

```

1 . set linesize 80

2 . set seed 1010101

3 . set matsize 11000

4 .
5 .
6 . *****
7 .
8 . *   This script requires pre-installation of spost2 by J. Scott Long for fit
   > stat command
9 . *   It also requires installation of title2.ado, title3.ado
10 . *
11 . *       for the fitstat command to function
12 . *****
13 . di "$User"
    Robert Alan Yaffee

14 . * 16 June 2012
15 .
16 . *----- Primary objective: Hypothesis 1 tests for Part 2 of Nottingham hea
   > lth profile
17 .
18 . ***** Hypothesis tests      Robert A. Yaffee      10 June 2012 main effec
   > ts and moderator identification approach
19 . * protocol is to test Health profile subscales against potential confounder
   > s including socio-demog vars,
20 . *       major neg life events, stresses and hassles, social supports, perceive
   > d health, distance,
21 . *       threat and dose to see whether there is a dose-psych response
22 .
23 . * We construct a full model, trimmed model (at .1 level), and then test int
   > eractions with dose if there is a
24 . *       significant main effect dose psych response
25 .

```

```

26 . *      Trimming is performed with backward elimination to the .1 level
27 . *
28 . *      This approach identifies the moderating variables for our path analysis.
    >      We analyze our
29 . *      final models for congruence with regression assumptions with the rdiag
    >      program for a validity assessment
30 .
31 . *-----
    > -----
32 .
33 . *----- Organization of the program -----
    > -----
34 . *      main effects regresssions are run for all part 1 health profile subscales
    >      except that of emotional
35 . *      reaction for both males and females separately
36 . *      these models are trimmed with backward elimination to determine whether t
    >      he main effect of avg cumulative dose
37 . *      is significant for that wave
38 . *      If the main effect of average cumulative dose for that wave is not stati
    >      stically significant with the
39 . *      covariates controlled we do not go further along that path
40 . *      If the main effect of average cumulative dose for that wave is statistic
    >      ally significant, we trim the
41 . *      model to a p = .1
42 . *      If average cumulative dose is not significant, we stop
43 . *      If average cumulative dose is significant we perform a hierarchical regr
    >      ession with interactions between dose
44 . *      and other significant main effects
45 . *      We proceed to test for mediating effects of those other significant expl
    >      anatory variable
46 . *      We evaluate the model for statistical congenuity.
47 . *      This concludes the test of part 1 of H1
48 . ***-----
    > -----
49 .
50 . * Part 2 Nottingham subscales
51 . *      1: hp2work

```



```

68 .
69 . cd /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests/h1
    > pt2
    /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests/h1pt2

70 . use chwid1jul2012, clear
    (Zero for missing on all icdx)

71 . cd /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests/h1
    > pt2
    /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests/h1pt2

72 .
73 .
74 . di "{hline}"


---



75 . di "{hline}"


---



76 .
77 . title "Chunk 1 Hyp 1: radiation dose and Nottingham Health profile subscales"

*****
> *
*****
> *
***** *****
> *
***** *****
> *
*****Chunk 1 Hyp 1: radiation dose and Nottingham Health profile subscales *****
> *
***** *****
> *
***** *****
> *
***** 1 Jul 2012 14:58:43 *****
> *
*****
> *
*****
> *

```

```

78 .
79 .
80 . // there is substantial intercorrelation among the items warranting a
81 . // multivariate regression model
82 . cap dummies educ

83 . cap order educ1-educ8, after(educ)

84 .
85 . * These variables are substantially correlated
86 . pwcorr HP2work HP2hmcare HP2probsoc HP2pbfhm HP2sxlife HP2inthob HP2vacatn,
    > ///
    >     obs sig

```

	HP2work	HP2hmc~e	HP2pro~c	HP2pbfhm	HP2sxl~e	HP2int~b	HP2vac~n
HP2work	1.0000						
	703						
HP2hmcare	0.4878	1.0000					
	0.0000						
	703	703					
HP2probsoc	0.4587	0.5420	1.0000				
	0.0000	0.0000					
	703	703	703				
HP2pbfhm	0.2832	0.4150	0.4745	1.0000			
	0.0000	0.0000	0.0000				
	703	703	703	703			
HP2sxlife	0.4968	0.4576	0.5589	0.4192	1.0000		
	0.0000	0.0000	0.0000	0.0000			
	703	703	703	703	703		
HP2inthob	0.3787	0.4757	0.5956	0.5089	0.5401	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0000		
	703	703	703	703	703	703	
HP2vacatn	0.4166	0.4757	0.5956	0.4416	0.5211	0.6840	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
	703	703	703	703	703	703	703


```
100 . set more off
```

```
101 . foreach var in HP2work HP2hmcare HP2probsoc HP2pbfhm HP2sxlife HP2inthob ///
>     HP2vacatn {
2.     forvalues k=2/2 {
3.     logit `var' avgcumdosew2 if gender==`k', nolog
4.     eststo w2`var'dose
5.     }
6. }
```

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(1)      =           6.63
                                                    Prob > chi2     =          0.0100
Log likelihood = -203.24758                        Pseudo R2       =          0.0160
```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.2046594	.0826501	2.48	0.013	.0426681	.3666507
_cons	-1.260388	.1448325	-8.70	0.000	-1.544255	-.9765218

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(1)      =           0.01
                                                    Prob > chi2     =          0.9082
Log likelihood = -233.72194                        Pseudo R2       =          0.0000
```

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0093108	.0810645	-0.11	0.909	-.1681944	.1495727
_cons	-.6356448	.13193	-4.82	0.000	-.8942228	-.3770668

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(1)      =          25.69
                                                    Prob > chi2     =          0.0000
Log likelihood = -170.72516                        Pseudo R2       =          0.0700
```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5024747	.1391198	3.61	0.000	.229805	.7751444
_cons	-1.841993	.1807682	-10.19	0.000	-2.196292	-1.487694

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	1.97
	Prob > chi2	=	0.1602
Log likelihood = -138.91068	Pseudo R2	=	0.0070

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1290516	.0853896	1.51	0.131	-.0383089	.2964121
_cons	-2.03386	.1824844	-11.15	0.000	-2.391523	-1.676197

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	13.99
	Prob > chi2	=	0.0002
Log likelihood = -200.62862	Pseudo R2	=	0.0337

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.3220323	.1022608	3.15	0.002	.1216048	.5224598
_cons	-1.353229	.1520692	-8.90	0.000	-1.65128	-1.055179

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	5.33
	Prob > chi2	=	0.0210
Log likelihood = -169.44834	Pseudo R2	=	0.0155

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1881347	.0796521	2.36	0.018	.0320195	.34425
_cons	-1.691176	.1610367	-10.50	0.000	-2.006802	-1.37555

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	4.26
	Prob > chi2	=	0.0389
Log likelihood = -165.38435	Pseudo R2	=	0.0127

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1706012	.0795148	2.15	0.032	.0147551	.3264474
_cons	-1.730143	.1632828	-10.60	0.000	-2.050172	-1.410115

```

102 .
103 .
104 . *----- estout code snippt
105 .
106 . estout *,      cells(b(star fmt(%9.3f)) se(par) t p)          ///
>      stats( bic N, fmt(%9.3f %9.0g) )          ///
>      legend collabels(none) varlabels(_cons Constant)  ///
>      mlabels(workw2  homecarew2 socprobsw2 pbfhwm2 sexlifew2 inth
> obw2 vactnw2) ///
>      title("Zero-order regression coefficients" /
> //
>      "of reconstructed dose for females in wave 2")

```

Zero-order regression coefficients of reconstructed dose for females in wave 2

```

> -----
>      workw2      homecarew2      socprobsw2      pbfhwm2
>      sexlifew2      inthobw2      vactnw2
> -----
main
>
avgcumdosew2      0.205*      -0.009      0.502***      0.129
>      0.322**      0.188*      0.171*
>      (0.083)      (0.081)      (0.139)      (0.085)
>      (0.102)      (0.080)      (0.080)
>      2.476      -0.115      3.612      1.511
>      3.149      2.362      2.146
>      0.013      0.909      0.000      0.131
>      0.002      0.018      0.032
Constant      -1.260***      -0.636***      -1.842***      -2.034***
>      -1.353***      -1.691***      -1.730***
>      (0.145)      (0.132)      (0.181)      (0.182)
>      (0.152)      (0.161)      (0.163)
>      -8.702      -4.818      -10.190      -11.145
>      -8.899      -10.502      -10.596
>      0.000      0.000      0.000      0.000
>      0.000      0.000      0.000
> -----
bic      418.284      479.233      353.239      289.610
>      413.046      350.685      342.558
N      363      363      363      363
>      363      363      363
> -----
>
* p<0.05, ** p<0.01, *** p<0.001

```

```

107 .
108 .
109 .
110 .
111 . // signif zero order relationships in wave 2 are
112 .
113 . // female work social life sex life interest and hobbies vacation plans
114 . // no significant male zero order effects
115 .
116 .
117 .
118 . local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40

119 . local w2bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

120 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0

121 .
122 . *-----
    > ----
123 . * Hypothesis 1 Part 2 wave 2 tests male and female
124 . * endogeneous Nottingham pt 2 subscales: HP2work HP2hmcare HP2probsoc HP2pbfh
    > m ///
    > *
                                HP2sxlife HP2inthob HP2vacatn
125 . * structure of models
126 . * 1. general models on all Pt 2 subscales with all potential confounders
127 . * 2. trimmed models on all Pt 2 subscales with from all potential confoun
    > ders
128 . * 3. from trimmed models examination of possible moderator variables
129 . * 4. from trimmed models examination of possible mediator variables
130 . * 5. Summary analysis and model evaluation of final models only
131 . * program is divided into 8 chunks one a general model and 1 for each
132 . * endogenous variable
133 . *-----
    > ----
134 . * Chunk 1 General models for all part 2 of Nottingham Health Profile

```



```

140 . di as input "Full main model for `var' for wave= `j' "
      8. di _skip(4)
      9. di as input "chunk 2 H1 test:Gender= `k' model Wave = `j' for `e(depva
> r)' "
      10. di _skip(4)
      11.
141 .      xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
>          marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
> //
>          radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>          deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>          illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
> chrw`j' ///
>          havmilsq if gender==`k', coef nolog difficult iterate(50)
      12.          estat class
      13.          estat gof
      14.          fitstat
      15. }
      16. }
      17. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996

inc4w2	double %15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float %9.0g		bf1 = max(0, kzchorn - 40)
bf4	float %9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float %9.0g		bf9= max(0, 30 - shhlw1)
bf11	float %9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float %9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float %9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float %9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float %9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2work for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2vacatn

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
 _Ieduc_4 dropped and 13 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly
 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
 _Ieduc_8 dropped and 2 obs not used

note: bf17 != 0 predicts failure perfectly
 bf17 dropped and 5 obs not used

note: sepaw2 != 0 predicts failure perfectly
 sepaw2 dropped and 6 obs not used

note: _Ieduc_6 omitted because of collinearity

Logistic regression	Number of obs	=	308
	LR chi2(49)	=	125.45
	Prob > chi2	=	0.0000
Log likelihood = -101.11616	Pseudo R2	=	0.3828

