

PROBLEM SET 4: SOLUTIONS

Point Distribution:

- 1): 15 points
- 2), 3): 10 points each
- 4), 5): 15 points each

1)

```
. use http://fmwww.bc.edu/ec-p/data/dmackinnon/earnings
. regress earnings group1 group2 group3, nocons
```

Source	SS	df	MS	Number of obs =	4266
Model	2.7934e+12	3	9.3114e+11	F(3, 4263) =	3842.49
Residual	1.0330e+12	4263	242327533	Prob > F =	0.0000
Total	3.8265e+12	4266	896967282	R-squared =	0.7300
				Adj R-squared =	0.7298
				Root MSE =	15567

earnings	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
group1	22880.48	467.4505	48.95	0.000	21964.03	23796.92
group2	25080.17	380.0191	66.00	0.000	24335.14	25825.21
group3	27973.63	404.7784	69.11	0.000	27180.06	28767.21

```
. predict uhat, residuals
. gen uhatsq = uhat * uhat
. regress uhatsq group1 group2 group3, nocons
```

Source	SS	df	MS	Number of obs =	4266
Model	2.5243e+20	3	8.4144e+19	F(3, 4263) =	434.94
Residual	8.2472e+20	4263	1.9346e+17	Prob > F =	0.0000
				R-squared =	0.2344

```
-----+-----
Total | 1.0772e+21  4266  2.5250e+17
Adj R-squared = 0.2338
Root MSE      = 4.4e+08
```

```
-----+-----
uhatsq |      Coef.   Std. Err.    t    P>|t|    [95% Conf. Interval]
-----+-----
group1 |  2.15e+08   1.32e+07   16.27  0.000   1.89e+08   2.41e+08
group2 |  2.34e+08   1.07e+07   21.77  0.000   2.13e+08   2.55e+08
group3 |  2.72e+08   1.14e+07   23.80  0.000   2.50e+08   2.95e+08
-----+-----
```

```
. test group1 = group2 = group3
```

- (1) group1 - group2 = 0
- (2) group1 - group3 = 0

```
F( 2, 4263) = 5.87
Prob > F = 0.0028
```

```
. gen group = group1 * 1 + group2 * 2 + group3 * 3
```

```
. robvar uhatsq, by(group)
```

```

      |      Summary of uhatsq
group |      Mean   Std. Dev.   Freq.
-----+-----
  1 |  2.149e+08  4.247e+08   1109
  2 |  2.337e+08  4.243e+08   1678
  3 |  2.722e+08  4.675e+08   1479
-----+-----
Total |  2.422e+08  4.403e+08   4266
```

```
W0 = 7.1509260  df(2, 4263)  Pr > F = 0.00079358
W50 = 4.6029258  df(2, 4263)  Pr > F = 0.01007233
W10 = 5.3990598  df(2, 4263)  Pr > F = 0.0045518
```

The squared residuals of the regression of earnings on the group dummies are regressed on these group dummies, and an F-test is performed to test for equality of the coefficients of this second regression across groups i.e. the null hypothesis of such a test is that the group does not affect the variance. This test leads us to reject this null hypothesis at all conventional levels.

Next, the robvar command carries out three tests of the hypothesis that the variance of the residuals across groups is the same. All three tests reject the null hypothesis of constant variance across groups at the 5% level.

2) First, notice that $u_{t+j} = \rho^j u_t + \sum_{i=0}^{j-1} \rho^i \epsilon_{t+j-i}$. Then,

$$\begin{aligned} \text{cov}(u_t, u_{t+j}) &= \text{cov}\left(u_t, \rho^j u_t + \sum_{i=0}^{j-1} \rho^i \epsilon_{t+j-i}\right) \\ &= \text{cov}(u_t, \rho^j u_t) + \text{cov}\left(u_t, \sum_{i=0}^{j-1} \rho^i \epsilon_{t+j-i}\right) \\ &= \rho^j \text{var}(u_t) \end{aligned}$$

where we have used the independence of the innovation ϵ_k with respect to u_j for all $k > j$. Similarly, $\text{cov}(u_t, u_{t-j}) = \rho^j \text{var}(u_{t-j})$. Stationarity implies $\text{var}(u_t) = \text{var}(u_{t-j})$ for all integer values of j . Thus, we have that $\text{cov}(u_t, u_{t-j}) = \text{cov}(u_t, u_{t+j})$.

