# PUBPOL 639: ASSIGNMENT 5 - Solutions Winter 2011

Due: Monday, April 11<sup>th</sup> at the start of class

**NOTE:** This assignment explores various transformations that let you estimate non-linear relationships using OLS. Be sure to copy your do and log files into the back of your solutions. Courier 8 or 9 pt font works well. Your log file may be long, so don't worry about cleaning/formatting it.

In 1995, the newly elected government (headed by Nelson Mandela) has identified racial differences in earnings as a major concern. The administration believes that education is the key to reducing observed differences in pay. Prior to implementing new policy, the South African Labor and Development Unit (SALDRU) is hired to asses the current value of education in the labor market. Your task as one of the primary researchers in the unit is to complete the preliminary analysis below using the 1994 October Household Survey Data (ohs94.dta).

#### Final Notes:

- After completing the analysis, be sure to create two tables to present your regression output (one for each part)
- In running the models below, use the following omitted categories throughout:

o Race => blacks Union => non-union member

o Gender => females Location => rural

### PART I

- 1. Estimate a model relating monthly income to education (continuous), age, race, and gender.
  - a. Interpret the coefficient on education

A one year increase in school completed is associated with a 182.08 rand increase in monthly income, holding age, race, and gender constant.

b. Interpret the coefficients on the race indicator variables

Coloured respondents earn 166.11 rand more than black respondents on average controlling for age, education, and gender.

Indian respondents earn 316.37 rand more than black respondents on average controlling for age, education, and gender.

White respondents ear 1041.62 rand more than black respondents on average controlling for age, education, and gender.

- 2. Now run the same regression, but including a quadratic age variable.
  - a. Holding race, gender, and education constant, what is the predicted change in income associated with a one-year increase in age for a 34 year old respondent?

A one-year increase in age for a 34 year old respondent is associated with a 43.77 rand increase in average monthly income. (See do-file for calculation)

b. Holding race, gender, and education constant, what is the predicted change in income associated with a one-year increase in age for a 54 year old respondent?

A one-year increase in age for a 54 year old respondent is associated with a 1.95 rand decrease in average monthly income. (See do-file for calculation)

c. Can we reject the linear model from question 1 in favor of this quadratic model? Explain.

To test whether the quadratic or linear specification fits better we need to test the null hypothesis that the coefficient on the age squared term is equal to zero. Looking at the p-value associated with the age squared term, it is well below an alpha level of .01, which allows for the rejection of the null hypothesis. This suggests that we are confident that a non-linear relationship does exist.

3. To simplify the task of interpreting quadratic terms, write a program (called "coef2") that will provide you with the information found in question 2, parts (a) and (b). At the very least, the program should work for the model estimated in question 2, but if possible, it should work with any model estimated with any number of independent variables. Once the program is completed, confirm your answers to question 2 parts (a) and (b) using the program.

(See do-file & log file for details)

- 4. Now estimate a model relating income to education (continuous), race, and interactions between education and race.
  - a. Which racial group receives the largest return for their educational attainment?

Looking at the interaction terms, white respondents receive the largest return from an additional year of education as the white\*education coefficient is the largest positive value observed relative to the other interactions.

b. Calculate the change in predicted income associated with a one year increase in education for each racial group, holding race constant.

For black respondents, an additional year of education is associated with a 127.41 rand increase in monthly income.

For coloured respondents, an additional year of education is associated with a 150.51 rand increase in monthly income. This value is found summing the coefficient of education and the coloured\*education interaction coefficient.

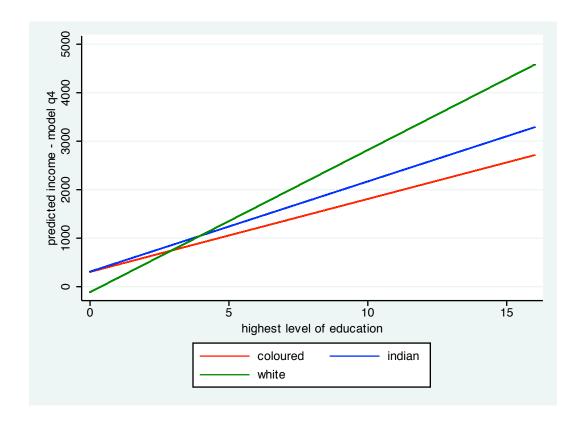
For indian respondents, an additional year of education is associated with a 186.03 rand increase in monthly income. This value is found summing the coefficient of education and the indian\*education interaction coefficient.

For white respondents, an additional year of education is associated with a 293.15 rand increase in monthly income. This value is found summing the coefficient of education and the white\*education interaction coefficient.

c. Check your calculations by plotting the predicted (fitted) relationship between income and education for each racial group. To do this, you should first generate a variable called pinc (predicted income) by typing "predict pinc" after your regression. You can then plot this predicted value by education separately by racial group by typing:

```
twoway line pinc educ if race == 2, lc(red) ||
    line pinc educ if race == 3, lc(blue) ||
    line pinc educ if race == 4, lc(green) ||,
    legend(lab(1 "coloured") lab(2 "indian") lab(3 "white"));
```

Note: You may need to sort the data by education first depending on version of Stata, otherwise can get crazy graph.



## **PART II**

Prior to extending your analysis in Part I, the head researcher at SALDRU suggests you use a log transform on income given the distribution is positively skewed. Using this suggestion, complete the items below.

- 5. Now regress log(income) on education (continuous), race, and gender.
  - a. Interpret the coefficient on education

A one year increase in school completed is associated with a 13.85% increase in monthly income, holding race and gender constant. [Important to note here that percentage change is calculated using exponentiation given level is great than 10% - (See do-file for calculations)]

### b. Interpret the coefficients on the race indicator variables

Coloured respondents earn 17.25% percent more than black respondents on average controlling for education and gender.

Indian respondents earn 41.36% percent more than black respondents on average controlling for education and gender.

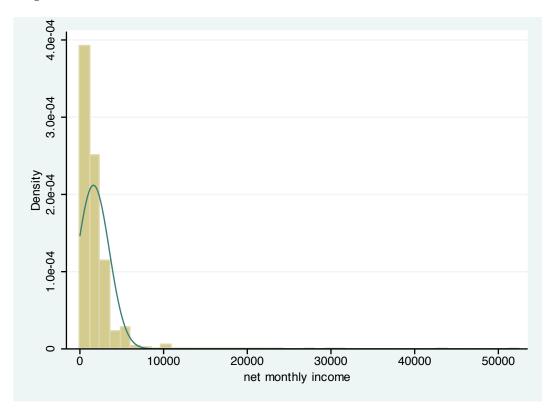
White respondents earn 73.27% percent more than black respondents on average controlling for education and gender.

