

# Probit Regression in R, Python, Stata, and SAS

Shi Lan, Roya Talibova, Bo Qu, Jiehui Ding

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## Model Introduction

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## Dataset: Mroz

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## Languages

R

Python

Stata

SAS

### 1.Data Summary

Firstly, We import the Mroz data from website and show the first six rows of the dataset.

```
*Importing data
import delimited https://vincentarelbundock.github.io/Rdatasets/csv/carData/Mroz.csv,
clear
save mroz,replace
use mroz,clear
*List the first six rows
list if v1<=6
```

	v1	lfp	k5	k618	age	wc	hc	lw	inc
1.	1	yes	1	0	32	no	no	1.210165	10.91
2.	2	yes	0	2	30	no	no	.3285041	19.5
3.	3	yes	1	3	35	no	no	1.514128	12.04
4.	4	yes	0	3	34	no	no	.0921151	6.8
5.	5	yes	1	2	31	yes	no	1.52428	20.1
6.	6	yes	0	0	54	no	no	1.556486	9.859

Then, We change all binary variables to be numeric, and we get a summary of the data. Our response is lfp and its mean is 0.57. The range of age is from 30 to 60.

```
*Change variables with values yes/no to 1/0
gen lfp = 1 if lfp == "yes"
replace lfp = 0 if lfp == "no"
gen wfec = 1 if wfec == "yes"
replace wfec = 0 if wfec == "no"
gen husbc = 1 if hc == "yes"
replace husbc = 0 if hc == "no"
drop lfp wfec hc
rename lfp lfp
rename wfec wfec
rename husbc husbc
*Get the summary of the data
summ
```

Variable	Obs	Mean	Std. Dev.	Min	Max
v1	753	377	217.5167	1	753
k5	753	.2377158	.523959	0	3
k618	753	1.353254	1.319874	0	8
age	753	42.53785	8.072574	30	60
lw	753	1.097115	.5875564	-2.054124	3.218876
inc	753	20.12897	11.6348	-.029	96
lfp	753	.5683931	.4956295	0	1
wfec	753	.2815405	.4500494	0	1
hc	753	.3917663	.4884694	0	1

## 2.Fitting model by Probit Regression

Now, we fit our data by probit regression. lfp is the response and the remaining variables are predictors. Looking at the p-values, all variables have highly significant, except k618 and hc.

```
*Fitting the data by probit regression
probit lfp k5 k618 lw inc i.wfec i.hc
```

```

Iteration 0: log likelihood = -514.8732
Iteration 1: log likelihood = -452.84838
Iteration 2: log likelihood = -452.69498
Iteration 3: log likelihood = -452.69496

```

```

Probit regression                                Number of obs   =          75
> 3                                              LR chi2(7)      =        124.3
> 6                                              Prob > chi2     =         0.000
> 0                                              Pseudo R2      =         0.120
Log likelihood = -452.69496
> 8

```

```

-----
> -
      lfp |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval
> ]
-----+-----
> -
      k5 |  -.8747111   .1135584    -7.70   0.000    -1.097281    -.652140
> 8
      k618 | -.0385945   .0404893    -0.95   0.340    -.1179521    .040763
> 1
      age | -.0378235   .0076093    -4.97   0.000    -.0527375    -.022909
> 5
      lwg |  .3656287   .0877792     4.17   0.000    .1935846    .537672
> 7
      inc | -.020525    .0047769    -4.30   0.000    -.0298875    -.011162
> 5
      1.wc |  .4883144   .1354873     3.60   0.000    .2227641    .753864
> 7
      1.hc |  .0571703   .1240053     0.46   0.645    -.1858755    .300216
> 2
      _cons | 1.918422    .3806539     5.04   0.000    1.172354    2.6644
> 9
-----
> -

```

We get a summary of the probit prediction from the fitted model, we get the smallest probability is 0.005691 and the largest probability is 0.9745. The 50% percentile is 0.5782336, which is close to its mean we showed above.

```

*Predicting the probability of labor-force participation
predict prob_lfp
summ prob_lfp, detail