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0178547	.02477	0.72	0.471	-.0306936	.066403
_Ieduc_2	.9615826	1.161557	0.83	0.408	-1.315028	3.238193
_Ieduc_3	.1912036	.4980888	0.38	0.701	-.7850324	1.16744
_Ieduc_4	0	(omitted)				
_Ieduc_5	.2718345	.6506078	0.42	0.676	-1.003333	1.547002
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-1.858647	2.691228	-0.69	0.490	-7.133356	3.416062
occ2w2	-.9190027	2.701749	-0.34	0.734	-6.214333	4.376327
occ3w2	-1.367634	2.744529	-0.50	0.618	-6.746813	4.011544
occ4w2	-1.016435	2.721494	-0.37	0.709	-6.350464	4.317595
occ5w2	-.5999128	2.751196	-0.22	0.827	-5.992157	4.792331
occ6w2	-.5670745	3.449094	-0.16	0.869	-7.327174	6.193025
occ7w2	2.144137	2.835688	0.76	0.450	-3.413709	7.701983
occ8w2	-2.120696	2.805072	-0.76	0.450	-7.618536	3.377144
marrw21	14.38867	1053.846	0.01	0.989	-2051.112	2079.889
marrw22	16.49882	1053.847	0.02	0.988	-2049.002	2082
marrw23	12.83702	1053.846	0.01	0.990	-2052.664	2078.338
marrw25	16.98709	1053.848	0.02	0.987	-2048.516	2082.49
marrw26	10.7478	1053.85	0.01	0.992	-2054.761	2076.257
inc1w2	-1.841061	2.889059	-0.64	0.524	-7.503512	3.82139
inc2w2	-.6970371	2.730495	-0.26	0.799	-6.048709	4.654635
inc3w2	.9384724	2.718417	0.35	0.730	-4.389527	6.266472
inc4w2	-.858635	3.109771	-0.28	0.782	-6.953674	5.236404
radhlw2	.0018692	.0077721	0.24	0.810	-.0133638	.0171022
havmil	.0022022	.0068548	0.32	0.748	-.0112329	.0156372
avgcumdosew2	.070113	.0753046	0.93	0.352	-.0774813	.2177072
bf1	-.0449847	.0685219	-0.66	0.512	-.179285	.0893157
bf4	-.1461292	.1896969	-0.77	0.441	-.5179284	.2256699
bf2	.0001003	.000156	0.64	0.520	-.0002054	.000406
bf4m	-.1398009	.1731245	-0.81	0.419	-.4791186	.1995169
bf5m	.0035939	.0017506	2.05	0.040	.0001629	.0070249
bf7m	.0007449	.0005463	1.36	0.173	-.0003258	.0018155
bf8	-.0001778	.0000525	-3.39	0.001	-.0002807	-.000075
bf15m	.0003329	.0002956	1.13	0.260	-.0002465	.0009123
bf17	0	(omitted)				
bf20	.0339605	.0629951	0.54	0.590	-.0895076	.1574286
bf22	.0001355	.0001659	0.82	0.414	-.0001898	.0004607
bf29	.0000158	.0000126	1.26	0.209	-8.86e-06	.0000405
bf30	-.0008498	.0004225	-2.01	0.044	-.001678	-.0000217
bf40	.2709577	.2293641	1.18	0.237	-.1785876	.720503
deaw2	-.1725628	.3614849	-0.48	0.633	-.8810602	.5359345
dvcew2	.1194741	2.327974	0.05	0.959	-4.44327	4.682218
sepaw2	0	(omitted)				
accdw2	.5158656	.4604363	1.12	0.263	-.3865729	1.418304

movew2	.5486063	.5239018	1.05	0.295	-.4782225	1.575435
illw2	-.3094309	.3968427	-0.78	0.436	-1.087228	.4683664
shfamw2	.0096065	.0075095	1.28	0.201	-.0051119	.0243249
shhlw2	.025216	.0096203	2.62	0.009	.0063606	.0440714
shjobw2	-.0077587	.0087746	-0.88	0.377	-.0249567	.0094392
shrelaw2	-.0309717	.0089502	-3.46	0.001	-.0485137	-.0134296
suprtw2	-.0064843	.0062583	-1.04	0.300	-.0187504	.0057818
suchrw2	.0039898	.0060514	0.66	0.510	-.0078708	.0158504
havmilsq	-3.35e-06	.0000119	-0.28	0.779	-.0000267	.00002
_cons	-13.33296	1053.852	-0.01	0.990	-2078.845	2052.179

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	39	14	53
-	30	225	255
Total	69	239	308

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	56.52%
Specificity	$\Pr(- \sim D)$	94.14%
Positive predictive value	$\Pr(D +)$	73.58%
Negative predictive value	$\Pr(\sim D -)$	88.24%

False + rate for true ~D	$\Pr(+ \sim D)$	5.86%
False - rate for true D	$\Pr(- D)$	43.48%
False + rate for classified +	$\Pr(\sim D +)$	26.42%
False - rate for classified -	$\Pr(D -)$	11.76%

Correctly classified	85.71%
----------------------	--------

Logistic model for HP2work, goodness-of-fit test

number of observations =	308
number of covariate patterns =	308
Pearson $\chi^2(258)$ =	291.84
Prob > χ^2 =	0.0724

Measures of Fit for **logistic** of **HP2work**

Log-Lik Intercept Only:	-163.843	Log-Lik Full Model:	-101.116
D(252):	202.232	LR(49):	125.453
		Prob > LR:	0.000
McFadden's R2:	0.383	McFadden's Adj R2:	0.041
Maximum Likelihood R2:	0.335	Cragg & Uhler's R2:	0.511
McKelvey and Zavoina's R2:	0.690	Efron's R2:	0.405
Variance of y*:	10.621	Variance of error:	3.290
Count R2:	0.857	Adj Count R2:	0.362
AIC:	1.020	AIC*n:	314.232
BIC:	-1241.753	BIC':	155.322

Full main model for HP2work for wave= 2

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2work

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 12 obs not used

note: sepaw2 != 0 predicts failure perfectly
 sepaw2 dropped and 7 obs not used

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	343
	LR chi2(50)	=	108.12
	Prob > chi2	=	0.0000
Log likelihood = -145.38882	Pseudo R2	=	0.2710

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0346814	.0173019	2.00	0.045	.0007704	.0685925
_Ieduc_2	-12.41086	627.6909	-0.02	0.984	-1242.662	1217.841
_Ieduc_3	-12.75017	627.6907	-0.02	0.984	-1243.001	1217.501
_Ieduc_4	-11.4477	627.6909	-0.02	0.985	-1241.699	1218.804
_Ieduc_5	-12.87307	627.6909	-0.02	0.984	-1243.125	1217.378
_Ieduc_6	-12.46967	627.6908	-0.02	0.984	-1242.721	1217.782
_Ieduc_7	-13.03665	627.6932	-0.02	0.983	-1243.293	1217.219
_Ieduc_8	0	(omitted)				
occ1w2	-1.438425	1.492752	-0.96	0.335	-4.364164	1.487314
occ2w2	-1.219105	1.521371	-0.80	0.423	-4.200936	1.762727
occ3w2	-.4904819	1.510651	-0.32	0.745	-3.451303	2.470339
occ4w2	-.7947689	1.589999	-0.50	0.617	-3.911109	2.321571
occ5w2	-1.879935	1.884007	-1.00	0.318	-5.572521	1.812651
occ6w2	-1.41539	1.738012	-0.81	0.415	-4.82183	1.991051
occ7w2	-.4577922	1.461285	-0.31	0.754	-3.321858	2.406274
occ8w2	.0350208	1.713285	0.02	0.984	-3.322957	3.392998

marrw21	-1.099109	1.06403	-1.03	0.302	-3.18457	.9863517
marrw22	-.6975171	1.30484	-0.53	0.593	-3.254956	1.859922
marrw23	-.3956567	.7323121	-0.54	0.589	-1.830962	1.039649
marrw25	-.7188967	1.177006	-0.61	0.541	-3.025787	1.587994
marrw26	0	(omitted)				
inclw2	-.0941374	1.513476	-0.06	0.950	-3.060495	2.872221
inc2w2	.386998	1.46305	0.26	0.791	-2.480528	3.254524
inc3w2	1.121465	1.474278	0.76	0.447	-1.768066	4.010997
inc4w2	-.1060071	1.96548	-0.05	0.957	-3.958277	3.746263
radhlw2	.0065443	.006673	0.98	0.327	-.0065345	.0196232
havmil	-.0029953	.0026107	-1.15	0.251	-.0081121	.0021215
avgcumdosew2	.0909294	.1016445	0.89	0.371	-.1082903	.290149
bf1	.0126789	.0317569	0.40	0.690	-.0495634	.0749212
bf4	-.5949349	.2433538	-2.44	0.014	-1.0719	-.1179702
bf2	.0000735	.0001079	0.68	0.496	-.000138	.0002851
bf4m	.4176215	.2303793	1.81	0.070	-.0339136	.8691567
bf5m	.0024297	.0013344	1.82	0.069	-.0001856	.0050451
bf7m	.0006992	.000527	1.33	0.185	-.0003337	.0017321
bf8	-.0000458	.0000327	-1.40	0.161	-.0001099	.0000182
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0183297	.0268984	-0.68	0.496	-.0710496	.0343903
bf22	-.0000828	.0001199	-0.69	0.490	-.0003178	.0001523
bf29	.0000183	.0000373	0.49	0.624	-.0000549	.0000915
bf30	-.0001261	.0002961	-0.43	0.670	-.0007064	.0004542
bf40	.1798311	.1314097	1.37	0.171	-.0777271	.4373893
deaw2	.2386669	.2047617	1.17	0.244	-.1626586	.6399924
dvcew2	-.6260314	1.520804	-0.41	0.681	-3.606752	2.354689
sepaw2	0	(omitted)				
accdw2	.6391808	.5174116	1.24	0.217	-.3749273	1.653289
movew2	-.2794343	.5405557	-0.52	0.605	-1.338904	.7800355
illw2	.0571776	.1835422	0.31	0.755	-.3025585	.4169137
shfamw2	-.007536	.0064071	-1.18	0.240	-.0200936	.0050216
shhlw2	.0061348	.0064298	0.95	0.340	-.0064673	.0187369
shjobw2	-.0013978	.005787	-0.24	0.809	-.0127401	.0099444
shrelaw2	-.0084778	.0068136	-1.24	0.213	-.0218322	.0048765
suprtw2	-.0040427	.0050205	-0.81	0.421	-.0138827	.0057973
suchrw2	.0071509	.0055885	1.28	0.201	-.0038025	.0181042
havmilsq	5.93e-07	1.54e-06	0.38	0.701	-2.43e-06	3.62e-06
_cons	8.163054	627.6961	0.01	0.990	-1222.099	1238.425

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	46	16	62
-	46	235	281
Total	92	251	343

