Part I.

The first 5 questions are based on the following information: Suppose a researcher is interested in the effect of class attendance on college performance, and plans to estimate the following model: \( \text{colGPA} = \beta_0 + \beta_1 \text{hsGPA} + \beta_2 \text{ACT} + \beta_3 \text{skipped} + u \), where \( \text{colGPA} \) is current GPA, \( \text{hsGPA} \) is high school GPA, \( \text{ACT} \) is score on a college entrance exam and \( \text{skipped} \) is the average number of classes skipped per week. The researcher believes that a component of \( u \) is the student’s inherent laziness.

1. OLS estimates of this model will most likely
   a) be biased and inconsistent, because skipped is endogenous
   The researcher believes that inherent laziness is a component of \( u \). Assuming that lazier students skip more classes, \( \text{skipped} \) would be correlated with \( u \), and thus OLS will be biased and inconsistent.

2. The researcher has information on the distance in miles students live from class (\( \text{dist} \)) and whether they have any classes at 8am (\( \text{early} \)), and regresses \( \text{skipped} \) on \( \text{dist} \), \( \text{early} \), \( \text{hsGPA} \), and \( \text{ACT} \). He then saves the residuals, \( \text{uhat} \), from this regression. If he is planning on doing IV, he should
   b) test for the joint significance of \( \text{dist} \) and \( \text{early} \)
   The researcher has just run the first stage regression. For \( \text{early} \) and \( \text{dist} \) to be valid instruments, they must be correlated with \( \text{skipped} \). So, they need to be jointly significant in this first stage regression.

3. The researcher next obtains the following estimates:

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 141</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>4.53802712</td>
<td>4</td>
<td>1.13450678</td>
<td>F( 4, 136) = 10.38</td>
</tr>
<tr>
<td>Residual</td>
<td>14.8680723</td>
<td>136</td>
<td>.109324061</td>
<td>Prob &gt; F = 0.0000</td>
</tr>
<tr>
<td>Total</td>
<td>19.4060994</td>
<td>140</td>
<td>.138614996</td>
<td>R-squared = 0.2338</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Adj R-squared = 0.2113</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Root MSE = .33064</td>
</tr>
</tbody>
</table>

| Source | Coef. | Std. Err. | t | P>|t| | [95% Conf. Interval] |
|--------|-------|-----------|---|------|---------------------|
| colGPA | .4135611 | .0943636 | 4.383 | 0.000 | .2269514 .6001708 |
| hsGPA  | .0144984 | .0106536 | 1.361 | 0.176 | -.0065698 .0355666 |
| ACT    | -.0796302 | .0308488 | -2.581 | 0.011 | -.1406356 -.0186249 |
| skipped| -.0122316 | .0578108 | -0.212 | 0.833 | -.1265559 .1020928 |
| _cons  | 1.385228 | .3333431 | 4.156 | 0.000 | .7260219 2.044434 |

We can conclude that:
   d) all of the above
   This is a Hausman test for the endogeneity of \( \text{skipped} \). Since \( \text{uhat} \) is not significant, we conclude that IV and OLS are not significantly different. This implies that we reject the null that skipped is endogenous, so the OLS estimates are consistent. Additionally, we can interpret these IV estimates, which imply that skipping reduces GPA by about .08 points.

4. The researcher estimates the model using IV, saves the residuals (\( \text{uhativ} \)) and then obtains:

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 141</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>.09339178</td>
<td>4</td>
<td>.023347945</td>
<td>F( 4, 136) = 0.21</td>
</tr>
<tr>
<td>Residual</td>
<td>14.7815227</td>
<td>136</td>
<td>.108687667</td>
<td>Prob &gt; F = 0.9298</td>
</tr>
</tbody>
</table>

R-squared = 0.0063
The above estimates would imply that

**c) students probably can’t completely choose where to live and whether to have 8am classes or not**

This is an overID test of whether our instruments are truly exogenous. To carry out the test we form the $\text{nR}^2 = 141 \times 0.0063 = 0.8883$ which is very small. The critical value for significance at the 10% level is 2.71 for a chi-square distribution with 1 degree of freedom. Thus, we can’t reject the null that $\text{dist}$ and $\text{early}$ are exogenous (and hence unrelated to inherent laziness). If students could completely choose where to live and whether they have 8am classes, we might expect them to be related to laziness.

