

Truncated & Censored Data

Simulated Data

STATA command

```
*Generate Truncated Data (Sample Selection Biased #3)
set obs 200
g e=rnormal(0,1000)
g lnw=rnormal(2.75,0.6)
g ystar=-2500+1000*lnw+e
g y_truncate=ystar if ystar>0
```

```
*Generate Truncated Data (Sample Selection Biased #4)
g e2=rnormal(0,1)
g iq=abs(int(rnormal(100,15)))
g i=-10+0.1*iq+0.5*lnw+e2
g p=normal(i)
g shat=(p>0.5)
g e3=3500*shat+e
g ystar2=-6000+1000*lnw+e3
g y_heckit=ystar2 if ystar2>0
```

```
*Generate Censored Data
g y_censor=ystar
replace y_censor=0 if ystar<=0
```

```
*Generate Outlier Case
g y_out=ystar
g out=runiform(0,100000)
replace y_out=out if ystar>2000
```

```
*Generate Truncated Data (Sample Selection Biased #3)
```

```
. set obs 200
number of observations (_N) was 0, now 200
```

```
. g e=rnormal(0,1000)
. g lnw=rnormal(2.75,0.6)
. g ystar=-2500+1000*lnw+e
. g y_truncate=ystar if ystar>0
(94 missing values generated)
```

```
*Generate Truncated Data (Sample Selection Biased #4)
```

```
. g e2=rnormal(0,1)
. g iq=abs(int(rnormal(100,15)))
. g ihat=-10+0.1*iq+0.5*lnw+e2
. g phat=normal(ihat)
. g shat=(phat>0.5)
. g e3=3500*shat+e
. g ystar2=-6000+1000*lnw+e3
. g y_heckit=ystar2 if ystar2>0
(117 missing values generated)
```

```
*Generate Censored Data
```

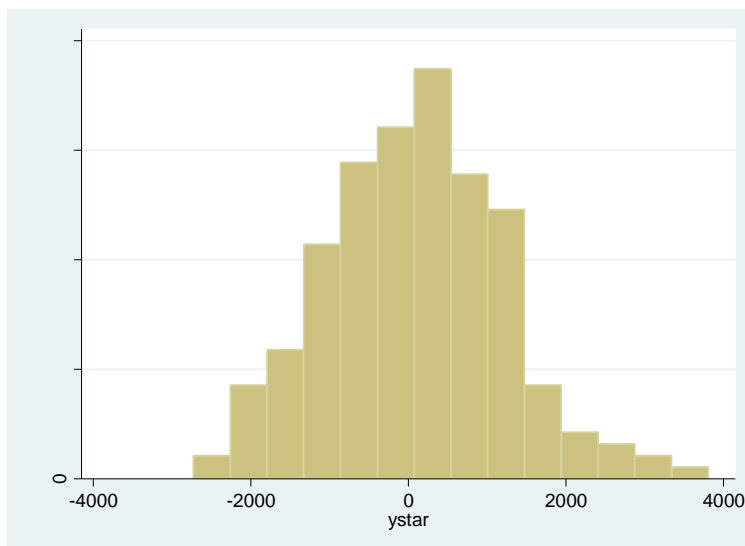
```
. g y_censor=ystar
. replace y_censor=0 if ystar<=0
(94 real changes made)
```

*Generate Outlier Case

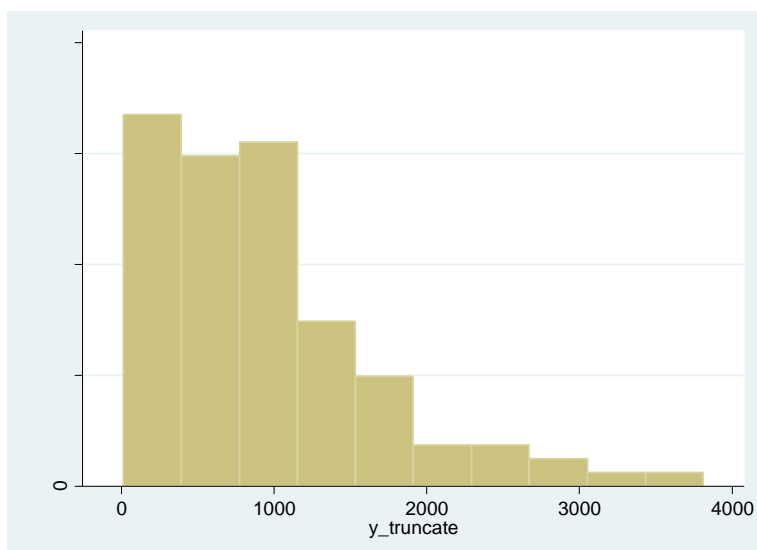
```
. g y_out=ystar
. g out=runiform(0,100000)
. replace y_out=out if ystar>2000
(10 real changes made)
. sum ystar y_truncate ystar2 y_heckit y_censor y_out lnw iq
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ystar	200	95.06321	1124.415	-2728.715	3812.745
y_truncate	106	932.4709	736.4561	14.26584	3812.745
ystar2	200	-692.4368	1892.71	-5192.655	3812.745
y_heckit	83	994.3141	772.8268	30.09209	3812.745
y_censor	200	494.2096	709.8276	0	3812.745
y_out	200	1909.285	10506.08	-2728.715	76160.63
lnw	200	2.748838	.5637259	1.384946	4.473701
iq	200	100.155	15.39957	52	139

