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Impacts of Labor Taxes

Motivation

There are many possible normative questions that might require analysis such as that performed in this exercise. For example, a policy maker wanting to impose a tax instrument to fund public works would like to know the specific impacts of different tax schedules. In particular, policy makers like to know the amount of distortion caused by subjecting citizens to payroll and income taxes and the relative effects in different income levels.

Positive Question

The positive questions analyzed in this paper are i) what are labor supply elasticities of men and women with respect to wage and income, ii) what are the labor supply impacts of payroll and income taxes, iii) what are the deadweight losses of different levels of labor taxes on men and women, and iv) what are the welfare effects (equivalent variation) of various degrees of labor taxes on men and women.

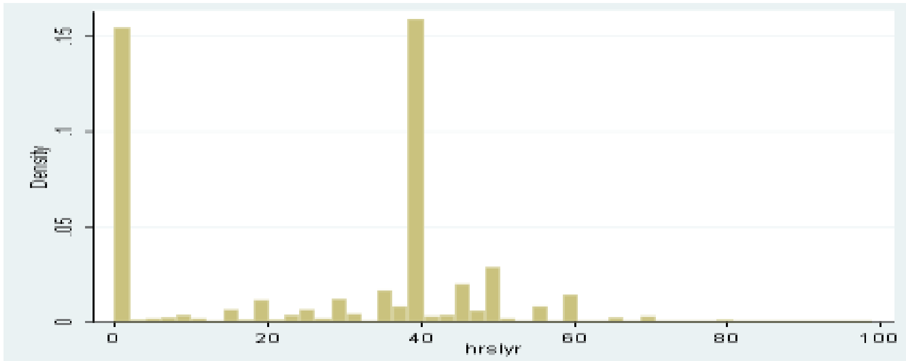
Assumptions and Imposed Structure

In order to tackle the questions at hand, as usual, I needed to assume that agents are rational utility maximizers. Further, to econometrically estimate the coefficients of various factors of labor supply, I needed to assume that my asserted factors of labor supply were neither collinear or endogenous.

Methodology

My first step was to analyze the histograms of labor supply in the data provided. The histogram suggested that there was a certain censoring effect present on labor supply at 0 hours. I used Heckit estimation to deal with this treatment effect. The histogram also indicated that there was a mass point at 40 hours of labor supply/week of comparable magnitude to the censored mass at 0. In a more rigorous version, I could identify another, more complicated treatment effect causing this mass point, or discretize the agents' choice set to generate this mass, however for the remaining discussion in this paper I proceeded to let that mass be, and only treat the mass accumulated at 0.

Histogram of Labor Supply in Data Sample



My second step was to postulate a labor supply equation capturing the factors determining agents' supply of labor. I wanted the specification of the equation to be simple such that it could eventually be integrable to identify explicit welfare effects, to be flexible enough such that if it appears there are misspecifications that I can easily tweak its components and better explain the data, to be economically sensible, and to be free of collinearity and endogeneity concerns. Further, in order to best utilize Heckit's procedure to account for the censoring, I would also need to identify regressors that are more prevalent in the labor participation decision than the quantity of labor supply decision. The regressors I chose were education variables. The argument is that an agent's labor supply decision depends heavily on their education, and the quantity of labor supply depends less prevalently on education level.

I initiated with a linear labor supply specification with dummy variable quintile bands on wage and outside income. The bands were chose to correspond to the different tax brackets given the 1994 data, and proved decent in that roughly 20% of the observations did fall in the bracket quintiles. In particular, the labor supply equation is

```
*heckman hrslyr quin1wage quin2wage quin3wage quin4wage quin1out quin2out
quin3out quin4out married child1 child2 age agesq if sex == 1,
select(working = quin1wage quin2wage quin3wage quin4wage quin1out quin2out
quin3out quin4out married child1 child2 age agesq grade12 hsgrad somecollege
collegegrad gradschool) rhosigma;
```

