

**Stata Textbook Examples**  
**Applied Regression Analysis by John Fox**  
**Chapter 15: Beyond Linear Least Squares**

**Section 15.1 Models for Dichotomous Data**

Figure 15.1 on page 440 on data file chile.

```
use http://www.ats.ucla.edu/stat/stata/examples/ara/chile, clear
gen voting=1 if (intvote==1)
replace voting = 0 if (intvote==2)

regress voting statquo
predict y, xb

logistic voting statquo
predict pred, p

ksm voting statquo, lowess gen(kp) bwidth(.4) nograph

sort statquo
graph voting y pred kp statquo, jitter(1) connect(.111) symbol(Oiii)
```

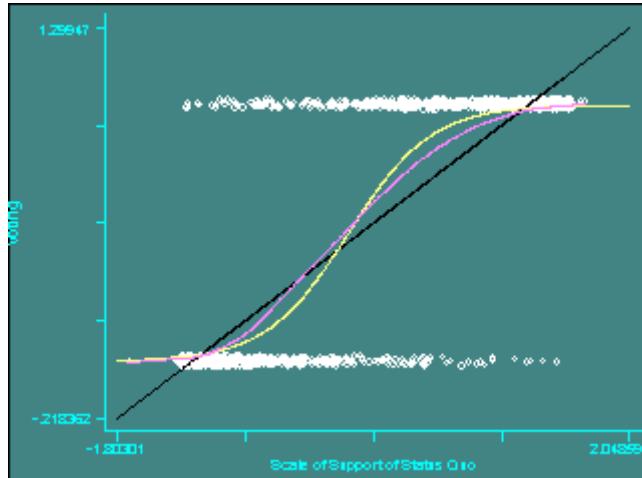


Table 15.1 and 15.2 on page 452 using data file womenlf.

```
use http://www.ats.ucla.edu/stat/stata/examples/ara/womenlf, clear

* Generating a new work status variable and an interaction variable
gen ws = 1 if( workstat==1 | workstat==2)
replace ws=0 if ( workstat==0)
gen ik = husbinc*chilpres

* Contrast between model 1 and 0 is the overall likelihood ratio of
* model 1 and the p-value is the overall Prob > chi2

xi: logistic ws husbinc i.chilpres i.region ik /*model 1 */

(Some output omitted here.)
```

```

Logit estimates                               Number of obs      =
263                                         LR chi2(7)       =
39.61                                       Prob > chi2      =
0.0000                                      Pseudo R2       =
Log likelihood = -158.27076
0.1112

(More output is omitted.)

lrtest, saving(m1)/* saving for further contrast test */

display -2*e(l1) /* displaying deviance */
316.54152

logistic ws /* model 0 */
display -2*e(l1)/* displaying deviance */
356.15089

xi: logistic ws husbinc i.chilpres i.region /* model 2 */
display -2*e(l1)
317.30107

lrtest, saving(m2)
lrtest, using(m1) /* contrast 2-1 */

Logistic: likelihood-ratio test           chi2(1)        =
0.76                                         Prob > chi2 =
0.3835

xi: logistic ws husbinc ik i.chilpres /* model 3 */

display -2*e(l1)
319.12422

lrtest, using(m1)/* constraint 3-1 */

Logistic: likelihood-ratio test           chi2(4)        =
2.58                                         Prob > chi2 =
0.6299

xi: logistic ws husbinc i.region /* model 4 */
display -2*e(l1)
347.84936

lrtest, using(m2)/* contrast 4-2 */

Logistic: likelihood-ratio test           chi2(1)        =
30.55                                         Prob > chi2 =
0.0000

xi: logistic ws i.chilpres i.region /* model 5 */
display -2*e(l1)
322.4267

lrtest, using(m2)/* contrast 5-2 */

```

```

Logistic: likelihood-ratio test          chi2(1)      =
5.13                                     Prob > chi2 =
0.0236

```

Figure 15.4 and formula on page 453. In order to add some text to the graph, we borrowed a program from Stata manual called **addtext** (see page 64 of Stata 6 Graphics Manual).

```
xi: logistic ws i.chilpres husbinc
```

```
i.chilpres          Ichilp_0-1  (naturally coded; Ichilp_0 omitted)
```