```
. histogram ystar
(bin=14, start=-2728.7151, width=467.24712)
```



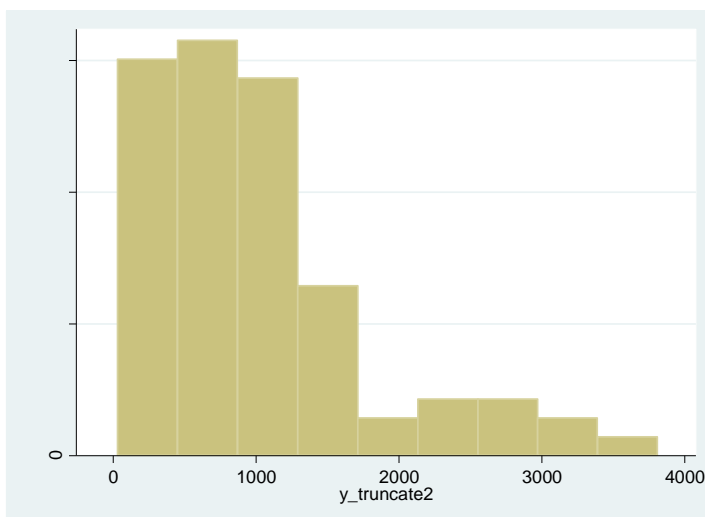
```
. histogram y_truncate
(bin=10, start=14.265841, width=379.84788)
```



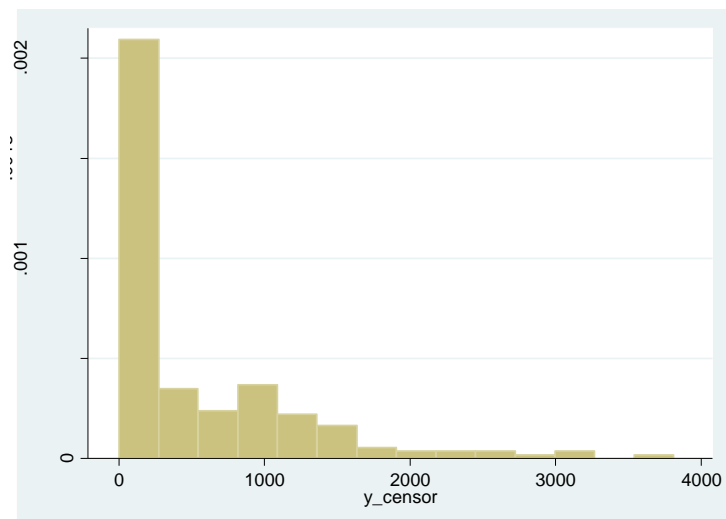
```
. histogram ystar2  
(bin=14, start=-5192.6553, width=643.24285)
```



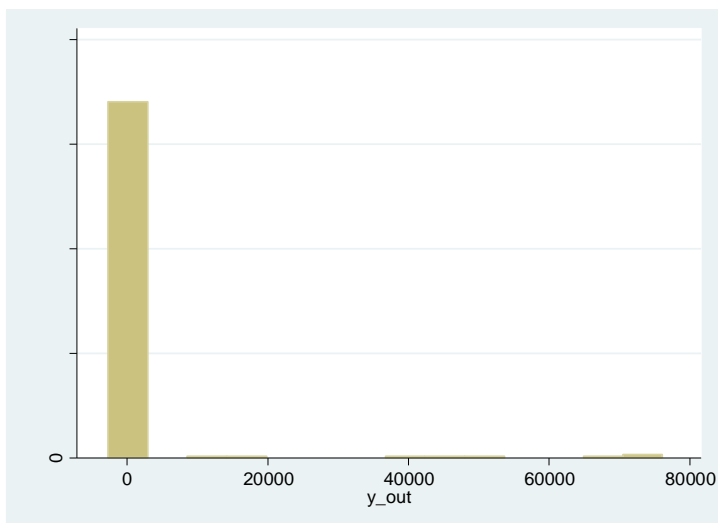
```
. histogram y_heckit  
(bin=9, start=30.092091, width=420.29473)
```



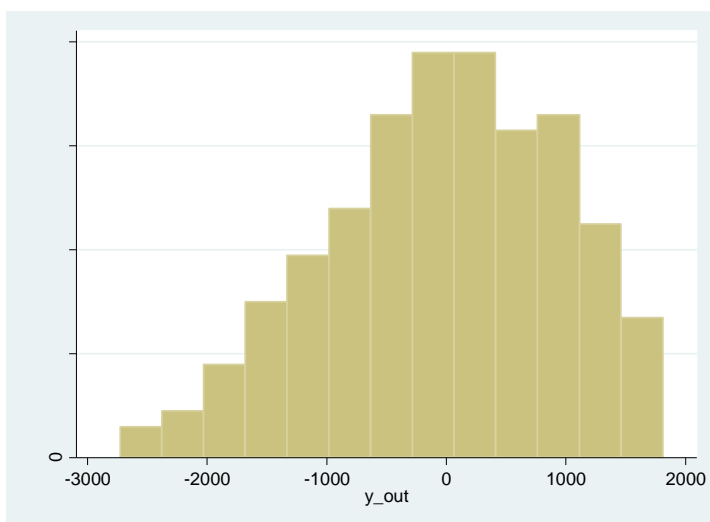
```
. histogram y_censor  
(bin=14, start=0, width=272.3389)
```



```
. histogram y_out
(bin=14, start=-2728.7151, width=5634.9534)
```



```
. histogram y_out if y_out<=2000
(bin=13, start=-2728.7151, width=349.18581)
```



```
. reg ystar lnw
```

Source	SS	df	MS	Number of obs	=	200
Model	70682512.1	1	70682512.1	F(1, 198)	=	77.36
Residual	180914930	198	913711.765	Prob > F	=	0.0000
				R-squared	=	0.2809
				Adj R-squared	=	0.2773
Total	251597442	199	1264308.75	Root MSE	=	955.88

ystar	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnw	1057.211	120.2016	8.80	0.000	820.171 1294.25
_cons	-2811.037	337.2571	-8.33	0.000	-3476.114 -2145.96

```
. predict uncensored
(option xb assumed; fitted values)
```

```
. est store m_ystar
```

Truncated Regression Model**Truncated Data #3 (Truncate both Y and X)**

```
. reg y_truncate lnw
```

Source	SS	df	MS	Number of obs	=	106
Model	9031908.27	1	9031908.27	F(1, 104)	=	19.60
Residual	47916691.2	104	460737.416	Prob > F	=	0.0000
				R-squared	=	0.1586
				Adj R-squared	=	0.1505
Total	56948599.5	105	542367.614	Root MSE	=	678.78

y_truncate	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnw	526.5597	118.9281	4.43	0.000	290.7207 762.3986
_cons	-627.6924	358.491	-1.75	0.083	-1338.594 83.20879

```
. predict y_that
(option xb assumed; fitted values)
```

```
. est store m_ythat
```

```
. truncreg y_truncate lnw, ll(0) nolog
(note: 0 obs. truncated)
```

Truncated regression

Limit: lower =	0	Number of obs	=	106
upper =	+inf	Wald chi2(1)	=	11.33
Log likelihood =	-818.34658	Prob > chi2	=	0.0008

y_truncate	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
lnw	1196.569	355.4781	3.37	0.001	499.845 1893.294
_cons	-3411.608	1356.581	-2.51	0.012	-6070.457 -752.7591
/sigma	1043.268	173.2952	6.02	0.000	703.6157 1382.921

```
. predict truncated, e(0,.)
```

```
. est store m_ytrunc
```

Test Appropriateness of Truncated Regression Model

```
. lrtest m_ythat m_ytrunc, force
```

Likelihood-ratio test	LR chi2(1) =	44.40
(Assumption: m_ythat nested in m_ytrunc)	Prob > chi2 =	0.0000

Marginal Effects

```
. mfx compute, predict(e(0,)) at(mean)
```

Marginal effects after truncreg

```
y = E(y_truncate|y_truncate>0) (predict, e(0,))
= 882.92127
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
lnw	469.3786	102.92	4.56	0.000	267.655 671.103	2.96294

```
. mfx compute, predict(e(0,)) at(median)
```

Marginal effects after truncreg

y = E(y_truncate|y_truncate>0) (predict, e(0,.))
= 871.71836

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
lnw	461.7475	99.761	4.63	0.000	266.22 657.275	2.93887

. mfx compute, predict(e(0,.)) at(0)

Marginal effects after truncreg

y = E(y_truncate|y_truncate>0) (predict, e(0,.))
= 276.59986

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
lnw	75.03293	10.673	7.03	0.000	54.1142 95.9516	0

Heckit Model

Censored Data #4 (Truncate only Y not X)

. reg y_heckit lnw

Source	SS	df	MS	Number of obs	=	83
Model	9511473.82	1	9511473.82	F(1, 81)	=	19.52
Residual	39463947.3	81	487209.226	Prob > F	=	0.0000
				R-squared	=	0.1942
				Adj R-squared	=	0.1843
Total	48975421.1	82	597261.233	Root MSE	=	698

y_heckit	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnw	610.591	138.1924	4.42	0.000	335.6314 885.5506
_cons	-864.1064	427.5293	-2.02	0.047	-1714.756 -13.45715

. g s=(y_heckit!=.)

