 + nearc + daded + momed, data = dat
)
summary(model)
```

```
##
## Call:
## lm(formula = res2SLS ~ smsa + south + age + age2 + nearc + daded +
##     momed, data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.77692 -0.23319  0.02737  0.25027  1.34299
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1217866  0.6568267   0.185    0.853
## smsa        -0.0033287  0.0167668  -0.199    0.843
## south        0.0022077  0.0150378   0.147    0.883
## age         -0.0090297  0.0460389  -0.196    0.845
## age2         0.0001543  0.0007991   0.193    0.847
## nearc        0.0135069  0.0163672   0.825    0.409
## daded       -0.0041105  0.0025788  -1.594    0.111
## momed        0.0041103  0.0028127   1.461    0.144
##
## Residual standard error: 0.3843 on 3002 degrees of freedom
## Multiple R-squared:  0.00123,    Adjusted R-squared:  -0.001099
## F-statistic: 0.5282 on 7 and 3002 DF,  p-value: 0.8138
```

– End of document –