Logit estimates	Number of obs	=
263	LR chi2(2)	=
36.42	Prob > chi2	=
0.0000	Pseudo R2	=
Log likelihood = -159.86627		
0.1023		

---

ws	Odds Ratio	Std. Err.	z	P> z	[95% Conf.
Interval]					
-----+-----					
Ichilp_1   .2068734 .0604614	-5.391	0.000	.1166622		
.3668421					
husbinc   .9585741 .0189607	-2.139	0.032	.9221229		
.9964661					

---

```
logit
```

Logit estimates	Number of obs	=
263	LR chi2(2)	=
36.42	Prob > chi2	=
0.0000	Pseudo R2	=
Log likelihood = -159.86627		
0.1023		

---

ws	Coef.	Std. Err.	z	P> z	[95% Conf.
Interval]					
-----+-----					
Ichilp_1   -1.575648 .2922629	-5.391	0.000	-2.148473	-	
1.002824					
husbinc   -.0423084 .0197801	-2.139	0.032	-.0810767	-	
.0035401					
_cons   1.33583 .3837632	3.481	0.000	.5836677		
2.087992					

---

```
predict pw, p
```

```
xi: regress ws i.chilpres husbinc
```

```

i.chilpres           Ichilp_0-1   (naturally coded; Ichilp_0 omitted)

      Source |       SS        df       MS
263
-----+----- Number of obs = 260
20.43
      Model | 8.64321054      2  4.32160527 Prob > F    =
0.0000
      Residual | 55.0069796    260  .211565306 R-squared    =
0.1358
-----+----- Adj R-squared =
0.1291
      Total | 63.6501901    262  .242939657 Root MSE     =
.45996
-----+-----[95% Conf.

      ws |     Coef.    Std. Err.      t    P>|t|
Interval]
-----+-----[95% Conf.

      Ichilp_1 | -.3673736   .061906    -5.934  0.000  -.4892745  -
.2454727
      husbinc | -.0085375   .0039351    -2.170  0.031  -.0162863  -
.0007887
      _cons |  .7936535   .0766814    10.350  0.000  .6426578  -
.9446491
-----+-----[95% Conf.

      predict lw, xb
gen pw1=pw if(chilpres==1)
gen pw2=pw if(chilpres==0)
gen lw1=lw if(chilpres==1)
gen lw2=lw if(chilpres==0)
sort husbinc
graph pw1 pw2 lw1 lw2 husbinc, connect(1111) symbol(iiii)
program define addtext, rclass

      local y1 =.15
      local x1 =10
      local y2 =.75
      local x2 =30

      gph open
      graph
      local ay=r(ay)
      local ax=r(ax)
      local by=r(by)
      local bx=r(bx)
      local r1 = `ay'*`y1' + `by'
      local c1 = `ax'*`x1' + `bx'
      local r2 = `ay'*`y2' + `by'
      local c2 = `ax'*`x2' + `bx'
      gph pen 1
      gph text `r1' `c1' 0 0 Children Present
      gph text `r2' `c2' 0 0 Children Absent
      gph close
end

addtext