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	50.00%
Specificity	$\Pr(- \sim D)$	93.63%
Positive predictive value	$\Pr(D +)$	74.19%
Negative predictive value	$\Pr(\sim D -)$	83.63%
False + rate for true ~D	$\Pr(+ \sim D)$	6.37%
False - rate for true D	$\Pr(- D)$	50.00%
False + rate for classified +	$\Pr(\sim D +)$	25.81%
False - rate for classified -	$\Pr(D -)$	16.37%
Correctly classified		81.92%

Logistic model for HP2work, goodness-of-fit test

```

      number of observations =      343
number of covariate patterns =      343
      Pearson chi2(292) =      491.86
          Prob > chi2 =      0.0000

```

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-199.448	Log-Lik Full Model:	-145.389
D(287):	290.778	LR(50):	108.119
		Prob > LR:	0.000
McFadden's R2:	0.271	McFadden's Adj R2:	-0.010
Maximum Likelihood R2:	0.270	Cragg & Uhler's R2:	0.393
McKelvey and Zavoina's R2:	0.502	Efron's R2:	0.313
Variance of y*:	6.601	Variance of error:	3.290
Count R2:	0.819	Adj Count R2:	0.326
AIC:	1.174	AIC*n:	402.778
BIC:	-1384.651	BIC':	183.768

Full main model for HP2hmcare for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2work

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
_Ieduc_4 dropped and 13 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
_Ieduc_8 dropped and 2 obs not used

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 44 obs not used

note: bf17 != 0 predicts failure perfectly
bf17 dropped and 3 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 6 obs not used

note: _Ieduc_7 omitted because of collinearity

Logistic regression	Number of obs	=	270
	LR chi2(49)	=	112.39
	Prob > chi2	=	0.0000
Log likelihood = -98.319474	Pseudo R2	=	0.3637

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0339056	.0231493	1.46	0.143	-.0114661	.0792774
_Ieduc_2	-4.046801	2.06481	-1.96	0.050	-8.093754	.0001521
_Ieduc_3	-2.332961	1.654719	-1.41	0.159	-5.576151	.9102284
_Ieduc_4	0	(omitted)				
_Ieduc_5	-2.109138	1.662617	-1.27	0.205	-5.367807	1.149531
_Ieduc_6	-2.575578	1.598895	-1.61	0.107	-5.709355	.5581988
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occlw2	.2791915	3.076664	0.09	0.928	-5.750959	6.309342
occ2w2	-.2043325	3.082144	-0.07	0.947	-6.245223	5.836559
occ3w2	.5280791	3.097215	0.17	0.865	-5.542352	6.59851
occ4w2	.3530379	3.103258	0.11	0.909	-5.729235	6.435311
occ5w2	1.030726	3.128223	0.33	0.742	-5.100479	7.161931
occ6w2	1.834194	3.454783	0.53	0.595	-4.937056	8.605444
occ7w2	.6310877	3.205439	0.20	0.844	-5.651457	6.913633
occ8w2	0	(omitted)				
marrw21	-1.774375	1.681557	-1.06	0.291	-5.070167	1.521417
marrw22	-3.603201	2.051956	-1.76	0.079	-7.624961	.4185589
marrw23	-3.822298	1.717545	-2.23	0.026	-7.188624	-.4559723
marrw25	-.1941937	2.536946	-0.08	0.939	-5.166517	4.77813
marrw26	-3.213845	2.602626	-1.23	0.217	-8.314899	1.887208
inclw2	2.821191	3.187221	0.89	0.376	-3.425647	9.068029
inc2w2	2.680447	3.109489	0.86	0.389	-3.41404	8.774935
inc3w2	2.9859	3.107015	0.96	0.337	-3.103737	9.075536

inc4w2	1.060877	3.414563	0.31	0.756	-5.631544	7.753298
radhlw2	.0009802	.0078741	0.12	0.901	-.0144527	.0164132
havmil	.0033106	.008219	0.40	0.687	-.0127982	.0194195
avgcumdosew2	-.0408898	.0892564	-0.46	0.647	-.2158292	.1340496
bf1	-.0224294	.0411105	-0.55	0.585	-.1030045	.0581457
bf4	-.1579765	.2337949	-0.68	0.499	-.616206	.300253
bf2	.0000992	.0001626	0.61	0.542	-.0002196	.000418
bf4m	-.1739281	.2154639	-0.81	0.420	-.5962296	.2483734
bf5m	.0006314	.0017487	0.36	0.718	-.002796	.0040589
bf7m	.0005115	.000594	0.86	0.389	-.0006527	.0016757
bf8	-.0000403	.0000473	-0.85	0.394	-.0001331	.0000525
bf15m	-.0001301	.0003714	-0.35	0.726	-.000858	.0005979
bf17	0	(omitted)				
bf20	.0027387	.0345917	0.08	0.937	-.0650597	.0705372
bf22	-.0000529	.0001896	-0.28	0.780	-.0004245	.0003187
bf29	2.63e-06	.0000221	0.12	0.905	-.0000407	.0000459
bf30	-.0002608	.0004218	-0.62	0.536	-.0010875	.0005659
bf40	.3296594	.2457937	1.34	0.180	-.1520874	.8114062
deaw2	.0069355	.3395872	0.02	0.984	-.6586432	.6725142
dvcew2	-.8346564	3.597118	-0.23	0.817	-7.884878	6.215565
sepaw2	0	(omitted)				
accdw2	.1481124	.4606844	0.32	0.748	-.7548124	1.051037
movew2	.2192344	.5237343	0.42	0.676	-.807266	1.245735
illw2	-.2794365	.3922624	-0.71	0.476	-1.048257	.4893838
shfamw2	-.0130582	.0087013	-1.50	0.133	-.0301125	.0039961
shhlw2	-.0041104	.0095817	-0.43	0.668	-.0228901	.0146694
shjobw2	.0000993	.009716	0.01	0.992	-.0189438	.0191423
shrelaw2	.0041598	.0074695	0.56	0.578	-.0104802	.0187997
suprtw2	.0129457	.0070817	1.83	0.068	-.0009342	.0268256
suchrw2	-.0024472	.0063512	-0.39	0.700	-.0148953	.010001
havmilsq	-8.45e-06	.000015	-0.56	0.573	-.0000379	.000021
_cons	3.897935	3.960914	0.98	0.325	-3.865314	11.66118

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	41	17	58
-	29	183	212
Total	70	200	270

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2hmcare != 0

Sensitivity	Pr(+ D)	58.57%
Specificity	Pr(- ~D)	91.50%
Positive predictive value	Pr(D +)	70.69%
Negative predictive value	Pr(~D -)	86.32%
False + rate for true ~D	Pr(+ ~D)	8.50%
False - rate for true D	Pr(- D)	41.43%
False + rate for classified +	Pr(~D +)	29.31%
False - rate for classified -	Pr(D -)	13.68%
Correctly classified		82.96%

Logistic model for HP2hmcare, goodness-of-fit test

```

number of observations =      270
number of covariate patterns =    270
    Pearson chi2(220) =    227.64
        Prob > chi2 =      0.3476

```

Measures of Fit for **logistic** of HP2hmcare

Log-Lik Intercept Only:	-154.516	Log-Lik Full Model:	-98.319
D(214):	196.639	LR(49):	112.393
		Prob > LR:	0.000
McFadden's R2:	0.364	McFadden's Adj R2:	0.001
Maximum Likelihood R2:	0.340	Cragg & Uhler's R2:	0.500
McKelvey and Zavoina's R2:	0.594	Efron's R2:	0.390
Variance of y*:	8.112	Variance of error:	3.290
Count R2:	0.830	Adj Count R2:	0.343
AIC:	1.143	AIC*n:	308.639
BIC:	-1001.423	BIC':	161.930

Full main model for HP2hmcare for wave= 2

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2hmcare

```

i.educ          _Ieduc_1-8          (naturally coded; _Ieduc_1 omitted)
note: bf29 != 0 predicts success perfectly
      bf29 dropped and 4 obs not used

```

```

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
convergence not achieved

```

Logistic regression

Number of obs = 358

LR chi2(51) = 177.21

Prob > chi2 = 0.0000

Pseudo R2 = 0.3881

Log likelihood = -139.72732

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0689184	.0184884	3.73	0.000	.0326818	.105155
_Ieduc_2	-17.33023	2.370203	-7.31	0.000	-21.97575	-12.68472
_Ieduc_3	-17.85228	2.271622	-7.86	0.000	-22.30458	-13.39998
_Ieduc_4	-16.22367	2.322199	-6.99	0.000	-20.7751	-11.67225
_Ieduc_5	-17.51753	2.330541	-7.52	0.000	-22.0853	-12.94975
_Ieduc_6	-18.46499	2.320848	-7.96	0.000	-23.01377	-13.91621
_Ieduc_7	-17.72595	3.034199	-5.84	0.000	-23.67287	-11.77903
_Ieduc_8	0	(omitted)				
occ1w2	-2.066459	1.51974	-1.36	0.174	-5.045095	.9121779
occ2w2	-2.243078	1.553998	-1.44	0.149	-5.288858	.8027026
occ3w2	-1.29392	1.568233	-0.83	0.409	-4.367601	1.77976
occ4w2	-3.169244	1.685231	-1.88	0.060	-6.472236	.1337472
occ5w2	-4.174961	1.966604	-2.12	0.034	-8.029433	-.3204881
occ6w2	-5.016961	2.033875	-2.47	0.014	-9.003283	-1.030639
occ7w2	-1.338521	1.557092	-0.86	0.390	-4.390365	1.713323
occ8w2	.0102882	1.823109	0.01	0.995	-3.56294	3.583517
marrw21	-.4364242	1.195764	-0.36	0.715	-2.780078	1.907229
marrw22	.2779117	1.516808	0.18	0.855	-2.694977	3.2508
marrw23	1.982364	.8407589	2.36	0.018	.3345069	3.630221
marrw25	.7265557	1.247315	0.58	0.560	-1.718137	3.171248
marrw26	0	(omitted)				
inc1w2	2.1918	1.615301	1.36	0.175	-.9741308	5.357731
inc2w2	3.722591	1.551917	2.40	0.016	.6808895	6.764292
inc3w2	3.205652	1.561296	2.05	0.040	.1455678	6.265737
inc4w2	3.577016	1.917029	1.87	0.062	-.1802924	7.334325
radhlw2	-.0017814	.0069396	-0.26	0.797	-.0153829	.01182
havmil	.0004744	.0029523	0.16	0.872	-.005312	.0062609
avgcumdosew2	-.232422	.1275125	-1.82	0.068	-.4823419	.017498
bf1	-.0155252	.0283044	-0.55	0.583	-.0710008	.0399503
bf4	-.6331543	.2104116	-3.01	0.003	-1.045553	-.2207551
bf2	.0002047	.0001148	1.78	0.075	-.0000203	.0004296
bf4m	.369727	.1901433	1.94	0.052	-.0029469	.742401
bf5m	-.0009929	.001436	-0.69	0.489	-.0038073	.0018215
bf7m	.0003779	.0005084	0.74	0.457	-.0006186	.0013744
bf8	-5.36e-07	.0000355	-0.02	0.988	-.0000702	.0000691
bf15m	-.0123361	.496536	-0.02	0.980	-.9855287	.9608566
bf17	.0006265	.0248268	0.03	0.980	-.0480332	.0492861
bf20	-.0134138	.0231788	-0.58	0.563	-.0588434	.0320158
bf22	-.0000815	.0001207	-0.67	0.500	-.000318	.0001551
bf29	0	(omitted)				
bf30	-.0000914	.0002999	-0.30	0.760	-.0006791	.0004963

