Stata Textbook Examples

Introductory Econometrics: A Modern Approach by Jeffrey M. Wooldridge (1st & 2d eds.) Chapter 17 - Limited Dependent Variable Models and Sample Selection Corrections

Example 17.1: Married Woman's Labor Force Participation

可以直接输入这个命令 引用数据。

use http://fmwww.bc.edu/ec-p/data/wooldridge/MROZ, clear

regress inlf nwifeinc educ exper expersq age kidslt6 kidsge6

Source	SS	df 	MS		Number of obs F(7, 745)	= 7! = 38.2	53 22
Model Residual	48.8080578 135.919698		97257968 82442547 		Prob > F R-squared Adj R-squared	= 0.000 $= 0.264$ $= 0.25$	00 42
Total	184.727756	752 .2	45648611		Root MSE	= .427	
inlf	Coef.	Std. Err	. t	P> t	[95% Conf.	Interva	1]
nwifeinc educ exper expersq age kidslt6 kidsge6 _cons	0034052 .0379953 .0394924 0005963 0160908 2618105 .0130122 .5855192	.0014485 .007376 .0056727 .0001848 .0024847 .0335058 .013196 .154178	5.15 6.96 -3.23 -6.48 -7.81	0.019 0.000 0.000 0.001 0.000 0.000 0.324 0.000	0062488 .023515 .0283561 0009591 0209686 3275875 0128935 .2828442	000563 .052479 .050628 000233 01123 196033 .038917 .888194	56 87 35 13 35 79

logit inlf nwifeinc educ exper expersq age kidslt6 kidsge6

Iteration	0:	log	likelihood	=	-514.8732
Iteration	1:	log	likelihood	=	-406.94123
Iteration	2:	log	likelihood	=	-401.85151
Iteration	3:	log	likelihood	=	-401.76519
Iteration	4:	log	likelihood	=	-401.76515

Logit estimate	Logit estimates					=	753 226.22
Log likelihood = -401.76515				Prob > chi2 Pseudo R2		=	0.000
inlf	Coef.	Std. Err.				Conf.	Interval]
·	0213452			0.011		509	0048394

5.09

0.000

.1360303

.3063105

.2211704 .0434396

educ

exper	.2058695	.0320569	6.42	0.000	.1430391	.2686999
expersq	0031541	.0010161	-3.10	0.002	0051456	0011626
age	0880244	.014573	-6.04	0.000	116587	0594618
kidslt6	-1.443354	.2035849	-7.09	0.000	-1.842373	-1.044335
kidsge6	.0601122	.0747897	0.80	0.422	086473	.2066974
_cons	.4254524	.8603696	0.49	0.621	-1.260841	2.111746

probit inlf nwifeinc educ exper expersq age kidslt6 kidsge6

```
Iteration 0: log likelihood = -514.8732
Iteration 1: log likelihood = -405.78215
Iteration 2: log likelihood = -401.32924
Iteration 3: log likelihood = -401.30219
Iteration 4: log likelihood = -401.30219
```

Probit estimates	Number of obs	=	753
	LR chi2(7)	=	227.14
	Prob > chi2	=	0.0000
Log likelihood = -401.30219	Pseudo R2	=	0.2206

inlf	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
nwifeinc educ exper expersq age	0120237 .1309047 .1233476 0018871 0528527	.0048398 .0252542 .0187164 .0006	-2.48 5.18 6.59 -3.15 -6.23	0.013 0.000 0.000 0.002 0.000		
kidslt6 kidsge6 _cons	8683285 .036005 .2700768	.1185223 .0434768 .508593	-7.33 0.83 0.53	0.000 0.408 0.595	-1.100628 049208 7267472	636029 .1212179 1.266901

Changes in probability if kidslt6 changes

mfx compute, at(mean kidslt6=1)

Marginal effects after probit
 y = Pr(inlf) (predict)
 = .32416867

variable	dy/dx	Std. Err.	Z	P> z	[95% C.I.]	X
nwifeinc educ exper expersq age	004323 .047065 .0443479 0006785 0190025	.00175 .00912 .00704 .00022	-2.48 5.16 6.30 -3.11 -6.69	0.013 0.000 0.000 0.002 0.000	007744000902 .029187 .064943 .03055 .058146 001106000251 024568013437	20.1290 12.2869 10.6308 178.039 42.5378

kidslt6	3121957	.03077	-10.15	0.000	372509	251882	1.00000
kidsge6	.0129451	.0157	0.82	0.410	017829	.04372	1.35325

mfx compute, at(mean kidslt6=1.5)

