(Note: I cut my index finger open while cooking on 2/8, typing is challenging.)
1.

csipolate rcons quarter, gen(cub)
ipolate rcons quarter, gen(lin)

```
.         su diff_perc if mi(rcons), d

                          diff_perc
-------------------------------------------------------------
      Percentiles      Smallest
 1%    -.0031216      -.0039958
 5%    -.0019897      -.0031216
10%    -.0018348      -.0028738       Obs                 108
25%    -.0008816      -.0020952       Sum of Wgt.         108

50%     .0000535                      Mean          -.0000867
                        Largest       Std. Dev.      .0012649
75%     .0005097       .0025883
90%     .0014312       .0026875       Variance       1.60e-06
95%     .0019485       .0033632       Skewness       .0584529
99%     .0033632       .0039727       Kurtosis        4.21895
```

No notable differences between models.

2.

A.

```
. tobit ecolbs lecoprc lfaminc lregprc educ hhsize num5_17

Iteration 0:   log likelihood = -1535.1136
Iteration 1:   log likelihood = -1535.1136

Tobit regression                                Number of obs     =        660
                                                   Uncensored     =        660
Limits: lower = -inf                               Left-censored  =          0
        upper = +inf                               Right-censored =          0

                                                LR chi2(6)        =      24.82
                                                Prob > chi2       =     0.0004
Log likelihood = -1535.1136                     Pseudo R2         =     0.0080

------------------------------------------------------------------------------
      ecolbs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lecoprc |   -2.56959   .5833995    -4.40   0.000    -3.715152   -1.424028
     lfaminc |    .203861   .1551377     1.31   0.189    -.1007671    .5084891
     lregprc |   2.204184   .5871618     3.75   0.000     1.051234    3.357134
        educ |   .0251628   .0455542     0.55   0.581    -.0642873    .1146129
      hhsize |   .0015866   .0882216     0.02   0.986    -.1716452    .1748184
     num5_17 |   .1111276   .1336623     0.83   0.406    -.1513314    .3735865
       _cons |   .7307278   .7570337     0.97   0.335     -.755782    2.217238
-------------+----------------------------------------------------------------
var(e.ecolbs)|   6.134829   .3377112                      5.506283    6.835125
------------------------------------------------------------------------------


. margins, dydx(*) predict(ystar(0,.))

Average marginal effects                        Number of obs     =        660
Model VCE    : OIM

Expression   : E(ecolbs*|ecolbs>0), predict(ystar(0,.))
dy/dx w.r.t. : lecoprc lfaminc lregprc educ hhsize num5_17

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lecoprc |  -1.851027   .4184455    -4.42   0.000    -2.671165   -1.030889
     lfaminc |   .1468531   .1117172     1.31   0.189    -.0721086    .3658149
     lregprc |   1.587804   .4217173     3.77   0.000     .7612532    2.414355
        educ |   .0181263   .0328134     0.55   0.581    -.0461868    .0824393
      hhsize |   .0011429   .0635513     0.02   0.986    -.1234153    .1257011
     num5_17 |   .0800518   .0962688     0.83   0.406    -.1086317    .2687352
------------------------------------------------------------------------------
```