bf40	.1554702	.1284498	1.21	0.226	-.0962868	.4072271
deaw2	.7476902	.2584678	2.89	0.004	.2411026	1.254278
dvcew2	1.232183	1.276036	0.97	0.334	-1.268802	3.733168
sepaw2	-1.82805	1.829743	-1.00	0.318	-5.41428	1.75818
accdw2	-.7440138	.5452818	-1.36	0.172	-1.812746	.3247189
movew2	-.5229006	.4948092	-1.06	0.291	-1.492709	.4469077
illw2	-.1315546	.1759029	-0.75	0.455	-.4763179	.2132087
shfamw2	-.0038201	.0062872	-0.61	0.543	-.0161429	.0085027
shhlw2	-.0093005	.0066582	-1.40	0.162	-.0223502	.0037493
shjobw2	.0003285	.005919	0.06	0.956	-.0112724	.0119295
shrelaw2	-.0125743	.0072115	-1.74	0.081	-.0267086	.00156
suprtw2	-.0093988	.0049637	-1.89	0.058	-.0191275	.0003299
suchrw2	.0039959	.0055359	0.72	0.470	-.0068542	.0148461
havmilsq	-6.92e-07	2.48e-06	-0.28	0.780	-5.56e-06	4.18e-06
_cons	12.62346	.	.	.	.	.

Note: 4 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	86	29	115
-	34	209	243
Total	120	238	358

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	71.67%
Specificity	$\Pr(- \sim D)$	87.82%
Positive predictive value	$\Pr(D +)$	74.78%
Negative predictive value	$\Pr(\sim D -)$	86.01%
False + rate for true ~D	$\Pr(+ \sim D)$	12.18%
False - rate for true D	$\Pr(- D)$	28.33%
False + rate for classified +	$\Pr(\sim D +)$	25.22%
False - rate for classified -	$\Pr(D -)$	13.99%
Correctly classified		82.40%

Logistic model for HP2hmcare, goodness-of-fit test

```

      number of observations =      358
number of covariate patterns =      358
      Pearson chi2(305) =      382.80
      Prob > chi2 =      0.0016

```

Measures of Fit for **logistic** of **HP2hmcare**

Log-Lik Intercept Only:	-228.331	Log-Lik Full Model:	-139.727
D(302):	279.455	LR(51):	177.208
		Prob > LR:	0.000
McFadden's R2:	0.388	McFadden's Adj R2:	0.143
Maximum Likelihood R2:	0.390	Cragg & Uhler's R2:	0.542
McKelvey and Zavoina's R2:	0.930	Efron's R2:	0.437
Variance of y*:	47.071	Variance of error:	3.290
Count R2:	0.824	Adj Count R2:	0.475
AIC:	1.093	AIC*n:	391.455
BIC:	-1496.466	BIC':	122.699

Full main model for HP2probsoc for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2hmcare

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
 _Ieduc_4 dropped and 13 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly
 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
 _Ieduc_8 dropped and 2 obs not used

note: occ6w2 != 0 predicts failure perfectly
 occ6w2 dropped and 5 obs not used

note: occ7w2 != 0 predicts failure perfectly
 occ7w2 dropped and 14 obs not used

note: occ8w2 != 0 predicts failure perfectly
 occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly
 marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly
 marrw26 dropped and 1 obs not used

note: inc4w2 != 0 predicts failure perfectly
 inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 14 obs not used

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 5 obs not used

note: marrw25 != 0 predicts success perfectly
marrw25 dropped and 1 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	217
	LR chi2(40)	=	113.21
	Prob > chi2	=	0.0000
Log likelihood = -47.096671	Pseudo R2	=	0.5459

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1159429	.0419803	2.76	0.006	.0336631	.1982228
_Ieduc_2	-.0479004	1.407174	-0.03	0.973	-2.80591	2.710109
_Ieduc_3	-.8284731	.7880615	-1.05	0.293	-2.373045	.716099
_Ieduc_4	0	(omitted)				
_Ieduc_5	.2454375	1.100079	0.22	0.823	-1.910677	2.401552
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-1.3725	16.54078	-0.08	0.934	-33.79183	31.04683
occ2w2	-1.244674	16.53791	-0.08	0.940	-33.65838	31.16903
occ3w2	-.7835828	16.55903	-0.05	0.962	-33.23868	31.67152
occ4w2	-3.862736	16.57719	-0.23	0.816	-36.35344	28.62797
occ5w2	-2.775301	16.58962	-0.17	0.867	-35.29036	29.73976
occ6w2	0	(omitted)				
occ7w2	0	(omitted)				
occ8w2	0	(omitted)				
marrw21	12.58162	1075.856	0.01	0.991	-2096.057	2121.22
marrw22	0	(omitted)				
marrw23	10.03646	1075.856	0.01	0.993	-2098.602	2118.675
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inc1w2	.0757099	16.62358	0.00	0.996	-32.50591	32.65733
inc2w2	2.619578	16.55703	0.16	0.874	-29.83159	35.07075
inc3w2	4.14916	16.572	0.25	0.802	-28.33137	36.62969
inc4w2	0	(omitted)				
radhlw2	.0130005	.0142344	0.91	0.361	-.0148985	.0408995

havmil	-.002818	.0090337	-0.31	0.755	-.0205238	.0148877
avgcumdosew2	.0114306	.0823526	0.14	0.890	-.1499776	.1728387
bf1	.0037783	.0642153	0.06	0.953	-.1220814	.129638
bf4	.016836	.3033169	0.06	0.956	-.5776542	.6113261
bf2	.0006302	.0003126	2.02	0.044	.0000175	.0012428
bf4m	-.5319968	.2823116	-1.88	0.060	-1.085317	.0213237
bf5m	.0058806	.0028091	2.09	0.036	.0003749	.0113862
bf7m	.0013216	.0011466	1.15	0.249	-.0009257	.0035688
bf8	-.0001829	.0000911	-2.01	0.045	-.0003616	-4.31e-06
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0241214	.0536769	-0.45	0.653	-.1293262	.0810833
bf22	.0004188	.0002855	1.47	0.142	-.0001407	.0009783
bf29	-.000073	.0001017	-0.72	0.473	-.0002723	.0001263
bf30	-.0016782	.0007996	-2.10	0.036	-.0032455	-.000111
bf40	-.1773534	.3453449	-0.51	0.608	-.854217	.4995102
deaw2	-.7039739	.7523846	-0.94	0.349	-2.178621	.7706728
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0469037	.8655378	-0.05	0.957	-1.743327	1.649519
movew2	1.585081	.8835966	1.79	0.073	-.1467362	3.316899
illw2	-.6496621	.6161215	-1.05	0.292	-1.857238	.5579138
shfamw2	-.0160373	.0116025	-1.38	0.167	-.0387778	.0067033
shhlw2	-.0105176	.0138341	-0.76	0.447	-.0376321	.0165968
shjobw2	.0250231	.0129193	1.94	0.053	-.0002983	.0503445
shrelaw2	-.0217826	.0114409	-1.90	0.057	-.0442063	.0006412
suprtw2	.0083099	.0108445	0.77	0.444	-.012945	.0295648
suchrw2	.0212997	.0111718	1.91	0.057	-.0005966	.0431959
havmilsq	6.25e-06	.0000101	0.62	0.537	-.0000136	.0000261
_cons	-13.61182	1075.864	-0.01	0.990	-2122.266	2095.042

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	26	4	30
-	14	173	187
Total	40	177	217

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	65.00%
Specificity	$\Pr(- \sim D)$	97.74%
Positive predictive value	$\Pr(D +)$	86.67%
Negative predictive value	$\Pr(\sim D -)$	92.51%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	2.26%
False - rate for true D	$\Pr(- D)$	35.00%
False + rate for classified +	$\Pr(\sim D +)$	13.33%
False - rate for classified -	$\Pr(D -)$	7.49%
Correctly classified		91.71%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations = **217**
 number of covariate patterns = **217**
 Pearson $\chi^2(176)$ = **158.28**
 Prob > χ^2 = **0.8270**

Measures of Fit for logistic of HP2probsoc

Log-Lik Intercept Only:	-103.704	Log-Lik Full Model:	-47.097
D(161):	94.193	LR(40):	113.215
		Prob > LR:	0.000
McFadden's R2:	0.546	McFadden's Adj R2:	0.006
Maximum Likelihood R2:	0.407	Cragg & Uhler's R2:	0.660
McKelvey and Zavoina's R2:	0.840	Efron's R2:	0.562
Variance of y*:	20.586	Variance of error:	3.290
Count R2:	0.917	Adj Count R2:	0.550
AIC:	0.950	AIC*n:	206.193
BIC:	-771.970	BIC':	101.981

Full main model for HP2probsoc for wave= 2

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2probsoc

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: occ6w2 != 0 predicts failure perfectly
 occ6w2 dropped and 9 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 12 obs not used

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression

Number of obs = 341
LR chi2(50) = 174.30
Prob > chi2 = 0.0000
Pseudo R2 = 0.4921

Log likelihood = -89.934458

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1034919	.0270041	3.83	0.000	.0505648	.1564191
_Ieduc_2	-13.17654	1236.407	-0.01	0.991	-2436.49	2410.137
_Ieduc_3	-13.38577	1236.407	-0.01	0.991	-2436.699	2409.928
_Ieduc_4	-12.54323	1236.407	-0.01	0.992	-2435.857	2410.771
_Ieduc_5	-12.47221	1236.407	-0.01	0.992	-2435.786	2410.842
_Ieduc_6	-13.80248	1236.407	-0.01	0.991	-2437.116	2409.511
_Ieduc_7	-15.17121	1236.497	-0.01	0.990	-2438.662	2408.319
_Ieduc_8	0	(omitted)				
occ1w2	-1.147886	3.571925	-0.32	0.748	-8.14873	5.852957
occ2w2	-1.271517	3.611241	-0.35	0.725	-8.349419	5.806385
occ3w2	.2117582	3.586153	0.06	0.953	-6.816973	7.24049
occ4w2	-1.534382	3.689834	-0.42	0.678	-8.766324	5.69756
occ5w2	-2.414751	3.8284	-0.63	0.528	-9.918277	5.088775
occ6w2	0	(omitted)				
occ7w2	-.6787306	3.585162	-0.19	0.850	-7.70552	6.348058
occ8w2	2.909649	3.844529	0.76	0.449	-4.625489	10.44479
marrw21	-1.181403	1.729099	-0.68	0.494	-4.570375	2.207569
marrw22	1.066113	1.762045	0.61	0.545	-2.387432	4.519658
marrw23	.6150888	.9283649	0.66	0.508	-1.204473	2.434651
marrw25	.4424041	1.311023	0.34	0.736	-2.127154	3.011962
marrw26	0	(omitted)				
inclw2	.302891	3.591795	0.08	0.933	-6.736898	7.34268
inc2w2	1.142371	3.560505	0.32	0.748	-5.836091	8.120833
inc3w2	.8314334	3.569583	0.23	0.816	-6.164821	7.827688
inc4w2	.0290561	3.848853	0.01	0.994	-7.514557	7.57267
radhlw2	.0111407	.0096438	1.16	0.248	-.0077607	.0300422
havmil	.0005515	.0077361	0.07	0.943	-.0146109	.0157139
avgcumdosew2	.546822	.23001	2.38	0.017	.0960107	.9976333
bf1	.0275412	.0390831	0.70	0.481	-.0490602	.1041427
bf4	-.4078914	.2433269	-1.68	0.094	-.8848033	.0690205
bf2	.0001427	.0001416	1.01	0.314	-.0001349	.0004204
bf4m	.1372093	.2260724	0.61	0.544	-.3058844	.5803031
bf5m	-.0016005	.0026021	-0.62	0.538	-.0067005	.0034995
bf7m	.0002743	.0007319	0.37	0.708	-.0011601	.0017087
bf8	.0000233	.0000548	0.42	0.671	-.0000841	.0001306
bf15m	0	(omitted)				
bf17	0	(omitted)				