Now, $u_t = \sum_{i=0}^{\infty} \rho^i \epsilon_{t-i}$, if we assume that $\lim_{i \rightarrow \infty} \rho^i u_{t-i} = 0$. Then,

$$\begin{aligned} \text{var}(u_t) &= \text{var}\left(\sum_{i=0}^{\infty} \rho^i \epsilon_{t-i}\right) \\ &= \sum_{i=0}^{\infty} (\rho^2)^i \text{var}(\epsilon_{t-i}) \\ &= \sum_{i=0}^{\infty} (\rho^2)^i \sigma_\epsilon^2 = \frac{\sigma_\epsilon^2}{1 - \rho^2} \end{aligned}$$

where we have used the independence assumption of the innovations to assert $\text{cov}(u_{t-i}, u_{t-k}) = 0$ iff $i \neq k$.

Thus, we have that $\text{cov}(u_t, u_{t-j}) = \rho^j \frac{\sigma_\epsilon^2}{1 - \rho^2}$, and it follows immediately that $\text{corr}(u_t, u_{t-j}) = \frac{\text{cov}(u_t, u_{t-j})}{\sqrt{\text{var}(u_t) \text{var}(u_{t-j})}} = \rho^j$.

3) Given $c_t = \delta_0 + \delta_1 y_t + \rho u_{t-1} + \epsilon_t$ and $c_{t-1} = \delta_0 + \delta_1 y_{t-1} + u_{t-1}$, we can multiply the second equation by ρ and subtract it from the first yield

$$c_t - \rho c_{t-1} = \delta_0(1 - \rho) + \delta_1 y_t - \delta_1 \rho y_{t-1} + \epsilon_t$$

Comparing coefficients we notice that this is a special case of the general model with parameters mapped as follows:

$$\alpha = \delta_0(1 - \rho), \quad \beta = \rho, \quad \gamma_0 = \delta_1, \quad \gamma_1 = -\rho \delta_1$$

Since the original model has four parameters, but the special case has only three, we must lose a degree of freedom. The parameter mapping above proves this; the first three parameters (α, β, γ_0) are free, but the fourth parameter (γ_1) is determined by β and γ_0 . Thus we conclude that there is one restriction.

4)

. use <http://fmwww.bc.edu/ec-p/data/dmackinnon/consumption>

. gen c = log(CE)

```
. gen y = log(YD)
```

```
. regress c L.c y L.y if year > 1952
```

Source	SS	df	MS	Number of obs =	176
Model	45.1518963	3	15.0506321	F(3, 172) =	.
Residual	.015852826	172	.000092168	Prob > F	= 0.0000
Total	45.1677491	175	.258101424	R-squared	= 0.9996
				Adj R-squared	= 0.9996
				Root MSE	= .0096

c	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
L1.c	.9692255	.02231	43.44	0.000	.9251888	1.013262
L1.y	.2909892	.0551121	5.28	0.000	.182206	.3997724
L1.y	-.2651525	.056445	-4.70	0.000	-.3765666	-.1537384
_cons	.0639353	.0216598	2.95	0.004	.021182	.1066886

```
. nlcom _b[_cons] / (1 - _b[L1.c])
```

```
_nl_1: _b[_cons] / (1 - _b[L1.c])
```

c	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_nl_1	2.07754	1.198914	1.73	0.085	-.2889387	4.444018

```
. nlcom -_b[L.y]/_b[L.c]
```

```
_nl_1: -_b[L.y]/_b[L.c]
```

c	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_nl_1	.2735716	.0569143	4.81	0.000	.1612312	.3859119

From this OLS regression, we obtain an estimate of $\delta_0 \equiv \frac{\alpha}{1-\beta} = 2.07754$ and of $\delta_1 \equiv \gamma_0 = 0.2909892$. An alternative estimate of $\delta_1 = -\gamma_1/\beta = 0.2735716$. Also, $\rho \equiv \beta = 0.9692255$. These estimates are consistent but inefficient.

```
. gen Lc = L.c
(1 missing value generated)

. gen Ly = L.y
(1 missing value generated)

. nl (c = {delta0}*(1 - {rho}) + {delta1}*y - {delta1}*{rho}*Ly + {rho}*Lc) if year > 1952, ///
> initial(delta0 2.0775 delta1 0.290988 rho 0.969225) variables(Ly Lc)
(obs = 176)
```

```
Iteration 0: residual SS = .2033905
Iteration 1: residual SS = .0159923
Iteration 2: residual SS = .015977
Iteration 3: residual SS = .015977
```

Source	SS	df	MS		
Model	45.1517721	2	22.5758861	Number of obs =	176
Residual	.015977007	173	.000092353	R-squared =	0.9996
Total	45.1677491	175	.258101424	Adj R-squared =	0.9996
				Root MSE =	.00961
				Res. dev. =	-1138.581

c	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
/delta0	10.03034	.9619419	10.43	0.000	8.131689	11.929
/rho	.9950142	.0020338	489.24	0.000	.991	.9990284
/delta1	.2836779	.0548059	5.18	0.000	.1755035	.3918523