Where

Child1	#children<6
Child2	#children>6

When I estimate the above model it became apparent that my piecewise approximation by dummies for the relationship approximated a logarithmic relationship. Further the selection- step Probit regression was generating large standard errors. Therefore I decided to go ahead and specify the suggested logarithmic relationship between those variables, and regress again. (This model coefficients were comparable to the piecewise approximation, but with smaller standard errors.) The model specification is

```
heckman lhrs lwage loutsideinc married child1 child2 age agesq if sex ==1, twostep
select(working = lwage loutsideinc married child1 child2 age agesq grade12 hsgrad
somecollege collegegrad gradschool) rhosigma;
```

All coefficient values and standard errors appear in the appendix.

My third step was to run the regression for the logarithmic specification. I chose the 1-step Heckit given that Stata had a timely turnaround and thus eliminate any extra collinearity noise that might creep in from unnecessarily separating the procedure into a probit selection-step and an output step. Also, I ran a Heckit regression as opposed to a Tobit regression since the censoring at zero was not just a data treatment effect, but also appears as budget constraint in the agents' labor supply choice set.

Results and Findings

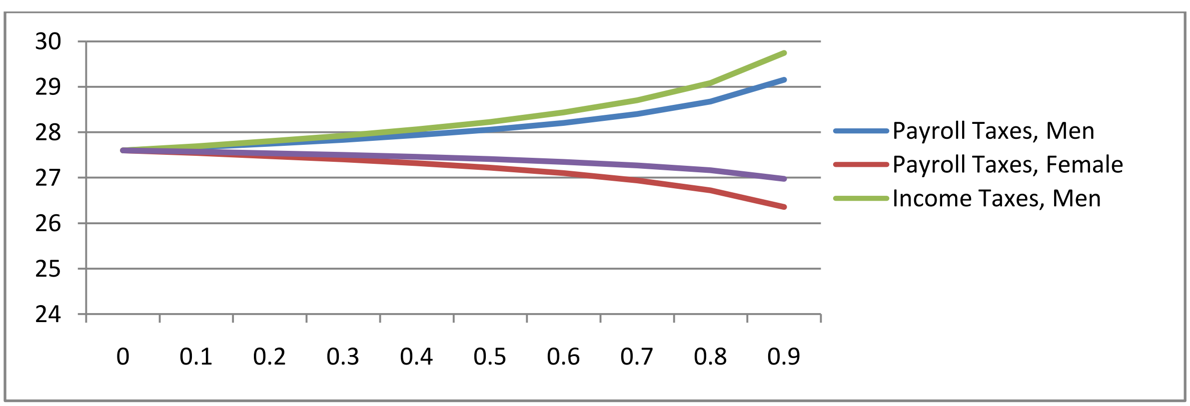
The labor supply elasticities for men and women with respect to payroll and income taxes reduce nicely with the logarithmic specification on the labor supply equation.

The elasticities simply correspond to the coefficients on labor and income respectively.

Labor supply elasticity wrt	Men	Female
wage	-.0238	.02
outside income	-.00875	-.01

The impact of labor taxes on the supply of men's and women's labor captures the information of the elasticity values. Graphed below are the impacts of percentages of payroll and income taxes on labor supply. For ease of comparison, with no taxes, I started both men and women at the sample average of 27.6 hours worked/week.