. heckman y_heckit lnw, select(s=iq lnw) twostep

Heckman selection model -- two-step estimates		Number of obs	=	200
(regression model with sample selection)		Censored obs	=	117
		Uncensored obs	=	83
		Wald chi2(1)	=	12.78
		Prob > chi2	=	0.0004

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y_heckit					
lnw	1050.129	293.8055	3.57	0.000	474.2813 1625.978
_cons	-2683.291	1137.001	-2.36	0.018	-4911.772 -454.8098
s					
iq	.0261638	.00682	3.84	0.000	.0127969 .0395307
lnw	1.261181	.2148837	5.87	0.000	.8400171 1.682346
_cons	-6.338834	.9643107	-6.57	0.000	-8.228848 -4.44882
mills					
lambda	666.5792	371.6204	1.79	0.073	-61.78329 1394.942
rho	0.79511				
sigma	838.34915				

. est store m_ytrunc2

Manually Two-step Heckman

*First Step estimate Probit model and predict index value (ihat)

```
. probit s iq lnw, nolog
```

```
Probit regression                               Number of obs   =       200
                                                LR chi2(2)      =       59.40
                                                Prob > chi2     =       0.0000
Log likelihood = -106.02769                    Pseudo R2      =       0.2188
```

```
-----+-----
      s |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      iq |   .0261638     .00682     3.84   0.000     .0127969     .0395307
      lnw |   1.261181     .2148837    5.87   0.000     .8400171     1.682346
      _cons | -6.338834     .9643107   -6.57   0.000    -8.228848    -4.44882
-----+-----
```

```
. predict ihat, xb
```

```
. g lambda=normalden(ihat)/normal(ihat)
```

*Second Step estimate Linear model using lambda as another independent variable

```
. reg y_heckit lnw lambda
```

```
-----+-----
Source |          SS          df           MS       Number of obs   =       83
-----+-----
Model | 11165797.9           2    5582898.93   F(2, 80)         =       11.81
Residual | 37809623.2          80    472620.29   Prob > F          =       0.0000
-----+-----
Total | 48975421.1          82    597261.233   R-squared         =       0.2280
                                                Adj R-squared    =       0.2087
                                                Root MSE        =       687.47
-----+-----
```

```
-----+-----
y_heckit |          Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      lnw | 1050.129     271.5115     3.87   0.000     509.8043     1590.454
      lambda | 666.5792     356.2851     1.87   0.065    -42.45072     1375.609
      _cons | -2683.291     1059.61     -2.53   0.013    -4791.981    -574.6004
-----+-----
```

```
. heckman y_heckit lnw, select(s=iq lnw) twostep
```

```
Heckman selection model -- two-step estimates   Number of obs   =       200
(regression model with sample selection)        Censored obs    =       117
                                                Uncensored obs  =       83
                                                Wald chi2(1)    =       12.78
                                                Prob > chi2     =       0.0004
```

```
-----+-----
      |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
y_heckit |
      lnw | 1050.129     293.8055     3.57   0.000     474.2813     1625.978
      _cons | -2683.291     1137.001    -2.36   0.018    -4911.772    -454.8098
-----+-----
```

```
s
      |
      iq |   .0261638     .00682     3.84   0.000     .0127969     .0395307
      lnw |   1.261181     .2148837    5.87   0.000     .8400171     1.682346
      _cons | -6.338834     .9643107   -6.57   0.000    -8.228848    -4.44882
-----+-----
```

```
mills
      |
      lambda | 666.5792     371.6204     1.79   0.073    -61.78329     1394.942
-----+-----
```

```
      rho |   0.79511
      sigma | 838.34915
-----+-----
```

Tobit Model**Censored Data #3 (Both variables can be observed but y is censored)**

```
. reg y_censor lnw
```

Source	SS	df	MS	Number of obs	=	200
Model	23213531.4	1	23213531.4	F(1, 198)	=	59.65
Residual	77053652.3	198	389159.86	Prob > F	=	0.0000
				R-squared	=	0.2315
				Adj R-squared	=	0.2276
Total	100267184	199	503855.194	Root MSE	=	623.83

y_censor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnw	605.8653	78.44577	7.72	0.000	451.1689	760.5618
_cons	-1171.216	220.1003	-5.32	0.000	-1605.258	-737.1745

```
. predict y_chat
(option xb assumed; fitted values)
```

```
. est store m_ychat
```

```
. tobit y_censor lnw, ll(0)
```

Tobit regression	Number of obs	=	200
	LR chi2(1)	=	54.42
	Prob > chi2	=	0.0000
Log likelihood = -938.40494	Pseudo R2	=	0.0282

y_censor	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnw	1064.249	144.4785	7.37	0.000	779.3438	1349.154
_cons	-2840.529	425.9706	-6.67	0.000	-3680.525	-2000.534
/sigma	971.0231	72.23195			828.5849	1113.461

```
94 left-censored observations at y_censor <= 0
106 uncensored observations
0 right-censored observations
```

```
. predict censored, ystar(0,.)
```

```
. est store m_ycensor
```

```
. lrtest m_ychat m_ycensor, force
```

Likelihood-ratio test	LR chi2(1)	=	1263.10
(Assumption: m_ychat nested in m_ycensor)	Prob > chi2	=	0.0000

```
. mfx compute, predict(ystar(0,)) at(mean)
```

```
Marginal effects after tobit
```

```
y = E(y_censor*|y_censor>0) (predict, ystar(0,))
= 431.32202
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		X
lnw	569.2075	77.128	7.38	0.000	418.039	720.376	2.74884

```
. mfx compute, predict(ystar(0,)) at(median)
```

```
Marginal effects after tobit
```

```
y = E(y_censor*|y_censor>0) (predict, ystar(0,))
```

= 430.76061

```
-----+-----
variable |      dy/dx   Std. Err.    z    P>|z|   [   95% C.I.   ]    X
-----+-----
lnw |    568.7501    77.02    7.38   0.000   417.793   719.707   2.74785
-----+-----
```

. mfx compute, predict(ystar(0,.)) at(0)

Marginal effects after tobit

y = E(y_censor*|y_censor>0) (predict, ystar(0,.))
= .48195414

```
-----+-----
variable |      dy/dx   Std. Err.    z    P>|z|   [   95% C.I.   ]    X
-----+-----
lnw |    1.831199    2.30802    0.79   0.428   -2.69244   6.35484    0
-----+-----
```

. reg y_out lnw

```
-----+-----
Source |      SS          df           MS       Number of obs   =      200
-----+-----
Model | 1.5746e+09          1   1.5746e+09   F(1, 198)       =      15.29
Residual | 2.0391e+10        198   102982831   Prob > F        =      0.0001
-----+-----
Total | 2.1965e+10        199   110377668   R-squared       =      0.0717
Adj R-squared =      0.0670
Root MSE   =      10148
-----+-----
```

```
-----+-----
y_out |      Coef.   Std. Err.    t    P>|t|   [95% Conf. Interval]
-----+-----
lnw | 4989.815   1276.109    3.91   0.000   2473.305   7506.326
_cons | -11806.91  3580.461   -3.30   0.001  -18867.64  -4746.177
-----+-----
```

. predict y_ohat

(option xb assumed; fitted values)

. est store m_yout

. reg y_out lnw if y_out<=2000