5. Turning to the IV estimates the researcher must have obtained in question 4, we can predict that

**d) the coefficient on skipped will definitely be exactly -.0796302**

We know that 2SLS is the same as IV, except for the standard errors. We also know that the Hausman test in 3 is a form of 2SLS. So, when the researcher did IV, he would get exactly the same estimates.

6. Which of the following are true about time-series estimation?

**c) Seasonality is not an issue when using annual time series observations**

With time series data, we do not have a random sample and can’t just assume that observations are independent. In fact, most time series processes are correlated over time. There is no problem using a trending variable as a dependent variable – we may need to be careful with interpretation, and often will want to include a trend as an independent variable. Since seasonality refers to differences across months or quarters or such, it is impossible to have seasonality in data collected at the year level.

---

**Part II. Stata Problems.**

1. Before starting Stata, I opened smoke.xls and chose “Save As” from the file menu. I then chose “Text (tab delimited)” and saved the file as smoke.txt.

   `. insheet using smoke.txt
   (7 vars, 807 obs)
   . desc

Contains data

- obs: 807
- vars: 7
- size: 14,526 (100.0% of memory free)

<table>
<thead>
<tr>
<th>variable name</th>
<th>type</th>
<th>format</th>
<th>label</th>
<th>variable label</th>
</tr>
</thead>
<tbody>
<tr>
<td>education</td>
<td>float</td>
<td>%9.0g</td>
<td></td>
<td>Education</td>
</tr>
<tr>
<td>cigprice</td>
<td>float</td>
<td>%9.0g</td>
<td></td>
<td>Cig Price</td>
</tr>
</tbody>
</table>
whitedummy byte %8.0g      White Dummy
age     byte %8.0g         Age
income  int  %8.0g         Income
cigsperday byte %8.0g      Cigs per Day
restaurantres~s byte %8.0g Restaurant Restrictions

Sorted by:

Note:  dataset has changed since last saved

sum

Variable |     Obs        Mean   Std. Dev.       Min        Max
-------------+-----------------------------------------------------
education |     807    12.47088   3.057161          6         18
cigprice |     807    60.30041   4.738469     44.004     70.129
whitedummy |     807    .8785626   .3268375          0          1
age |     807    41.23792   17.02729         17         88
income |     807    19304.83   9142.958        500      30000
cigsperday |     807    8.686493   13.72152          0         80
restaurant~s |     807    .2465923   .4312946          0          1

a) In order to estimate the model, I need to create a couple variables.

. gen lincome=ln(income)

. gen agesq=age^2

. reg lincome cigsperday education whitedummy age agesq, robust

Regression with robust standard errors

|               Robust
| Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
cigsperday |   .0017166   .0014324     1.20   0.231    -.0010951    .0045284
education |   .0601146   .0074493     8.07   0.000     .0454922     .074737
whitedummy |  -.1004146   .0615368    -1.63   0.103     -.221207    .0203777
age    |   .0582598   .0091838     6.34   0.000     .0402326    .0762871
agesq  |  -.0006375   .0000981    -6.50   0.000    -.0008301    -.000445
_cons |   7.877208   .2118737    37.18   0.000     7.461314    8.293101

b) The reduced form models regress the endogenous variables (cigsperday and lincome) on all of the exogenous variables in the system. Since these are the first stage regressions for an IV estimate of the original model, I also test for the significance of the instruments (cigprice and restaurantrestrictions)