Only the log price of eco and regular apples is significant at 95% level.
B.

```
.  keep if ecolbs>0
(248 observations deleted)

. reg ecolbs lecoprc lfaminc lregprc educ hhsize num5_17

      Source |       SS           df       MS      Number of obs   =       412
-------------+----------------------------------   F(6, 405)       =      0.52
       Model |  25.7635854         6  4.29393091   Prob > F        =    0.7897
    Residual |  3315.22097       405  8.18573079   R-squared       =    0.0077
-------------+----------------------------------   Adj R-squared   =   -0.0070
       Total |  3340.98456       411   8.1289162   Root MSE        =    2.8611

------------------------------------------------------------------------------
      ecolbs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lecoprc |  -1.139816   .8353574    -1.36   0.173    -2.781994    .5023619
     lfaminc |   .1634253    .238272     0.69   0.493    -.3049792    .6318297
     lregprc |   1.365922   .8666128     1.58   0.116    -.3376985    3.069543
        educ |  -.0467014   .0671759    -0.70   0.487    -.1787585    .0853556
      hhsize |  -.0272838   .1302264    -0.21   0.834     -.283288    .2287204
     num5_17 |   .0482239   .1856715     0.26   0.795    -.3167764    .4132242
       _cons |    2.70005   1.173709     2.30   0.022     .3927268    5.007373
------------------------------------------------------------------------------

. margins, dydx(*)

Average marginal effects                        Number of obs     =        412
Model VCE    : OLS

Expression   : Linear prediction, predict()
dy/dx w.r.t. : lecoprc lfaminc lregprc educ hhsize num5_17

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lecoprc |  -1.139816   .8353574    -1.36   0.173    -2.781994    .5023619
     lfaminc |   .1634253    .238272     0.69   0.493    -.3049792    .6318297
     lregprc |   1.365922   .8666128     1.58   0.116    -.3376985    3.069543
        educ |  -.0467014   .0671759    -0.70   0.487    -.1787585    .0853556
      hhsize |  -.0272838   .1302264    -0.21   0.834     -.283288    .2287204
     num5_17 |   .0482239   .1856715     0.26   0.795    -.3167764    .4132242
------------------------------------------------------------------------------
```

No variables are significant at the 95% level for the OLS model. This appears because of the model’s selection bias from only selected people who purchase a single eco labeled apple.

3.

A.

heckman gift resplast avggift propresp mailsyear weekslast, select(respond = resplast avggift propresp mailsyear weekslast)

```
Heckman selection model                         Number of obs     =      4,268
(regression model with sample selection)              Selected    =      1,707
                                                      Nonselected =      2,561

                                                Wald chi2(5)      =     137.73
Log likelihood = -9750.451                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gift         |
    resplast |   .0357605   1.487353     0.02   0.981    -2.879399     2.95092
     avggift |   .0249004   .0053889     4.62   0.000     .0143383    .0354625
    propresp |  -26.69666   3.304079    -8.08   0.000    -33.17253   -20.22078
   mailsyear |   1.150477   .8424015     1.37   0.172    -.5006001    2.801553
   weekslast |   .1081762   .0231094     4.68   0.000     .0628826    .1534698
       _cons |   44.83067    3.58776    12.50   0.000     37.79879    51.86255
-------------+----------------------------------------------------------------
respond      |
    resplast |   .0329906   .0565128     0.58   0.559    -.0777725    .1437537
     avggift |   .0212896   .0013692    15.55   0.000     .0186059    .0239733
    propresp |   1.734545   .1125834    15.41   0.000     1.513885    1.955204
   mailsyear |   .0585138    .031464     1.86   0.063    -.0031544    .1201821
   weekslast |  -.0051586   .0007123    -7.24   0.000    -.0065546   -.0037626
       _cons |  -1.444665   .1116397   -12.94   0.000    -1.663475   -1.225855
-------------+----------------------------------------------------------------
     /athrho |  -1.330056   .0958632   -13.87   0.000    -1.517944   -1.142167
    /lnsigma |   3.270655   .0383795    85.22   0.000     3.195432    3.345877
-------------+----------------------------------------------------------------
         rho |   -.869263   .0234272                     -.9083387   -.8151426
       sigma |   26.32857   1.010477                      24.42073    28.38546
      lambda |  -22.88645    1.45797                     -25.74402   -20.02888
------------------------------------------------------------------------------
LR test of indep. eqns. (rho = 0):   chi2(1) =   103.46   Prob > chi2 = 0.0000
```

```
. margins, dydx(*) predict(yexpected)

Average marginal effects                        Number of obs     =      4,268
Model VCE    : OIM

Expression   : E(gift*|Pr(respond)), predict(yexpected)
dy/dx w.r.t. : resplast avggift propresp mailsyear weekslast

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    resplast |   .3360517   .4893041     0.69   0.492    -.6229666     1.29507
     avggift |    .217525   .0148459    14.65   0.000     .1884276    .2466224
    propresp |    7.28027   1.060428     6.87   0.000     5.201869    9.358671
   mailsyear |   .9912053   .2917781     3.40   0.001     .4193306     1.56308
   weekslast |  -.0111895   .0070835    -1.58   0.114    -.0250729     .002694
------------------------------------------------------------------------------
```