Marginal effects after probit
 y = Pr(inlf) (predict)

= .1866692

variable	dy/dx	Std. Err.	z	P> z	[95%	C.I.]	X
nwifeinc	0032274	.00136	-2.37	0.018	005892	000563	20.1290
educ	.0351375	.00789	4.46	0.000	.019683	.050592	12.2869
exper	.033109	.00683	4.85	0.000	.019731	.046487	10.6308
expersq	0005065	.00018	-2.88	0.004	000851	000162	178.039
age	0141867	.00232	-6.12	0.000	018733	00964	42.5378
kidslt6	2330773	.01067	-21.84	0.000	253993	212162	1.50000
kidsge6	.0096645	.01189	0.81	0.416	013647	.032976	1.35325

Example 17.2: Married Women's Annual Labor Supply

use http://fmwww.bc.edu/ec-p/data/wooldridge/MROZ, clear

regress hours nwifeinc educ exper expersq age kidslt6 kidsge6

Source	SS	df	MS		Number of obs	
Model Residual	151647606 419262118		3943.7 67.944		F(7, 745) Prob > F R-squared Adj R-squared	= 0.0000 = 0.2656
Total	570909724	752 7591	88.463		Root MSE	= 750.18
hours	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
nwifeinc	-3.446636	2.544	-1.35	0.176	-8.440898	1.547626
educ	28.76112	12.95459	2.22	0.027	3.329284	54.19297
exper	65.67251	9.962983	6.59	0.000	46.11365	85.23138
expersq	7004939	.3245501	-2.16	0.031	-1.337635	0633524
age	-30.51163	4.363868	-6.99	0.000	-39.07858	-21.94469
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
_cons	1330.482	270.7846	4.91	0.000	798.8906	1862.074

tobit hours nwifeinc educ exper expersq age kidslt6 kidsge6, 11(0)

Tobit estimates				Number of obs $=$			753
				LR ch	i2(7)	=	271.59
				Prob	> chi2	=	0.0000
Log likelihood = -3819.0946					lo R2	=	0.0343
hours	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]
		4 450006	1 00		15 5601		0.602.505
nwifeinc	-8.814243	4.459096	-1.98	0.048	-17.5681	.⊥	0603725
educ	80.64561	21.58322	3.74	0.000	38.2745	3	123.0167
exper	131.5643	17.27938	7.61	0.000	97.6423	31	165.4863
expersq	-1.864158	.5376615	-3.47	0.001	-2.91966	57	8086479

_se | 1122.022 41.57903 (Ancillary parameter)

-7.33 0.000

-7.99 0.000

0.675

0.031

-0.42

2.16

-68.96862

-92.07675

88.88531

-1113.655 -674.3887

-39.8414

59.64075

1841.725

Obs. summary: 325 left-censored observations at hours<=0 428 uncensored observations

Changes in probability

* fixup for expersq : take square of mean rather than mean of square per JMW summ exper, meanonly

local exp2=r(mean)^2

kidsge6

_cons |

mfx compute, at(mean expersq=`exp2') predict(ystar(0,.))

```
Marginal effects after tobit
y = E(hours*|hours>0) (predict, ystar(0,.))
= 687.31745
```

age | -54.40501 7.418496

-16.218 38.64136

965.3053 446.4358

kidslt6 | -894.0217 111.8779

variable	dy/dx	Std. Err.	Z	P> z	[95%	C.I.]	X
nwifeinc	-5.687381	2.87788	-1.98	0.048	-11.3279	046836	20.1290
educ	52.03649	13.82	3.77	0.000	24.9495	79.1234	12.2869
exper	84.89173	12.398	6.85	0.000	60.593	109.19	10.6308
expersq	-1.202846	.36661	-3.28	0.001	-1.92139	484297	113.014
age	-35.10478	4.66947	-7.52	0.000	-44.2568	-25.9528	42.5378
kidslt6	-576.8666	70.93	-8.13	0.000	-715.887	-437.847	.237716
kidsge6	-10.46465	24.94	-0.42	0.675	-59.3456	38.4163	1.35325

._____

* marginal effects conditional on positive hours

mfx compute, at(mean expersq=`exp2') predict(e(0,.))