```

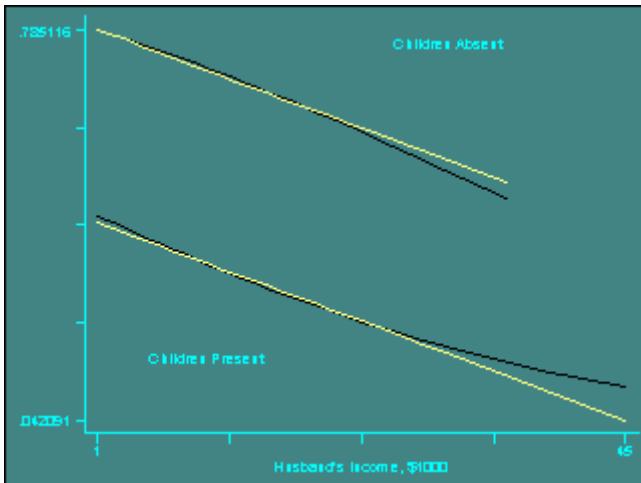


Figure 15.5 on page 459. We can't get the exact lowess smooth as in the book as it needs more than one iterative reweighting steps as there are outliers in the data and Stata's command **ksm** does not have an option on that yet. See the corresponding part of SAS for a better lowess smoothing result.

```
logistic ws chilpres husbinc
predict prob
gen par=(ws-prob)/(prob*(1-prob))-0.0423*husbinc /*creating partial
residual*/
ksm par husbinc, lowess bwidth(0.9) gen(kprob) nog /*lowess smoothing*/
reg par husbinc
predict y
graph kprob y par husbinc, connect(l1.) symbol(iio)
```

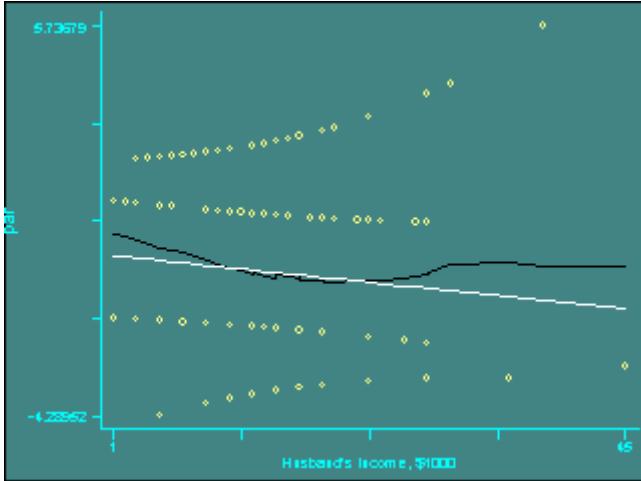


Figure 15.6 on page 461. Notice that in Stata all the diagnostic statistics for logistic regression are adjusted for the number of covariate patterns, so called *m-asymptotic* instead of *n-asymptotic*, i.e., for the number of observations. So we have to do some calculations here in order to get the results in the text book.

```
logistic ws chilpres husbinc
predict yhat /*the predicted value*/
gen pr=(ws-yhat)/sqrt(yhat*(1-yhat)) /* generating Pearson residual on a
case by case basis */
predict myhat, hat
predict pattern, number
egen count=count(obs), by(pattern) /*number of obs sharing a c.p.*/
gen nhat=myhat/count /*hat diagonal on per observation basis*/
gen sr = pr/sqrt(1-nhat)/*studentized pearson residual*/
graph sr nhat, l1(Studentized Residual) ylab(-2(2) 4) yline(-2 0 2) /*
*/ xlabel(0(.01) .06) xline(0.0228 .034) b1("Hat-value") b2(" ")
```