bf20	-.04615	.0319322	-1.45	0.148	-.1087361	.016436
bf22	9.68e-06	.0001672	0.06	0.954	-.000318	.0003374
bf29	-.0000266	.0000488	-0.54	0.586	-.0001221	.000069
bf30	.0001087	.0003798	0.29	0.775	-.0006357	.0008531
bf40	-.0077229	.1716746	-0.04	0.964	-.344199	.3287532
deaw2	-.0328171	.2515674	-0.13	0.896	-.5258803	.460246
dvcew2	1.645199	1.729548	0.95	0.341	-1.744652	5.03505
sepaw2	-.787699	2.185185	-0.36	0.718	-5.070584	3.495186
accdw2	-.7482691	.7741464	-0.97	0.334	-2.265568	.7690299
movev2	-.1983887	.9882329	-0.20	0.841	-2.13529	1.738512
illw2	.037099	.2627647	0.14	0.888	-.4779104	.5521084
shfamw2	-.0189411	.0086476	-2.19	0.028	-.03589	-.0019922
shhlw2	.0013266	.0086367	0.15	0.878	-.0156011	.0182542
shjobw2	-.0022444	.0078272	-0.29	0.774	-.0175855	.0130966
shrelaw2	-.0057107	.0089259	-0.64	0.522	-.0232051	.0117837
suprtw2	.0019185	.0068705	0.28	0.780	-.0115475	.0153845
suchrw2	-.0030114	.0077253	-0.39	0.697	-.0181526	.0121298
havmilsq	-5.64e-06	.0000161	-0.35	0.725	-.0000371	.0000258
_cons	8.438379	1236.411	0.01	0.995	-2414.883	2431.76

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	52	13	65
-	21	255	276
Total	73	268	341

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	71.23%
Specificity	$\Pr(- \sim D)$	95.15%
Positive predictive value	$\Pr(D +)$	80.00%
Negative predictive value	$\Pr(\sim D -)$	92.39%
False + rate for true ~D	$\Pr(+ \sim D)$	4.85%
False - rate for true D	$\Pr(- D)$	28.77%
False + rate for classified +	$\Pr(\sim D +)$	20.00%
False - rate for classified -	$\Pr(D -)$	7.61%
Correctly classified		90.03%

Logistic model for HP2probsoc, goodness-of-fit test

```
number of observations =      341
number of covariate patterns =    341
    Pearson chi2(290) =    351.64
        Prob > chi2 =      0.0077
```

Measures of Fit for **logistic** of **HP2probsoc**

Log-Lik Intercept Only:	-177.084	Log-Lik Full Model:	-89.934
D(285):	179.869	LR(50):	174.299
		Prob > LR:	0.000
McFadden's R2:	0.492	McFadden's Adj R2:	0.176
Maximum Likelihood R2:	0.400	Cragg & Uhler's R2:	0.619
McKelvey and Zavoina's R2:	0.858	Efron's R2:	0.531
Variance of y*:	23.160	Variance of error:	3.290
Count R2:	0.900	Adj Count R2:	0.534
AIC:	0.856	AIC*n:	291.869
BIC:	-1482.218	BIC':	117.295

Full main model for HP2pbfhm for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2probsoc

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_2 != 0 predicts failure perfectly

 _Ieduc_2 dropped and 10 obs not used

note: _Ieduc_4 != 0 predicts failure perfectly

 _Ieduc_4 dropped and 13 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly

 _Ieduc_8 dropped and 2 obs not used

note: occ5w2 != 0 predicts failure perfectly

 occ5w2 dropped and 17 obs not used

note: occ6w2 != 0 predicts failure perfectly

 occ6w2 dropped and 5 obs not used

note: occ8w2 != 0 predicts failure perfectly

 occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly

 marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly
marrw26 dropped and 3 obs not used

note: inclw2 != 0 predicts failure perfectly
inclw2 dropped and 13 obs not used

note: inc4w2 != 0 predicts failure perfectly
inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 12 obs not used

note: bf29 != 0 predicts failure perfectly
bf29 dropped and 4 obs not used

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 4 obs not used

note: marrw25 != 0 predicts success perfectly
marrw25 dropped and 1 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	188
	LR chi2(37)	=	54.88
	Prob > chi2	=	0.0294
Log likelihood = -38.373257	Pseudo R2	=	0.4169

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0444593	.0428518	1.04	0.299	-.0395286	.1284472
_Ieduc_2	0	(omitted)				
_Ieduc_3	-1.216759	1.079528	-1.13	0.260	-3.332594	.8990769
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.8969887	1.218662	-0.74	0.462	-3.285522	1.491544
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-.1675434	7.199614	-0.02	0.981	-14.27853	13.94344
occ2w2	-.7756164	7.209263	-0.11	0.914	-14.90551	13.35428
occ3w2	1.02351	7.214423	0.14	0.887	-13.1165	15.16352
occ4w2	1.180132	7.249556	0.16	0.871	-13.02874	15.389
occ5w2	0	(omitted)				
occ6w2	0	(omitted)				

occ7w2	-1.331976	7.411247	-0.18	0.857	-15.85775	13.1938
occ8w2	0	(omitted)				
marrw21	11.23886	2191.219	0.01	0.996	-4283.471	4305.948
marrw22	0	(omitted)				
marrw23	11.19426	2191.219	0.01	0.996	-4283.515	4305.904
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inclw2	0	(omitted)				
inc2w2	1.591635	7.274442	0.22	0.827	-12.66601	15.84928
inc3w2	2.001132	7.228455	0.28	0.782	-12.16638	16.16864
inc4w2	0	(omitted)				
radhlw2	.0450707	.0190833	2.36	0.018	.0076681	.0824733
havmil	-.0149705	.0133639	-1.12	0.263	-.0411632	.0112223
avgcumdosew2	-.0788123	.3549706	-0.22	0.824	-.7745419	.6169173
bf1	-.1607809	.1318246	-1.22	0.223	-.4191523	.0975906
bf4	-.2790034	.3019344	-0.92	0.355	-.8707839	.3127772
bf2	.0006459	.0003574	1.81	0.071	-.0000546	.0013465
bf4m	.1083622	.270079	0.40	0.688	-.4209828	.6377072
bf5m	.0014293	.004266	0.34	0.738	-.0069319	.0097905
bf7m	.0014124	.0012328	1.15	0.252	-.0010038	.0038286
bf8	-.0000455	.0000891	-0.51	0.610	-.0002201	.0001291
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0990519	.1141451	0.87	0.386	-.1246683	.3227721
bf22	.0000324	.0003377	0.10	0.924	-.0006295	.0006943
bf29	0	(omitted)				
bf30	-.0005162	.0007544	-0.68	0.494	-.0019949	.0009625
bf40	-.3427693	.4881552	-0.70	0.483	-1.299536	.6139973
deaw2	1.277518	.6289072	2.03	0.042	.0448826	2.510153
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.8756107	1.266217	-0.69	0.489	-3.35735	1.606128
movew2	.2828439	1.570553	0.18	0.857	-2.795383	3.36107
illw2	1.383819	.6666357	2.08	0.038	.0772372	2.690401
shfamw2	-.0048065	.0139543	-0.34	0.731	-.0321564	.0225433
shhlw2	-.0126567	.0158426	-0.80	0.424	-.0437076	.0183942
shjobw2	.0113436	.0152838	0.74	0.458	-.018612	.0412992
shrelaw2	-.0154518	.0162014	-0.95	0.340	-.047206	.0163025
suprtw2	-.0271504	.0129849	-2.09	0.037	-.0526003	-.0017006
suchrw2	.0166833	.0117501	1.42	0.156	-.0063465	.039713
havmilsq	.0000156	.0000131	1.19	0.234	-.00001	.0000412
_cons	-21.58182	2191.227	-0.01	0.992	-4316.307	4273.143

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	8	4	12
-	13	163	176
Total	21	167	188

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	38.10%
Specificity	$\Pr(- \sim D)$	97.60%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	92.61%
False + rate for true ~D	$\Pr(+ \sim D)$	2.40%
False - rate for true D	$\Pr(- D)$	61.90%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	7.39%
Correctly classified		90.96%