. reg cigsperday cigprice restaurantrestrictions education whitedummy age agesq > q, robust

Regression with robust standard errors

|               Robust
| Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
. test cigprice  restaurantrestrictions
( 1)  cigprice = 0.0
( 2)  restaurantrestrictions = 0.0

    F(  2,   800) =    3.89
    Prob > F =    0.0209

. reg lincome cigprice  restaurantrestrictions education whitedummy age agesq, robust
Regression with robust standard errors
Number of obs =     807
F(  6,   800) =   28.92
Prob > F      =  0.0000
R-squared     =  0.1727
Root MSE      =  .65067

|               Robust
lincome |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
cigprice |   .0076459   .0052416     1.46   0.145    -.0026431    .0179349
restaurant-restrictions |   .0955453   .0529191     1.81   0.071    -.0083314     .199422
table-edgation |   .0582089   .0073100     7.96   0.000       .04386    .0725579
whitedummy |  -.0807037   .0614338    -1.31   0.189    -.2012942    .0398868
age |   .0593675    .009088     6.53   0.000      .041528    .0772066
agesq |  -.0006505   .0000966    -6.74   0.000    -.0008401    -.0004610
_3onst |   7.394159    .403195     18.34   0.000     6.602714    8.185604

. reg lincome cigsperday education whitedummy age agesq, robust
IV (2SLS) regression with robust standard errors
Number of obs =     807
F(  5,   801) =   19.72
Prob > F      =  0.0000
R-squared     =       .
Root MSE      =  .84426

|               Robust
lincome |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
cigsperday |  -.0380873   .0232067    -1.64   0.101    -.0836403    .0074658
table-edication |   .0413177   .0148594     2.78   0.006       .012497    .0704858
whitedummy |  -.1097679   .0798215    -1.38   0.169    -.2664519    .0469161
age |   .0911009    .021652     4.21   0.000      .048598    .1336038

\(c)\) Only the first equation is identified. This is because cigprice and restaurantrestrictions are excluded from the income equation, and thus can be used as instruments for cigsperday. There is nothing excluded from the cigsperday equation that can be used as an instrument for lincome.
2. Look at the data.

```
. use consump, clear
. desc
Contains data from consump.dta
    obs:              37
    vars:             24
 20 May 2002 22:37
size:             3,626 (100.0% of memory free)

storage  display    value
variable name   type   format  label      variable label
-------------------------------------------------------------------------------
year            int    %9.0g                  1959-1995
i3              float  %9.0g                  3 mo. T-bill rate
inf             float  %9.0g                  inflation rate; CPI
rdisp           float  %9.0g                  disp. inc., 1992 $, bils.
rnondc          float  %9.0g                  nondur. cons., 1992 $, bils.
rserv           float  %9.0g                  services, 1992 $, bils.
pop             float  %9.0g                  population, 1000s
y               float  %9.0g                  per capita real disp. inc.
rcons           float  %9.0g                  rnondc + rserv
r3              float  %9.0g                  i3 - inf; real ex post int.
lc              float  %9.0g                  log(c)
ly              float  %9.0g                  log(y)
gc              float  %9.0g                  lc - lc[_n-1]
gy              float  %9.0g                  ly - ly[_n-1]
gc_1            float  %9.0g                  gc[_n-1]
gy_1            float  %9.0g                  gy[_n-1]
r3_1            float  %9.0g                  r3[_n-1]
lc_ly           float  %9.0g                  lc - ly
lc_ly_1         float  %9.0g                  lc_ly[_n-1]
gc_2            float  %9.0g                  gc[_n-2]
gy_2            float  %9.0g                  gy[_n-2]
r3_2            float  %9.0g                  r3[_n-2]
lc_ly_2         float  %9.0g                  lc_ly[_n-2]
-------------------------------------------------------------------------------
Sorted by: 
. sum
```

```
Variable |   Obs  | Mean   | Std. Dev.  | Min   |Max    |
-----|-------|--------|------------|-------|-------|
year  |  37   | 1977   | 10.82436   | 1959  | 1995  |
i3    |  37   | 6.061622| 2.678825   | 2.38  |14.03  |
infl  |  37   | 4.637838| 3.124042   | .7    | 13.5  |
rdisp |  37   | 3154.111| 1046.487   | 1530.1|4945.8 |
rnondc|  37   | 1003.87 | 245.8753   | 606.3 |1421.9 |
rserv |  37   | 1556.989| 586.6619   | 687.4 |2577   |
pop   |  37   | 220748.9| 24755.96   | 177830|263034 |
y     |  37   | 13940.48| 8604.285   | 8604.285|18802.89|
rcons |  37   | 2560.859| 831.7756   | 1293.7|3998.9 |
c     |  36   | 11328.65| 7274.925   | 15202.98|
r3    |  37   | 1.423784| 2.064335   | -3.26 | 5.43  |
lc    |  37   | 9.309927 | .2309508   | 8.892189 |9.629247 |
gc    |  36   | .0204738 | .0126375  | -.0091066| .0402088 |
gy    |  36   | .0217153 | .0182399  | -.0169735| .061985 |
```
2.a) and b) While I could just use year to reflect the trend, I created a trend variable that goes from 1 to 37. The series do appear to be related, even more once they have been detrended. (See commands below that obtained these graphs).

```
. gen t=year-1958

. reg ly t
```