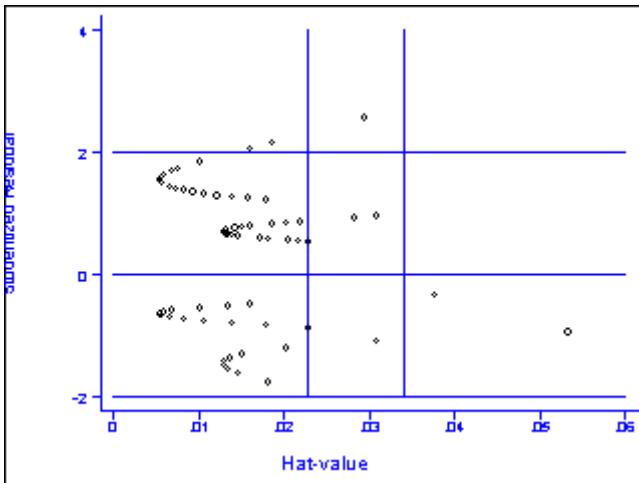
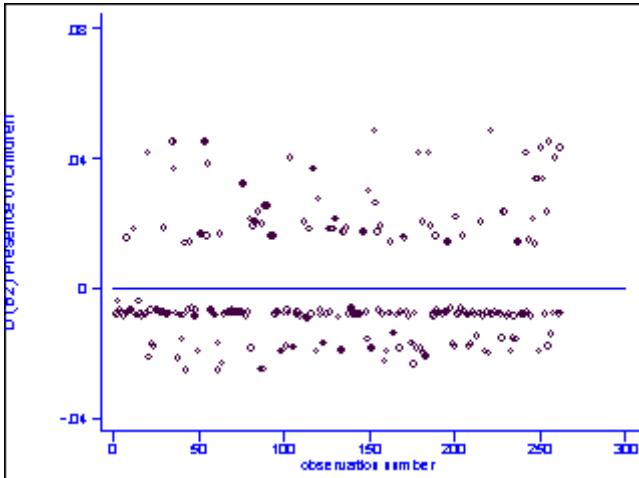
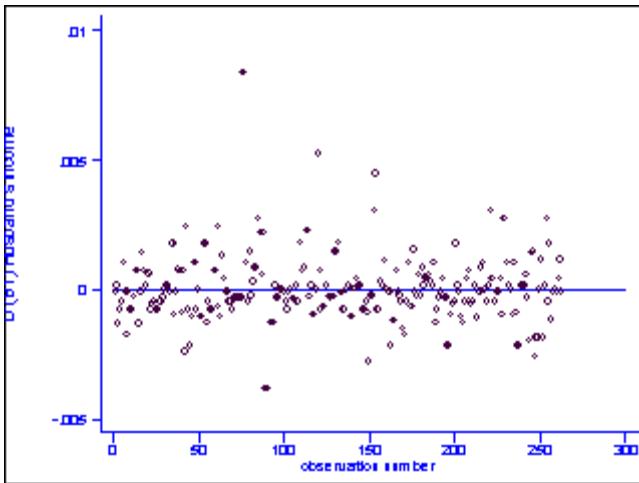


Figure 15.7 (a) and (b) on page 462. Stata does not have built-in command for Dfbeta. We use formula [15.21] to create the required statistics for these figures. This example is continuation of the previous one.

```
gen id=1
set matsize 300
mkmat chilpres husbinc id, matrix(X)
matrix d=e(V)*X'
matrix dt=d'
svmat dt, name(mydf)
gen md1=mydf1*(ws-yhat)/(1-nhat)/*kidDfbeta*/
graph md1 obs, ylab(-0.04(0.04) 0.08) yline(0)11(D*(B2) Presence of
Children)/*
*/xlab(0(50) 300)
```



```
gen md2=mydf2*(ws-yhat)/(1-nhat)/*husbincDfbeta*/
graph md1 obs, ylab(-0.005(0.005) 0.01) yline(0)11(D*(B2) Husband's
Income)/*
*/xlab(0(50) 300)
```



## Section 15.2 Models for Polytomous Data

Calculation and Figure 15.8 on page 468 and 469. We also show how to add text to a graph at the end of this example. Both Figure 15.8 (a) and Figure 15.8 (b) need to run the suitable program **addtext1** to have the text shown.

```
mlogit workstat husbinc chilpre, base(0)
```

```
Iteration 0: log likelihood = -250.24628
Iteration 1: log likelihood = -214.24438
Iteration 2: log likelihood = -211.495
Iteration 3: log likelihood = -211.44102
Iteration 4: log likelihood = -211.44096
```

```
Multinomial regression                               Number of obs     =
263                                                 LR chi2(4)      =
77.61                                              Prob > chi2    =
0.0000                                            Pseudo R2      =
0.1551
```

	Coef.	Std. Err.	z	P> z	[95% Conf.]
<hr/>					
workstat [Interval]					
parttime					
husbinc	.0068921	.0234548	0.294	0.769	-.0390784
.0528627					
chilpres	.0214911	.4690366	0.046	0.963	-.8978037
.940786					
_cons	-1.432307	.5924623	-2.418	0.016	-2.593512
.2711023					-
<hr/>					
fulltime					
husbinc	-.0972307	.0280958	-3.461	0.001	-.1522975
.0421639					-
chilpres	-2.558595	.362199	-7.064	0.000	-3.268492
1.848698					-