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      188
number of covariate patterns =    188
Pearson chi2(150) =      103.39
Prob > chi2 =      0.9986

```

Measures of Fit for logistic of HP2pbfhm

Log-Lik Intercept Only:	-65.811	Log-Lik Full Model:	-38.373
D(132):	76.747	LR(37):	54.876
		Prob > LR:	0.029
McFadden's R2:	0.417	McFadden's Adj R2:	-0.434
Maximum Likelihood R2:	0.253	Cragg & Uhler's R2:	0.503
McKelvey and Zavoina's R2:	0.754	Efron's R2:	0.356
Variance of y*:	13.351	Variance of error:	3.290
Count R2:	0.910	Adj Count R2:	0.190
AIC:	1.004	AIC*n:	188.747
BIC:	-614.464	BIC':	138.873

Full main model for HP2pbfhm for wave= 2

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2pbfhm

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: occ6w2 != 0 predicts failure perfectly
occ6w2 dropped and 9 obs not used

note: marrw22 != 0 predicts failure perfectly
marrw22 dropped and 8 obs not used

note: inc4w2 != 0 predicts failure perfectly
inc4w2 dropped and 9 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 12 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 5 obs not used

note: movew2 != 0 predicts failure perfectly
movew2 dropped and 37 obs not used

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf17 omitted because of collinearity
convergence not achieved

Logistic regression	Number of obs	=	282
	LR chi2(45)	=	115.64
	Prob > chi2	=	0.0000
Log likelihood = -69.237721	Pseudo R2	=	0.4551

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0573216	.0276334	2.07	0.038	.0031611	.1114822
_Ieduc_2	24.79783	5.419934	4.58	0.000	14.17495	35.4207
_Ieduc_3	25.40648	5.405293	4.70	0.000	14.8123	36.00065
_Ieduc_4	26.0435	5.498915	4.74	0.000	15.26582	36.82117
_Ieduc_5	25.99152	5.477282	4.75	0.000	15.25625	36.7268
_Ieduc_6	25.22458	5.399044	4.67	0.000	14.64265	35.80651
_Ieduc_7	24.91381	.	.	.	.	.
_Ieduc_8	0	(omitted)				
occ1w2	.1268694	2.741862	0.05	0.963	-5.247082	5.50082
occ2w2	-2.180454	2.943693	-0.74	0.459	-7.949987	3.589079
occ3w2	.8729362	2.776498	0.31	0.753	-4.568899	6.314772
occ4w2	-1.353704	2.942107	-0.46	0.645	-7.120128	4.41272
occ5w2	2.7416	3.183927	0.86	0.389	-3.498782	8.981982
occ6w2	0	(omitted)				
occ7w2	1.723368	2.749238	0.63	0.531	-3.66504	7.111775
occ8w2	1.071406	3.004006	0.36	0.721	-4.816337	6.959149
marrw21	1.363708	1.652619	0.83	0.409	-1.875365	4.602781
marrw22	0	(omitted)				

marrw23	.3462148	1.088773	0.32	0.750	-1.78774	2.48017
marrw25	1.049262	1.686487	0.62	0.534	-2.256193	4.354717
marrw26	0	(omitted)				
inclw2	-.4454501	2.822154	-0.16	0.875	-5.976771	5.085871
inc2w2	1.223562	2.740806	0.45	0.655	-4.148319	6.595444
inc3w2	.8897543	2.773723	0.32	0.748	-4.546642	6.326151
inc4w2	0	(omitted)				
radhlw2	.0162494	.0128872	1.26	0.207	-.0090091	.0415079
havmil	.0034284	.0174028	0.20	0.844	-.0306804	.0375372
avgcumdosew2	.2841701	.2286177	1.24	0.214	-.1639122	.7322525
bf1	-.0034211	.0428716	-0.08	0.936	-.0874479	.0806057
bf4	-.5482161	.2947147	-1.86	0.063	-1.125846	.0294141
bf2	.0001496	.0001782	0.84	0.401	-.0001996	.0004989
bf4m	.2436517	.2745867	0.89	0.375	-.2945285	.7818318
bf5m	-.0026475	.0036526	-0.72	0.469	-.0098065	.0045114
bf7m	-.0008652	.0008476	-1.02	0.307	-.0025264	.000796
bf8	.0000586	.0000741	0.79	0.429	-.0000867	.0002038
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0232359	.0348214	-0.67	0.505	-.0914845	.0450127
bf22	.0000587	.0002121	0.28	0.782	-.0003569	.0004744
bf29	.0000275	.0000434	0.63	0.527	-.0000576	.0001126
bf30	.0000875	.0005016	0.17	0.862	-.0008956	.0010706
bf40	-.3662342	.2446561	-1.50	0.134	-.8457514	.1132829
deaw2	.0470792	.2393731	0.20	0.844	-.4220834	.5162419
dvcew2	-1.779925	2.445695	-0.73	0.467	-6.573399	3.013549
sepaw2	0	(omitted)				
accdw2	-2.474844	1.428768	-1.73	0.083	-5.275177	.3254891
movew2	0	(omitted)				
illw2	-.2222062	.2628556	-0.85	0.398	-.7373938	.2929813
shfamw2	.0141915	.0093043	1.53	0.127	-.0040446	.0324276
shhlw2	.0087578	.0103731	0.84	0.399	-.0115731	.0290887
shjobw2	-.0066068	.0093228	-0.71	0.479	-.0248791	.0116655
shrelaw2	-.0301632	.0120406	-2.51	0.012	-.0537624	-.0065641
suprtw2	-.0125721	.0077017	-1.63	0.103	-.0276672	.002523
suchrw2	-.0060097	.0083821	-0.72	0.473	-.0224384	.010419
havmilsq	-.0000291	.000055	-0.53	0.597	-.0001368	.0000787
_cons	-27.59558	6.62482	-4.17	0.000	-40.57999	-14.61117

Note: 3 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	29	7	36
-	18	228	246
Total	47	235	282

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	61.70%
Specificity	$\Pr(- \sim D)$	97.02%
Positive predictive value	$\Pr(D +)$	80.56%
Negative predictive value	$\Pr(\sim D -)$	92.68%
False + rate for true ~D	$\Pr(+ \sim D)$	2.98%
False - rate for true D	$\Pr(- D)$	38.30%
False + rate for classified +	$\Pr(\sim D +)$	19.44%
False - rate for classified -	$\Pr(D -)$	7.32%
Correctly classified		91.13%

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      282
number of covariate patterns =    282
Pearson chi2(235) =      241.50
Prob > chi2 =      0.3715

```

Measures of Fit for logistic of HP2pbfhm

Log-Lik Intercept Only:	-127.058	Log-Lik Full Model:	-69.238
D(226):	138.475	LR(45):	115.641
		Prob > LR:	0.000
McFadden's R2:	0.455	McFadden's Adj R2:	0.014
Maximum Likelihood R2:	0.336	Cragg & Uhler's R2:	0.566
McKelvey and Zavoina's R2:	0.950	Efron's R2:	0.475
Variance of y*:	65.351	Variance of error:	3.290
Count R2:	0.911	Adj Count R2:	0.468
AIC:	0.888	AIC*n:	250.475
BIC:	-1136.596	BIC':	138.245

Full main model for HP2sxlife for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2pbfhm

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
 _Ieduc_4 dropped and 13 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly
 _Ieduc_7 dropped and 4 obs not used

note: occ8w2 != 0 predicts failure perfectly
 occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly
 marrw22 dropped and 8 obs not used

note: inc4w2 != 0 predicts failure perfectly
 inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 15 obs not used

note: bf29 != 0 predicts failure perfectly
 bf29 dropped and 7 obs not used

note: dvcew2 != 0 predicts failure perfectly
 dvcew2 dropped and 5 obs not used

note: marrw25 != 0 predicts success perfectly
 marrw25 dropped and 1 obs not used

note: sepaw2 != 0 predicts failure perfectly
 sepaw2 dropped and 1 obs not used

note: _Ieduc_8 omitted because of collinearity
 note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	230
	LR chi2(43)	=	118.95
	Prob > chi2	=	0.0000
Log likelihood = -79.289222	Pseudo R2	=	0.4286

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0432555	.0255157	1.70	0.090	-.0067543	.0932653
_Ieduc_2	.5443827	2.506052	0.22	0.828	-4.367389	5.456154
_Ieduc_3	.1796978	2.28739	0.08	0.937	-4.303504	4.6629
_Ieduc_4	0	(omitted)				
_Ieduc_5	.4368682	2.317398	0.19	0.850	-4.105148	4.978884
_Ieduc_6	.0186117	2.278221	0.01	0.993	-4.446619	4.483842
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-1.105479	2.816517	-0.39	0.695	-6.62575	4.414792
occ2w2	-1.682569	2.827571	-0.60	0.552	-7.224506	3.859369
occ3w2	-1.865477	2.89914	-0.64	0.520	-7.547687	3.816733
occ4w2	-1.59066	2.872678	-0.55	0.580	-7.221004	4.039685
occ5w2	-2.726982	3.04188	-0.90	0.370	-8.688957	3.234994
occ6w2	-.2649406	3.127605	-0.08	0.932	-6.394934	5.865053
occ7w2	-.4867933	2.955714	-0.16	0.869	-6.279885	5.306299
occ8w2	0	(omitted)				
marrw21	12.4944	2424.109	0.01	0.996	-4738.671	4763.66
marrw22	0	(omitted)				
marrw23	12.40066	2424.109	0.01	0.996	-4738.765	4763.566
marrw25	0	(omitted)				
marrw26	11.43457	2424.11	0.00	0.996	-4739.733	4762.602
inclw2	2.196401	3.02039	0.73	0.467	-3.723454	8.116257
inc2w2	2.746044	2.89601	0.95	0.343	-2.930031	8.422118
inc3w2	2.442664	2.894545	0.84	0.399	-3.23054	8.115869
inc4w2	0	(omitted)				
radhlw2	.017419	.0089507	1.95	0.052	-.000124	.0349621
havmil	-.00067	.0081563	-0.08	0.935	-.0166561	.0153161
avgcumdosew2	.0428691	.0600095	0.71	0.475	-.0747474	.1604856
bf1	.0291477	.0465434	0.63	0.531	-.0620756	.1203711
bf4	-.2016289	.2378115	-0.85	0.397	-.667731	.2644731
bf2	.0001142	.0001714	0.67	0.505	-.0002218	.0004501
bf4m	-.1000095	.2151889	-0.46	0.642	-.5217719	.321753
bf5m	.0017962	.0020545	0.87	0.382	-.0022305	.0058229
bf7m	.0013709	.0007292	1.88	0.060	-.0000582	.0028001
bf8	-.0000501	.0000511	-0.98	0.327	-.0001502	.0000501
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0313008	.0383214	-0.82	0.414	-.1064094	.0438077
bf22	-.0000976	.0002072	-0.47	0.637	-.0005038	.0003085
bf29	0	(omitted)				
bf30	-.000152	.0004096	-0.37	0.711	-.0009547	.0006507
bf40	.4229922	.2840028	1.49	0.136	-.1336431	.9796275
deaw2	-.1048722	.3851952	-0.27	0.785	-.8598409	.6500964
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0405016	.5549457	-0.07	0.942	-1.128175	1.047172

movew2	.116116	.6197485	0.19	0.851	-1.098569	1.330801
illw2	.1039214	.3746121	0.28	0.781	-.6303047	.8381476
shfamw2	-.0104564	.0087383	-1.20	0.231	-.0275832	.0066703
shhlw2	-.0161825	.0102333	-1.58	0.114	-.0362395	.0038744
shjobw2	.018921	.0100999	1.87	0.061	-.0008744	.0387165
shrelaw2	-.008619	.0087825	-0.98	0.326	-.0258323	.0085944
suprtw2	.0043231	.0078499	0.55	0.582	-.0110624	.0197086
suchrw2	.006568	.0072888	0.90	0.368	-.0077177	.0208538
havmilsq	-9.54e-07	.000013	-0.07	0.941	-.0000264	.0000245
_cons	-15.57434	2424.111	-0.01	0.995	-4766.744	4735.596

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	46	14	60
-	21	149	170
Total	67	163	230

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	68.66%
Specificity	$\Pr(- \sim D)$	91.41%
Positive predictive value	$\Pr(D +)$	76.67%
Negative predictive value	$\Pr(\sim D -)$	87.65%
False + rate for true ~D	$\Pr(+ \sim D)$	8.59%
False - rate for true D	$\Pr(- D)$	31.34%
False + rate for classified +	$\Pr(\sim D +)$	23.33%
False - rate for classified -	$\Pr(D -)$	12.35%
Correctly classified		84.78%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	230
number of covariate patterns =	230
Pearson $\chi^2(186)$ =	248.57
Prob > χ^2 =	0.0015