* (SEs, P values, CIs, and correlations are asymptotic approximations)
Parameter delta0 taken as constant term in model & ANOVA table

Since the restricted SSR from the nonlinear regression is 0.015977007, and the unrestricted SSR from the OLS regression is 0.015852826, the F statistic is

$$F(1, 172) = \frac{0.015977007 - 0.015852826}{0.015852826 / (176 - 4)} = 1.34733908$$

The p-value for this test statistic, based on the $F(1, 172)$ distribution, is 0.247, so the null hypothesis that the restriction is valid is not rejected.

5) a)

```
. use http://fmwww.bc.edu/ec-p/data/wooldridge/discrim.dta
```

```
. count if !NJ
```

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b)

```
. summ wagest
```

Variable	Obs	Mean	Std. Dev.	Min	Max
wagest	390	4.615641	.3470151	4.25	5.75

c)

```
. ttest income, by(state)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
1	331	48052.58	745.0526	13555.04	46586.93	49518.23
2	78	42815.32	1189.756	10507.64	40446.21	45184.43
combined	409	47053.78	651.6738	13179.29	45772.73	48334.84
diff		5237.257	1640.415		2012.512	8462.001

diff = mean(1) - mean(2) t = 3.1926
Ho: diff = 0 degrees of freedom = 407

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.9992 Pr(|T| > |t|) = 0.0015 Pr(T > t) = 0.0008

The null hypothesis that the difference in the means of income between the two states is zero is rejected at the 1% level.

d)

```
. ttest pentree == 1.39
```

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
pentree	398	1.322186	.0322349	.6430845	1.258813	1.385558

mean = mean(pentree) t = -2.1037
Ho: mean = 1.39 degrees of freedom = 397

Ha: mean < 1.39	Ha: mean != 1.39	Ha: mean > 1.39
Pr(T < t) = 0.0180	Pr(T > t) = 0.0360	Pr(T > t) = 0.9820

The null hypothesis that the price of an entree is \$1.39 is rejected at the 5% level.

e)

```
. program drop _all

. program define ols
  1.      args lnf mu sigma
  2.      qui replace `lnf' = ln(normalden(($ML_y-`mu')/`sigma'))-ln(`sigma')
  3. end

. program define olsalt
  1.      args lnf mu sigma2
  2.      qui replace `lnf' = ln(normalden(($ML_y-`mu')/sqrt(`sigma2')))) - 0.5*ln(`sigma2')
  3. end

.

. ml model lf ols (pfries = income prpbck) ()

. * ml check
. ml maximize //, trace grad
```

```
initial:      log likelihood =    -<inf> (could not be evaluated)
feasible:     log likelihood = -236.94341
rescale:      log likelihood = -236.94341
rescale eq:   log likelihood =   238.066
Iteration 0:  log likelihood =   238.066
Iteration 1:  log likelihood =  314.20716
Iteration 2:  log likelihood =  339.06104
Iteration 3:  log likelihood =  339.27361
Iteration 4:  log likelihood =  339.2744
Iteration 5:  log likelihood =  339.2744
```

Log likelihood =	339.2744	Number of obs =	392
		Wald chi2(2) =	31.75
		Prob > chi2 =	0.0000

	pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
eq1							
	income	2.37e-06	4.34e-07	5.47	0.000	1.52e-06	3.22e-06

```

      prpblck |   .1114181   .0308421    3.61  0.000   .0509687   .1718675
        _cons |   .7979156   .0227235   35.11  0.000   .7533783   .8424529
-----+-----
eq2      |
        _cons |   .1018316   .0036368    28.00  0.000   .0947036   .1089597
-----+-----

```

```
. ml model lf olsalt (pfries = income prpblck) ()
```

```
. * ml check
```

```
. ml maximize //, trace grad
```

```

initial:      log likelihood =    -<inf>  (could not be evaluated)
feasible:     log likelihood = -298.58366
rescale:      log likelihood = -298.58366
rescale eq:   log likelihood =    238.066
Iteration 0:  log likelihood =    238.066
Iteration 1:  log likelihood =    305.94977
Iteration 2:  log likelihood =    338.19066
Iteration 3:  log likelihood =    339.27129
Iteration 4:  log likelihood =    339.2744
Iteration 5:  log likelihood =    339.2744

```

```

Log likelihood =    339.2744
                                     Number of obs =          392
                                     Wald chi2(2)   =          31.75
                                     Prob > chi2    =          0.0000

```