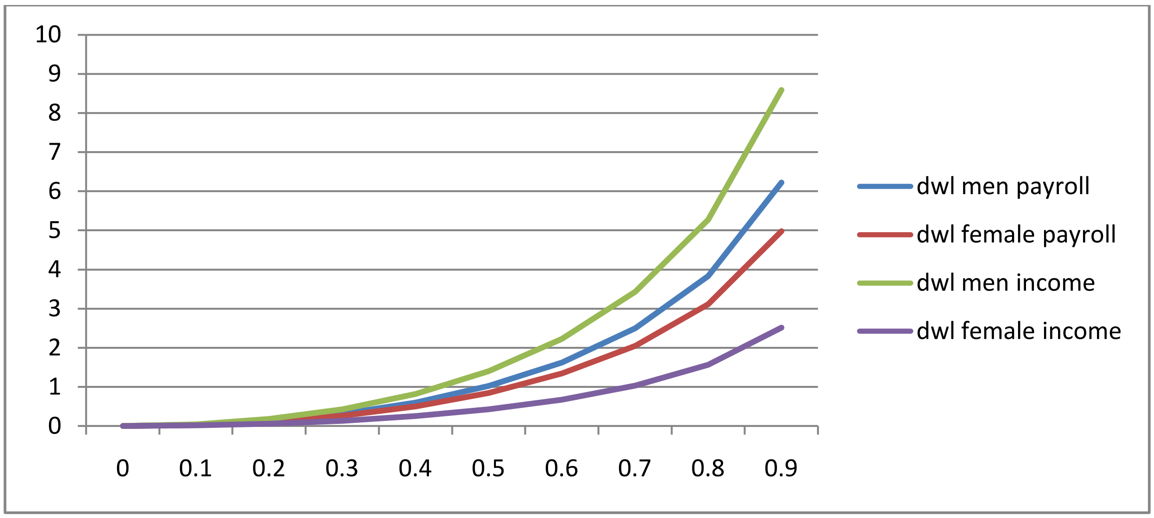
Labor Supply vs. Tax Percentage (Payroll and Labor)



Next, graphed below are the generated Dead-Weight Losses associated with both payroll taxes and income taxes for men and women. The units are in terms of dollars/hour, but can easily convert.

Variables still specified at mean levesl, but to adapt the analysis to a particular income distribution, one can simply break into quintiles and calculate each quintile according to its particular conditional means.

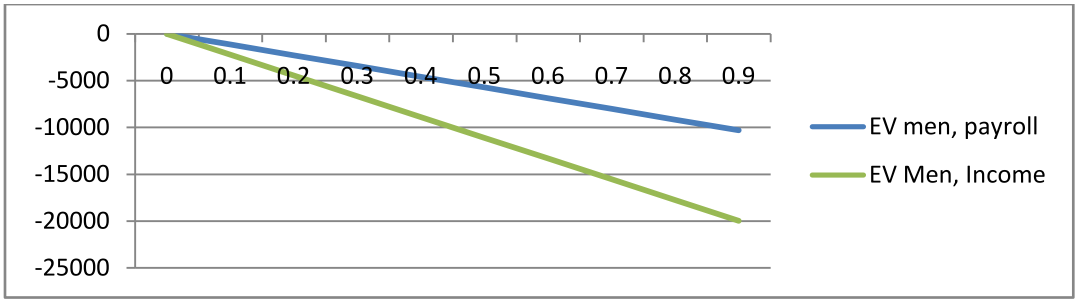
Dead-Weight Loss vs. Tax Percentage (Payroll and Labor)



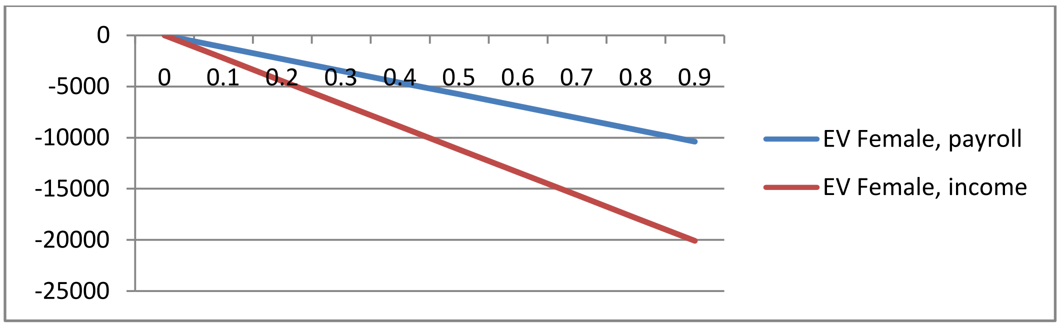
One further caution before drawing implications from the graphs. Although it may appear that welfare effects are more tragic from income taxes, it should be noted that a percentage income tax generates more government revenue than a percentage of payroll tax, since the income tax is over all sources of income. A policy maker may like to further compare labor tax instruments with revenue generated given a particular income distribution.