[Important to note here that percentage difference is calculated using exponentiation given level is great than 10% - (See do-file for calculations)]

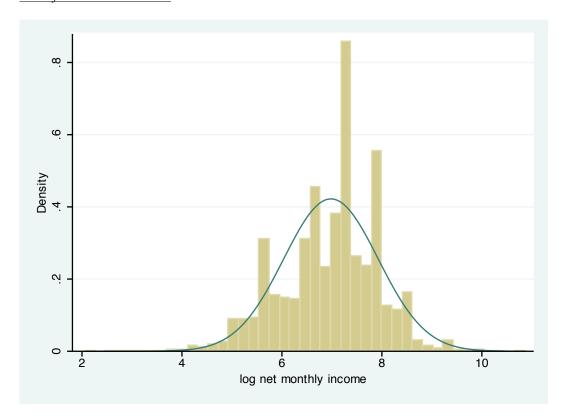
c. Does the transformation on income seem appropriate given the data and your findings? Explain.

Yes, the transformation is appropriate given the highly positively skewed distribution of monthly income. The transformation will normalize the distribution.

### Original Distribution



### Transformed Distribution



- 6. Now regress log(income) on education (continuous), age, race, and gender.
  - a. Interpret the coefficient on education

A one year increase in school completed is associated with a 14.48% increase in monthly income, holding race, age, and gender constant. [Important to note here that percentage change is calculated using exponentiation given level is great than 10% - (See do-file for calculations)]

b. Why has the coefficient on education changed from the regression in question 5? Explain in terms of the framework used in class.

The coefficient on education increases from .129 in model Q5 to .135 in model Q6. Omitting age results in a negative omitted variable bias on the education coefficient in model Q5.

Indeed, given the sign of the coefficient in model Q6, age is positively correlated with log income holding race, gender, and education constant. Additionally, given the history of the country, young and middle age adults tend to have higher levels of education than older adults producing a negative relationship between age and education. This combination of the positive and negative associations leads to our negative bias.

- 7. Now regress log(income) on education (continuous), age, age-squared, race, gender, union membership, location (urban/rural), and interactions between education and race.
  - a. Using the model specified, in addition to previous results, summarize the general overall findings.

In general it is quite clear that racial differences in average income are substantial even after controlling for numerous independent factors. Relative to blacks, all other racial groups are earning at least 15% more on average, with whites earning 134% more. Thus, even when education levels are controlled (along with numerous additional factors) large differences in income are still observed by race.

While racial differences dominate the substantive findings, other distinctions in workers matter as well. As expected, education has a strong positive relationship with earnings. Additionally, it appears that the returns to education are fairly similar for the different racial groups (with the findings actually suggesting that blacks receive a slightly larger return than any other group). Gender differences are also quite large, with male workers earning 32% more female workers controlling for all other factors. Similar differences are observed for unionization and location as well.

b. Discuss how the findings inform the administration's assumption (listed below). Additionally, provide the administration with your recommendation on how to best reduce racial differences in earnings.

<u>Assumption</u>: The administration assumes that increasing educational attainment will reduce racial differences in earnings.

It is clear why the administration may have made this assumption given that Indian and white respondents have almost twice the years of school completed as black and coloured workers on average. Although looking at the regression analysis, even when education is controlled for large racial differences are still observed. This suggests that even if education levels are similar, differences in earnings would still persist. If we are confident that model Q7 specification is adequate, then the administration may need to consider the behavior of employers as a possible cause for the observed differences in earnings between the racial groups.

8. Using the existing data, are there improvements that could be made to the "final" model specified in question 7? If so, describe any changes you believe would improve the model.

There are several possible changes to model Q7 that could potentially improve the specification. See list below.

- use categorical measurement of education -> it seems the response to education in the labor market would be better capture looking at degree thresholds vs. a constant return to an additional year of schooling
- add province indicators -> any regional difference in labor markets is lost in model Q7, including provincial indicator variables could possibly capture these differences
- interactions with gender -> there are large gender differences in many of the distributions we are working with, would be useful to look at interactions with several of the other regressors including: race, union membership, location, education, and age
- interact everything with race -> given the role of race in this country it may be the case that each of our regressors varies by race, instead of constructing interactions with every other independent variable, could run models separately for each racial group (may make sense to do the same for gender as well)
- 9. Describe how any data limitations impact the analysis in questions 1-7. Be as specific as possible. [Note: I would like you to briefly discuss possible variables omitted from the data file, but a majority of the discussion should focus on measurement and operationalization of variables in the data file]

The OHS data is a bit limited in terms of the information collected. Ideally, would have been beneficial to include additional variables that most likely explain a share of the differences in monthly income. Those variables would include: labor force experience, sector of employment, employment industry, and quality of schooling.

The existing data also has limitations that could possibly be impacting our analysis. The most problematic limitation is the measurement of education. There was no continuous form of the variable in the data and so we had to construct one based on the existing categorical variable. The new proxy for continuous education is not very precise and could create misleading results if the imprecision is large enough. Ideally, we would have wanted a data set with continuous education. Additionally, the treatment of those respondents with missing income, zero income, unemployed, and those not looking for work was highly problematic. Based on the coding of the data it was extremely difficult to identify each of the previous groups. To make the data usable for the analysis, users are forced to drop all 9,999,999 and 0 income values. It is somewhat unclear who remains in the sample after this procedure and could lead to misleading inferences.

10. You are reminded that the OHS data is not a simple random sample and that weights should be utilized. Use the weights provided to re-estimate the "final model" requested in question 7. How, if at all, does this change your findings? Note: To use the weights insert the following code at the end of your regress command -> [aw=weight]

Using the sample weights reduces several of the large group differences that were observed in model Q7. Racial, gender, and location differences are all reduced once the data is properly weighted. All these reductions are quite subtle though, still leading to the same general set of conclusions. Given the proportional shares of these groups in the data it seems this is a proportional sample, if alternatively we would have seen a disproportional sample, where groups are quite different in their relative size in the sample vs. the population, then we could have seen larger differences with and without using sample weights.

#### OPTIONAL CHALLENGE QUESTIONS

Note: The questions below are completely optional and are not required.

I. Write a program that finds the difference in estimated standard errors for a given regression model when the robust option is and is not utilized.

(See do-file & log file for details)

II. Provide evidence for the improvements suggested in question 8. More specifically, actually run the analysis suggested to provide evidence of your claim.