```

-----+-----
      pfries |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
eq1      |
      income |  2.37e-06   4.34e-07     5.47  0.000   1.52e-06   3.22e-06
      prpblck |  .1114181   .0308421     3.61  0.000   .0509687   .1718675
        _cons |  .7979156   .0227235    35.11  0.000   .7533783   .8424529
-----+-----
eq2      |
        _cons |  .0103697   .0007407    14.00  0.000   .008918    .0118214
-----+-----

```

f)

```
. ml model lf ols (pfries = income prpblck) () if state == 1
```

```
. * ml check
```

```
. ml maximize //, trace grad
```



```

initial:      log likelihood =    -<inf> (could not be evaluated)
feasible:    log likelihood = -200.93227
rescale:     log likelihood = -200.93227
rescale eq:  log likelihood =  229.72377
Iteration 0: log likelihood =  229.72377
Iteration 1: log likelihood =   275.9703
Iteration 2: log likelihood =   281.7878
Iteration 3: log likelihood =   281.89288
Iteration 4: log likelihood =   281.89308
Iteration 5: log likelihood =   281.89308

```

```

                                          Number of obs =      316
                                          Wald chi2(2)  =      9.35
Log likelihood =  281.89308              Prob > chi2   =      0.0093

```

```

-----+-----
      pfries |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
eq1         |
      income |   1.46e-06   4.78e-07     3.05  0.002     5.23e-07   2.40e-06
      prpblck |   .0456923   .0323636     1.41  0.158    -.0177392   .1091238
      _cons   |   .8655968   .0259617    33.34  0.000     .8147128   .9164809
-----+-----
eq2         |
      _cons   |   .0991615   .0039444    25.14  0.000     .0914306   .1068925
-----+-----

```

```

. ml model lf olsalt (pfries = income prpblck) () if state == 1

. * ml check
. ml maximize //, trace grad

```

```

initial:      log likelihood =    -<inf> (could not be evaluated)
feasible:    log likelihood = -245.65842
rescale:     log likelihood = -245.65842
rescale eq:  log likelihood =  229.72377
Iteration 0: log likelihood =  229.72377
Iteration 1: log likelihood =  264.41684
Iteration 2: log likelihood =  281.42678
Iteration 3: log likelihood =  281.89128
Iteration 4: log likelihood =  281.89308
Iteration 5: log likelihood =  281.89308

```

```

                                          Number of obs =      316
                                          Wald chi2(2)  =      9.35
Log likelihood =  281.89308              Prob > chi2   =      0.0093

```

	pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
eq1							
	income	1.46e-06	4.78e-07	3.05	0.002	5.23e-07	2.40e-06
	prpblck	.0456923	.0323636	1.41	0.158	-.0177392	.1091238
	_cons	.8655968	.0259617	33.34	0.000	.8147128	.9164809
eq2							
	_cons	.009833	.0007823	12.57	0.000	.0082998	.0113662

g)

. reg pfries income prpblck

Source	SS	df	MS	Number of obs =	392
Model	.329251146	2	.164625573	F(2, 389) =	15.75
Residual	4.06491547	389	.010449654	Prob > F =	0.0000
				R-squared =	0.0749
				Adj R-squared =	0.0702
Total	4.39416662	391	.011238278	Root MSE =	.10222

pfries	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
income	2.37e-06	4.36e-07	5.45	0.000	1.52e-06	3.23e-06
prpblck	.1114181	.0309608	3.60	0.000	.0505467	.1722895
_cons	.7979156	.022811	34.98	0.000	.7530674	.8427638

. bootstrap: reg pfries income prpblck
(running regress on estimation sample)

Bootstrap replications (50)

-----+----- 1 ----+----- 2 ----+----- 3 ----+----- 4 ----+----- 5
..... 50

Linear regression	Number of obs	=	392
	Replications	=	50
	Wald chi2(2)	=	38.04
	Prob > chi2	=	0.0000
	R-squared	=	0.0749
	Adj R-squared	=	0.0702
	Root MSE	=	0.1022

```
-----
```

	Observed	Bootstrap			Normal-based	
pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
income	2.37e-06	3.86e-07	6.14	0.000	1.62e-06	3.13e-06
prpblck	.1114181	.033164	3.36	0.001	.0464178	.1764184
_cons	.7979156	.0206537	38.63	0.000	.7574352	.838396

```
-----
```

```
. reg pfries income prpblck, vce(bootstrap, reps(10000) nodots)
```

```
Linear regression
```

Number of obs	=	392
Replications	=	10000
Wald chi2(2)	=	34.30
Prob > chi2	=	0.0000
R-squared	=	0.0749
Adj R-squared	=	0.0702
Root MSE	=	0.1022