The elasticity is .94.

b) From these regressions we can see that income and consumption are both growing by about 2% per year (2.22 and 2.11 respectively).

```
. reg ly t
```
. predict lydetrend, resid

. reg lc t

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 37</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>1.87972918</td>
<td>1</td>
<td>1.87972918</td>
<td>F(1,35) = 1626.49</td>
</tr>
<tr>
<td>Residual</td>
<td>.040449391</td>
<td>35</td>
<td>.001155697</td>
<td>Prob &gt; F = 0.0000</td>
</tr>
<tr>
<td>Total</td>
<td>1.92017857</td>
<td>36</td>
<td>.053338294</td>
<td>Adj R-squared = 0.9783</td>
</tr>
</tbody>
</table>

| lc | Coef.   | Std. Err.   | t     | P>|t|  | [95% Conf. Interval] |
|----|---------|-------------|-------|------|---------------------|
| t  | .0211103 | .0005234    | 40.33 | 0.000 | .0200477 - .0221729 |
| _cons | 8.908832 | .0114082    | 780.92| 0.000 | 8.885672 - 8.931992 |

. predict lcdetrend, resid

. graph lydetrend lcdetrend t

c) We get an elasticity of .72 with the detrended data (or just including a trend), which is lower than before. Some of the relationship estimated before was due to both variables trending up.

. reg lcdetrend lydetrend

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 37</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>.038788413</td>
<td>1</td>
<td>.038788413</td>
<td>F(1,35) = 817.35</td>
</tr>
<tr>
<td>Residual</td>
<td>.001660979</td>
<td>35</td>
<td>.000047457</td>
<td>Prob &gt; F = 0.0000</td>
</tr>
<tr>
<td>Total</td>
<td>.040449392</td>
<td>36</td>
<td>.001123594</td>
<td>Adj R-squared = 0.9578</td>
</tr>
</tbody>
</table>

| lcdetrend | Coef.   | Std. Err.   | t     | P>|t|  | [95% Conf. Interval] |
|-----------|---------|-------------|-------|------|---------------------|
| lydetrend | .7187684 | .0251412    | 28.59 | 0.000 | .6677291 - .7698078 |
| _cons    | -1.81e-10 | .0011325   | -0.00 | 1.000 | -.0022991 - .0022991 |