(See do-file & log file for details)

#### Do file

```
* Public Policy 639 Assignment 5 - Solutions
 ______
clear all
set mem 300m
capture log close
log using assignment5solns.log, text replace
** Open Data File
use http://www-personal.umich.edu/~thomasjl/pp639/ohs94.dta, clear
** Data Management
* INCOME
recode income (0 = .) (9999999 = .), gen(inc)
lab var inc "net monthly income"
gen lninc = ln(inc)
lab var lninc "log net monthly income"
* EDUCATION
recode educ (14/15 = .) (13 = 16) (11 = 9) (12 = 10), gen(ed)
lab var ed "highest level of education"
gen black = (race==1) if !missing(race)
lab var black "black indicator variable"
gen coloured = (race==2) if !missing(race)
lab var coloured "coloured indicator variable"
gen indian = (race==3) if !missing(race)
lab var indian "indian indicator variable"
gen white = (race==4) if !missing(race)
lab var white "white indicator variable"
* RACE-EDUCATION Interactions
gen bed = black*ed
lab var bed "black * education"
gen ced = coloured*ed
lab var bed "coloured * education"
gen ied = indian*ed
lab var ied "indian * education"
gen wed = white*ed
lab var wed "white * education"
recode gender (2=0 "female") (1=1 "male"), gen(male)
lab var male "male indicator variable"
* UNTON
recode union (1=1 "yes") (2=0 "no"), gen(unionm)
lab var unionm "union member indicator"
* LOCATION
recode urban (1=1 "urban") (2=0 "rural"), gen(urb)
lab var urb "urban indicator"
* AGE
gen age2 = age*age
lab var age2 "age-squared"
```

```
* SAMPLE OF INTEREST
gen sample = (age>=25 & age<=65) if !missing(age)</pre>
lab var sample "sample of interest indicator"
** ANALYSIS
* Note: For all regression models, I first use Stata's Factor Variable syntax to run model
        then I use the standard syntax form to run the same model, output is identical
* PART I
* Ouestion 1
reg inc ed age i.race male if sample==1, r
reg inc ed age coloured indian white male if sample==1, r
est store q1
* Question 2
reg inc ed age age2 i.race male if sample==1, r
reg inc ed age age2 coloured indian white male if sample==1, r
est store q2
di "Impact of 1 year change for 25 = " (( b[age]*26) + ( b[age2]*26*26)) - (( b[age]*25) +
( b[age21*25*25))
di "Impact of 1 year change for 34 = "((\_b[age]*35) + (\_b[age2]*35*35)) - ((b[age]*34) + (\_b[age2]*35*35))
( b[age2]*34*34))
di "Impact of 1 year change for 54 = " (( b[age]*55) + ( b[age2]*55*55)) - (( b[age]*54) +
( b[age2]*54*54))
* Ouestion 3
/*
Note: There are numerous ways to write this program. I have included a couple different
      versions to show you what is possible.
* Version #1
This version of the program is similar to a calculator. The user simply provides all
the information and Stata does the calculation. When running the program users need
to provide
1st = coefficient of non-squared variable
2nd = coefficient of squared variable
3rd = larger value of non-squared variable
4th = smaller value of non-squared variable
This program can be run at any time, do not need data set open, do not need to have
run regression model prior to using command.
capture program drop coef2
program define coef2
di ((`1'*`3') + (`2'*`3'*`3')) - ((`1'*`4') + (`2'*`4'*`4'))
end
* Confirm Results in Question 2, parts (a) and (b)
coef2 83.97987 -.7883657 35 34
coef2 83.97987 -.7883657 55 54
* Version #2
/*
```

```
This version will work with any model specification. When running the program user need
to provide four pieces of information:
1st = variable name of non-squared distribution
2nd = variable name of squared distribution
3rd = value of non-squared variable
4th = amount of positive change observed
This is a post-estimation command meaning it must be run after running regression. Additionally,
note that if you run command "return list" after program "coef2" the predicted change has been
stored in a scalar value.
capture program drop coef2
program define coef2, rclass
args b1 b2 x dx
local y = `x' + `dx'
di "Impact of `dx' unit change in `b1' for `b1'=`x' is: " (( b[`b1']*`y') + (_b[`b2']*`y'*`y')) -
(( b[`b1']*`x') + ( b[`b2']*`x'*`x'))
return scalar dy `x'to`y' = (( b[`b1']*`y') + ( b[`b2']*`y'*`y')) - (( b[`b1']*`x') +
( b[`b2']*`x'*`x'))
end
* Confirm Results in Question 2, parts (a) and (b)
coef2 age age2 34 1
coef2 age age2 54 1
* Question 4
reg inc c.ed##i.race if sample==1, r
reg inc ed coloured indian white ced ied wed if sample==1, r
est store q4
di "Change in Predicted Income for Blacks = " b[ed]
di "Change in Predicted Income for Coloureds = " b[ed] + b[ced]
di "Change in Predicted Income for Indians = "_b[ed] + _b[ied] di "Change in Predicted Income for Whites = "_b[ed] + _b[wed]
predict pinc
lab var pinc "predicted income - model q4"
twoway line pinc ed if race == 2, lc(red) || line pinc ed if race == 3, lc(blue) || line pinc ed if
race == 4, lc(green) ||, legend(lab(1 "coloured") lab(2 "indian") lab(3 "white"))
* Note: It is possible to also include the reference category in the graph as well (in this case
blacks)
twoway line pinc ed if race == 1, lc(black) || line pinc ed if race == 2, lc(red) || line pinc ed if
race == 3, lc(blue) || line pinc ed if race == 4, lc(green) ||, legend(lab(1 "black") lab(2 "coloured")
lab(3 "indian") lab(4 "white"))
est table q1 q2 q4, b(%9.3f) stats(r2 a N) star
* PART II
* Question 5
reg lninc ed i.race male if sample==1, r
reg lninc ed coloured indian white male if sample==1, r
est store a5
* part a - interpretation of education coefficient
di "Percent Change in Y = " 100 * ( exp(b[ed]) - 1)
* part b - interpretation of race indicator coefficients
di "Percentage of earnings difference for coloureds = " 100 * ( exp( b[coloured]) - 1)
di "Percentage of earnings difference for indians = " 100 * (exp(_b[indian]) - 1) di "Percentage of earnings difference for whites = " 100 * (exp(_b[white]) - 1)
* part c
hist inc if sample==1, norm
hist lninc if sample==1, norm
```

```
* Question 6
reg lninc ed age i.race male if sample==1, r
reg lninc ed age coloured indian white male if sample==1, r
est store q6
* part a - interpretation of education coefficient di "Percent Change in Y = " 100 * (exp(b[ed]) - 1)
* Question 7
reg lninc c.ed##i.race age age2 male unionm urb if sample==1, r
reg lninc ed age age2 coloured indian white male unionm urb ced ied wed if sample==1, r
* Question 10
req lninc c.ed##i.race age age2 male unionm urb if sample==1 [aw=weight], r
reg lninc ed age age2 coloured indian white male unionm urb ced ied wed if sample==1 [aw=weight], r
est store q10
est table q7 q10, b(%9.3f) stats(r2 a N) star
* Optional Challenge Question I
This program produces differences for all se's in a given model. When running the
program user needs to provide variable specification as if running model in Stata
(dependent variable followed by independent variables).
* Note: Program requires matrix program - matewmf to execute
       can download ado file off CTools site
capture program drop sediff
program define sediff, rclass
quietly reg `*', robust
quietly matrix vr = e(V)
quietly matrix xr = vecdiag(vr)
quietly matrix ver = xr'
quietly matewmf ver ser, function(sqrt)
quietly reg `*'
quietly matrix vnr = e(V)
quietly matrix xnr = vecdiag(vnr)
quietly matrix venr = xnr'
quietly matewmf venr senr, function(sqrt)
quietly matrix diff = senr - ser
quietly matrix all = senr, ser, diff
quietly matrix colnames all = "SE, ~rob" "SE, rob" Diff
matrix list all
end
* Test SEDIFF command
sediff lninc ed age age2 male unionm urb if sample==1
* Optional Challenge Question II
* Race Specific Models
/* These Models provide the race specific effects of each of the independent variables.
  This is like specifying interactions between race and other iv's
```

```
reg lninc ed age age2 male unionm urb if sample==1 & race==1, r
est store black
reg lninc ed age age2 male unionm urb if sample==1 & race==2, r
est store coloured
reg lninc ed age age2 male unionm urb if sample==1 & race==3, r
est store indian
reg lninc ed age age2 male unionm urb if sample==1 & race==4, r
est store white
est table black coloured indian white, b(%9.3f) stats(r2 a N) star
* Gender Specific Models
reg lninc ed age age2 coloured indian white unionm urb ced ied wed if sample==1 & male==0, r
est store female
reg lninc ed age age2 coloured indian white unionm urb ced ied wed if sample==1 & male==1, r
est store male
est table male female, b(%9.3f) stats(r2_a N) star
* Categorical Education
* Create new education variable
gen ed0 = (ed<10) if !missing(ed)
gen ed1 = (ed==10) if !missing(ed)
gen ed2 = (ed==16) if !missing(ed)
reg lninc ed1 ed2 age age2 coloured indian white male unionm urb ced ied wed if sample==1, r
```