I calculated welfare effects of the different labor taxes using the welfare metric of Equivalent Variation. I did not need to generalize the metric as the economy is essentially one good, labor supply. As usual, the Equivalent Variation identifies the cost to an agent of a policy in pre-policy dollars. The agent identified is an agent of mean demographics, except that he or she works 48 weeks/year for sake of interest. The values were calculated using Hausman 1981 solutions to some labor supply specifications, of which logs is one.

Equivalent Variation for Tax Percentages, Men



Similarly, Equivalent Variation for Tax Percentages, Females



Using this metric of welfare, the effects of labor taxes on men and women of the same demographic characteristics are very similar. The Dead-Weight Loss metric of welfare, however, suggests that even if men and women are of similar demographic characteristics, the effects are different and that the tax incidence should fall to men predominantly. It should be remembered that I specified men and women of equal characteristics for ease of comparison, and that is not necessarily the real case, thus changing desired tax incidence. In particular, using the standard Ramsey result of taxation and the labor supply elasticity results, since female labor supply is more elastic, it should be subjected to lesser income tax levels.

Final conclusions stipulate that policy makers should consult with their particular constituency's income distribution and conditional demographics for each bracket. Then, using the methods and estimates brought forth in this paper, impose tax instruments that generate the needed public funds while minimizing the welfare impact of their choice, preferably the Equivalent Variation metric.

Linear (w income bands)

```
Iteration 0:   log likelihood = -119539.32
Iteration 1:   log likelihood = -119505.21
Iteration 2:   log likelihood = -119505.07
Iteration 3:   log likelihood = -119505.07

Heckman selection model                         Number of obs      =     38198
(regression model with sample selection)        Censored obs       =      8332
                                                Uncensored obs     =     29866

                                                Wald chi2(13)      =   4123.24
Log likelihood = -119505.1                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
hrslyr       |
   quin1wage |  -.3564692    .012633   -28.22   0.000    -.3812293    -.331709
   quin2wage |  -.0336169   .0039956    -8.41   0.000     -.041448   -.0257857
   quin3wage |  -.1134009    .010155   -11.17   0.000    -.1333044   -.0934974
   quin4wage |  -.0219229   .0026686    -8.21   0.000    -.0271534   -.0166925
    quin1out |  -.0001409   7.82e-06   -18.02   0.000    -.0001562   -.0001255
    quin2out |  -.0000607   .0000118    -5.12   0.000    -.0000839   -.0000375
    quin3out |   .0000272   .0000154     1.77   0.077    -2.91e-06    .0000573
    quin4out |   8.96e-06   9.03e-06     0.99   0.321    -8.74e-06    .0000267
     married |   1.006611     .18871     5.33   0.000     .6367462    1.376476
      child1 |   .2352235    .111333     2.11   0.035     .0170148    .4534322
      child2 |   .3083191   .0721847     4.27   0.000     .1668396    .4497986
         age |   .8160833   .0323272    25.24   0.000     .7527231    .8794435
       agesq |  -.0100847   .0003502   -28.80   0.000     -.010771   -.0093983
       _cons |   28.46021   .7074448    40.23   0.000     27.07364    29.84677
-------------+----------------------------------------------------------------
working      |
   quin1wage |   7524.537   1.47e+08     0.00   1.000    -2.88e+08    2.88e+08
   quin2wage |   4.024531   3.18e+07     0.00   1.000    -6.24e+07    6.24e+07
   quin3wage |   1.824284   261968.1     0.00   1.000    -513446.3    513449.9
   quin4wage |   1.171852   421010.7     0.00   1.000    -825164.6    825166.9
    quin1out |  -.0000299   8.48e-07   -35.32   0.000    -.0000316   -.0000283
    quin2out |  -.0000525   562.2446    -0.00   1.000    -1101.979    1101.979
    quin3out |  -.0000519   18.82921    -0.00   1.000    -36.90462    36.90451
    quin4out |   .0004754   406.1294     0.00   1.000    -795.9985    795.9994
     married |   .5071223   .0373051    13.59   0.000     .4340056     .580239
      child1 |  -.0109447   .0299948    -0.36   0.715    -.0697334     .047844
      child2 |   .0665077   .0184079     3.61   0.000     .0304288    .1025865
         age |   .0882326    .006475    13.63   0.000     .0755417    .1009234
       agesq |  -.0011801     .00006   -19.66   0.000    -.0012977   -.0010624
     grade12 |   .0188349   .0605278     0.31   0.756    -.0997975    .1374673
      hsgrad |   .5764339   .0488188    11.81   0.000     .4807509    .6721169
 somecollege |   .8921738   .0511298    17.45   0.000     .7919613    .9923863
 collegegrad |   1.352237   .0545074    24.81   0.000     1.245404    1.459069
  gradschool |   1.744193   .0600709    29.04   0.000     1.626456    1.861929
       _cons |  -1.907306   .1720959   -11.08   0.000    -2.244608   -1.570004
-------------+----------------------------------------------------------------
     /athrho |   .1369073   .0168926     8.10   0.000     .1037983    .1700162
    /lnsigma |   2.390432    .004095   583.75   0.000     2.382405    2.398458
-------------+----------------------------------------------------------------
         rho |   .1360583   .0165799                      .1034271    .1683968
       sigma |    10.9182   .0447099                      10.83093    11.00619
      lambda |   1.485512   .1814404                      1.129895    1.841128
------------------------------------------------------------------------------
LR test of indep. eqns. (rho = 0):   chi2(1) =   -20.80   Prob > chi2 = 1.0000
------------------------------------------------------------------------------
```