```
-----
```

	Observed	Bootstrap			Normal-based	
pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
income	2.37e-06	4.07e-07	5.82	0.000	1.57e-06	3.17e-06
prpblck	.1114181	.0348967	3.19	0.001	.0430218	.1798144
_cons	.7979156	.0219084	36.42	0.000	.7549759	.8408553

```
-----
```

```
. reg pfries income prpblck if state == 1
```

Source	SS	df	MS	Number of obs	=	316
Model	.091970048	2	.045985024	F(2, 313)	=	4.63
Residual	3.10723024	313	.009927253	Prob > F	=	0.0104
Total	3.19920029	315	.010156191	R-squared	=	0.0287
				Adj R-squared	=	0.0225
				Root MSE	=	.09964

```
-----
```

pfries	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
income	1.46e-06	4.80e-07	3.04	0.003	5.14e-07	2.40e-06
prpblck	.0456923	.0325183	1.41	0.161	-.0182898	.1096745
_cons	.8655968	.0260859	33.18	0.000	.814271	.9169226

```
-----
```

```
. bootstrap: reg pfries income prpblck if state == 1
(running regress on estimation sample)
```

```
Bootstrap replications (50)
```

```
-----+----- 1 ----+----- 2 ----+----- 3 ----+----- 4 ----+----- 5
..... 50
```

```
Linear regression          Number of obs    =      316
                          Replications          =       50
                          Wald chi2(2)          =     16.03
                          Prob > chi2           =     0.0003
                          R-squared              =     0.0287
                          Adj R-squared          =     0.0225
                          Root MSE             =     0.0996
```

	Observed	Bootstrap			Normal-based	
pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
income	1.46e-06	3.74e-07	3.90	0.000	7.26e-07	2.19e-06
prpblck	.0456923	.0354046	1.29	0.197	-.0236994	.1150841
_cons	.8655968	.0218178	39.67	0.000	.8228348	.9083589

```
. regress pfries income prpblck if state == 1, vce(bootstrap, reps(10000) nodots)
```

```
Linear regression          Number of obs    =      316
                          Replications          =    10000
                          Wald chi2(2)          =     12.84
                          Prob > chi2           =     0.0016
                          R-squared              =     0.0287
                          Adj R-squared          =     0.0225
                          Root MSE             =     0.0996
```

	Observed	Bootstrap			Normal-based	
pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
income	1.46e-06	4.14e-07	3.53	0.000	6.48e-07	2.27e-06
prpblck	.0456923	.0357392	1.28	0.201	-.0243553	.1157399
_cons	.8655968	.0237188	36.49	0.000	.8191089	.9120848

```
. reg pfries income prpblck if state == 1, vce(bootstrap, reps(100000) nodots)
```

```
Linear regression          Number of obs    =      316
```

```

Replications      = 100000
Wald chi2(2)     = 12.86
Prob > chi2      = 0.0016
R-squared        = 0.0287
Adj R-squared    = 0.0225
Root MSE        = 0.0996

```

	Observed	Bootstrap			Normal-based	
pfries	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
income	1.46e-06	4.14e-07	3.53	0.000	6.49e-07	2.27e-06
prpblck	.0456923	.0358945	1.27	0.203	-.0246596	.1160443
_cons	.8655968	.0237355	36.47	0.000	.819076	.9121176

First, note that the regressions yield the same parameter estimates as the ML programs above, which we expect since the ML estimator and the OLS estimator are the same when the errors are assumed to be distributed normally. The bootstrap standard errors are roughly the same as those obtained by the regression. The bootstrap standard errors are larger for the `prpblck` but smaller for the constant term and for `income`. This is true for complete sample as well as the New Jersey subset, when the number of repetitions is high (10,000 and 100,000 in the case above). If too few repetitions are used this pattern does not have to hold.

By the very nature of bootstrapping (it involves random sampling of the data with replacement), rerunning the bootstrap will yield different results every time, unless the same seed is used for the random number generator (in Stata, this can be done with the `seed(#)` option. Sometimes the estimates are higher than the OLS regression estimate, sometimes they are lower. An alternative way to obtain bootstrapped standard errors is to use the option `vce(bootstrap)` when running `regress`.

Increasing the number of repetitions will lower the variance of the bootstrap estimated standard errors obtained by repeated runs of the bootstrap procedure. See above for the results of 10,000 and 100,000 repetitions (the 100,000 repetitions takes a few minutes). However, if the size of the dataset is rather small, it is possible that the distribution of the data does not reflect the true distribution; bootstrapping will not solve this problem.