# Log file

log close

```
name: <unnamed>
log: assignment5solns.log
log type: text

.
. ** Open Data File
use http://www-personal.umich.edu/~thomasjl/pp639/ohs94.dta, clear
(October Household Survey - 1994)

.
. ** Data Management
. * INCOME
recode income (0 = .) (9999999 = .), gen(inc)
(75110 differences between income and inc)
. lab var inc "net monthly income"
. gen lninc = ln(inc)
(103657 missing values generated)
. lab var lninc "log net monthly income"
```

```
. * EDUCATION
. recode educ (14/15 = .) (13 = 16) (11 = 9) (12 = 10), gen(ed)
(6833 differences between educ and ed)
. lab var ed "highest level of education"
. * RACE
. gen black = (race==1) if !missing(race)
. lab var black "black indicator variable"
. gen coloured = (race==2) if !missing(race)
. lab var coloured "coloured indicator variable"
. gen indian = (race==3) if !missing(race)
. lab var indian "indian indicator variable"
. gen white = (race==4) if !missing(race)
. lab var white "white indicator variable"
. * RACE-EDUCATION Interactions
. gen bed = black*ed
(353 missing values generated)
. lab var bed "black * education"
. gen ced = coloured*ed
(353 missing values generated)
. lab var bed "coloured * education"
. gen ied = indian*ed
(353 missing values generated)
. lab var ied "indian * education"
. gen wed = white*ed
(353 missing values generated)
. lab var wed "white * education"
. * GENDER
. recode gender (2=0 "female") (1=1 "male"), gen(male)
(69872 differences between gender and male)
. lab var male "male indicator variable"
. * UNION
. recode union (1=1 "yes") (2=0 "no"), gen(unionm)
(24077 differences between union and unionm)
. lab var unionm "union member indicator"
. * LOCATION
. recode urban (1=1 "urban") (2=0 "rural"), gen(urb)
(56262 differences between urban and urb)
. lab var urb "urban indicator"
```

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```
. * AGE
. gen age2 = age*age
. lab var age2 "age-squared"
. * SAMPLE OF INTEREST
. gen sample = (age >= 25 \& age <= 65) if !missing(age)
. lab var sample "sample of interest indicator"
. ** ANALYSIS
. * Note: For all regression models, I first use Stata's Factor Variable syntax to run model
          then I use the standard syntax form to run the same model, output is identical
. * PART I
. * Question 1
. reg inc ed age i.race male if sample==1, r
                                                          Number of obs = 23989
Linear regression
                                                          F(6, 23982) = 598.18
                                                          Prob > F = 0.0000

R-squared = 0.2663
                                                          R-squared
                                                          Root MSE
                                                                       = 1612.5
                              Robust.
        inc | Coef. Std. Err. t P>|t| [95% Conf. Interval]
         ed | 182.0849 4.576782 39.78 0.000 173.1141 191.0557 age | 18.32571 1.29814 14.12 0.000 15.78128 20.87015
        race |
         2 | 166.1174 17.79169 9.34 0.000 131.2445 200.9902
3 | 316.371 36.3839 8.70 0.000 245.0562 387.6857
4 | 1041.626 31.10463 33.49 0.000 980.659 1102.593
       male | 569.3923 21.57462 26.39 0.000 527.1046 611.6799 

_cons | -1081.013 77.23482 -14.00 0.000 -1232.398 -929.6275
. reg inc ed age coloured indian white male if sample==1, r
                                                          Number of obs = 23989
Linear regression
                                                          F(6, 23982) = 598.18
                                                          Prob > F = 0.0000
R-squared = 0.2663
                                                                       = 1612.5
                                                          Root MSE
                             Robust
                   Coef. Std. Err.
        inc |
                                           t P>|t|
                                                            [95% Conf. Interval]
   . est store q1
. * Question 2
```

. reg inc ed age age2 i.race male if sample==1, r

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inc	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed age age2	181.6978   83.97987  7883657	4.579382 9.041891 .1116576	39.68 9.29 -7.06	0.000 0.000 0.000	172.7219 66.2572 -1.007221	190.6737 101.7025 5695098
race 2 3 4	   168.7718   311.8314   1042.646	17.79439 36.29858 31.0672	9.48 8.59 33.56	0.000 0.000 0.000	133.8937 240.6839 981.7527	203.6499 382.9789 1103.54
male _cons	572.3591 -2367.886	21.55121 184.2838	26.56 -12.85	0.000	530.1173 -2729.094	614.6008 -2006.679

. reg inc ed age age2 coloured indian white male if sample==1, r

Linear regression

Number of obs = 23989 F( 7, 23981) = 514.82 Prob > F = 0.0000 R-squared = 0.2681 Root MSE = 1610.6

 inc	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed   age   age2   coloured   indian   white   male   cons	181.6978 83.97987 7883657 168.7718 311.8314 1042.646 572.3591 -2367.886	4.579382 9.041891 .1116576 17.79439 36.29858 31.0672 21.55121 184.2838	39.68 9.29 -7.06 9.48 8.59 33.56 26.56 -12.85	0.000 0.000 0.000 0.000 0.000 0.000 0.000	172.7219 66.2572 -1.007221 133.8937 240.6839 981.7527 530.1173 -2729.094	190.6737 101.7025 5695098 203.6499 382.9789 1103.54 614.6008 -2006.679