. reg lc ly t

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>Number of obs = 37</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>1.91851759</td>
<td>2</td>
<td>.959258795</td>
<td>F(2,34) = 19635.89</td>
</tr>
<tr>
<td>Residual</td>
<td>.001660979</td>
<td>34</td>
<td>.000048852</td>
<td>Prob &gt; F = 0.0000</td>
</tr>
<tr>
<td>Total</td>
<td>1.92017857</td>
<td>36</td>
<td>.053338294</td>
<td>Adj R-squared = 0.9991</td>
</tr>
</tbody>
</table>

| lc | Coef.   | Std. Err.   | t     | P>|t|  | [95% Conf. Interval] |
|----|---------|-------------|-------|------|---------------------|
| ly  | .7187684 | .0255082    | 28.18 | 0.000 | .6669294 - .770674 |
| _cons | 2.372793 | .2319681    | 10.23 | 0.000 | 1.901377 - 2.844209 |
| t   | .0051721 | .0005758    | 8.98  | 0.000 | .004002 - .0063423 |
d) In order to estimate Newey-West standard errors or use Cochrane-Orcutt estimation we need to tell stata what the time variable is.
   . tsset t
      time variable:  t, 1 to 37

   . newey lc ly t, lag(4)

Regression with Newey-West standard errors          Number of obs  =        37
maximum lag : 4                                     F(  2,    34)  = 19535.97
Prob > F       =    0.0000
------------------------------------------------------------------------------
|                 Newey-West
lc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   ly |   .7187684   .0277335    25.92   0.000     .6624072    .7751297
   t |   .0051721   .0006073     8.52   0.000     .003938    .0064063
 _cons | 2.372793   .2518517     9.42   0.000     1.860969    2.884618
------------------------------------------------------------------------------

These are the same coefficients as OLS, but different standard errors. That’s what we expected.

   . prais lc ly t, corc

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.3742
Iteration 2:  rho = 0.3941
Iteration 3:  rho = 0.3976
Iteration 4:  rho = 0.3983
Iteration 5:  rho = 0.3984
Iteration 6:  rho = 0.3984
Iteration 7:  rho = 0.3984
Iteration 8:  rho = 0.3984

Cochrane-Orcutt AR(1) regression -- iterated estimates

| Coef.   Std. Err.   t   P>|t|     [95% Conf. Interval] |
|--------|------------------|-----|-----|------------------|-----------------|
| lc | ly | .7187684  .0277335  25.92  0.000  .6624072  .7751297 |
|   t | .0051721  .0006073  8.52   0.000  .003938    .0064063 |
| _cons | 2.372793   .2518517  9.42   0.000  1.860969    2.884618 |

Durbin-Watson statistic (original)    1.236912
Durbin-Watson statistic (transformed) 1.900697

This is a different estimator – it’s based on assuming exactly AR(1) serial correlation, but the implications are similar to the previous estimates, which is also as expected.

3. Look at the data.
   . use intdef, clear
. desc

Contains data from intdef.dta
obs:            49
size:         2,499 (100.0% of memory free)

-------------------------------------------------------------------
storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------
year            int    %9.0g                  1948-1996
i3              float  %9.0g                  3 mo. T bill rate
inf             float  %9.0g                  CPI inf. rate
rec             float  %9.0g                  fed. receipts, % GDP
out             float  %9.0g                  fed. outlays, % GDP
def             float  %9.0g                  out - rec
i3_1            float  %9.0g                  i3[_n-1]
inf_1           float  %9.0g                  inf[_n-1]
def_1           float  %9.0g                  def[_n-1]
ci3             float  %9.0g                  i3 - i3_1
ccinf            float  %9.0g                  inf - inf_1
cdef            float  %9.0g                  def - def_1
y77             byte   %9.0g                  =1 year >= 1977; change in FY
-------------------------------------------------------------------
Sorted by:
.
.sum