```

```

                                Pr(lfp)
-----
Percentiles      Smallest
1%      .0874537    .005691
5%      .2087887    .0280799
10%     .3134367    .0322375
25%     .4470239    .056195
50%     .5782336
75%     .7189098    .9530371
90%     .8133735    .9554808
95%     .8603116    .966253
99%     .9348801    .9744748

Obs          753
Sum of Wgt.  753

Mean         .5705144
Std. Dev.    .1928416

Variance     .0371879
Skewness     -.3429077
Kurtosis     2.709472

```

### 3. Marginal effect

Now, we predict the data for groups defined by levels of categorical variables. ##### Group by hc First, we make a table of frequently count of hc and lfp we predict the lfp for two groups: hc=0 and hc=1, and we keep other variables at mean.

```
tab lfp hc
```

lfp	hc		Total
	0	1	
0	207	118	325
1	251	177	428
Total	458	295	753

```
*use margins for each level of hc
margins hc, atmeans
```

```
Adjusted predictions          Number of obs    =      75
> 3
Model VCE      : OIM
Expression     : Pr(lfp), predict()
at             : k5              =    .2377158 (mean)
               : k618            =    1.353254 (mean)
               : age              =   42.53785 (mean)
               : lwg              =    1.097115 (mean)
               : inc              =   20.12897 (mean)
               : 0.wc             =    .7184595 (mean)
               : 1.wc             =    .2815405 (mean)
               : 0.hc             =    .6082337 (mean)
               : 1.hc             =    .3917663 (mean)
```

```
-----
> -
      |      Delta-method
      |      Margin   Std. Err.      z    P>|z|    [95% Conf. Interval]
> |-----+-----
> -
      | hc |
> 0 |   .5693818   .0273369   20.83   0.000   .5158024   .622961
> 1 |   .5917197   .0345427   17.13   0.000   .5240172   .659422
> 1
-----
> -
```

The marginal probability of hc=1 (husband has attained college) is 0.59 and it slightly higher than the marginal probability of hc=0 (husband has not attained college), which is 0.57. There is not obvious difference. It is reasonable because the p-value of hc is very high.

## Group by wc

The table of frequently shows that when wc=0, the proportion of lfp is average, which is closed to 0.5. However, when wc=1, the proportion of lfp=1 is much higher.

```
tab lfp wc
```

lfp	wc		Total
	0	1	
0	257	68	325
1	284	144	428
Total	541	212	753

we predict the lfp for two groups: wc=0 and wc=1, and we keep other variables at mean.

```
*use margins for each level of wc
margins wc, atmeans
```

```
Adjusted predictions      Number of obs      =      75
> 3
Model VCE      : OIM

Expression      : Pr(lfp), predict()
at
  : k5           =      .2377158 (mean)
    k618         =      1.353254 (mean)
    age          =      42.53785 (mean)
    lwg          =      1.097115 (mean)
    inc          =      20.12897 (mean)
    0.wc         =      .7184595 (mean)
    1.wc         =      .2815405 (mean)
    0.hc         =      .6082337 (mean)
    1.hc         =      .3917663 (mean)
```

```
> -
      |      Delta-method
      |      Margin      Std. Err.      z    P>|z|      [95% Conf. Interval]
> ]
-----+-----
> -
      |      wc |
> 6   0 |      .5238097      .0241197     21.72   0.000      .4765359      .571083
> 6   1 |      .708165      .0380449     18.61   0.000      .6335984      .782731
> -
```

The result shows that the marginal probability is 0.71 when wc=1 and the marginal probability is 0.52 when wc=0. The probability of participating labor-force is higher when wife has attended college. We can say that wife's college attendance is an important predictor.