```
. est store q2
```

. \* Version #1

```
> This version of the program is similar to a calculator. The user simply provides all
> the information and Stata does the calculation. When running the program users need
> to provide
> 1st = coefficient of non-squared variable
> 2nd = coefficient of squared variable
> 3rd = larger value of non-squared variable
> 4th = smaller value of non-squared variable
> This program can be run at any time, do not need data set open, do not need to have
> run regression model prior to using command.
. capture program drop coef2
. program define coef2
  1. di ((`1'*`3') + (`2'*`3'*`3')) - ((`1'*`4') + (`2'*`4'*`4'))
  2. end
. * Confirm Results in Question 2, parts (a) and (b)
. coef2 83.97987 -.7883657 35 34
29.582637
. coef2 83.97987 -.7883657 55 54
-1.9519913
. * Version #2
> This version will work with any model specification. When running the program user need
> to provide four pieces of information:
> 1st = variable name of non-squared distribution
> 2nd = variable name of squared distribution
> 3rd = value of non-squared variable
> 4th = amount of positive change observed
> This is a post-estimation command meaning it must be run after running regression. Additionally, > note that if you run command "return list" after program "coef2" the predicted change has been
> stored in a scalar value.
> */
. capture program drop coef2
. program define coef2, rclass
  1. args b1 b2 x dx
  2. local y = x' + dx'
  3. di "Impact of `dx' unit change in `b1' for `b1'=`x' is: " (( b[`b1']*`y') + ( b[`b2']*`y'*`y')) -
((_b[`b1']*`x') + (_b[`b2']*`x'*`x'))
  \overline{4}. return scalar \overline{dy} `x'to`y' = ((_b[`b1']*`y') + (_b[`b2']*`y'*`y')) - ((_b[`b1']*`x') +
 (_b[`b2']*`x'*`x'))
  5. end
. * Confirm Results in Question 2, parts (a) and (b)
 . coef2 age age2 34 1
Impact of 1 unit change in age for age=34 is: 29.58264
. coef2 age age2 54 1
Impact of 1 unit change in age for age=54 is: -1.9519868
. * Question 4
. reg inc c.ed##i.race if sample==1, r
```

Prob > F = 0.0000 R-squared = 0.2456 Root MSE = 1635.1

\_\_\_\_\_\_

inc	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed	127.4118 	3.08015	41.37	0.000	121.3745	133.4491
race						
2	-31.01306	27.36814	-1.13	0.257	-84.65633	22.63022
3	-24.37371	111.6997	-0.22	0.827	-243.3122	194.5648
4	-448.5553	219.4672	-2.04	0.041	-878.7249	-18.38576
race#c.ed	! 					
2	23.10366	5.198957	4.44	0.000	12.91338	33.29395
3	58.61983	14.39903	4.07	0.000	30.39683	86.84283
4	165.7409	23.57246	7.03	0.000	119.5374	211.9444
_cons	   335.1206	16.1871	20.70	0.000	303.3929	366.8483

. reg inc ed coloured indian white ced ied wed if sample==1, r

Linear regression

Number of obs = 23989 F( 7, 23981) = 1065.10 Prob > F = 0.0000 R-squared = 0.2456 Root MSE = 1635.1

Robust inc | Coef. Std. Err. t P>|t| [95% Conf. Interval] \_\_\_\_\_\_ ed | 127.4118 3.08015 41.37 0.000 121.3745 133.4491 coloured | -31.01306 27.36814 -1.13 0.257 -84.65633 22.63022 111.6997 -0.22 0.827 -243.3122 219.4672 -2.04 0.041 -878.7249 5.198957 4.44 0.000 12.91338 indian | -24.37371 194.5648 white | -448.5553 -18.38576 5.198957 33.29395 23.10366 ced I 14.39903 4.07 0.000 30.39683 23.57246 7.03 0.000 119.5374 16.1871 20.70 0.000 303.3929 58.61983 30.39683 ied | 86.84283 211.9444 wed | 165.7409 \_cons | 335.1206 16.1871 366.8483

. est store q4

. di "Change in Predicted Income for Blacks = " $_{\rm b}$ [ed] Change in Predicted Income for Blacks = 127.41183

- . di "Change in Predicted Income for Coloureds = "  $_{\rm b[ed]}$  +  $_{\rm b[ced]}$  Change in Predicted Income for Coloureds = 150.51549
- . di "Change in Predicted Income for Indians = "  $_{\rm b[ed]}$  +  $_{\rm b[ied]}$  Change in Predicted Income for Indians = 186.03166
- . di "Change in Predicted Income for Whites = "  $_{\rm b}$ [ed] +  $_{\rm b}$ [wed] Change in Predicted Income for Whites = 293.15271
- . predict pinc
  (option xb assumed; fitted values)
  (353 missing values generated)
- . lab var pinc "predicted income model q4"
- . twoway line pinc ed if race == 2, lc(red) || line pinc ed if race == 3, lc(blue) || line pinc ed if race == 4, lc(green) ||, legend(lab(1 "coloured") lab(2 "indian") lab(3 "white"))

.  $\star$  Note: It is possible to also include the reference category in the graph as well (in this case blacks)

. twoway line pinc ed if race == 1, lc(black) || line pinc ed if race == 2, lc(red) || line pinc ed if race == 3, lc(blue) || line pinc ed if race == 4, lc(green) ||, legend(lab(1 "black") lab > (2 "coloured") lab(3 "indian") lab(4 "white"))

. est table q1 q2 q4, b(\$9.3f) stats(r2 a N) star

Variable	q1	q2	q4
ed age coloured indian white	182.085*** 18.326*** 166.117*** 316.371*** 1041.626***	181.698*** 83.980*** 168.772*** 311.831*** 1042.646***	127.412*** -31.013 -24.374 -448.555*
male age2 ced ied wed _cons	569.392***             -1081.013***	572.359*** -0.788*** -2367.886***	23.104*** 58.620*** 165.741*** 335.121***
r2_a N	0.266   23989	0.268 23989	0.245 23989

legend: \* p<0.05; \*\* p<0.01; \*\*\* p<0.001

. \* PART II

. \* Question 5

. reg lninc ed i.race male if sample==1, r

Linear regression

lninc	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
ed	.129736	.0014448	89.80	0.000	.1269042	.1325679
race						
2	.1591345	.0117975	13.49	0.000	.1360108	.1822583
3	.3461424	.0156513	22.12	0.000	.3154648	.3768199
4	.5496654	.0125073	43.95	0.000	.5251503	.5741805
male	.2732818	.0095804	28.53	0.000	.2545036	.29206
_cons	5.673454	.0140189	404.70	0.000	5.645976	5.700932

. reg lninc ed coloured indian white male if sample==1, r

Linear regression Number of obs = 23989

F(5, 23983) = 3341.18 Prob > F = 0.0000R-squared = 0.4396

Root MSE = .70745

     lninc	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed	.129736	.0014448	89.80	0.000	.1269042	.1325679
coloured	.1591345	.0117975	13.49	0.000	.1360108	.1822583
indian	.3461424	.0156513	22.12	0.000	.3154648	.3768199
white	.5496654	.0125073	43.95	0.000	.5251503	.5741805