Logs

```
Heckman selection model -- two-step estimates   Number of obs      =     33183
(regression model with sample selection)        Censored obs       =      8089
                                                Uncensored obs     =     25094

                                                Wald chi2(14)      =   8885.90
                                                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
lhrs         |
       lwage |  -.0238204   .0029246    -8.14   0.000    -.0295525   -.0180883
 loutsideinc |  -.0087545   .0010335    -8.47   0.000    -.0107802   -.0067288
     married |   .0491682   .0066896     7.35   0.000     .0360569    .0622795
      child1 |   .0017276   .0038357     0.45   0.652    -.0057903    .0092455
      child2 |    .003565   .0024213     1.47   0.141    -.0011807    .0083107
         age |   .0380848   .0010923    34.87   0.000     .0359439    .0402257
       agesq |  -.0004673   .0000116   -40.32   0.000      -.00049   -.0004446
       _cons |   3.113913     .02498   124.66   0.000     3.064953    3.162873
-------------+----------------------------------------------------------------
working      |
       lwage |   1.300984    .022672    57.38   0.000     1.256547     1.34542
 loutsideinc |  -.2998976     .01084   -27.67   0.000    -.3211436   -.2786515
     married |   .4730802   .0420972    11.24   0.000     .3905713    .5555891
      child1 |   -.055129   .0375442    -1.47   0.142    -.1287143    .0184563
      child2 |   .0634792   .0216885     2.93   0.003     .0209706    .1059878
         age |   .0462817   .0066736     6.94   0.000     .0332017    .0593618
       agesq |   -.000684   .0000598   -11.44   0.000    -.0008012   -.0005668
     grade12 |   .0079503   .0561729     0.14   0.887    -.1021466    .1180472
      hsgrad |   .2996004   .0460556     6.51   0.000      .209333    .3898677
 somecollege |   .4482005   .0506294     8.85   0.000     .3489687    .5474322
 collegegrad |   .6332278   .0580793    10.90   0.000     .5193945    .7470611
  gradschool |    .994337   .0634819    15.66   0.000     .8699148    1.118759
       _cons |   1.203638   .1905541     6.32   0.000     .8301592    1.577117
-------------+----------------------------------------------------------------
mills        |
      lambda |  -.0962721   .0090638   -10.62   0.000    -.1140367   -.0785074
-------------+----------------------------------------------------------------
         rho |   -0.28493
       sigma |   .3378814
      lambda | -.09627207   .0090638
------------------------------------------------------------------------------
```