We can go deeper on the predictor wc. We predict lfp for group by age and wc. Age is at every 10 years of age from 30 to 60. Since the output of marginal function is long, we make a plot to visualize the output and it is easier to interpret.

```
*use margins for each level of wc and age
margins, at(age=(30(10)60) wc=(0 1)) atmeans vsquish
```



Adjusted predictions                      Number of obs       =       75

> 3  
Model VCE       : OIM

Expression     : Pr(lfp), predict()

1._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	30	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	0	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
2._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	30	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	1	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
3._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	40	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	0	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
4._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	40	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	1	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
5._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	50	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	0	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
6._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	50	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	1	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
7._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	60	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	0	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)
8._at	:	k5	=	.2377158	(mean)
		k618	=	1.353254	(mean)
		age	=	60	
		lwg	=	1.097115	(mean)
		inc	=	20.12897	(mean)
		wc	=	1	
		0.hc	=	.6082337	(mean)
		1.hc	=	.3917663	(mean)

> -

		Delta-method			
	Margin	Std. Err.	z	P> z	[95% Conf. Interval
> ]					

```
> -
```

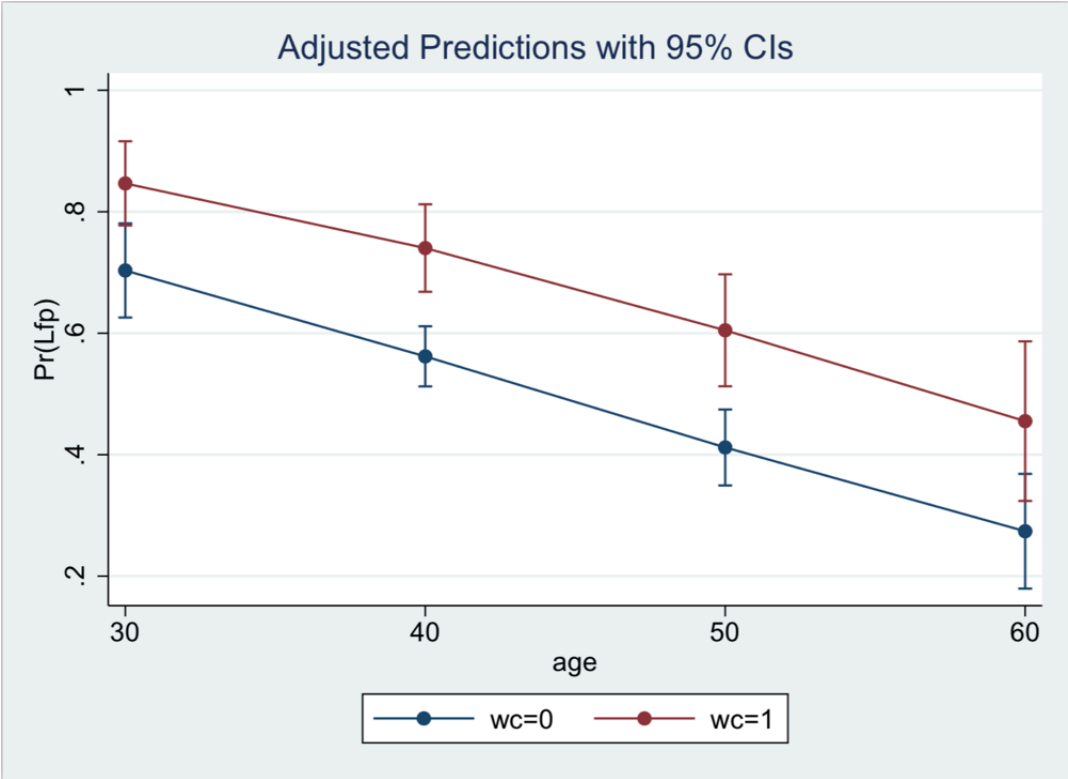
	_at						
> 1	1		.7033095	.0395332	17.79	0.000	.6258258 .780793
> 2	2		.8466704	.0353618	23.94	0.000	.7773626 .915978
> 3	3		.5618684	.0252363	22.26	0.000	.5124062 .611330
> 6	4		.7402195	.0367492	20.14	0.000	.6681924 .812246
> 6	5		.4119518	.0319053	12.91	0.000	.3494185 .474485
> 1	6		.6047985	.0470611	12.85	0.000	.5125605 .697036
> 5	7		.2739992	.048177	5.69	0.000	.1795741 .368424
> 4	8		.4552342	.0670442	6.79	0.000	.32383 .586638

```
> 4
```

---

```
> -
```

marginsplot



From the marginal plot, we can conclude that when age is increasing, the probability is decreasing. Also, The probability of wc=1 is always higher than wx=0. At age 60, the variability is the highest because the 95% confidence interval is the widest.