```
male | .2732818 .0095804 28.53 0.000 .2545036 .29206 
_cons | 5.673454 .0140189 404.70 0.000 5.645976 5.700932
. est store a5
. * part a - interpretation of education coefficient
. di "Percent Change in Y = " 100 * (exp(b[ed]) - 1)
Percent Change in Y = 13.852779
. * part b - interpretation of race indicator coefficients
. di "Percentage of earnings difference for coloureds = " 100 * (exp(b[coloured]) - 1)
Percentage of earnings difference for coloureds = 17.249569
. di "Percentage of earnings difference for indians = " 100 * ( exp( b[indian]) - 1)
Percentage of earnings difference for indians = 41.360385
. di "Percentage of earnings difference for whites = " 100 \star (exp(b[white]) - 1)
Percentage of earnings difference for whites = 73.267316
. * part c
. hist inc if sample==1, norm
(bin=43, start=8, width=1220.7442)
. hist lninc if sample==1, norm
(bin=43, start=2.0794415, width=.2043983)
. * Question 6
. reg lninc ed age i.race male if sample==1, r
                                                         Number of obs = 23989
Linear regression
                                                         F(6, 23982) = 2863.24
                                                         Prob > F = 0.0000

R-squared = 0.4472
                                                                     = .70264
                                                         Root MSE
                            Robust
                  Coef. Std. Err.
      lninc |
                                          t P>|t|
                                                          [95% Conf. Interval]
        ed | .135212 .0014695 92.01 0.000 .1323317 .1380922 age | .0087547 .0004904 17.85 0.000 .0077934 .009716
        race |
               .1705928 .0117013 14.58 0.000 .1476576
.3339924 .0155913 21.42 0.000 .3034324
         2 |
                                                                        .1935281
         4 |
                .518292 .0125666 41.24 0.000 .4936607
                 .2659966 .0095272 27.92 0.000
                                                           .2473226
       male |
       _cons | 5.303452 .0247531 214.25 0.000 5.254934 5.351969
. reg lninc ed age coloured indian white male if sample==1, r
                                                         Number of obs = 23989
Linear regression
                                                         F(6, 23982) = 2863.24
                                                         Prob > F = 0.0000
                                                                    = 0.4472
= .70264
                                                         R-squared
                                                         Root MSE
______
                            Robust
      lninc | Coef. Std. Err. t P>|t| [95% Conf. Interval]
   ed | .135212 .0014695 92.01 0.000 .1323317 age | .0087547 .0004904 17.85 0.000 .0077934 coloured | .1705928 .0117013 14.58 0.000 .1476576
                                                                      .1380922
                                                                      .009716
.1935281
     indian | .3339924 .0155913 21.42 0.000 .3034324 .3645524 white | .518292 .0125666 41.24 0.000 .4936607 .5429233
```

```
male | .2659966 .0095272 27.92 0.000 .2473226 .2846705 

_cons | 5.303452 .0247531 214.25 0.000 5.254934 5.351969
. est store a6
```

. \* part a - interpretation of education coefficient . di "Percent Change in Y = " 100 \* (exp(b[ed]) - 1)Percent Change in Y = 14.477942

. \* Question 7

. reg lninc c.ed##i.race age age2 male unionm urb if sample==1, r

Number of obs = 23989Linear regression F(12, 23976) = 1769.07

Prob > F = 0.0000= 0.4828 R-squared Root MSE

Robust. lninc | Coef. Std. Err. t P>|t| [95% Conf. Interval] ed | .1249175 .0019636 63.62 0.000 .1210688 .1287662 race | .1900253 2 | .145534 .0226989 6.41 0.000 .1010428 
 3
 |
 .5108085
 .0444032
 11.50
 0.000
 .4237755

 4
 |
 .8522006
 .044144
 19.31
 0.000
 .7656757
 .5978415 .044144 .9387255 race#c.ed | .0032788 0.32 0.751 -5.53 0.000 2 | .0010384 -.0053882 .007465 -.0377567 -.0179952 3 I -.027876 .005041 .0044686 -8.33 0.000 -.0459928 -.0284754 -.0372341 4 | age | .0461053 age2 | -.0004574 .0036622 12.59 0.000 .0036622 12.59 0.000 .0389272 .0532835 .000044 -10.39 0.000 -.0005436 -.0003711 .0093511 29.77 0.000 .2600775 .009676 19.97 0.000 .1742788 .0114755 23.75 0.000 .2500308 .2967351 male | .2784063 .2122098 unionm | .1932443

. reg lninc ed age age2 coloured indian white male unionm urb ced ied wed if sample==1, r

Linear regression

.2725235

\_cons | 4.432359 .0746123 59.41 0.000

urb |

Number of obs = 23989 F(12, 23976) = 1769.07Prob > F = 0.0000= 0.4828 R-squared Root MSE = .67968

4.286114

.2950161

4.578603

\_\_\_\_\_\_ Robust. Coef. Std. Err. lninc | t P>|t| [95% Conf. Interval] .1932443 .009676 19.97 0.000 .1742788 .2725235 .0114755 23.75 0.000 .2500308 .0010384 .0032788 0.32 0.751 -.0053882 -.027876 .005041 -5.53 0.000 -.0377567 unionm | .2122098 .2950161 ced .007465 wed | -.0372341 .0044686 -8.33 0.000 -.0459928 \_cons | 4.432359 .0746123 59.41 0.000 4.286114 -.0179952 ied | -.0284754 4.578603

<sup>.</sup> est store a7