Measures of Fit for **logistic** of **HP2sxlife**

Log-Lik Intercept Only:	-138.763	Log-Lik Full Model:	-79.289
D(174):	158.578	LR(43):	118.947
		Prob > LR:	0.000
Mcfadden's R2:	0.429	Mcfadden's Adj R2:	0.025
Maximum Likelihood R2:	0.404	Cragg & Uhler's R2:	0.576
McKelvey and Zavoina's R2:	0.727	Efron's R2:	0.487
Variance of y*:	12.053	Variance of error:	3.290
Count R2:	0.848	Adj Count R2:	0.478
AIC:	1.176	AIC*n:	270.578
BIC:	-787.647	BIC':	114.891

Full main model for HP2sxlife for wave= 2

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2sxlife

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
 note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 12 obs not used

note: bf29 != 0 predicts success perfectly
 bf29 dropped and 4 obs not used

note: _Ieduc_8 omitted because of collinearity
 note: marrw26 omitted because of collinearity
 note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	346
	LR chi2(50)	=	172.45
	Prob > chi2	=	0.0000
Log likelihood = -111.04151	Pseudo R2	=	0.4371

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1025465	.0220099	4.66	0.000	.0594079	.145685
_Ieduc_2	-15.48089	5580.75	-0.00	0.998	-10953.55	10922.59
_Ieduc_3	-13.96022	5580.75	-0.00	0.998	-10952.03	10924.11
_Ieduc_4	-13.71505	5580.75	-0.00	0.998	-10951.78	10924.35
_Ieduc_5	-14.90906	5580.75	-0.00	0.998	-10952.98	10923.16
_Ieduc_6	-14.036	5580.75	-0.00	0.998	-10952.1	10924.03
_Ieduc_7	-14.35246	5580.751	-0.00	0.998	-10952.42	10923.72
_Ieduc_8	0	(omitted)				
occ1w2	-1.981003	1.626317	-1.22	0.223	-5.168525	1.20652
occ2w2	-1.199181	1.677697	-0.71	0.475	-4.487407	2.089044
occ3w2	-.7937582	1.670584	-0.48	0.635	-4.068042	2.480526
occ4w2	-.8102305	1.76353	-0.46	0.646	-4.266686	2.646225
occ5w2	-.5056346	1.89785	-0.27	0.790	-4.225353	3.214084
occ6w2	-1.645496	1.931022	-0.85	0.394	-5.430229	2.139237
occ7w2	-1.288749	1.611028	-0.80	0.424	-4.446306	1.868809
occ8w2	-.2492981	1.896994	-0.13	0.895	-3.967338	3.468742

marrw21	-.8001566	1.260909	-0.63	0.526	-3.271493	1.67118
marrw22	-.5650635	1.458662	-0.39	0.698	-3.423989	2.293861
marrw23	-1.064868	.8865967	-1.20	0.230	-2.802566	.6728293
marrw25	-2.27112	1.443829	-1.57	0.116	-5.100972	.5587328
marrw26	0	(omitted)				
inclw2	.5165366	1.706152	0.30	0.762	-2.82746	3.860533
inc2w2	.9386295	1.604285	0.59	0.558	-2.205712	4.082971
inc3w2	-.0514022	1.646264	-0.03	0.975	-3.27802	3.175215
inc4w2	.0543252	2.074029	0.03	0.979	-4.010697	4.119348
radhlw2	.0162077	.0081749	1.98	0.047	.0001852	.0322303
havmil	-.0014745	.0033419	-0.44	0.659	-.0080244	.0050754
avgcumdosew2	.1675129	.1251712	1.34	0.181	-.0778182	.412844
bf1	-.0006699	.0354295	-0.02	0.985	-.0701104	.0687707
bf4	-.6290339	.2665349	-2.36	0.018	-1.151433	-.1066351
bf2	.0000625	.000131	0.48	0.633	-.0001943	.0003193
bf4m	.4940985	.2505491	1.97	0.049	.0030312	.9851658
bf5m	-.002308	.0018303	-1.26	0.207	-.0058953	.0012792
bf7m	.00018	.0006254	0.29	0.773	-.0010457	.0014058
bf8	6.11e-06	.0000425	0.14	0.886	-.0000772	.0000894
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0009967	.0290168	-0.03	0.973	-.0578686	.0558752
bf22	-.0001321	.0001453	-0.91	0.363	-.0004169	.0001527
bf29	0	(omitted)				
bf30	-.0003317	.0003532	-0.94	0.348	-.001024	.0003605
bf40	.149372	.145042	1.03	0.303	-.1349052	.4336491
deaw2	.0989356	.2231863	0.44	0.658	-.3385014	.5363726
dvcew2	-14.61462	1422.458	-0.01	0.992	-2802.582	2773.353
sepaw2	13.19252	1422.46	0.01	0.993	-2774.778	2801.163
accdw2	-.3607593	.7071147	-0.51	0.610	-1.746679	1.02516
movew2	.2363995	.5198633	0.45	0.649	-.7825137	1.255313
illw2	.5572231	.2374511	2.35	0.019	.0918274	1.022619
shfamw2	.001878	.0072955	0.26	0.797	-.0124209	.0161768
shhlw2	.0092925	.0072946	1.27	0.203	-.0050046	.0235896
shjobw2	-.0069643	.0067203	-1.04	0.300	-.0201358	.0062073
shrelaw2	-.0169606	.0081044	-2.09	0.036	-.032845	-.0010762
suprtw2	-.0129953	.0058047	-2.24	0.025	-.0243723	-.0016183
suchrw2	.0118245	.0068566	1.72	0.085	-.0016142	.0252632
havmilsq	-6.39e-08	2.74e-06	-0.02	0.981	-5.43e-06	5.30e-06
_cons	5.841436	5580.75	0.00	0.999	-10932.23	10943.91

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	57	17	74
-	32	240	272
Total	89	257	346