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
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<td>year</td>
<td>49</td>
<td>1972</td>
<td>14.28869</td>
<td>1948</td>
<td>1996</td>
</tr>
<tr>
<td>i3</td>
<td>49</td>
<td>5.06898</td>
<td>2.965661</td>
<td>.95</td>
<td>14.03</td>
</tr>
<tr>
<td>inf</td>
<td>49</td>
<td>4.108163</td>
<td>3.182821</td>
<td>-1.2</td>
<td>13.5</td>
</tr>
<tr>
<td>rec</td>
<td>49</td>
<td>17.83878</td>
<td>1.058855</td>
<td>14.5</td>
<td>19.7</td>
</tr>
<tr>
<td>out</td>
<td>49</td>
<td>19.69184</td>
<td>2.514528</td>
<td>11.7</td>
<td>23.6</td>
</tr>
<tr>
<td>def</td>
<td>49</td>
<td>1.853061</td>
<td>2.04268</td>
<td>-4.7</td>
<td>6</td>
</tr>
<tr>
<td>i3_1</td>
<td>48</td>
<td>5.07</td>
<td>2.997035</td>
<td>.95</td>
<td>14.03</td>
</tr>
<tr>
<td>inf_1</td>
<td>48</td>
<td>4.13125</td>
<td>3.212354</td>
<td>-1.2</td>
<td>13.5</td>
</tr>
<tr>
<td>def_1</td>
<td>48</td>
<td>1.8625</td>
<td>2.063216</td>
<td>-4.7</td>
<td>6</td>
</tr>
<tr>
<td>ci3</td>
<td>48</td>
<td>.0829167</td>
<td>1.381285</td>
<td>-3.34</td>
<td>2.97</td>
</tr>
<tr>
<td>cinf</td>
<td>48</td>
<td>-.10625</td>
<td>2.566926</td>
<td>-9.3</td>
<td>6</td>
</tr>
<tr>
<td>cdef</td>
<td>48</td>
<td>.1270833</td>
<td>1.496057</td>
<td>-3.200001</td>
<td>4.499999</td>
</tr>
<tr>
<td>y77</td>
<td>49</td>
<td>.4081633</td>
<td>.496587</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

a) The finite distributed lag model has one lag of each independent variable:
.
.reg i3 inf inf_1 def def_1

. sum

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>i3</td>
<td>48</td>
<td>.4251947</td>
<td>.1288993</td>
<td>3.30</td>
<td>0.002</td>
</tr>
<tr>
<td>inf_1</td>
<td>48</td>
<td>.2732321</td>
<td>.1412654</td>
<td>1.93</td>
<td>0.060</td>
</tr>
</tbody>
</table>
\[
\begin{align*}
\text{def} & | \quad 0.1630251 \quad 0.2569521 \quad 0.63 \quad 0.529 \quad -0.3551682 \quad 0.6812185 \\
\text{def} \_1 & | \quad 0.4047176 \quad 0.217547 \quad 1.86 \quad 0.070 \quad -0.0340078 \quad 0.8434431 \\
_\text{cons} & | \quad 1.234579 \quad 0.4410125 \quad 2.80 \quad 0.008 \quad 0.3451927 \quad 2.123966
\end{align*}
\]

\begin{itemize}
\item[a)] The impact propensity is the coefficient on the current time period. Thus the impact propensity for inflation is 0.425 and for the deficit it is 0.163.
\item[b)] The long-run propensity is the sum of the coefficients on the current and lagged variables. For inflation it is 0.698 for the deficit it is 0.568. We need to test whether this sum is significant—not whether the two coefficients are jointly significant.
\end{itemize}

\begin{verbatim}
. test inf + inf\_1=0
( 1)  inf + inf\_1 = 0.0
    F(  1,   43) =   66.70
    Prob > F =   0.0000

. test def+def\_1=0
( 1)  def + def\_1 = 0.0
    F(  1,   43) =   16.25
    Prob > F =   0.0002
\end{verbatim}

Both long-run propensities are statistically significant.