

Trabajo Práctico N° 5: **Modelos para Variables Dependientes Limitadas - Tobit.**

Ejercicio 1: Variables Censuradas (Modelo Tobit I).

El modelo Tobit es relevante cuando la variable dependiente y de una regresión lineal se observa solo en algún intervalo de su soporte, porque, en este caso, los estimadores de MCC no son consistentes.

(a) Considerar la base “auto.dta”. Estimar el modelo:

$$mpg = \alpha + \beta wgt + u,$$

donde $wgt = \frac{weight}{1000}$. Luego, estimar el modelo generando una variable censurada suponiendo que no se observan autos con $mpg \leq 17$. Estimar por MCC y utilizando un modelo Tobit. Comparar.

OLS:

Source	SS	df	MS	Number of obs	=	74
Model	1591.99024	1	1591.99024	F(1, 72)	=	134.62
Residual	851.469221	72	11.8259614	Prob > F	=	0.0000
Total	2443.45946	73	33.4720474	R-squared	=	0.6515
				Adj R-squared	=	0.6467
				Root MSE	=	3.4389

mpg	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
wgt	-6.008687	.5178782	-11.60	0.000	-7.041058	-4.976316
_cons	39.44028	1.614003	24.44	0.000	36.22283	42.65774

OLS (ll(17)):

Source	SS	df	MS	Number of obs	=	74
Model	1138.32073	1	1138.32073	F(1, 72)	=	95.06
Residual	862.219806	72	11.9752751	Prob > F	=	0.0000
Total	2000.54054	73	27.4046649	R-squared	=	0.5690
				Adj R-squared	=	0.5630
				Root MSE	=	3.4605

mpg_a	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
wgt	-5.080912	.5211373	-9.75	0.000	-6.11978	-4.042044
_cons	37.12539	1.62416	22.86	0.000	33.88769	40.3631

Tobit (ll(17)):

Tobit regression	Number of obs	=	74
	Uncensored	=	56
Limits: Lower = 17	Left-censored	=	18
Upper = +inf	Right-censored	=	0
	LR chi2(1)	=	72.85
	Prob > chi2	=	0.0000
Log likelihood = -164.25438	Pseudo R2	=	0.1815

mpg_a	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
wt	-6.87305	.700257	-9.82	0.000	-8.268661	-5.47744
_cons	41.49856	2.058384	20.16	0.000	37.3962	45.60091

var(e.mpg_a)	14.78942	2.817609			10.11698	21.61977

Tabla comparativa:

	(1) OLS	(2) OLS ll(17)	(3) Tobit ll(17)
main			
wt	-6.009*** (0.518)	-5.081*** (0.521)	-6.873*** (0.700)
_cons	39.44*** (1.614)	37.13*** (1.624)	41.50*** (2.058)

/			
var(e.mpg_a)			14.79*** (2.818)

N	74	74	74
R-sq	0.652	0.569	
pseudo R-sq			0.182

Standard errors in parentheses
 * p<0.10, ** p<0.05, *** p<0.01

(b) Repetir el inciso anterior suponiendo que, ahora, no se observan autos con mpg ≥ 24 .

OLS (ul(24)):

Source	SS	df	MS	Number of obs	=	74
Model	690.810491	1	690.810491	F(1, 72)	=	186.15
Residual	267.189509	72	3.7109654	Prob > F	=	0.0000
				R-squared	=	0.7211
				Adj R-squared	=	0.7172
Total	958	73	13.1232877	Root MSE	=	1.9264

mpg_b	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
wgt	-3.958119	.2901034	-13.64	0.000	-4.536429	-3.379808
_cons	31.95138	.9041273	35.34	0.000	30.14903	33.75372

Tobit (ul(24)):

Tobit regression	Number of obs	=	74
	Uncensored	=	51
Limits: Lower = -inf	Left-censored	=	0
Upper = 24	Right-censored	=	23
	LR chi2(1)	=	90.72
	Prob > chi2	=	0.0000
Log likelihood = -129.8279	Pseudo R2	=	0.2589

mpg_b	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
wgt	-5.080645	.4349309	-11.68	0.000	-5.947461	-4.213829
_cons	36.08037	1.432059	25.19	0.000	33.22628	38.93446
var(e.mpg_b)	5.689927	1.166256			3.781783	8.560846

Tabla comparativa:

	(1) OLS	(2) OLS ul (24)	(3) Tobit ul (24)
main			
wgt	-6.009*** (0.518)	-3.958*** (0.290)	-5.081*** (0.435)
_cons	39.44*** (1.614)	31.95*** (0.904)	36.08*** (1.432)
/			
var(e.mpg_b)			5.690*** (1.166)
N	74	74	74
R-sq	0.652	0.721	
pseudo R-sq			0.259

Standard errors in parentheses
 * p<0.10, ** p<0.05, *** p<0.01

(c) ¿Cómo se interpretan los coeficientes del modelo? Computar los efectos marginales.