B.

```
. reg respond resplast avggift propresp mailsyear weekslast

      Source |       SS           df       MS      Number of obs   =     4,268
-------------+----------------------------------   F(5, 4262)      =    232.68
       Model |  219.642439         5  43.9284878   Prob > F        =    0.0000
    Residual |  804.637552     4,262  .188793419   R-squared       =    0.2144
-------------+----------------------------------   Adj R-squared   =    0.2135
       Total |  1024.27999     4,267  .240046869   Root MSE        =     .4345

------------------------------------------------------------------------------
     respond |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    resplast |   .0664608   .0190156     3.50   0.000     .0291804    .1037413
     avggift |   .0001827   .0000846     2.16   0.031     .0000169    .0003486
    propresp |   .6503363    .036999    17.58   0.000     .5777989    .7228736
   mailsyear |   .0519748   .0101928     5.10   0.000     .0319917     .071958
   weekslast |  -.0010783   .0002086    -5.17   0.000    -.0014874   -.0006692
       _cons |   .0165182   .0355887     0.46   0.643    -.0532541    .0862906
------------------------------------------------------------------------------
```

```
. keep if gift>0
(2,561 observations deleted)

.
. reg gift resplast avggift propresp mailsyear weekslast

      Source |       SS           df       MS      Number of obs   =     1,707
-------------+----------------------------------   F(5, 1701)      =      7.32
       Model |  12912.6411         5  2582.52823   Prob > F        =    0.0000
    Residual |  600318.174     1,701  352.920737   R-squared       =    0.0211
-------------+----------------------------------   Adj R-squared   =    0.0182
       Total |  613230.815     1,706  359.455343   Root MSE        =    18.786

------------------------------------------------------------------------------
        gift |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    resplast |   1.119617   1.236872     0.91   0.365    -1.306335    3.545569
     avggift |   .0171787   .0037487     4.58   0.000     .0098261    .0245314
    propresp |  -.7658592   2.394956    -0.32   0.749    -5.463229    3.931511
   mailsyear |   2.692177   .7116409     3.78   0.000     1.296394    4.087961
   weekslast |   .0141803   .0198824     0.71   0.476    -.0248162    .0531769
       _cons |   11.81369   2.704796     4.37   0.000      6.50861    17.11876
------------------------------------------------------------------------------
```

The models have very different AMEs. Given most gifts are small or zero and you cannot have a negative gift the tobit type2 model fits our scenario. While, OLS overlooks these conditions causing incorrect estimates.

4.

A.

npregress kernel bwght faminc, reps(500) seed(1)

```
Local-linear regression                    Number of obs      =      1,196
Kernel    : epanechnikov                   E(Kernel obs)      =      1,196
Bandwidth: cross validation                R-squared          =     0.0193
```

bwght	Observed Estimate	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
Mean						
bwght	118.4696	.5948006	199.18	0.000	117.1872	119.624
Effect						
faminc	.2103005	.0536238	3.92	0.000	.1058769	.3138146

Note: Effect estimates are averages of derivatives.

margins, dydx(*) at((median)faminc) reps(500) seed(1)

```
Conditional marginal effects                    Number of obs     =     1,196
                                                Replications      =       500

Expression    : mean function, predict()
dy/dx w.r.t. : faminc
at            : faminc          =       22.5 (median)
```