Variable	Mean value
Hours	27.65
Wage	8.89
Outside income	10773

Band	Labor supply elasticity wrt wage	Labor supply elasticity wrt outside incom
1	-1.146	-.05455
2	-.011	-.02338
3	-.0365	.01052
4	-.0071	.00351

Labor supply elasticity wrt	Men	Female
wage	-.0238	.02
outside income	-.00875	-.01

Linear (w bands) women

```
working
   quin1wage     2696.848   1.96e+07     0.00   1.000    -3.84e+07   3.84e+07
   quin2wage     3.340942   141183.2     0.00   1.000    -276710.6   276717.3
   quin3wage      2.17621   626330.2     0.00   1.000     -1227582    1227587
   quin4wage     1.173651   67677.62     0.00   1.000    -132644.5   132646.9
    quin1out    -.0000103   7.74e-07   -13.26   0.000    -.0000118  -8.74e-06
    quin2out    -.0000343   2.179409    -0.00   1.000    -4.271597   4.271529
    quin3out     .0000378   115.5498     0.00   1.000    -226.4734   226.4735
    quin4out    -6.52e-06   21.49017    -0.00   1.000    -42.11997   42.11996
     married     .0457036   .0404378     1.13   0.258     -.033553   .1249601
      child1    -.2497805   .0254996    -9.80   0.000    -.2997587  -.1998023
      child2    -.0969918    .015687    -6.18   0.000    -.1277377  -.0662458
         age     .1157368   .0070706    16.37   0.000     .1018788   .1295948
       agesq    -.0014182   .0000699   -20.29   0.000    -.0015552  -.0012812
     grade12     .1856863   .0802518     2.31   0.021     .0283957   .3429768
      hsgrad     .6687836   .0673692     9.93   0.000     .5367424   .8008248
 somecollege     .9589431   .0688712    13.92   0.000      .823958   1.093928
 collegegrad     1.385701    .071416    19.40   0.000     1.245729   1.525674
  gradschool     1.892433   .0773709    24.46   0.000     1.740788   2.044077
       _cons     -3.55318   .1830149   -19.41   0.000    -3.911883  -3.194478
-------------------------------------------------------------------------------
     /athrho     .1193872   .0133893     8.92   0.000     .0931448   .1456297
    /lnsigma     2.442966   .0045084   541.87   0.000      2.43413   2.451803
-------------------------------------------------------------------------------
         rho     .1188232   .0132002                      .0928763   .1446089
       sigma     11.50712   .0518787                      11.40589   11.60925
      lambda     1.367314   .1521254                      1.069153   1.665474
-------------------------------------------------------------------------------
LR test of indep. eqns. (rho = 0):    chi2(1) =    79.60   Prob > chi2 = 0.0000
-------------------------------------------------------------------------------
```

```
Iteration 0:   log likelihood = -100434.06
Iteration 1:   log likelihood = -100416.88
Iteration 2:   log likelihood = -100416.87
Iteration 3:   log likelihood = -100416.87

Heckman selection model                         Number of obs      =     40538
(regression model with sample selection)        Censored obs       =     15971
                                                Uncensored obs     =     24567

                                                Wald chi2(13)      =   3708.76
Log likelihood = -100416.9                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
hrslyr       |
   quin1wage |  -.0573616   .0031448   -18.24   0.000    -.0635252   -.0511979
   quin2wage |  -.1877203   .0173747   -10.80   0.000    -.2217741   -.1536665
   quin3wage |  -.0028619   .0010895    -2.63   0.009    -.0049972   -.0007266
   quin4wage |   .0301257   .0049506     6.09   0.000     .0204226    .0398287
    quin1out |  -.0001961   6.90e-06   -28.42   0.000    -.0002097   -.0001826
    quin2out |   .0000476   .0000101     4.73   0.000     .0000279    .0000674
    quin3out |    .000096   .0000108     8.89   0.000     .0000748    .0001171
    quin4out |   .0001071   9.43e-06    11.36   0.000     .0000886    .0001255
     married |  -1.945465   .2097898    -9.27   0.000    -2.356645   -1.534284
      child1 |  -2.612077   .1412814   -18.49   0.000    -2.888983    -2.33517
      child2 |  -1.695626   .0863324   -19.64   0.000    -1.864835   -1.526418
         age |   .6537085    .036607    17.86   0.000     .5819601     .725457
       agesq |  -.0089218   .0004046   -22.05   0.000    -.0097149   -.0081287
       _cons |   29.15879   .7819606    37.29   0.000     27.62617     30.6914
-------------+----------------------------------------------------------------
```