Los coeficientes estimados miden cómo cambia la variable latente no observada con respecto a los cambios en las variables independientes, *ceteris paribus*.

Efectos marginales (condicionales) con censura en Tobit (ll(17)):

Conditional marginal effects
Model VCE: OIM

Number of obs = 74

Expression: $E(\text{mpg}_a | \text{mpg}_a > 17), \text{predict}(\text{ystar}(17, .))$

dy/dx wrt: wgt

1._at: wgt = 1

2._at: wgt = 2

3._at: wgt = 3

4._at: wgt = 4

		Delta-method		z	P> z	[95% conf. interval]	
		dy/dx	std. err.				
wgt	_at						
	1	-6.873035	1.389235	-4.95	0.000	-9.595886	-4.150183
	2	-6.855268	.7044715	-9.73	0.000	-8.236007	-5.47453
	3	-5.797116	.5880797	-9.86	0.000	-6.949731	-4.644501
	4	-1.499391	.3662326	-4.09	0.000	-2.217194	-.7815884

Efectos marginales (condicionales) con truncamiento en Tobit (ll(17)):

Conditional marginal effects
Model VCE: OIM

Number of obs = 74

Expression: $E(\text{mpg}_a | \text{mpg}_a > 17), \text{predict}(e(17, .))$

dy/dx wrt: wgt

1._at: wgt = 1

2._at: wgt = 2

3._at: wgt = 3

4._at: wgt = 4

		Delta-method		z	P> z	[95% conf. interval]	
		dy/dx	std. err.				
wgt	_at						
	1	-6.872705	.700472	-9.81	0.000	-8.245605	-5.499805
	2	-6.718373	.7348761	-9.14	0.000	-8.158703	-5.278042
	3	-4.345679	.4915117	-8.84	0.000	-5.309024	-3.382334
	4	-1.560439	.1287703	-12.12	0.000	-1.812825	-1.308054

Efectos marginales (condicionales) con censura en Tobit (ul(24)):

Conditional marginal effects
Model VCE: OIM

Number of obs = 74

Expression: $E(\text{mpg}_b | \text{mpg}_b < 24), \text{predict}(\text{ystar}(\cdot, 24))$

dy/dx wrt: wgt

1._at: wgt = 1

2._at: wgt = 2

3._at: wgt = 3

4._at: wgt = 4

		Delta-method		z	P> z	[95% conf. interval]	
		dy/dx	std. err.				
wgt							
	_at						
	1	-.0085382	.0114991	-0.74	0.458	-.031076	.0139997
	2	-1.069716	.2842071	-3.76	0.000	-1.626752	-.5126807
	3	-4.610593	.3715716	-12.41	0.000	-5.33886	-3.882326
	4	-5.079249	.4349007	-11.68	0.000	-5.931638	-4.226859

Efectos marginales (condicionales) con truncamiento en Tobit (ul(24)):

Conditional marginal effects
Model VCE: OIM

Number of obs = 74

Expression: $E(\text{mpg}_b | \text{mpg}_b < 24), \text{predict}(e(\cdot, 24))$

dy/dx wrt: wgt

1._at: wgt = 1

2._at: wgt = 2

3._at: wgt = 3

4._at: wgt = 4

		Delta-method		z	P> z	[95% conf. interval]	
		dy/dx	std. err.				
wgt							
	_at						
	1	-.3691762	.0534955	-6.90	0.000	-.4740255	-.2643269
	2	-1.13567	.1001953	-11.33	0.000	-1.332049	-.939291
	3	-3.681238	.3548315	-10.37	0.000	-4.376695	-2.985781
	4	-5.06274	.4362475	-11.61	0.000	-5.917769	-4.20771

Ejercicio 2: Variables Censuradas (Modelo Tobit II).