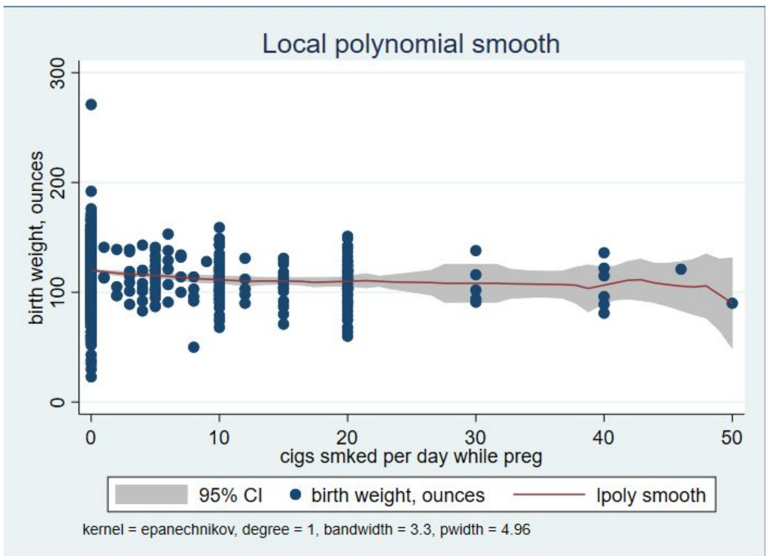
	Observed dy/dx	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
faminc	.2471097	.1104106	2.24	0.025	.0155378	.4625784

```
. margins, dydx(*)

Average marginal effects                        Number of obs     =      1,196

Expression   : mean function, predict()
dy/dx w.r.t. : faminc
```

	dy/dx
faminc	.2103005

```
Note: You may compute standard errors using vce(bootstrap) or reps().
```

lpoly bwght cigs, degree(1) ci



B.

npregress kernel bwght cigs faminc motheduc, reps(500) seed(1)

Bandwidth

	Mean	Effect
cigs	2.123657	2.682692
faminc	6.665646	8.420322
motheduc	.8968269	1.132909

Local-linear regression		Number of obs =	1,051
Kernel : epanechnikov		E(Kernel obs) =	1,051
Bandwidth: cross validation		R-squared =	0.1142

bwght	Observed Estimate	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
Mean						
bwght	118.3683	.8650189	136.84	0.000	117.4011	120.6112
Effect						
cigs	-.4662423	.6705554	-0.70	0.487	-2.023998	.7743301
faminc	.112927	.0759512	1.49	0.137	.0308194	.3249604
motheduc	.6280309	.6602792	0.95	0.342	-.1675812	2.341429

Note: Effect estimates are averages of derivatives.

margins, dydx(*) at((median) cigs faminc motheduc) reps(500) seed(1)

```
Conditional marginal effects                    Number of obs     =      1,051
                                                Replications      =        355

Expression   : mean function, predict()
dy/dx w.r.t. : cigs faminc motheduc
at           : cigs            =           0 (median)
               faminc          =        22.5 (median)
               motheduc        =          12 (median)
```

	Observed dy/dx	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
cigs	.8569527	1.057085	0.81	0.418	-1.537849	2.706943
faminc	.2949901	.1046279	2.82	0.005	.0801142	.4931624
motheduc	1.684065	.9111718	1.85	0.065	-.1697928	3.615321