Marginal effects after tobit

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

= 1065.1973

variable	dy/dx	Std. Err.	z	P> z	[95%	C.I.]	Х
nwifeinc	-3.987413	2.01764	-1.98	0.048		032909	20.1290
educ exper	36.48269 59.51744	9.68927 8.68378	3.77 6.85	0.000	17.4921 42.4975		12.2869 10.6308
expersq age	843313 -24.6119	.25692 3.27362	-3.28 -7.52	0.001		339765 -18.1957	113.014 42.5378
kidslt6 kidsge6	-404.4402 -7.336744	49.722 17.485	-8.13 -0.42	0.000 0.675	-501.893 -41.607	-306.987 26.9335	.237716 1.35325

Example 17.3: Poisson Regression for Number of Arrests

use http://fmwww.bc.edu/ec-p/data/wooldridge/CRIME1, clear

reg narr86 pcnv avgsen tottime ptime86 qemp86 inc86 black hispan born60

Source	SS	df 	MS		Number of obs F(9, 2715)	= 2725 = 23.57
Model Residual	145.702778 1864.64438		891976 793509		Prob > F R-squared Adj R-squared	= 0.0000 = 0.0725
Total	2010.34716	2724 .738	012906		Root MSE	= .82873
narr86	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
pcnv avgsen tottime ptime86	131886 0113316 .0120693 0408735	.0404037 .0122413 .0094364 .008813	-3.26 -0.93 1.28 -4.64	0.001 0.355 0.201 0.000	2111112 0353348 006434 0581544	0526609 .0126717 .0305725 0235925
qemp86 inc86 black	0408733 0513099 0014617 .3270097	.008813 .0144862 .000343 .0454264	-3.54 -4.26 7.20	0.000 0.000 0.000	0381344 079715 0021343 .2379359	0233925 0229047 0007891 .4160835
hispan born60	.1938094 022465	.0397156 .0332945	4.88 -0.67	0.000 0.500	.1159335 0877502	.2716853 .0428202

_cons | .576566 .0378945 15.22 0.000 .502261 .6508711

poisson narr86 pcnv avgsen tottime ptime86 qemp86 inc86 black hispan born60

Iteration 0: log likelihood = -2249.0104
Iteration 1: log likelihood = -2248.7614
Iteration 2: log likelihood = -2248.7611
Iteration 3: log likelihood = -2248.7611

Poisson regression Number of obs = 2725

LR chi2(9) = 386.32Prob > chi2 = 0.0000

Log likelihood = -2248.7611

Pseudo R2 = 0.0791

narr86	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
pcnv avgsen tottime ptime86 qemp86 inc86 black	4015713 0237723 .0244904 0985584 0380187 0080807 .6608376	.0849712 .019946 .0147504 .0206946 .0290242 .001041 .0738342	-4.73 -1.19 1.66 -4.76 -1.31 -7.76 8.95	0.000 0.233 0.097 0.000 0.190 0.000	5681117 0628658 0044199 1391192 0949051 010121 .5161252	2350308 .0153212 .0534006 0579977 .0188677 0060404 .80555
hispan born60 _cons	.4998133 0510286 5995888	.0739267 .0640518 .0672501	6.76 -0.80 -8.92	0.000 0.426 0.000	.3549196 1765678 7313966	.644707 .0745106 467781

Change in expected arrests if pcnv changes by .10

display "Change in expected arrests if pcnv changes by .10 is " _b[pcnv]*.10

Change in expected arrests if pcnv changes by .10 is -.04015713

Example 17.4: Duration of Recidivism

use http://fmwww.bc.edu/ec-p/data/wooldridge/RECID, clear

cnreg ldurat workprg priors tserved felon alcohol drugs black married educ age, censored(cens)

Censored normal regression

Number of obs = 1445

LR chi2(10) = 166.74Prob > chi2 = 0.0000Log likelihood = -1597.059 Pseudo R2 = 0.0496

ldurat	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
workprg priors tserved felon alcohol drugs black married educ	0625715 1372529 0193305 .4439947 6349093 2981602 5427179 .3406837 .0229196	.1200369 .0214587 .0029779 .1450865 .1442166 .1327356 .1174428 .1398431 .0253974	-0.52 -6.40 -6.49 3.06 -4.40 -2.25 -4.62 2.44 0.90	0.602 0.000 0.000 0.002 0.000 0.025 0.000 0.015 0.367	2980382 1793466 0251721 .1593903 9178072 5585367 7730958 .066365 0269004	.17289510951592013489 .72859913520113037783631234 .6150024 .0727395
age _cons 	.0039103 4.099386 1.81047	.0006062 .3475351 .0623022	6.45 11.80	0.000 0.000	.0027211 3.417655 ary parameter)	.0050994 4.781117

Obs. summary: 552 uncensored observations 893 right-censored observations

Change in durat if a man serves for a felony

mfx compute, nose

Marginal effects after cnreg

y = Fitted values (predict)