El siguiente ejercicio está tomado de Cameron & Trivedi. La variable dependiente para el gasto ambulatorio (*ambulatory expenditure*, *ambexp*) y los regresores (*age*, *female*, *educ*, *blhisp*, *totchr*, *ins*) se obtienen de la encuesta Medical Expenditure Panel Survey de 2001.

(a) Abrir y describir la base “*mus16datav2.dta*”. ¿Qué se puede decir sobre el cumplimiento de las condiciones que requiere un Tobit?

Variable	Obs	Mean	Std. dev.	Min	Max
ambexp	3,328	1386.519	2530.406	0	49960
age	3,328	4.056881	1.121212	2.1	6.4
female	3,328	.5084135	.5000043	0	1
educ	3,328	13.40565	2.574199	0	17
blhisp	3,328	.3085938	.4619824	0	1
totchr	3,328	.4831731	.7720426	0	5
ins	3,328	.3650841	.4815261	0	1

ambexp				
Percentiles	Smallest			
1%	22	1		
5%	67	2		
10%	107	2	Obs	2,802
25%	275	4	Sum of wgt.	2,802
50%	779		Mean	1646.8
		Largest	Std. dev.	2678.914
75%	1913	28269		
90%	3967	30920	Variance	7176579
95%	6027	34964	Skewness	5.799312
99%	12467	49960	Kurtosis	65.81969

Lo que se puede decir sobre el cumplimiento de las condiciones que requiere Tobit es que, en principio, la asimetría y la curtosis no normal (alejadas de 0 y 3, respectivamente) de la variable dependiente *ambexp* podrían deberse a regresores que están sesgados.

Tobit:

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Tobit regression                                Number of obs   =   3,328
                                                Uncensored     =   2,802
Limits: Lower =      0                        Left-censored  =    526
        Upper = +inf                        Right-censored =     0

                                                LR chi2(6)      =   694.07
                                                Prob > chi2     =   0.0000
Log likelihood = -26359.424                    Pseudo R2      =   0.0130
    
```

ambexp	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
age	314.1479	42.63366	7.37	0.000	230.557	397.7388
female	684.9918	92.85464	7.38	0.000	502.9337	867.0498
educ	70.8656	18.57365	3.82	0.000	34.44865	107.2825
blhisp	-530.311	104.2669	-5.09	0.000	-734.7448	-325.8772
totchr	1244.578	60.51376	20.57	0.000	1125.93	1363.226
ins	-167.4714	96.46088	-1.74	0.083	-356.6002	21.65734
_cons	-1882.591	317.4305	-5.93	0.000	-2504.971	-1260.212
var(e.ambexp)	6635296	179247.7			6292994	6996217

(b) Computar los efectos marginales.

Efectos marginales (promedio) con censura en Tobit:

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Average marginal effects                        Number of obs = 3,328
Model VCE: OIM
    
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Expression: E(ambexp*|ambexp>0), predict(ystar(0,.))
dy/dx wrt: age female educ blhisp totchr ins
    
```

	Delta-method					
	dy/dx	std. err.	z	P> z	[95% conf. interval]	
age	201.4409	27.29283	7.38	0.000	147.9479	254.9338
female	439.2368	59.32556	7.40	0.000	322.9608	555.5127
educ	45.4411	11.89795	3.82	0.000	22.12154	68.76066
blhisp	-340.0509	66.77218	-5.09	0.000	-470.922	-209.1799
totchr	798.06	38.00729	21.00	0.000	723.5671	872.5529
ins	-107.3876	61.86227	-1.74	0.083	-228.6354	13.86024

Efectos marginales (promedio) con truncamiento en Tobit:

Average marginal effects
Model VCE: OIM

Number of obs = 3,328

Expression: $E(\text{ambexp} | \text{ambexp} > 0)$, $\text{predict}(e(0, .))$
dy/dx wrt: age female educ blhisp totchr ins

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
age		147.796	20.14716	7.34	0.000	108.3083	187.2838
female		322.2656	43.7895	7.36	0.000	236.4397	408.0914
educ		33.33988	8.742173	3.81	0.000	16.20554	50.47422
blhisp		-249.4935	49.12834	-5.08	0.000	-345.7832	-153.2037
totchr		585.5322	29.01047	20.18	0.000	528.6727	642.3917
ins		-78.78967	45.40264	-1.74	0.083	-167.7772	10.19787

Efectos marginales (condicionales) con censura en Tobit:

Conditional marginal effects
Model VCE: OIM

Number of obs = 3,328

Expression: $E(\text{ambexp} * | \text{ambexp} > 0)$, $\text{predict}(\text{ystar}(0, .))$
dy/dx wrt: age female educ blhisp totchr ins

At: age = 4.056881 (mean)
female = .5084135 (mean)
educ = 13.40565 (mean)
blhisp = .3085938 (mean)
totchr = .4831731 (mean)
ins = .3650841 (mean)

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
age		207.526	28.2054	7.36	0.000	152.2444	262.8076
female		452.5052	61.30341	7.38	0.000	332.3528	572.6577
educ		46.81378	12.26552	3.82	0.000	22.77381	70.85375
blhisp		-350.3232	68.86825	-5.09	0.000	-485.3025	-215.3439
totchr		822.1678	40.61039	20.25	0.000	742.5729	901.7627
ins		-110.6315	63.74577	-1.74	0.083	-235.5709	14.30787

Efectos marginales (condicionales) con truncamiento en Tobit:

Conditional marginal effects
Model VCE: OIM

Number of obs = 3,328

Expression: $E(ambexp|ambexp>0), predict(e(0,.))$
dy/dx wrt: age female educ blhisp totchr ins
At: age = 4.056881 (mean)
female = .5084135 (mean)
educ = 13.40565 (mean)
blhisp = .3085938 (mean)
totchr = .4831731 (mean)
ins = .3650841 (mean)

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
age		145.524	19.7808	7.36	0.000	106.7543	184.2936
female		317.3113	42.99069	7.38	0.000	233.0511	401.5716
educ		32.82734	8.601086	3.82	0.000	15.96952	49.68516
blhisp		-245.658	48.29427	-5.09	0.000	-340.313	-151.0029
totchr		576.5307	28.50492	20.23	0.000	520.6621	632.3993
ins		-77.57842	44.7012	-1.74	0.083	-165.1912	10.03432

(c) *Computar los efectos marginales haciendo las cuentas con los comandos de escalares y matrices de Stata.*

Stata.

(d) *Considerar la variable dependiente en logaritmos. ¿Qué interpretación tiene esto sobre la variable dependiente? ¿Qué complicaciones introduce en el análisis? Estimar un Tobit para el logaritmo de ambexp.*

La variable dependiente en logaritmos introduce dos complicaciones en el análisis: un umbral distinto de cero y una variable dependiente lognormal.

OLS (con variable dependiente en logaritmos):

Source	SS	df	MS	Number of obs	=	3,328
Model	5772.79592	6	962.132653	F(6, 3321)	=	169.68
Residual	18831.0239	3,321	5.67028725	Prob > F	=	0.0000
				R-squared	=	0.2346
				Adj R-squared	=	0.2332
Total	24603.8199	3,327	7.39519683	Root MSE	=	2.3812

lambexp	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
age	.3247317	.038348	8.47	0.000	.2495436	.3999199
female	1.144695	.0833418	13.73	0.000	.9812886	1.308102
educ	.114108	.0165414	6.90	0.000	.0816757	.1465403
blhisp	-.7341754	.0928854	-7.90	0.000	-.9162938	-.5520571
totchr	1.059395	.0553699	19.13	0.000	.9508324	1.167958
ins	.2078343	.0869061	2.39	0.017	.0374394	.3782293
_cons	1.728764	.2812597	6.15	0.000	1.177304	2.280224

Tobit (con variable dependiente en logaritmos):

Tobit regression	Number of obs	=	3,328
	Uncensored	=	2,802
Limits: Lower = -0.00	Left-censored	=	526
Upper = +inf	Right-censored	=	0
	LR chi2(6)	=	831.03
	Prob > chi2	=	0.0000
Log likelihood = -7494.29	Pseudo R2	=	0.0525

lambexp	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
age	.3630699	.0453222	8.01	0.000	.2742077	.4519321
female	1.341809	.0986074	13.61	0.000	1.148471	1.535146
educ	.138446	.0196568	7.04	0.000	.0999054	.1769866
blhisp	-.8731611	.1102504	-7.92	0.000	-1.089327	-.6569955
totchr	1.161268	.0649655	17.88	0.000	1.033891	1.288644
ins	.2612202	.102613	2.55	0.011	.0600292	.4624112
_cons	.9237178	.3350343	2.76	0.006	.2668233	1.580612
var(e.lambexp)	7.735265	.2181984			7.319064	8.175133