_cons		1.982822	.4841771	4.095	0.000	1.033853
2.931792						

---  
---  
(Outcome workstat==not work is the comparison group)

```

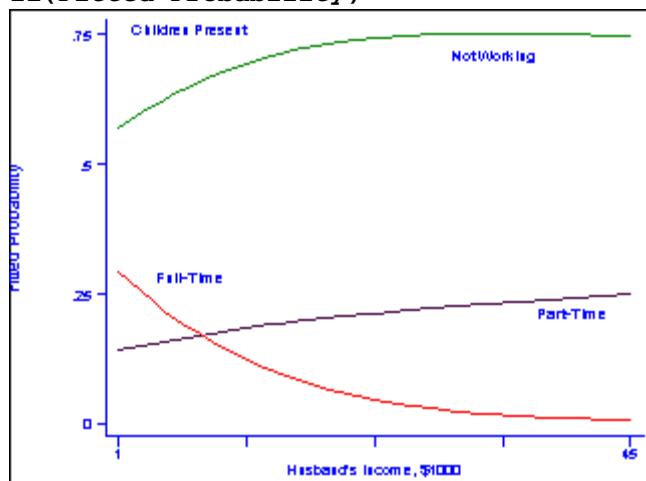
predict p1 if e(sample), outcome(1)
predict p2 if e(sample), outcome(2)
predict p0 if e(sample), outcome(0)
gen kp1=p1 if(chilpres==0)
gen knp1=p1 if (chilpres ==1)
gen kp2=p2 if(chilpres==0)
gen knp2=p2 if(chilpres==1)
gen kp0=p0 if(chilpres==0)
gen knp0 =p0 if(chilpres==1)
sort husbinc

```

```

graph knp1 knp2 knp0 husbinc, connect(l1l) symbol(iii) ylab(0(.25) .75)
l1(Fitted Probability)

```



```

graph kp2 kp1 kp0 husbinc, connect(l1l) symbol(iii) l1(Fitted Probability)
ylab(0(.25) 1)

```

```

program define addtext1, rclass
    local y1 =1
    local x1 =5
    local y2 =.75
    local x2 =12
    local y3 =.65
    local x3 =30
    local y4 =0.15
    local x4=20

    gph open
    graph
    local ay=r(ay)
    local ax=r(ax)
    local by=r(by)
    local bx=r(bx)

    local r1 = `ay'*`y1' + `by'
    local c1 = `ax'*`x1' + `bx'
    local r2 = `ay'*`y2' + `by'
    local c2 = `ax'*`x2' + `bx'
    local r3 = `ay'*`y3' + `by'
    local c3 = `ax'*`x3' + `bx'

```

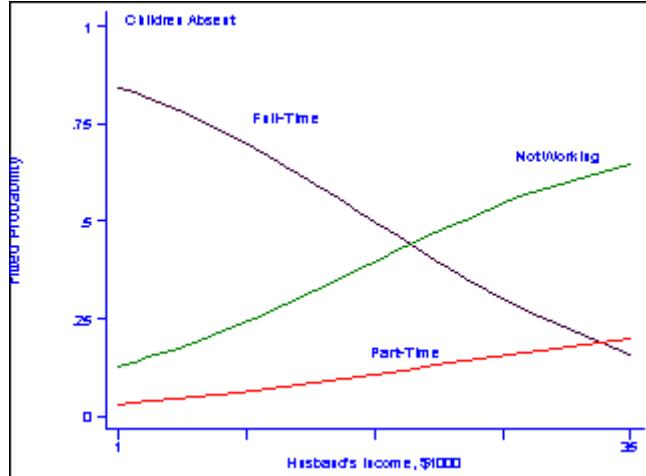
```

        local r4 = `ay'*`y4' + `by'
        local c4 = `ax'*`x4' + `bx'

        gph pen 1
        gph text `r1' `c1' 0 0 Children Absent
        gph text `r2' `c2' 0 0 Full-Time
        gph text `r3' `c3' 0 0 Not Working
        gph text `r4' `c4' 0 0 Part-Time
        gph close
end