```
. * Question 10
```

. reg lninc c.ed##i.race age age2 male unionm urb if sample==1 [aw=weight], r (sum of wqt is 6.8345e+06)

Linear regression

Number of obs = 23989 F(12, 23976) = 1181.64 Prob > F = 0.0000 R-squared = 0.4663 Root MSE = .68823

Robust Coef. Std. Err. t P>|t| lninc | [95% Conf. Interval] \_\_\_\_\_\_ ed | .1210572 .0022262 54.38 0.000 .1166937 .1254207 race | 2 | .1794265 .0263461 6.81 0.000 .1277864 3 | .4276853 .0552518 7.74 0.000 .3193883 4 | .7143135 .0511103 13.98 0.000 .6141342 .2310665 .5359822 .8144928 race#c.ed | -.0041331 .0037291 -1.11 0.268 -.0114424 .0031762 -.0231736 .0062978 -3.68 0.000 -.0355177 -.0108294 2 | 3 I -.0212476 .0050907 -4.17 0.000 -.0312257 -.0112695 4 | 8.79 0.000 .0497663 .0406899 .0046307 .0316135 age | age2 | -.0003831 .000056 -6.84 0.000 -.0004929 -.0002734 unionm |

. reg lninc ed age age2 coloured indian white male unionm urb ced ied wed if sample==1 [aw=weight], r (sum of wgt is 6.8345e+06)

Linear regression

Number of obs = 23989F(12, 23976) = 1181.64Prob > F = 0.0000R-squared = 0.4663Root MSE = .68823

Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
.1210572 .0406899 0003831 .1794265 .4276853 .7143135 .2544953 .226595 .25336	.0022262 .0046307 .000056 .0263461 .0552518 .0511103 .0113932 .0119657 .014074	54.38 8.79 -6.84 6.81 7.74 13.98 22.34 18.94 18.00 -1.11	0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000	.1166937 .0316135 0004929 .1277864 .3193883 .6141342 .232164 .2031416 .2257742	.1254207 .0497663 0002734 .2310665 .5359822 .8144928 .2768266 .2500484 .2809458
0231736 0212476 4.579702	.0062978 .0050907 .093779	-3.68 -4.17 48.84	0.000 0.000 0.000	0355177 0312257 4.395889	0108294 0112695 4.763515
	.1210572 .0406899 0003831 .1794265 .4276853 .7143135 .2544953 .226595 .25336 0041331 0231736 0212476	Coef. Std. Err.	Coef. Std. Err. t	Coef. Std. Err. t P> t	Coef.         Std. Err.         t         P> t          [95% Conf.           .1210572         .0022262         54.38         0.000         .1166937           .0406899         .0046307         8.79         0.000         .0316135          0003831         .000056         -6.84         0.000        0004929           .1794265         .0263461         6.81         0.000         .1277864           .4276853         .0552518         7.74         0.000         .3193883           .7143135         .0511103         13.98         0.000         .6141342           .2544953         .0113932         22.34         0.000         .232164           .226595         .0119657         18.94         0.000         .2031416           .25336         .014074         18.00         0.000         .2257742          0041331         .0037291         -1.11         0.268        0114424          0231736         .0062978         -3.68         0.000        0355177          0212476         .0050907         -4.17         0.000        0312257

<sup>.</sup> est store q10

. est table q7 q10, b(\$9.3f) stats(r2 a N) star

Variable | q7 q10 ed | 0.125\*\*\* 0.121\*\*\* age | 0.046\*\*\* 0.041\*\*\*

```
-0.000***
                -0.000***
       age2 |
                               0.179***
               0.146***
    coloured |
                                0.428***
                  0.511***
     indian |
                 0.852***
      white |
                 0.278***
                                0.254***
       male |
                0.193***
                               0.227***
     unionm |
                  0.273***
                                0.253***
        urb |
                 0.001
        ced I
                               -0.004
        ied |
               -0.028***
                               -0.023***
               -0.037***
                               -0.021***
        wed I
                4.432***
                                4.580***
_cons | 4.432*** 4.580***
     r2_a | 0.483 0.466
N | 23989 23989
_____
   legend: * p<0.05; ** p<0.01; *** p<0.001
. * Optional Challenge Question I
> This program produces differences for all se's in a given model. When running the
> program user needs to provide variable specification as if running model in Stata
> (dependent variable followed by independent variables).
. * Note: Program requires matrix program - matewmf to execute
        can download ado file off CTools site
. capture program drop sediff
. program define sediff, rclass
. quietly reg `*', robust

    quietly matrix vr = e(V)
    quietly matrix xr = vecdiag(vr)