```
-----+-----
Source |      SS          df           MS       Number of obs   =      191
-----+-----
Model | 34734753.2          1   34734753.2   F(1, 189)       =      44.50
Residual | 147535536         189   780611.304   Prob > F        =      0.0000
-----+-----
Total | 182270290         190   959317.314   R-squared       =      0.1906
Adj R-squared =      0.1863
Root MSE   =      883.52
-----+-----
```

```
-----+-----
y_out |      Coef.   Std. Err.    t    P>|t|   [95% Conf. Interval]
-----+-----
lnw | 821.3192   123.1253    6.67   0.000   578.4429   1064.196
_cons | -2254.793  339.3867   -6.64   0.000  -2924.266  -1585.321
-----+-----
```

. predict y_ohat2000

(option xb assumed; fitted values)

. est store m_yout2000

. tobit y_out lnw, ul(2000)

```
Tobit regression                               Number of obs   =      200
LR chi2(1)                                     =      60.50
Prob > chi2                                     =      0.0000
Pseudo R2                                      =      0.0187
Log likelihood = -1587.9905
```

y_out	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lnw	1001.682	121.2511	8.26	0.000	762.5804	1240.784
_cons	-2670.814	338.5213	-7.89	0.000	-3338.363	-2003.264
/sigma	937.6824	48.43803			842.1647	1033.2

0 left-censored observations
191 uncensored observations
9 right-censored observations at y_out >= 2000

. predict y_outcensor
(option xb assumed; fitted values)

. est store m_youtcensor

. est table m_ystar m_ythat m_ytrunc m_ythat2 m_ytrunc2 m_ychat m_ycensor m_yout
m_yout2000 m_youtcensor, star(.1 .05 .01) stat(N N_cens rss ll rmse F chi2 r2
r2_a)

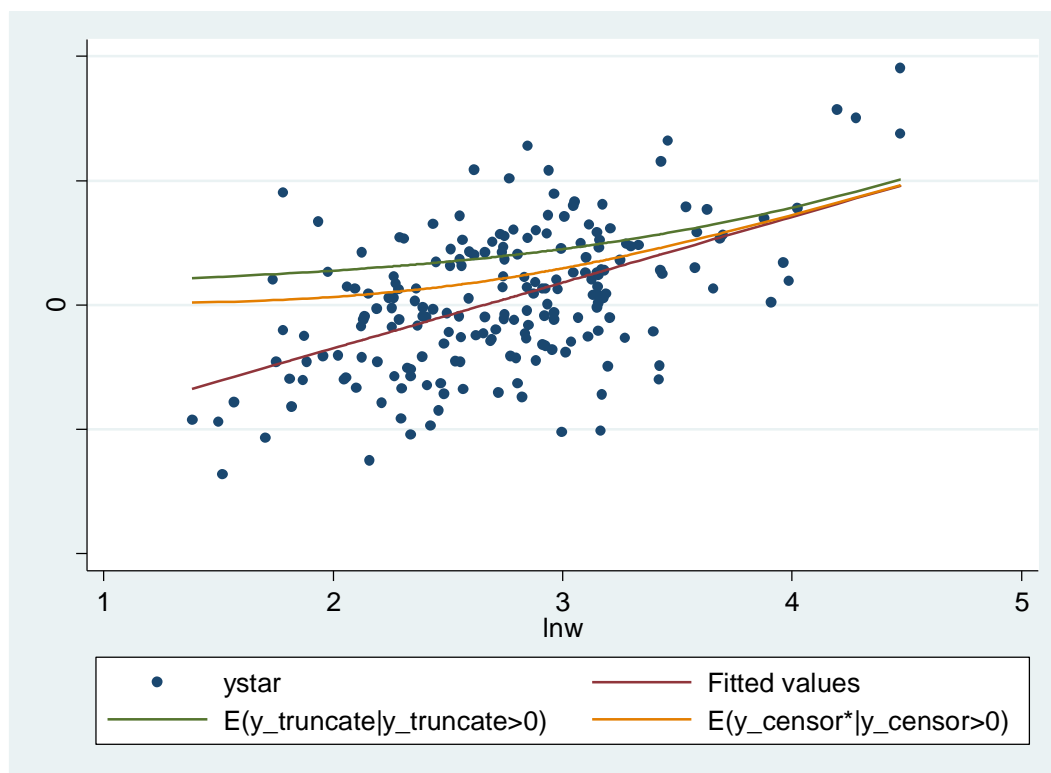
Variable	m_ystar	m_ythat	m_ytrunc	m_ythat2	m_yheckit	m_ychat	m_ycensor	m_yout	m_yout2000	m_youtcensor
lnw	1057.2106***	526.55967***		610.591***		605.86535***		4989.8154***	821.31922***	
_cons	-2811.0372***	-627.69241*		-864.1064**		-1171.216***		-11806.909***	-2254.7934***	
eq1			1196.5693***							
_cons			-3411.6083**							
sigma			1043.2681***				971.02312***			937.68243***
_cons										
y_heckit					1050.1294***					
lnw					-2683.291**					
_cons										
s					.02616383***					
iq					1.2611814***					
lnw					-6.338834***					
_cons										
mills					666.57923*					
lambda										
model							1064.249***			1001.6824***
lnw							-2840.5292***			-2670.8136***
_cons										
Statistics										
N	200	106	106	83	200	200	200	200	191	200
N_cens					117					
rss	1.809e+08	47916691		39463947		77053652		2.039e+10	1.475e+08	
ll	-1655.3097	-840.54886	-818.34658	-660.26228		-1569.9572	-938.40494	-2127.79	-1565.74	-1587.9905
rmse	955.88272	678.77641	698.00374	698.00374		623.82679		10148.046	883.5221	
F	77.357559	19.603158		19.52236		59.650374		15.289494	44.496862	
chi2			11.330525		12.775146		54.415606			60.498833
r2	.28093494	.15859755		.19420913		.23151674		.07168423	.19056728	
r2_a	.2773033	.15050714		.18426109		.22763551		.06699577	.18628457	

Legend: * p<.1; ** p<.05; *** p<.01

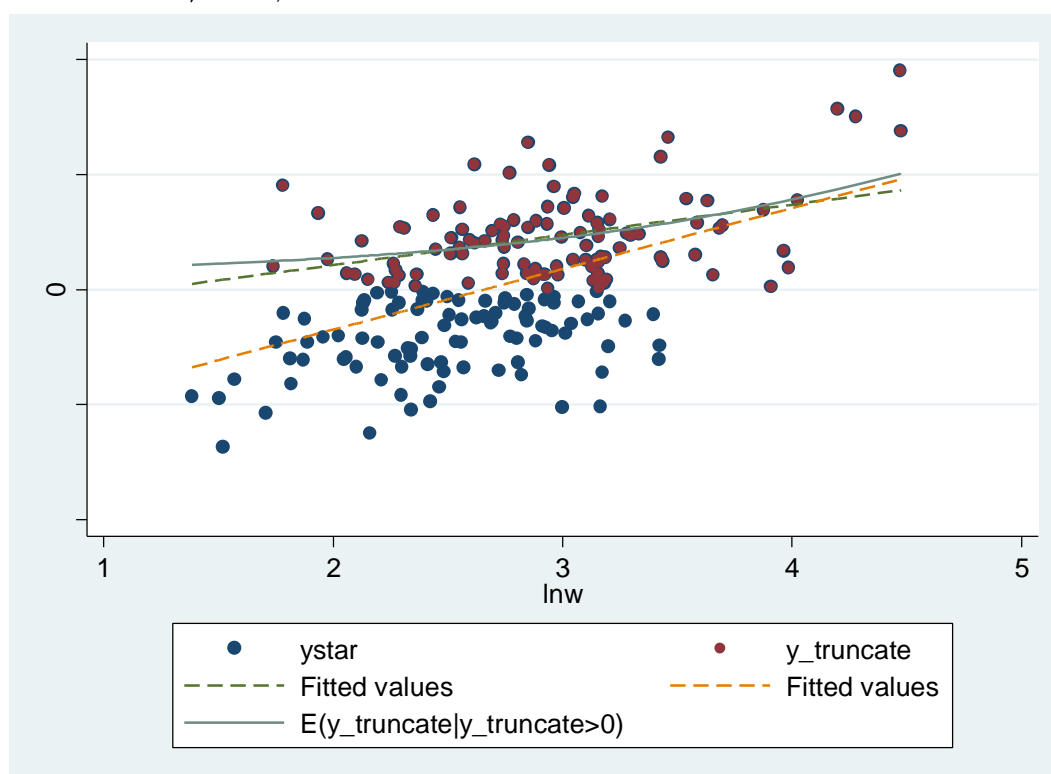
Variable	m_ystar	m_ythat	m_y trunc	m_ythat2	m_y Heckit	m_ychat	m_y censor	m_yout	m_yout 2000	m_yout censor
lnw	1057.21 ***	526.56 ***	1196.57 ***	610.59 ***	1050.13 ***	605.87 ***	1064.25 ***	4989.82 ***	821.32 ***	1001.68 ***
Constant	-2811.04 ***	-627.69 *	-3411.61 **	-864.11 **	-2683.29 **	-1171.22 ***	-2840.53 ***	-11806.91 ***	-2254.79 ***	-2670.81 ***
lambda					666.58 *					
s-(Selection)										
iq					0.03 ***					
lnw					1.26 ***					
Constant					-6.34 ***					
sigma			1043.27 ***				971.02 ***			937.68 ***
RMSE	955.88	678.78		698.00		623.83		10148.05	883.52	
Observations	200	106	106	83	200	200	200	200	191	200
Censored Obs.					117					
RSS	1.8E+08	4.8E+07		3.9E+07		7.7E+07		2.0E+10	1.5E+08	
Loglikelihood	-1655.31	-840.55	-818.35	-660.26		-1569.96	-938.40	-2127.79	-1565.74	-1587.99
F-test	77.36 ***	19.60 ***		19.52 ***		59.65 ***		15.29 ***	44.50 ***	
Chi-square Test			11.33 ***		12.78 ***		54.42 ***			60.50 ***
R-square	0.2809	0.1586		0.1942		0.2315		0.0717	0.1906	
Adj. R-square	0.2773	0.1505		0.1843		0.2276		0.0670	0.1863	
Pseudo R ²							0.0282			0.0187

Note: * significant at 0.1, ** significant at 0.05, and *** significant at 0.01

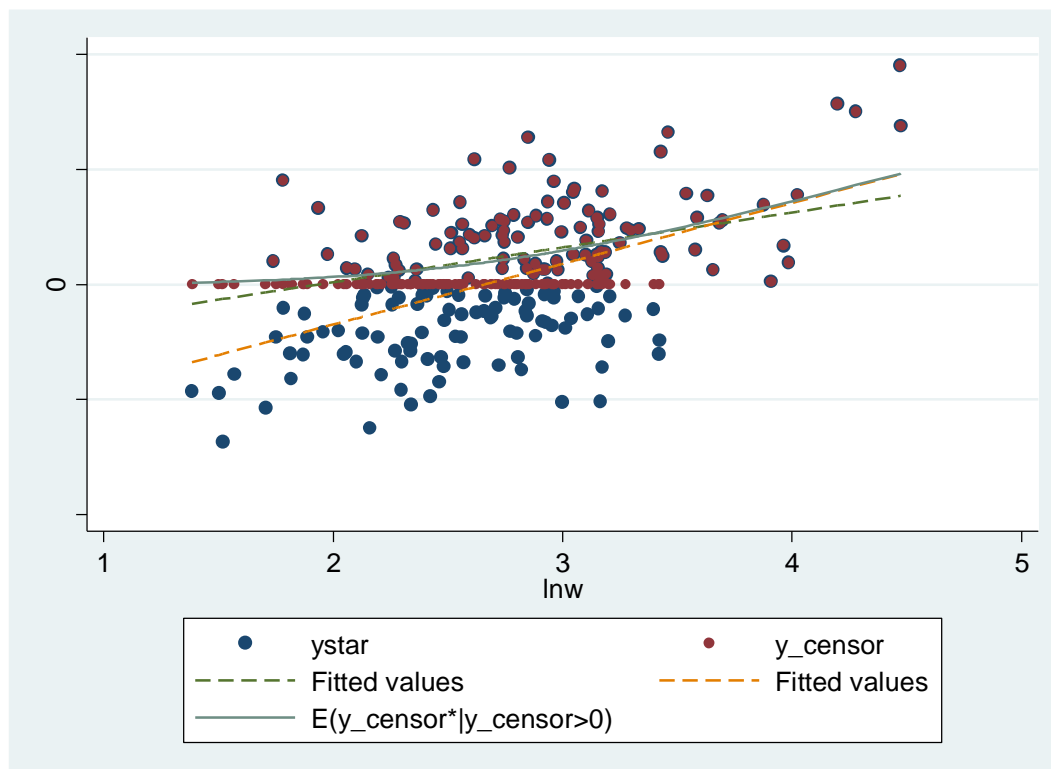
```
. graph twoway (scatter ystar lnw, ms(o)) (line uncensored lnw, sort) (line
truncated lnw, sort) (line censored lnw, sort)
```