```

### addtext1



Calculation on page 473.

```

gen wk=(workstat==0)
logistic wk husbinc chilpres

```

Logit estimates	Number of obs	=		
263	LR chi2(2)	=		
36.42	Prob > chi2	=		
0.0000	Pseudo R2	=		
Log likelihood = -159.86627				
0.1023				
<hr/>				
---				
wk   Odds Ratio	Std. Err.	z	P> z	[95% Conf.
Interval]				
<hr/>				
---				
husbinc   1.043216	.0206349	2.139	0.032	1.003546
1.084454				
chilpres   4.833875	1.412762	5.391	0.000	2.725968
8.57176				
<hr/>				
---				
<b>logit</b>				
Logit estimates	Number of obs	=		
263	LR chi2(2)	=		
36.42	Prob > chi2	=		
0.0000				

```

Log likelihood = -159.86627                         Pseudo R2      =
0.1023

-----
---  

      wk |      Coef.    Std. Err.          z      P>|z|      [95% Conf.  

Interval]  
-----+-----  
---  

husbinc |   .0423084   .0197801      2.139    0.032     .0035401  
.0810767  
chilpres |   1.575648   .2922629      5.391    0.000     1.002824  
2.148473  
  _cons |  -1.33583   .3837632     -3.481    0.000    -2.087992    -  
.5836677  
-----  
---  
lrtest, saving(0)  
logistic wk chilpres

Logit estimates                               Number of obs  =
263                                         LR chi2(1)      =
31.59                                         Prob > chi2    =
0.0000                                         Pseudo R2      =
Log likelihood = -162.27945
0.0887

-----
---  

      wk | Odds Ratio    Std. Err.          z      P>|z|      [95% Conf.  

Interval]  
-----+-----  
---  

chilpres |   4.781119   1.379609      5.422    0.000     2.71589  
8.416797  
-----  
---  
  
lrtest /*test on the bottom of page 473*/  
  
Logistic: likelihood-ratio test           chi2(1)      =
4.83                                         Prob > chi2    =
0.0280  
  
gen ptime=.  
replace ptime = 0 if (workstat==1)  
replace ptime=1 if(workstat==2)  
logistic ptime husbinc chilpres  
  
Logit estimates                               Number of obs  =
108                                         LR chi2(2)      =
39.85                                         Prob > chi2    =
0.0000                                         Pseudo R2      =
Log likelihood = -52.247423
0.2761

```

```

-----
---  

      ptime | Odds Ratio   Std. Err.          z      P>|z|      [95% Conf.  

Interval]  

-----+-----  

---  

husbinc |     .898285   .0351699    -2.740    0.006     .8319318  

.9699305  

chilpres |     .0705484   .0381719    -4.900    0.000     .0244301  

.2037278  

-----  

---  

logit  

Logit estimates                               Number of obs =  

108  

LR chi2(2) =  

39.85  

Prob > chi2 =  

0.0000  

Log likelihood = -52.247423  

Pseudo R2 =  

0.2761  

-----  

---  

      ptime |      Coef.   Std. Err.          z      P>|z|      [95% Conf.  

Interval]  

-----+-----  

---  

husbinc |   -.1072679   .0391522    -2.740    0.006    -.1840048    -  

.0305309  

chilpres |   -2.651456   .5410738    -4.900    0.000    -3.711941    -  

1.59097  

_cons |    3.477773   .7671069     4.534    0.000     1.974272  

4.981275  

-----  

---  

lrtest, saving(p1)  

logistic ptime chilpres  

Logit estimates                               Number of obs =  

108  

LR chi2(1) =  

30.87  

Prob > chi2 =  

0.0000  

Log likelihood = -56.738094  

Pseudo R2 =  

0.2138  

-----  

---  

      ptime | Odds Ratio   Std. Err.          z      P>|z|      [95% Conf.  

Interval]  

-----+-----  

---  

chilpres |     .0869565   .04288    -4.953    0.000     .0330794  

.2285846  

-----  

---
```

```

lrtest, using(p1)/*test on the top of page 474*/
Logistic: likelihood-ratio test                         chi2(1)      =
8.98                                         Prob > chi2 =
0.0027
Calculation on page 477.
xi: ologit workstat husbinc i.chilpres

i.chilpres          Ichilp_0-1  (naturally coded; Ichilp_0 omitted)

Iteration 0:  log likelihood = -250.24628
Iteration 1:  log likelihood = -221.36758
Iteration 2:  log likelihood = -220.83242
Iteration 3:  log likelihood = -220.83148

Ordered logit estimates                               Number of obs  =
263                                         LR chi2(2)      =
58.83                                         Prob > chi2 =
0.0000                                         Pseudo R2      =
0.1175

-----
---  

workstat |      Coef.    Std. Err.      z     P>|z|      [95% Conf.  

Interval]  

-----+-----  

---  

husbinc |  -.0539007   .01949    -2.766    0.006    -.0921004    -  

.0157009  

Ichilp_1 |  -1.971957   .2869478    -6.872    0.000    -2.534364    -  

1.40955  

-----+-----  

---  

 _cut1 |  -1.852037   .3862995           (Ancillary parameters)  

 _cut2 |  -.9409253   .3699303
-----  

---
```