Group by k5

The table of frequently shows that the proportion of lfp is decreasing when k5 is increasing.

tab lfp k5

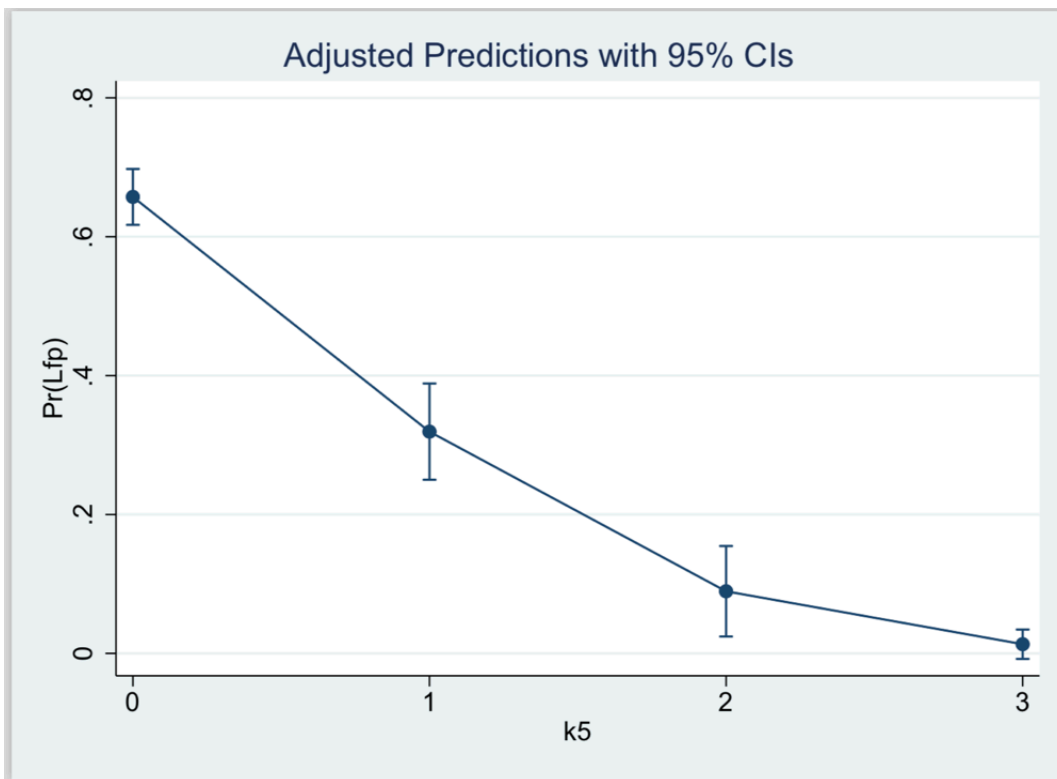


lfp	k5				Total
	0	1	2	3	
0	231	72	19	3	325
1	375	46	7	0	428
Total	606	118	26	3	753

we predict the lfp by k5= 0 1 2 3, and we keep other variables at mean. Also, we make a plot to visualize the data.

```
*use margins for each level of k5
margins, at(k5=(0 1 2 3)) atmeans
```





The output shows that when women do not have any children 5 years old or younger, the probability of participating labor-force is 0.66 which is higher than the average. However, after they had childrens, the probability of participating labor-force is decreasing. Therefore, we can conclude that k5 is a significant predictor.