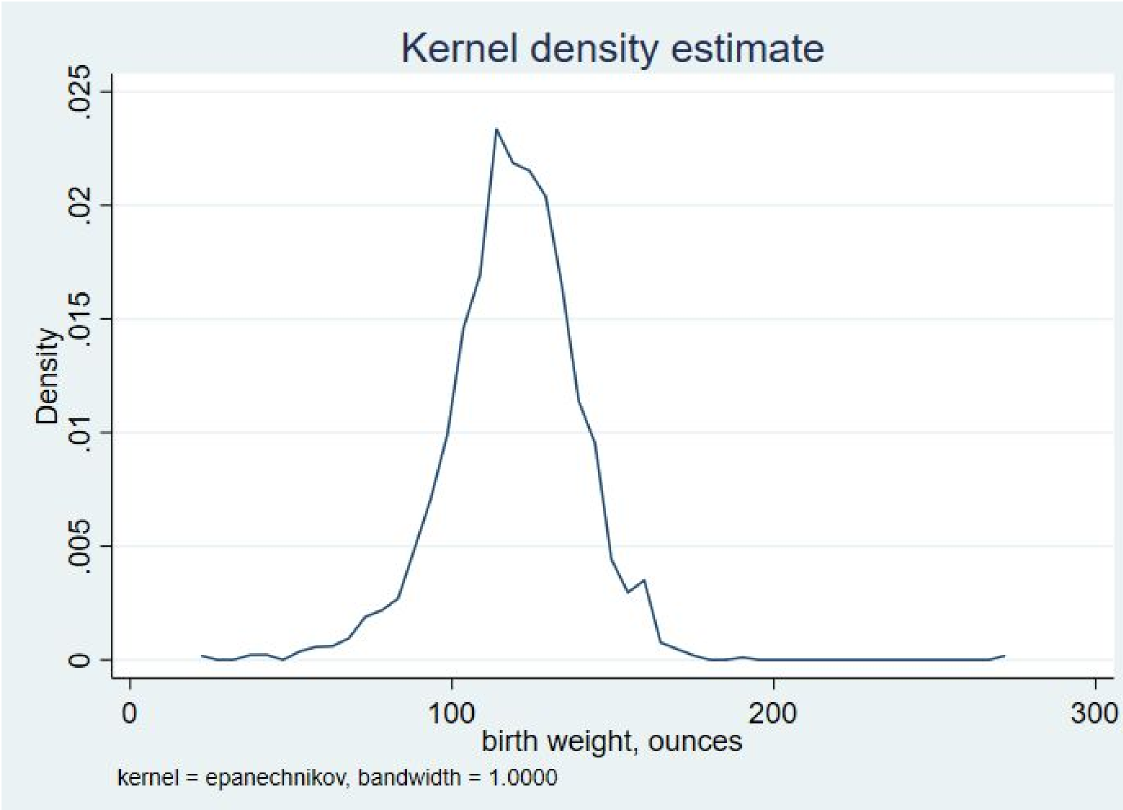
```
. margins, dydx(*)

Average marginal effects                        Number of obs     =      1,051

Expression   : mean function, predict()
dy/dx w.r.t. : cigs faminc motheduc
```

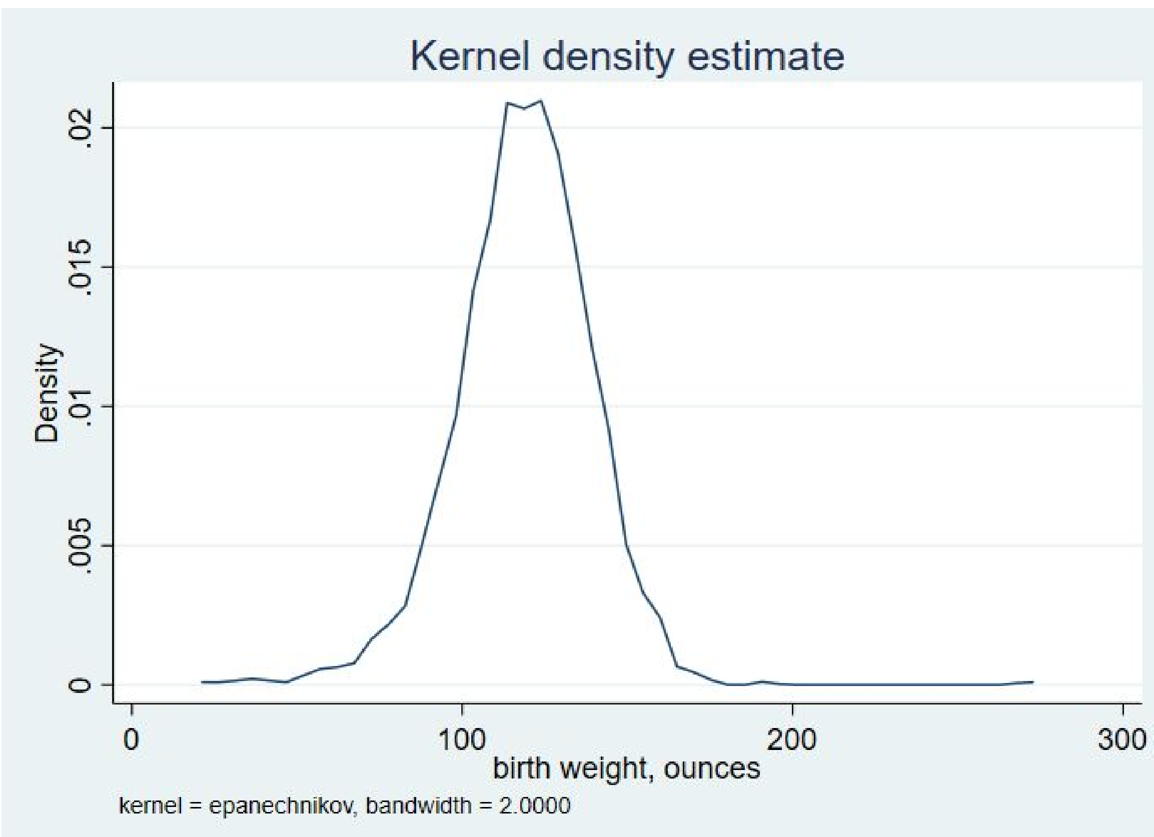
	dy/dx
cigs	-.4662423
faminc	.112927
motheduc	.6280309