Logs women

Heckman selection model -- two-step estimates
(regression model with sample selection)

Number of obs	=	36134
Censored obs	=	14771
Uncensored obs	=	21363
Wald chi2(14)	=	7989.32
Prob > chi2	=	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lhrs						
lwage	.0202536	.0058422	3.47	0.001	.0088032	.031704
loutsideinc	-.0103419	.0016349	-6.33	0.000	-.0135462	-.0071376
married	-.0353345	.0102809	-3.44	0.001	-.0554847	-.0151843
child1	-.1219608	.0067433	-18.09	0.000	-.1351774	-.1087441
child2	-.0784789	.0040358	-19.45	0.000	-.086389	-.0705689
age	.0336504	.0017323	19.42	0.000	.030255	.0370457
agesq	-.0004595	.0000188	-24.38	0.000	-.0004964	-.0004225
_cons	3.093321	.0386367	80.06	0.000	3.017594	3.169048
working						
lwage	1.921793	.0268423	71.60	0.000	1.869183	1.974403
loutsideinc	-.069363	.0068531	-10.12	0.000	-.0827947	-.0559312
married	.1123512	.0398282	2.82	0.005	.0342892	.1904131
child1	-.26923	.0259525	-10.37	0.000	-.3200961	-.218364
child2	-.0148982	.015343	-0.97	0.332	-.0449699	.0151735
age	.0406909	.0060982	6.67	0.000	.0287387	.0526431
agesq	-.0006737	.0000585	-11.51	0.000	-.0007884	-.000559
grade12	.0592631	.0620256	0.96	0.339	-.0623049	.1808311
hsgrad	.3536479	.0516826	6.84	0.000	.2523519	.4549439
somecollege	.5118641	.0543667	9.42	0.000	.4053074	.6184209
collegegrad	.4847172	.0617389	7.85	0.000	.3637112	.6057233
gradschool	.7895428	.0766208	10.30	0.000	.6393688	.9397169
_cons	-.9760696	.159566	-6.12	0.000	-1.288813	-.6633261
mills						
lambda	-.0593664	.0115118	-5.16	0.000	-.0819291	-.0368037
rho	-0.11798					
sigma	.50318283					
lambda	-.05936641	.0115118				

Summary stats for key variables

. summarize hrslyr wage outsideinc married child1 child2 age agesq sex lhrs lwage loutsideinc

Variable	Obs	Mean	Std. Dev.	Min	Max
hrslyr	88515	27.64699	21.23983	0	99
wage	88515	8.893941	44.69839	0	10550
outsideinc	78736	10773.43	18456.67	-19798	599994
married	88515	.7190194	.4494806	0	1
child1	88515	.2567813	.5943013	0	6
child2	88515	.5020279	.9009287	0	7
age	88515	47.62465	16.70519	16	90
agesq	88515	2547.168	1752.114	256	8100
sex	88515	1.543343	.4981207	1	2
lhrs	61143	3.616843	.4496596	0	4.59512
lwage	88515	1.488212	1.281518	-6.907755	9.263881
loutsideinc	69317	7.993806	2.297644	0	13.30468