```
. graph twoway (scatter ystar lnw) (scatter y_truncate lnw, ms(o)) (line y_that
lnw, sort lpattern(dash)) (line uncensored lnw, sort lpattern(dash)) (line
truncated lnw, sort)
```



```
. graph twoway (scatter ystar lnw) (scatter y_censor lnw, ms(o)) (line y_hat  
lnw, sort lpattern(dash)) (line uncensored lnw, sort lpattern(dash)) (line  
censored lnw, sort)
```



Truncated Regression Model

The model:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \varepsilon_i$$

where

- y_i = wife's hours of work
- x_{1i} = number of children younger than 6
- x_{2i} = number of children between 6 and 18
- x_{3i} = wife's age
- x_{4i} = wife's educational attainment
- ε_i = Error term

```
. regress y x1 x2 x3 x4
```

Source	SS	df	MS	Number of obs =	250
Model	16526046.1	4	4131511.52	F(4, 245) =	5.27
Residual	192218058	245	784563.5	Prob > F =	0.0004
				R-squared =	0.0792
				Adj R-squared =	0.0641
Total	208744104	249	838329.733	Root MSE =	885.76

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-462.1233	124.6768	-3.71	0.000	-707.6985	-216.5481
x2	-91.141	45.85001	-1.99	0.048	-181.4515	-.8305151
x3	-13.1577	8.334958	-1.58	0.116	-29.57502	3.259612
x4	53.26156	26.09369	2.04	0.042	1.864986	104.6581
_cons	940.0593	530.7197	1.77	0.078	-105.296	1985.415