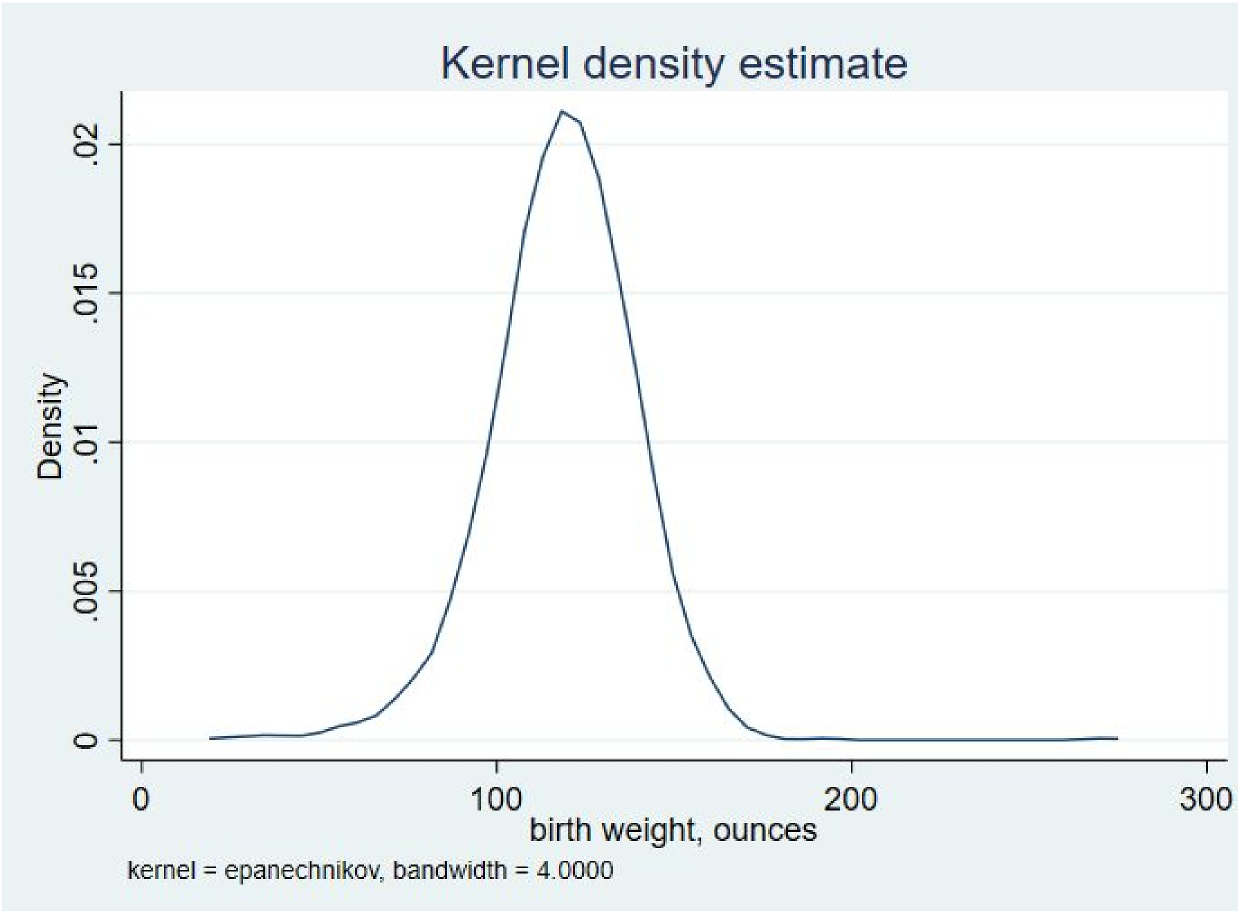
```
Note: You may compute standard errors using vce(bootstrap) or reps().

.
```