Tabla comparativa:

	(1)	(2)
	OLS (log)	Tobit (log)
main		
age	0.325*** (0.0383)	0.363*** (0.0453)
female	1.145*** (0.0833)	1.342*** (0.0986)
educ	0.114*** (0.0165)	0.138*** (0.0197)
blhisp	-0.734*** (0.0929)	-0.873*** (0.110)
totchr	1.059*** (0.0554)	1.161*** (0.0650)
ins	0.208** (0.0869)	0.261** (0.103)
_cons	1.729*** (0.281)	0.924*** (0.335)
/		
var(e.lamb~)		7.735*** (0.218)
N	3328	3328
R-sq	0.235	
pseudo R-sq		0.053

Standard errors in parentheses
 * p<0.10, ** p<0.05, *** p<0.01

Ejercicio 3: Variables Censuradas (Modelo Tobit III).

Considerar la base de datos “mroz.dta”, que posee datos que permiten estudiar la oferta laboral anual de mujeres casadas. Considerar las horas trabajadas, *hours*, y las explicativas *nwifeinc*, *educ*, *exper*, *expersq*, *age*, *kidslt6*, *kidsge6*. Estimar un modelo lineal y un modelo Tobit. Comparar. Computar los efectos marginales.

OLS:

Source	SS	df	MS	Number of obs	=	753
Model	151647606	7	21663943.7	F(7, 745)	=	38.50
Residual	419262118	745	562767.944	Prob > F	=	0.0000
Total	570909724	752	759188.463	R-squared	=	0.2656
				Adj R-squared	=	0.2587
				Root MSE	=	750.18

hours	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
kidslt6	-442.0899	58.8466	-7.51	0.000	-557.6148	-326.565
kidsge6	-32.77923	23.17622	-1.41	0.158	-78.2777	12.71924
age	-30.51163	4.363868	-6.99	0.000	-39.07858	-21.94469
educ	28.76112	12.95459	2.22	0.027	3.329283	54.19297
exper	65.67251	9.962983	6.59	0.000	46.11365	85.23138
nwifeinc	-3.446636	2.544	-1.35	0.176	-8.440898	1.547626
expersq	-.7004939	.3245501	-2.16	0.031	-1.337635	-.0633524
_cons	1330.482	270.7846	4.91	0.000	798.8906	1862.074

Tobit:

Tobit regression	Number of obs	=	753
	Uncensored	=	428
Limits: Lower = 0	Left-censored	=	325
Upper = +inf	Right-censored	=	0
	LR chi2(7)	=	271.59
	Prob > chi2	=	0.0000
Log likelihood = -3819.0946	Pseudo R2	=	0.0343

hours	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
kidslt6	-894.0202	111.8777	-7.99	0.000	-1113.653	-674.3875
kidsge6	-16.21805	38.6413	-0.42	0.675	-92.07668	59.64057
age	-54.40491	7.418483	-7.33	0.000	-68.9685	-39.84133
educ	80.64541	21.58318	3.74	0.000	38.27441	123.0164
exper	131.564	17.27935	7.61	0.000	97.64211	165.486
nwifeinc	-8.814226	4.459089	-1.98	0.048	-17.56808	-.0603706
expersq	-1.864153	.5376606	-3.47	0.001	-2.919661	-.8086455
_cons	965.3068	446.4351	2.16	0.031	88.88827	1841.725
var(e.hours)	1258927	93304.48			1088458	1456093

Tabla comparativa:

	(1) OLS	(2) Tobit
main		
kidslt6	-442.1*** (58.85)	-894.0*** (111.9)
kidsge6	-32.78 (23.18)	-16.22 (38.64)
age	-30.51*** (4.364)	-54.40*** (7.418)
educ	28.76** (12.95)	80.65*** (21.58)
exper	65.67*** (9.963)	131.6*** (17.28)
nwifeinc	-3.447 (2.544)	-8.814** (4.459)
expersq	-0.700** (0.325)	-1.864*** (0.538)
_cons	1330.5*** (270.8)	965.3** (446.4)
/		
var(e.hours)		1258926.8*** (93304.5)
N	753	753
R-sq	0.266	
pseudo R-sq		0.034

Standard errors in parentheses
 * p<0.10, ** p<0.05, *** p<0.01

Efectos marginales (promedio) con censura en Tobit:

Average marginal effects
Model VCE: OIM

Number of obs = 753

Expression: $E(\text{hours}^* | \text{hours} > 0)$, $\text{predict}(\text{ystar}(0, .))$
dy/dx wrt: kidslt6 kidsge6 age educ exper nwifeinc expersq

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
kidslt6		-526.2776	64.70619	-8.13	0.000	-653.0994	-399.4558
kidsge6		-9.546986	22.75224	-0.42	0.675	-54.14056	35.04659
age		-32.02622	4.29211	-7.46	0.000	-40.4386	-23.61384
educ		47.47306	12.6214	3.76	0.000	22.73558	72.21054
exper		77.44703	9.99765	7.75	0.000	57.85199	97.04206
nwifeinc		-5.188619	2.621409	-1.98	0.048	-10.32649	-.0507514
expersq		-1.09736	.3155945	-3.48	0.001	-1.715914	-.4788063

Efectos marginales (promedio) con truncamiento en Tobit:

Average marginal effects
Model VCE: OIM

Number of obs = 753

Expression: $E(\text{hours} | \text{hours} > 0)$, $\text{predict}(e(0, .))$
dy/dx wrt: kidslt6 kidsge6 age educ exper nwifeinc expersq

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
kidslt6		-402.5505	50.74874	-7.93	0.000	-502.0162	-303.0848
kidsge6		-7.302504	17.40426	-0.42	0.675	-41.41423	26.80922
age		-24.4969	3.362491	-7.29	0.000	-31.08726	-17.90654
educ		36.31221	9.703035	3.74	0.000	17.29461	55.32981
exper		59.23934	7.83368	7.56	0.000	43.88561	74.59308
nwifeinc		-3.968782	2.007582	-1.98	0.048	-7.903569	-.0339945
expersq		-.8393724	.2423183	-3.46	0.001	-1.314307	-.3644373

Efectos marginales (condicionales) con censura en Tobit:

Conditional marginal effects
Model VCE: OIM

Number of obs = 753

Expression: $E(\text{hours}^* | \text{hours} > 0), \text{predict}(\text{ystar}(0, .))$
 dy/dx wrt: kidslt6 kidsge6 age educ exper nwifeinc expersq
 At: kidslt6 = .2377158 (mean)
 kidsge6 = 1.353254 (mean)
 age = 42.53785 (mean)
 educ = 12.28685 (mean)
 exper = 10.63081 (mean)
 nwifeinc = 20.12896 (mean)
 expersq = 178.0385 (mean)

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
kidslt6		-540.2567	66.62387	-8.11	0.000	-670.8371	-409.6763
kidsge6		-9.800576	23.36132	-0.42	0.675	-55.58792	35.98677
age		-32.87691	4.457699	-7.38	0.000	-41.61384	-24.13998
educ		48.73405	12.9634	3.76	0.000	23.32625	74.14185
exper		79.50419	10.30495	7.72	0.000	59.30685	99.70153
nwifeinc		-5.32644	2.690724	-1.98	0.048	-10.60016	-.0527175
expersq		-1.126508	.3232603	-3.48	0.000	-1.760087	-.49293

Efectos marginales (condicionales) con truncamiento en Tobit:

Conditional marginal effects
Model VCE: OIM

Number of obs = 753

Expression: $E(\text{hours} | \text{hours} > 0), \text{predict}(e(0, .))$
 dy/dx wrt: kidslt6 kidsge6 age educ exper nwifeinc expersq
 At: kidslt6 = .2377158 (mean)
 kidsge6 = 1.353254 (mean)
 age = 42.53785 (mean)
 educ = 12.28685 (mean)
 exper = 10.63081 (mean)
 nwifeinc = 20.12896 (mean)
 expersq = 178.0385 (mean)

		Delta-method				[95% conf. interval]	
		dy/dx	std. err.	z	P> z		
kidslt6		-379.9678	46.79714	-8.12	0.000	-471.6885	-288.2471
kidsge6		-6.892841	16.42951	-0.42	0.675	-39.09409	25.3084
age		-23.12265	3.130037	-7.39	0.000	-29.25741	-16.98789
educ		34.27513	9.117076	3.76	0.000	16.40599	52.14427
exper		55.91608	7.239109	7.72	0.000	41.72769	70.10447
nwifeinc		-3.746137	1.89236	-1.98	0.048	-7.455095	-.03718
expersq		-.7922845	.2273444	-3.48	0.000	-1.237871	-.3466976