```
. regress y x1 x2 x3 x4 if y>0
```

Source	SS	df	MS	Number of obs =	150
Model	7326995.15	4	1831748.79	F(4, 145) =	2.80
Residual	94793104.2	145	653745.546	Prob > F =	0.0281
				R-squared =	0.0717
				Adj R-squared =	0.0461
Total	102120099	149	685369.794	Root MSE =	808.55

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-421.4822	167.9734	-2.51	0.013	-753.4748	-89.48953
x2	-104.4571	54.18616	-1.93	0.056	-211.5538	2.639668
x3	-4.784917	9.690502	-0.49	0.622	-23.9378	14.36797
x4	9.353195	31.23793	0.30	0.765	-52.38731	71.0937
_cons	1629.817	615.1301	2.65	0.009	414.0371	2845.597

```
. truncreg y x1 x2 x3 x4, ll(0) nolog
(note: 100 obs. truncated)
```

Truncated regression

Limit: lower = 0
 upper = +inf
 Log likelihood = -1200.9157

Number of obs = 150
 Wald chi2(4) = 10.05
 Prob > chi2 = 0.0395

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-803.0042	321.3614	-2.50	0.012	-1432.861	-173.1474
x2	-172.875	88.72898	-1.95	0.051	-346.7806	1.030578
x3	-8.821122	14.36848	-0.61	0.539	-36.98283	19.34059
x4	16.52873	46.50375	0.36	0.722	-74.61695	107.6744
_cons	1586.26	912.355	1.74	0.082	-201.9233	3374.442
/sigma	983.7262	94.44303	10.42	0.000	798.6213	1168.831

Marginal Effect on Truncated Expected Value

```
. mfx compute, predict(e(0,.))
```

```
Marginal effects after truncreg
  y = E(y|y>0) (predict, e(0,.))
    = 1310.0294
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	x
x1	-521.9979	199.4	-2.62	0.009	-912.818 -131.178	.173333
x2	-112.3785	56.487	-1.99	0.047	-223.091 -1.66638	1.31333
x3	-5.734226	9.31985	-0.62	0.538	-24.0008 12.5323	42.7867
x4	10.7446	30.21	0.36	0.722	-48.4655 69.9547	12.64

Marginal Effect on Censored Expected Value

```
. mfx compute, predict(ystar(0,.))
```

```
Marginal effects after truncreg
  y = E(y*|y>0) (predict, ystar(0,.))
    = 1123.2815
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	x
x1	-688.534	266.12	-2.59	0.010	-1210.11 -166.957	.173333
x2	-148.2313	74.802	-1.98	0.048	-294.841 -1.62154	1.31333
x3	-7.56365	12.299	-0.61	0.539	-31.6686 16.5413	42.7867
x4	14.17252	39.853	0.36	0.722	-63.9373 92.2823	12.64

Tobit Model: Factors Determining Research and Development Expenditures of the Firm in Thai Electronic Industry

Tobit (Censored regression) Model

Metakunnawat (1999) studied factors determined research and development (R&D) expenditures of the firm in Thai electronic industry. The study applied Tobit model since the data set was censored distributed. The model is as follows:

$$\begin{aligned} Z_i &= \alpha + \beta_1 MS_i + \beta_2 PCM_i + \beta_4 EXI_i + \beta_5 TOR_i + \beta_6 TOA_i + \beta_7 GOV_i + u_i && \text{if } Z_{ik} > 0 \\ Z_i &= 0 && \text{Otherwise} \end{aligned}$$

where:

- Z_i = Research and development expenditures of firm i
- MS_i = Market share of firm i
- PCM_i = Profit contribution margin of firm i
- CR_i = Concentration ratio of the industry
- EXI_i = Export concentration of the industry
- TOR_i = Dummy Variable = 1 if technology change within or more than 1 year
= 0 otherwise
- TOA_i = Dummy Variable = 1 if technology transfers from mother company
= 0 otherwise
- GOV_i = Dummy Variable = 1 if the industry receives government incentive for R&D
= 0 otherwise
- u_i = Error term

α and β_k are coefficients, where $\beta_1, \beta_2, \beta_3, \beta_7$ can be positive or negative, β_4 should be positive, β_5 and β_6 should be negative.

Since the data is censored distributed, the model should be estimated by using Maximum Likelihood Estimation (MLE) method. The log-likelihood function is as follows:

$$\ln L = \sum_0 \ln \left[\frac{1}{\sqrt{(2\pi\sigma^2)}} \right] - \sum_1 \frac{1}{2\sigma^2} (Z_i = \alpha + \beta_1 MS_i + \beta_2 PCM_i + \beta_4 EXI_i + \beta_5 TOR_i + \beta_6 TOA_i + \beta_7 GOV_i + u_i)^2$$

where \sum_0 is sum of observation N_0 for $Z_i = 0$
 \sum_1 is sum of observation N_1 for $Z_i > 0$

Estimate Tobit Model

```
. reg z ms pcm exi tor toa gov
```

Source	SS	df	MS	Number of obs =	39
Model	216.685223	6	36.1142038	F(6, 32) =	32.63
Residual	35.4154445	32	1.10673264	Prob > F =	0.0000
				R-squared =	0.8595
				Adj R-squared =	0.8332
Total	252.100667	38	6.63422808	Root MSE =	1.052

z	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ms	-.0640993	.0351223	-1.83	0.077	-.1356411 .0074426
pcm	.0309549	.0168661	1.84	0.076	-.0034001 .06531
exi	-.0400559	.0277357	-1.44	0.158	-.0965517 .0164399
tor	-.2361991	.7166092	-0.33	0.744	-1.695884 1.223486
toa	-.3944311	.8892493	-0.44	0.660	-2.205773 1.41691
gov	4.507958	.5964943	7.56	0.000	3.292939 5.722977
_cons	2.127431	.639876	3.32	0.002	.8240464 3.430816

```
. reg z ms pcm exi tor toa gov if z>0
```

Source	SS	df	MS	Number of obs =	32
Model	175.885314	6	29.314219	F(6, 25) =	28.21
Residual	25.9772868	25	1.03909147	Prob > F =	0.0000
				R-squared =	0.8713
				Adj R-squared =	0.8404
Total	201.862601	31	6.5116968	Root MSE =	1.0194

z	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ms	-.1203294	.039932	-3.01	0.006	-.2025708 -.038088
pcm	-3.27e-06	.0195447	-0.00	1.000	-.0402564 .0402498
exi	-.004589	.0555295	-0.08	0.935	-.1189541 .109776
tor	-.7234769	.7208991	-1.00	0.325	-2.208196 .7612425
toa	-.0729069	.8929615	-0.08	0.936	-1.911996 1.766182
gov	4.227732	.5889693	7.18	0.000	3.014727 5.440737
_cons	3.710537	.8150497	4.55	0.000	2.03191 5.389163

```
. tobit z ms pcm exi tor toa gov, ll
```

Tobit regression	Number of obs =	39
	LR chi2(6) =	72.99
	Prob > chi2 =	0.0000
Log likelihood = -50.51938	Pseudo R2 =	0.4194

z	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ms	-.0477107	.0371136	-1.29	0.208	-.1232189 .0277974
pcm	.0348347	.0176433	1.97	0.057	-.0010609 .0707303
exi	-.0868502	.037064	-2.34	0.025	-.1622576 -.0114429
tor	-.0636297	.7400413	-0.09	0.932	-1.569255 1.441996
toa	-.3227235	.9279608	-0.35	0.730	-2.210674 1.565227
gov	4.603485	.6137318	7.50	0.000	3.354838 5.852132
_cons	1.857899	.6802613	2.73	0.010	.4738968 3.241901
/sigma	1.078782	.1373532			.7993348 1.358229