C.

kdensity bwght, kernel(epanechnikov) bwidth(1)
kdensity bwght, kernel(epanechnikov) bwidth(2)
kdensity bwght, kernel(epanechnikov) bwidth(4)


Kernel density estimate
Density
0
.005
.01
.015
.02
.025
0
100
200
300
birth weight, ounces
kernel = epanechnikov, bandwidth = 1.0000


Kernel density estimate
Density
0
.005
.01
.015
.02
0
100
200
300
birth weight, ounces
kernel = epanechnikov, bandwidth = 2.0000



As bandwidth increases the curve smooths.

5.

A.

```
. mkspline lemploy = lemploy, cubic knots(2.52 3.44 4.36 5.28 6.2)

. reg lscrap lhrsemp lemploy?
```

Source	SS	df	MS			
Model	14.661224	5	2.93224479	Number of obs	=	32
Residual	38.7206984	26	1.48925763	F(5, 26)	=	1.97
				Prob > F	=	0.1170
Total	53.3819223	31	1.72199749	R-squared	=	0.2746
				Adj R-squared	=	0.1352
				Root MSE	=	1.2204

lscrap	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lhrsemp	-.1653659	.1542777	-1.07	0.294	-.4824882	.1517565
lemploy1	1.850432	.6949242	2.66	0.013	.421995	3.278869
lemploy2	-12.26077	5.457369	-2.25	0.033	-23.47855	-1.042985
lemploy3	31.70542	20.48572	1.55	0.134	-10.40358	73.81442
lemploy4	-23.7176	46.68793	-0.51	0.616	-119.686	72.25082
_cons	-4.120944	1.766979	-2.33	0.028	-7.753023	-.4888663

B.

```
. mkspline lemploynat = lemploy, cubic displayknots
```

	knot1	knot2	knot3	knot4	knot5
lemploy	1.930495	2.737093	3.218876	4.103436	5.314584

```
. reg lscrap lhrsemp lemploynat?
```

Source	SS	df	MS			
Model	16.1360516	5	3.22721032	Number of obs	=	32
Residual	37.2458707	26	1.43253349	F(5, 26)	=	2.25
				Prob > F	=	0.0790
Total	53.3819223	31	1.72199749	R-squared	=	0.3023
				Adj R-squared	=	0.1681
				Root MSE	=	1.1969

lscrap	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lhrsemp	-.1841329	.149243	-1.23	0.228	-.4909064	.1226405
lemploynat1	.6431411	1.196391	0.54	0.595	-1.816077	3.102359
lemploynat2	12.19826	10.04059	1.21	0.235	-8.440468	32.83699
lemploynat3	-78.47533	45.15421	-1.74	0.094	-171.2911	14.34049
lemploynat4	99.96958	50.49528	1.98	0.058	-3.824957	203.7641
_cons	-1.588732	2.677704	-0.59	0.558	-7.092832	3.915367

The initial expected change in percent scrap rate for percent change in annual firm sales stays about the same for both methods. Once the spline is added the models differ heavily mostly because of the different knot placements.

C.

```
. misschk scrap

Variables examined for missing values

   #  Variable        # Missing   % Missing
--------------------------------------------
   1  scrap                103        65.6
```

Rate is the same for all years, 66%. Since 2/3 of the firms are missing scrap data interpolation variance will be too large to be applicable.