  4. quietly matrix ver = xr'
 5. quietly matewmf ver ser, function(sqrt)
. quietly reg `*'
  7. quietly matrix vnr = e(V)
  8. quietly matrix xnr = vecdiag(vnr)
  9. quietly matrix venr = xnr'
10. quietly matewmf venr senr, function(sqrt)
11.
. quietly matrix diff = senr - ser
12.
. quietly matrix all = senr, ser, diff
13. quietly matrix colnames all = "SE, ~rob" "SE, rob" Diff
. matrix list all
15.
. end
. * Test SEDIFF command
. sediff lninc ed age age2 male unionm urb if sample==1
all[7,3]
         SE, ~rob
                     SE, rob
                                   Diff
   ed
        .00135888
                   .00143487 -.00007599
                   .00377664 -.0000269
.00004536 -7.077e-07
       .00374974
  age
        .00004465
 age2
                   .00957582 -.00004603
         .0095298
 male
       .01000496 .00962498 .00037997
unionm
       .01085156
                   .01130037 -.00044881
.07626488 .00003991
  urb
 cons
```

. \* Optional Challenge Question II

. \* Race Specific Models

. /\* These Models provide the race specific effects of each of the independent variables.

This is like specifying interactions between race and other iv's

. reg lninc ed age age2 male unionm urb if sample==1 & race==1, r

Linear regression

Number of obs = 10635F(6, 10628) = 1176.90= 0.0000 Prob > F R-squared = 0.3841 Root MSE = .70546

lninc		Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed	İ	.1204165	.0021075	57.14	0.000	.1162854	.1245476
age		.0371361	.0057712	6.43	0.000	.0258235	.0484487
age2		0003474	.000069	-5.03	0.000	0004826	0002121
male		.2255936	.0150619	14.98	0.000	.1960695	.2551178
unionm		.3442738	.0148383	23.20	0.000	.315188	.3733596
urb		.2460719	.0150833	16.31	0.000	.2165058	.2756379
_cons		4.626514	.1173128	39.44	0.000	4.396559	4.856469

. est store black

. reg lninc ed age age2 male unionm urb if sample==1 & race==2, r

Linear regression

Number of obs = 5297F(6, 5290) = 627.15 Prob > F = 0.0000 R-squared = 0.4150 = .63457 Root MSE

lninc	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed	.1109064	.0035638	31.12	0.000	.1039198	.117893
age	.0566034	.0072702	7.79	0.000	.0423508	.070856
age2	0006169	.0000879	-7.02	0.000	0007893	0004446
male	.2188881	.018133	12.07	0.000	.18334	.2544361
unionm	.157337	.0202563	7.77	0.000	.1176262	.1970478
urb	.4315379	.0253078	17.05	0.000	.3819241	.4811516
_cons	4.452872	.144953	30.72	0.000	4.168705	4.73704

. est store coloured

. reg lninc ed age age2 male unionm urb if sample==1 & race==3, r

Linear regression

Number of obs = 2214 F(6, 2207) = 80.88 Prob > F = 0.0000 R-squared = 0.1876 = .61521 Root MSE

\_\_\_\_\_\_ Robust lninc | Coef. Std. Err. t P>|t| [95% Conf. Interval] 

unionm		.014504	.0269862	0.54	0.591	0384171	.0674251
urb		.315058	.0374204	8.42	0.000	.2416752	.3884408
_cons		5.16778	.2402847	21.51	0.000	4.696572	5.638988

. est store indian

. reg lninc ed age age2 male unionm urb if sample==1 & race==4, r

Linear regression

\_\_\_\_\_\_ Robust Coef. Std. Err. t P>|t| [95% Conf. Interval] lning L ed | .0814586 .0040335 20.20 0.000 .0735515 age | .0516728 .0069174 7.47 0.000 .038112 age2 | -.0005194 .0000825 -6.30 0.000 -.0006812 .0893657 age | .0652335 age2 | -.0005194 .0179741 26.22 0.000 .4359904 .0195029 -2.57 0.010 -.088425 .0309875 1.69 0.091 -.0083299 male | .4712262 nionm | -.050192 .506462 unionm | -.0119591 .0524171 .113164 urb | \_cons | 5.384006 .1455013 37.00 0.000 5.098769 5.669242

. est store white

. est table black coloured indian white, b(%9.3f) stats(r2\_a N) star

Variable	black	coloured	indian	white
ed   age   age2   male   unionm   urb   _cons	0.120*** 0.037*** -0.000*** 0.226*** 0.344*** 0.246*** 4.627***	0.111*** 0.057*** -0.001*** 0.219*** 0.157*** 0.432*** 4.453***	0.091*** 0.043*** -0.000*** 0.232*** 0.015 0.315*** 5.168***	0.081*** 0.052*** -0.001*** 0.471*** -0.050* 0.052 5.384***
r2_a   N	0.384	0.414 5297	0.185 2214	0.190 5843

legend: \* p<0.05; \*\* p<0.01; \*\*\* p<0.001

. \* Gender Specific Models

. reg lninc ed age age2 coloured indian white unionm urb ced ied wed if sample==1 & male==0, r

Linear regression

Number of obs = 8888 F(11, 8876) = 517.29 Prob > F = 0.0000 R-squared = 0.4240 Root MSE = .67393

Robust lninc | Coef. Std. Err. t P>|t| [95% Conf. Interval] .1457078 .0035833 40.66 0.000 .1386837 .0324039 .0062227 5.21 0.000 .0202059 ed | age | .0446018 .000076 -4.19 0.000 -.0004678 age2 | -.0003187 .044996 5.33 0.000 .1515719 .083924 9.36 0.000 .6208373 .3279768 coloured | .2397744 indian | .7853478 .9498583 .9559935 .071689 13.34 0.000 white | .8154664 1.096521 unionm | .1789033 .0158157 11.31 0.000 .147901 urb | .2002103 .0199326 10.04 0.000 .1611378 .2099057 .147901 .2392828

ced	0093801	.0058798	-1.60	0.111	020906	.0021457
ied	0595112	.0091267	-6.52	0.000	0774016	0416208
wed	0631601	.0071904	-8.78	0.000	0772549	0490653
_cons	4.672836	.1262312	37.02	0.000	4.425393	4.920278

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. est store female

. reg lninc ed age age2 coloured indian white unionm urb ced ied wed if sample==1 & male==1, r

Linear regression

\_\_\_\_\_ Robust. t P>|t| [95% Conf. Interval] lninc | Coef. Std. Err. ed | .1132717 .0023982 47.23 0.000 .108571 .1179725 age | .056154 .0045362 12.38 0.000 .0472625 .0650454 -.0004558 .1630772 .4945118 .8217936 .0560652 14.66 0.000 .7118991 .1905523 .0122243 15.59 0.000 .1665912 .3150831 .0139297 22.62 0.000 .2877792 .9316881 white | .2145134 unionm | .342387 urb | ced | .0046844 .0040786 1.15 0.251 -.0033101 ied | -.0120209 .0060344 -1.99 0.046 -.0238492 wed | -.0227115 .0057146 -3.97 0.000 -.0339128 -.0001927 wed | -.0227115 .0057146 -3.97 0.000 -.0339128 \_cons | 4.515269 .0922187 48.96 0.000 4.334509 -.0115102 4.696029

. est store male

. est table male female, b(%9.3f) stats(r2 a N) star

Variable	   male	female
ed age age2 coloured indian white unionm urb ced ied wed _cons	0.113***   0.056***   -0.001***   0.112***   0.393***   0.822***   0.191***   0.315***   0.005   -0.012*   -0.023***   4.515***	0.146*** 0.032*** -0.000*** 0.240*** 0.785*** 0.956*** 0.179*** 0.200*** -0.009 -0.060*** -0.063*** 4.673***
r2_a N	+   0.516   15101	0.423 8888

legend: \* p<0.05; \*\* p<0.01; \*\*\* p<0.001

. \* Categorical Education

. \* Create new education variable
. gen ed0 = (ed<10) if !missing(ed)
(353 missing values generated)</pre>

. gen ed1 = (ed==10) if !missing(ed)
(353 missing values generated)

. gen ed2 = (ed==16) if !missing(ed)
(353 missing values generated)

. reg lninc ed1 ed2 age age2 coloured indian white male unionm urb ced ied wed if sample==1, r

Linear regression Number of obs = 23989

F(13, 23975) = 1408.56= 0.0000 = 0.4421 Prob > F R-squared Root MSE = .70596

lninc	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
ed1   ed2   age   age2   coloured   indian   white   male   unionm   urb   ced   ied	.5790345 1.121462 .0506855 0005459 2051571 .5351784 1.001512 .2420462 .2589028 .4202711 .0641154 0133156	.0122306 .0361033 .0038186 .0000459 .0218377 .0498086 .0597174 .0096817 .0098452 .0115939 .003178	47.34 31.06 13.27 -11.90 -9.39 10.74 16.77 25.00 26.30 36.25 20.17 -2.37	0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000	.5550618 1.050697 .0432007 0006359 2479604 .4375505 .8844617 .2230694 .2396056 .3975463 .0578864 0243175	.6030073 1.192227 .0581702 000456 1623538 .6328063 1.118561 .261023 .2782 .442996 .0703445 0023136
wed   _cons	0379373 4.91553	.0060644 .0768094	-6.26 64.00	0.000	0498238 4.764978	0260508 5.066081

. log close

name: <unnamed>
log: assignment5solns.log
log type: text

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