= 4.8341597

variable	dy/dx	X
workprg*	0625715	.465052
priors	1372529	1.43183
tserved	0193305	19.1820
felon*	.4439947	.314187
alcohol*	6349093	.209689
drugs*	2981602	.241522
black*	5427179	.485121
married*	.3406837	.255363
educ	.0229196	9.70242
age	.0039103	345.436

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

```
mat pct=e(Xmfx_dydx)
```

matmap pct pct, m(100*(exp(@)-1))

mat list pct

pct	[1,10]					
	workprg	priors	tserved	felon	alcohol	drugs
r1	-6.0654125	-12.825026	-1.9144899	55.892217	-47.001643	-25.781754
	black	married	educ	age		
r1	-41.883343	40.590851	2.3184231	.39179407		

Example 17.5: Wage Offer Equation for Married Women

use http://fmwww.bc.edu/ec-p/data/wooldridge/MROZ, clear

reg lwage educ exper expersq

Source	SS	df	MS		Number of obs F(3, 424)	
Model Residual	35.0223023 188.305149		6741008 4115917		Prob > F R-squared Adj R-squared	= 0.0000 = 0.1568
Total	223.327451	427 .523	3015108		Root MSE	= .66642
lwage	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
educ exper expersq _cons	.1074896 .0415665 0008112 5220407	.0141465 .0131752 .0003932 .1986321	7.60 3.15 -2.06 -2.63	0.000 0.002 0.040 0.009	.0796837 .0156697 0015841 9124668	.1352956 .0674633 0000382 1316145

heckman lwage educ exper expersq, sel(inlf = nwifeinc educ exper expersq age kidslt6 kidsge6) twostep

Heckman selection model two-step estimates	Number of obs	=	753
(regression model with sample selection)	Censored obs	=	325
	Uncensored obs	=	428
	Wald chi2(6)	=	180.10

Pro]	b >	chi2	=	0.	.0000

Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
.1090655	.015523	7.03	0.000	.0786411	.13949
.0438873	.0162611	2.70	0.007	.0120163	.0757584
0008591	.0004389	-1.96	0.050	0017194	1.15e-06
5781033	.3050062	-1.90	0.058	-1.175904	.0196979
0120237	.0048398	-2.48	0.013	0215096	0025378
.1309047	.0252542	5.18	0.000	.0814074	.180402
.1233476	.0187164	6.59	0.000	.0866641	.1600311
0018871	.0006	-3.15	0.002	003063	0007111
0528527	.0084772	-6.23	0.000	0694678	0362376
8683285	.1185223	-7.33	0.000	-1.100628	636029
.036005	.0434768	0.83	0.408	049208	.1212179
.2700768	.508593	0.53	0.595	7267472	1.266901
.0322619	.1336246	0.24	0.809	2296376	.2941613
0.04861 .66362876	1336246				
	.1090655 .0438873 0008591 5781033 	.1090655 .015523 .0438873 .0162611 0008591 .0004389 5781033 .3050062 	.1090655 .015523 7.03 .0438873 .0162611 2.70 0008591 .0004389 -1.96 5781033 .3050062 -1.90 0120237 .0048398 -2.48 .1309047 .0252542 5.18 .1233476 .0187164 6.59 0018871 .0006 -3.15 0528527 .0084772 -6.23 8683285 .1185223 -7.33 .036005 .0434768 0.83 .2700768 .508593 0.53 	.1090655 .015523 7.03 0.000 .0438873 .0162611 2.70 0.0070008591 .0004389 -1.96 0.0505781033 .3050062 -1.90 0.058 0120237 .0048398 -2.48 0.013 .1309047 .0252542 5.18 0.000 .1233476 .0187164 6.59 0.0000018871 .0006 -3.15 0.0020528527 .0084772 -6.23 0.0008683285 .1185223 -7.33 0.0008683285 .1185223 -7.33 0.000 .036005 .0434768 0.83 0.408 .2700768 .508593 0.53 0.595	.1090655 .015523 7.03 0.000 .0786411 .0438873 .0162611 2.70 0.007 .01201630008591 .0004389 -1.96 0.05000171945781033 .3050062 -1.90 0.058 -1.1759040120237 .0048398 -2.48 0.0130215096 .1309047 .0252542 5.18 0.000 .0814074 .1233476 .0187164 6.59 0.000 .08666410018871 .0006 -3.15 0.0020030630528527 .0084772 -6.23 0.00006946788683285 .1185223 -7.33 0.000 -1.100628 .036005 .0434768 0.83 0.408049208 .2700768 .508593 0.53 0.5957267472004861 .66362876

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