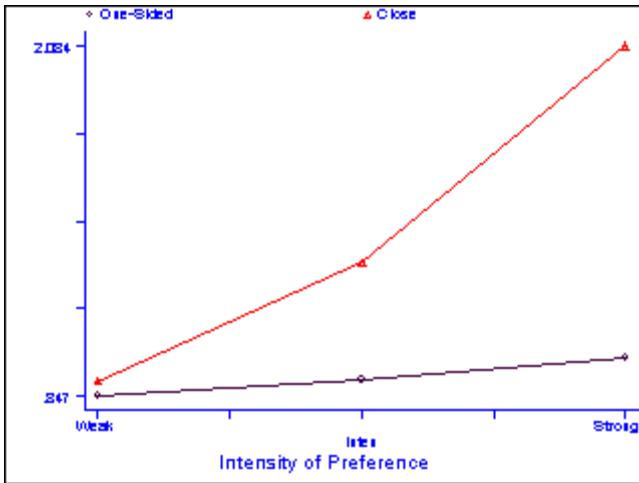
### Section 15.3 Discrete Independent Variables and Contingency Tables

The analysis in this section is based on Table 15.3, which is based on data from an example from **The American Voter** (Campbell, et al., 1960). The first data set we create here is based on Table 15.3 for Figure 15.3.

```

input logvl logvc inten
.847  .9    0
.904  1.318 1
.981  2.084 2
end
label define scale 0 Weak 1 Medium 2 Strong
label values inten scale
label variable logvl "One-Sided"
label variable logvc "Close"
graph logvl logvc inten, connect(l1) b1(Intensity of Preference)

```



Now we create another data set below to do the logistic regression and tests over different models. Thus we will have Table 15.4 and Table 15.5 on page 482.

```

input perclos inten1 inten2 voted wv
0 0 0 1 91
0 0 0 0 39
0 1 0 1 121
0 1 0 0 49
0 0 1 1 64
0 0 1 0 24
1 0 0 1 214
1 0 0 0 87
1 1 0 1 284
1 1 0 0 76
1 0 1 1 201
1 0 1 0 25
end

gen clspref1=perclos*inten1
gen clspref2=perclos*inten2

logistic voted perclos inten1 inten2 clspref1 clspref2 [fweight=wv]
(Output omitted.)

di -2*e(l1)/*deviance for model 1*/
1356.4343

lrtest, saving(t1)
logistic voted perclos inten1 inten2 [fweight=wv]
(Output omitted.)

di -2*e(l1) /*model 2*/
1363.5529

lrtest, saving(t2)
lrtest, using(t1)/*contrast 2-1*/

Logistic: likelihood-ratio test          chi2( 2)      =
7.12                                     Prob > chi2 =
0.0285

logistic voted perclos clspref1 clspref2 [fweight=wv]
(Output omitted.)

. di -2*e(l1) /*model 3 */

```