```
obs. summary:      7 left-censored observations at z<=0
                   32 uncensored observations
                   0 right-censored observations
```

Marginal Effect on Censored Expected Value

```
. mfx compute, predict(ystar(0,.))
```

```
Marginal effects after tobit
y = E(z*|z>0) (predict, ystar(0,.))
= 2.1685388
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	x
ms	-.0466297	.03637	-1.28	0.200	-.117921 .024661	8.87769
pcm	.0340454	.01723	1.98	0.048	.000284 .067807	25.741
exi	-.0848824	.03577	-2.37	0.018	-.154982 -.014783	7.34615
tor*	-.0621636	.72276	-0.09	0.931	-1.47874 1.35441	.384615
toa*	-.3142121	.89959	-0.35	0.727	-2.07738 1.44895	.307692
gov*	4.568452	.60762	7.52	0.000	3.37755 5.75936	.128205

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Marginal Effect on Truncated Expected Value

```
. mfx compute, predict(e(0,.))
```

```
Marginal effects after tobit
y = E(z|z>0) (predict, e(0,.))
= 2.2188111
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	x
ms	-.0423084	.03336	-1.27	0.205	-.107687 .023071	8.87769
pcm	.0308903	.0157	1.97	0.049	.000118 .061662	25.741
exi	-.0770161	.03163	-2.44	0.015	-.139005 -.015027	7.34615
tor*	-.0563431	.65456	-0.09	0.931	-1.33925 1.22656	.384615
toa*	-.2824412	.8012	-0.35	0.724	-1.85277 1.28789	.307692
gov*	4.442333	.59864	7.42	0.000	3.26902 5.61564	.128205

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tobit Model using Panel Data

The model:

```
. reg illiq cg3 cg4 cg5 priceinverse volatility age lnta lntv
```

Source	SS	df	MS	Number of obs	=	2,977
Model	56363870.5	8	7045483.82	F(8, 2968)	=	97.15
Residual	215247984	2,968	72522.9055	Prob > F	=	0.0000
				R-squared	=	0.2075
				Adj R-squared	=	0.2054
Total	271611854	2,976	91267.4241	Root MSE	=	269.3

illiq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
cg3	24.80985	13.18405	1.88	0.060	-1.040957 50.66066
cg4	-7.020101	13.5703	-0.52	0.605	-33.62825 19.58805
cg5	-.3996451	19.35628	-0.02	0.984	-38.35273 37.55344
priceinverse	17.58497	4.064562	4.33	0.000	9.61532 25.55461
volatility	49.96149	12.54445	3.98	0.000	25.36479 74.55819
age	-.7652942	.6221881	-1.23	0.219	-1.985258 .4546697
lnta	2.136847	3.549215	0.60	0.547	-4.822325 9.096019
lntv	-30.41288	1.190944	-25.54	0.000	-32.74804 -28.07772
_cons	410.1833	51.51606	7.96	0.000	309.1725 511.1941

```
. xtreg illiq cg3 cg4 cg5 priceinverse volatility age lnta lntv
```

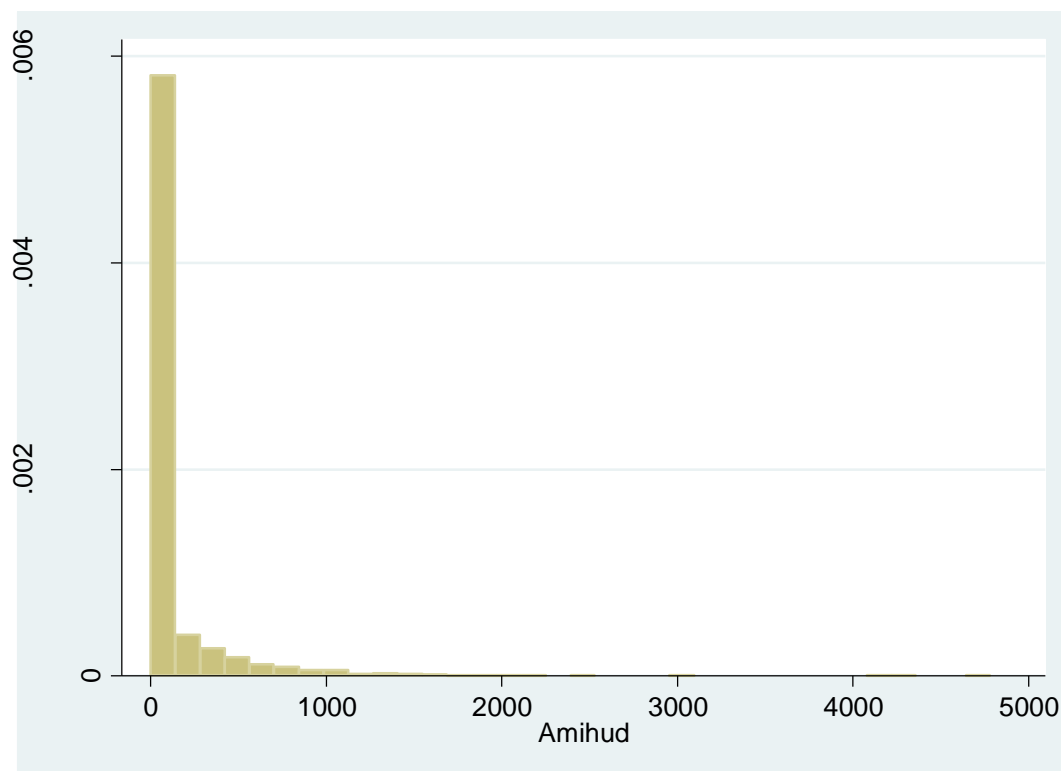
Random-effects GLS regression	Number of obs	=	2,977
Group variable: id	Number of groups	=	364

R-sq:	within = 0.2147	Obs per group:	min = 1
	between = 0.1891		avg = 8.2
	overall = 0.2075		max = 11

corr(u_i, X) = 0 (assumed)	Wald chi2(8)	=	777.19
	Prob > chi2	=	0.0000

illiq	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
cg3	24.80985	13.18405	1.88	0.060	-1.030415 50.65012
cg4	-7.020101	13.5703	-0.52	0.605	-33.6174 19.5772
cg5	-.3996451	19.35628	-0.02	0.984	-38.33726 37.53797
priceinverse	17.58497	4.064562	4.33	0.000	9.61857 25.55136
volatility	49.96149	12.54445	3.98	0.000	25.37482 74.54816
age	-.7652942	.6221881	-1.23	0.219	-1.98476 .4541722
lnta	2.136847	3.549215	0.60	0.547	-4.819487 9.093181
lntv	-30.41288	1.190944	-25.54	0.000	-32.74708 -28.07867
_cons	410.1833	51.51606	7.96	0.000	309.2137 511.1529
sigma_u	0				
sigma_e	263.35265				
rho	0	(fraction of variance due to u_i)			

```
. histogram illiq
(bin=34, start=0, width=140.68379)
```



```
. reg illiq cg3 cg4 cg5 priceinverse volatility age lnta lntv if illiq<=10
```

Source	SS	df	MS	Number of obs	=	1,955
Model	4107.06559	8	513.383199	F(8, 1946)	=	119.48
Residual	8361.3469	1,946	4.29668392	Prob > F	=	0.0000
Total	12468.4125	1,954	6.38096852	R-squared	=	0.3294
				Adj R-squared	=	0.3266
				Root MSE	=	2.0728

illiq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
cg3	.1123272	.1307872	0.86	0.391	-.1441704 .3688249
cg4	.0250911	.1295811	0.19	0.846	-.2290412 .2792234
cg5	-.2842084	.1745142	-1.63	0.104	-.6264628 .0580461
priceinverse	.0490283	.0361919	1.35	0.176	-.0219506 .1200072
volatility	.4704564	.3073261	1.53	0.126	-.1322667 1.073179
age	-.0057336	.0061178	-0.94	0.349	-.0177317 .0062646
lnta	-.0873353	.0322229	-2.71	0.007	-.1505304 -.0241403
lntv	-.3887633	.0141307	-27.51	0.000	-.4164762 -.3610503
_cons	8.613544	.4742816	18.16	0.000	7.683391 9.543697

```
. est store m_ols
```

```
. xtreg illiq cg3 cg4 cg5 priceinverse volatility age lnta lntv if illiq<=10
```

Random-effects GLS regression	Number of obs	=	1,955
Group variable: id	Number of groups	=	363
R-sq:	Obs per group:		
within = 0.2137	min =		1
between = 0.3917	avg =		5.4
overall = 0.3265	max =		11

```

corr(u_i, X) = 0 (assumed)
Wald chi2(8) = 675.63
Prob > chi2 = 0.0000

```

illiq	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
cg3	.1798028	.138313	1.30	0.194	-.0912858 .4508913
cg4	.0675304	.1518841	0.44	0.657	-.2301568 .3652177
cg5	-.3543256	.206638	-1.71	0.086	-.7593285 .0506774
priceinverse	.0458346	.0449247	1.02	0.308	-.0422162 .1338855
volatility	.4216365	.2782431	1.52	0.130	-.1237101 .966983
age	-.0055548	.0101237	-0.55	0.583	-.0253969 .0142873
lnta	-.1492212	.0498566	-2.99	0.003	-.2469383 -.0515042
lntv	-.3708759	.0156255	-23.74	0.000	-.4015014 -.3402505
_cons	9.305451	.753601	12.35	0.000	7.82842 10.78248
sigma_u	1.237113				
sigma_e	1.7903483				
rho	.32316608	(fraction of variance due to u_i)			

```
. est store m_re
```

```
. tobit illiq cg3 cg4 cg5 priceinverse volatility age lnta lntv, ul(10)
```

```

Tobit regression
Log likelihood = -6029.448
Number of obs = 2,977
LR chi2(8) = 2533.12
Prob > chi2 = 0.0000
Pseudo R2 = 0.1736

```

illiq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
cg3	.2172985	.2003655	1.08	0.278	-.1755708 .6101678
cg4	-.3826641	.202276	-1.89	0.059	-.7792795 .0139513
cg5	-1.071681	.2817109	-3.80	0.000	-1.624049 -.5193121
priceinverse	.4909429	.0600655	8.17	0.000	.3731686 .6087172
volatility	1.280187	.409213	3.13	0.002	.4778173 2.082557
age	-.0608728	.0093941	-6.48	0.000	-.0792925 -.0424532
lnta	.1099787	.0518977	2.12	0.034	.0082196 .2117379
lntv	-1.026462	.0198271	-51.77	0.000	-1.065339 -.9875858
_cons	16.63525	.7591861	21.91	0.000	15.14666 18.12383
/sigma	3.728514	.0639989			3.603027 3.854001

```

0 left-censored observations
1,955 uncensored observations
1,022 right-censored observations at illiq >= 10

```

```
. est store m_tobit
```

```
. xttobit illiq cg3 cg4 cg5 priceinverse volatility age lnta lntv, ul(10) tobit
```

```
Fitting comparison model:
```

```
Fitting constant-only model:
```

```
Iteration 0: log likelihood = -7610.0147
```

```
...
```

```
Iteration 4: log likelihood = -7296.0086
```

```
Fitting full model:
```

```
Iteration 0: log likelihood = -6428.0774
```

```
...
```

```
Iteration 4: log likelihood = -6029.448
```



```
. est table m_ols m_re m_tobit m_tobitRE, star(.1 .05 .01) stat(N rss ll rmse F chi2 r2)
```

Variable	m_ols	m_re	m_tobit	m_tobitRE
cg3	.11232723	.17980277		
cg4	.02509113	.06753045		
cg5	-.28420835	-.35432556*		
priceinverse	.04902826	.04583464		
volatility	.47045635	.42163649		
age	-.00573357	-.00555479		
lnta	-.08733535***	-.14922121***		
lntv	-.38876328***	-.37087594***		
_cons	8.6135439***	9.3054512***		
model				
cg3			.21729851	
cg4			-.38266409*	
cg5			-1.0716805***	
priceinverse			.4909429***	
volatility			1.2801871***	
age			-.06087281***	
lnta			.10997874**	
lntv			-1.0264622***	
_cons			16.635248***	
sigma				
_cons			3.7285138***	
illiq				
cg3				.2228948
cg4				-.45719339**
cg5				-1.3230978***
priceinverse				.45007892***
volatility				.97261821***
age				-.07275223***
lnta				.07527003
lntv				-1.1104994***
_cons				18.196771***
sigma_u				
_cons				1.787151***
sigma_e				
_cons				3.3716973***
Statistics				
N	1955	1955	2977	2977
rss	8361.3469			
ll	-4194.5565		-6029.448	-5963.092
rmse	2.0728444	1.7955137		
F	119.48359			
chi2		675.63485	2533.1212	2733.6048
r2	.32939764			

legend: * p<.1; ** p<.05; *** p<.01

Variable	m_ols	m_re	m_tobit	m_tobitRE
cg3	0.1123	0.1798	0.2173	0.2229
cg4	0.0251	0.0675	-0.3827 *	-0.4572 **
cg5	-0.2842	-0.3543 *	-1.0717 ***	-1.3231 ***
priceinverse	0.0490	0.0458	0.4909 ***	0.4501 ***
volatility	0.4705	0.4216	1.2802 ***	0.9726 ***
age	-0.0057	-0.0056	-0.0609 ***	-0.0728 ***
lnta	-0.0873 ***	-0.1492 ***	0.1100 **	0.0753
lntv	-0.3888 ***	-0.3709 ***	-1.0265 ***	-1.1105 ***
Constant	8.6135 ***	9.3055 ***	16.6352 ***	18.1968 ***
sigma_u				1.7872 ***
sigma_e			3.7285 ***	3.3717 ***
N	1955	1955	2977	2977
RSS	8361.35			
Log-likelihood	-4194.6		-6029.4	-5963.09
RMSE	2.07284	1.79551		
F-test	119.484 ***			
Chi-square Test		675.635 ***	2533.12 ***	2733.605 ***
Chi2 Comparison				132.712 ***
R-square	0.3294			
Overall R2		0.32654		
Pseudo R2			0.1736	