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	64.04%
Specificity	$\Pr(- \sim D)$	93.39%
Positive predictive value	$\Pr(D +)$	77.03%
Negative predictive value	$\Pr(\sim D -)$	88.24%
False + rate for true ~D	$\Pr(+ \sim D)$	6.61%
False - rate for true D	$\Pr(- D)$	35.96%
False + rate for classified +	$\Pr(\sim D +)$	22.97%
False - rate for classified -	$\Pr(D -)$	11.76%
Correctly classified		85.84%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      346
number of covariate patterns =    346
Pearson chi2(295) =      312.67
Prob > chi2 =      0.2294

```

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-197.267	Log-Lik Full Model:	-111.042
D(290):	222.083	LR(50):	172.450
		Prob > LR:	0.000
McFadden's R2:	0.437	McFadden's Adj R2:	0.153
Maximum Likelihood R2:	0.393	Cragg & Uhler's R2:	0.577
McKelvey and Zavoina's R2:	0.765	Efron's R2:	0.477
Variance of y*:	14.018	Variance of error:	3.290
Count R2:	0.858	Adj Count R2:	0.449
AIC:	0.966	AIC*n:	334.083
BIC:	-1473.384	BIC':	119.872

Full main model for HP2inthob for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2sxlife

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
 _Ieduc_4 dropped and 13 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly
 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
 _Ieduc_8 dropped and 2 obs not used

note: occ6w2 != 0 predicts failure perfectly
 occ6w2 dropped and 5 obs not used

note: occ8w2 != 0 predicts failure perfectly
 occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly
 marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly
 marrw26 dropped and 3 obs not used

note: inc4w2 != 0 predicts failure perfectly
 inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 14 obs not used

note: bf29 != 0 predicts failure perfectly
 bf29 dropped and 7 obs not used

note: dvcew2 != 0 predicts failure perfectly
 dvcew2 dropped and 5 obs not used

note: marrw25 != 0 predicts success perfectly
 marrw25 dropped and 1 obs not used

note: sepaw2 != 0 predicts failure perfectly
 sepaw2 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
 note: bf17 omitted because of collinearity
 convergence not achieved

Logistic regression

Log likelihood = **-56.065557**

Number of obs	=	222
LR chi2(38)	=	87.92
Prob > chi2	=	0.0000
Pseudo R2	=	0.4395

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0628957	.0331927	1.89	0.058	-.0021608	.1279522
_Ieduc_2	-1.6685	1.649966	-1.01	0.312	-4.902374	1.565374
_Ieduc_3	-1.215713	.7907875	-1.54	0.124	-2.765628	.334202
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.4779232	.8553091	-0.56	0.576	-2.154298	1.198452
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-1.082181	4.607241	-0.23	0.814	-10.11221	7.947846
occ2w2	-2.603476	4.649764	-0.56	0.576	-11.71685	6.509893
occ3w2	-1.004632	4.641	-0.22	0.829	-10.10083	8.091562
occ4w2	-2.019345	4.651526	-0.43	0.664	-11.13617	7.097479
occ5w2	.6122404	4.674482	0.13	0.896	-8.549576	9.774057
occ6w2	0	(omitted)				
occ7w2	-.673024	4.745659	-0.14	0.887	-9.974345	8.628297
occ8w2	0	(omitted)				
marrw21	20.61385	.	.	.	.	.
marrw22	0	(omitted)				
marrw23	18.42435	.9174041	20.08	0.000	16.62627	20.22243
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inc1w2	-2.249864	4.853935	-0.46	0.643	-11.7634	7.263674
inc2w2	-.5178361	4.628216	-0.11	0.911	-9.588972	8.5533
inc3w2	.1239712	4.620272	0.03	0.979	-8.931596	9.179539
inc4w2	0	(omitted)				
radhlw2	.0343977	.012966	2.65	0.008	.0089848	.0598107
havmil	.0008574	.0092743	0.09	0.926	-.01732	.0190348
avgcumdosew2	-.193618	.3161247	-0.61	0.540	-.8132111	.425975
bf1	-1.886122	.0917045	-20.57	0.000	-2.065859	-1.706384
bf4	-.3784715	.2556706	-1.48	0.139	-.8795766	.1226337
bf2	.0000547	.0002055	0.27	0.790	-.0003482	.0004575
bf4m	.0723497	.2259826	0.32	0.749	-.370568	.5152675
bf5m	.001341	.0024956	0.54	0.591	-.0035502	.0062323
bf7m	.0004844	.0009455	0.51	0.608	-.0013686	.0023375
bf8	-.0000611	.0000655	-0.93	0.351	-.0001895	.0000674
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	1.88387	.0868318	21.70	0.000	1.713682	2.054057
bf22	.0002363	.000249	0.95	0.343	-.0002517	.0007243
bf29	0	(omitted)				
bf30	-.0000596	.000538	-0.11	0.912	-.0011141	.0009949
bf40	.1920076	.3256519	0.59	0.555	-.4462584	.8302735
deaw2	.0505905	.5418118	0.09	0.926	-1.011341	1.112522
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	.6361143	.5519575	1.15	0.249	-.4457025	1.717931

movew2	1.255677	.7610419	1.65	0.099	-.2359377	2.747292
illw2	-.8504102	.5855803	-1.45	0.146	-1.998126	.2973061
shfamw2	-.0084797	.0105947	-0.80	0.423	-.029245	.0122856
shhlw2	-.0041615	.0127463	-0.33	0.744	-.0291439	.0208209
shjobw2	.0098894	.0132981	0.74	0.457	-.0161744	.0359532
shrelaw2	-.0107778	.0098723	-1.09	0.275	-.0301272	.0085716
suprtw2	-.0039714	.0091015	-0.44	0.663	-.0218101	.0138672
suchrw2	.0137146	.0086956	1.58	0.115	-.0033283	.0307576
havmilsq	-2.48e-06	.0000157	-0.16	0.875	-.0000333	.0000283
_cons	-98.68478	.	.	.	.	.

Note: 21 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	20	6	26
-	17	179	196
Total	37	185	222

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	54.05%
Specificity	$\Pr(- \sim D)$	96.76%
Positive predictive value	$\Pr(D +)$	76.92%
Negative predictive value	$\Pr(\sim D -)$	91.33%
False + rate for true ~D	$\Pr(+ \sim D)$	3.24%
False - rate for true D	$\Pr(- D)$	45.95%
False + rate for classified +	$\Pr(\sim D +)$	23.08%
False - rate for classified -	$\Pr(D -)$	8.67%
Correctly classified		89.64%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	222
number of covariate patterns =	222
Pearson chi2(181) =	382.48
Prob > chi2 =	0.0000

Measures of Fit for **logistic** of **HP2inthob**

Log-Lik Intercept Only:	-100.025	Log-Lik Full Model:	-56.066
D(166):	112.131	LR(38):	87.918
		Prob > LR:	0.000
McFadden's R2:	0.439	McFadden's Adj R2:	-0.120
Maximum Likelihood R2:	0.327	Cragg & Uhler's R2:	0.551
McKelvey and Zavoina's R2:	0.982	Efron's R2:	0.466
Variance of y*:	186.924	Variance of error:	3.290
Count R2:	0.896	Adj Count R2:	0.378
AIC:	1.010	AIC*n:	224.131
BIC:	-784.713	BIC':	117.384

Full main model for HP2inthob for wave= 2

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2inthob

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: bf15m != 0 predicts failure perfectly

 bf15m dropped and 12 obs not used

note: sepaw2 != 0 predicts failure perfectly

 sepaw2 dropped and 7 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw26 omitted because of collinearity

note: bf17 omitted because of collinearity

Logistic regression

Number of obs = **343**

LR chi2(50) = **122.71**

Prob > chi2 = **0.0000**

Log likelihood = **-105.17277**

Pseudo R2 = **0.3684**

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0823123	.0222811	3.69	0.000	.0386422	.1259824
_Ieduc_2	-11.49207	1090.325	-0.01	0.992	-2148.489	2125.505
_Ieduc_3	-10.49189	1090.324	-0.01	0.992	-2147.489	2126.505
_Ieduc_4	-9.521531	1090.325	-0.01	0.993	-2146.519	2127.476
_Ieduc_5	-10.03097	1090.325	-0.01	0.993	-2147.028	2126.966
_Ieduc_6	-10.65519	1090.325	-0.01	0.992	-2147.652	2126.342
_Ieduc_7	-10.56771	1090.33	-0.01	0.992	-2147.575	2126.44
_Ieduc_8	0	(omitted)				
occ1w2	-1.444251	1.786645	-0.81	0.419	-4.94601	2.057508
occ2w2	-1.72162	1.86422	-0.92	0.356	-5.375425	1.932185
occ3w2	-.6960307	1.813742	-0.38	0.701	-4.2509	2.858838
occ4w2	-1.340236	1.971898	-0.68	0.497	-5.205085	2.524613
occ5w2	-1.866674	2.177453	-0.86	0.391	-6.134403	2.401055
occ6w2	-.6630026	2.009767	-0.33	0.741	-4.602073	3.276067

occ7w2	-.3132082	1.768051	-0.18	0.859	-3.778525	3.152109
occ8w2	-.4424864	1.980995	-0.22	0.823	-4.325166	3.440193
marrw21	1.198754	1.252366	0.96	0.338	-1.255838	3.653346
marrw22	-.723147	1.45696	-0.50	0.620	-3.578736	2.132442
marrw23	-.1412732	.8614541	-0.16	0.870	-1.829692	1.547146
marrw25	.030411	1.273943	0.02	0.981	-2.466472	2.527294
marrw26	0	(omitted)				
inclw2	.7639278	1.820866	0.42	0.675	-2.804904	4.33276
inc2w2	1.088119	1.754837	0.62	0.535	-2.351299	4.527537
inc3w2	.8549853	1.806256	0.47	0.636	-2.685212	4.395182
inc4w2	2.107171	2.102907	1.00	0.316	-2.014451	6.228794
radhlw2	.0162662	.0092193	1.76	0.078	-.0018033	.0343356
havmil	.0028568	.0035632	0.80	0.423	-.004127	.0098406
avgcumdosew2	.1191237	.1112746	1.07	0.284	-.0989705	.3372179
bf1	-.0579291	.0444461	-1.30	0.192	-.1450419	.0291837
bf4	-.5134212	.2911522	-1.76	0.078	-1.084069	.0572265
bf2	.0000225	.0001357	0.17	0.868	-.0002436	.0002885
bf4m	.3813738	.2769085	1.38	0.168	-.1613568	.9241045
bf5m	-.0013491	.0018728	-0.72	0.471	-.0050196	.0023214
bf7m	-.0007653	.0006452	-1.19	0.236	-.0020299	.0004993
bf8	.0000124	.0000428	0.29	0.772	-.0000716	.0000964
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0409398	.0388667	1.05	0.292	-.0352376	.1171172
bf22	.0000496	.0001446	0.34	0.732	-.0002338	.0003329
bf29	.0000147	.0000386	0.38	0.704	-.000061	.0000904
bf30	.0005975	.0003487	1.71	0.087	-.0000859	.0012809
bf40	-.092913	.1571517	-0.59	0.554	-.4009247	.2150987
deaw2	.1650922	.2350487	0.70	0.482	-.2955947	.6257792
dvcew2	-.44027	1.751166	-0.25	0.801	-3.872493	2.991953
sepaw2	0	(omitted)				
accdw2	.3072193	.6191348	0.50	0.620	-.9062626	1.520701
movew2	-.4208456	.8150343	-0.52	0.606	-2.018283	1.176592
illw2	.146668	.2184808	0.67	0.502	-.2815466	.5748825
shfamw2	.0028218	.0077742	0.36	0.717	-.0124154	.018059
shhlw2	.0082475	.0076919	1.07	0.284	-.0068283	.0233233
shjobw2	-.0093426	.0067931	-1.38	0.169	-.0226569	.0039716
shrelaw2	-.0142034	.0081278	-1.75	0.081	-.0301336	.0017268
suprtw2	-.0099735	.0060387	-1.65	0.099	-.021809	.0018621
suchrw2	-.0045113	.0068989	-0.65	0.513	-.0180329	.0090102
havmilsq	-2.60e-06	4.34e-06	-0.60	0.550	-.0000111	5.92e-06
_cons	2.140849	1090.33	0.00	0.998	-2134.867	2139.148

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	32	12	44
-	33	266	299
Total	65	278	343

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	49.23%
Specificity	$\Pr(- \sim D)$	95.68%
Positive predictive value	$\Pr(D +)$	72.73%
Negative predictive value	$\Pr(\sim D -)$	88.96%
False + rate for true ~D	$\Pr(+ \sim D)$	4.32%
False - rate for true D	$\Pr(- D)$	50.77%
False + rate for classified +	$\Pr(\sim D +)$	27.27%
False - rate for classified -	$\Pr(D -)$	11.04%
Correctly classified		86.88%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      343
number of covariate patterns =    343
Pearson chi2(292) =      307.38
Prob > chi2 =      0.2568

```

Measures of Fit for logistic of HP2inthob

Log-Lik Intercept Only:	-166.528	Log-Lik Full Model:	-105.173
D(287):	210.346	LR(50):	122.710
		Prob > LR:	0.000
McFadden's R2:	0.368	McFadden's Adj R2:	0.032
Maximum Likelihood R2:	0.301	Cragg & Uhler's R2:	0.484
McKelvey and Zavoina's R2:	0.627	Efron's R2:	0.388
Variance of y*:	8.828	Variance of error:	3.290
Count R2:	0.869	Adj Count R2:	0.308
AIC:	0.940	AIC*n:	322.346
BIC:	-1465.083	BIC':	169.177

Full main model for HP2vacatn for wave= 2

chunk 2 H1 test:Gender= 1 model Wave = 2 for HP2inthob

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
_Ieduc_4 dropped and 13 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly
_Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
_Ieduc_8 dropped and 2 obs not used

note: occ6w2 != 0 predicts failure perfectly
occ6w2 dropped and 5 obs not used

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly
marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly
marrw26 dropped and 3 obs not used

note: inclw2 != 0 predicts failure perfectly
inclw2 dropped and 15 obs not used

note: inc4w2 != 0 predicts failure perfectly
inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 14 obs not used

note: bf29 != 0 predicts failure perfectly
bf29 dropped and 6 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 3 obs not used

note: marrw25 != 0 predicts success perfectly
marrw25 dropped and 2 obs not used

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression

Number of obs = 209

LR chi2(39) = 102.98

Prob > chi2 = 0.0000

Log likelihood = -47.602962

Pseudo R2 = 0.5196

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1088786	.0407817	2.67	0.008	.028948	.1888093
_Ieduc_2	-.9318847	1.583195	-0.59	0.556	-4.034891	2.171121
_Ieduc_3	-.3013966	.8062315	-0.37	0.709	-1.881581	1.278788
_Ieduc_4	0	(omitted)				
_Ieduc_5	.7382214	.9602436	0.77	0.442	-1.143821	2.620264
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	.5124208	2.878835	0.18	0.859	-5.129992	6.154834
occ2w2	-.4408554	2.792442	-0.16	0.875	-5.913941	5.03223
occ3w2	-2.00202	3.038272	-0.66	0.510	-7.956923	3.952884
occ4w2	-1.69795	2.828364	-0.60	0.548	-7.241441	3.84554
occ5w2	.7563117	3.026518	0.25	0.803	-5.175555	6.688178
occ6w2	0	(omitted)				
occ7w2	-1.936351	3.240951	-0.60	0.550	-8.288498	4.415797
occ8w2	0	(omitted)				
marrw21	-1.786228	2.087814	-0.86	0.392	-5.878268	2.305811
marrw22	0	(omitted)				
marrw23	-3.710107	2.110606	-1.76	0.079	-7.846818	.4266038
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inclw2	0	(omitted)				
inc2w2	6.638966	3.131338	2.12	0.034	.5016569	12.77628
inc3w2	6.255863	3.02429	2.07	0.039	.3283623	12.18336
inc4w2	0	(omitted)				
radhlw2	.0154566	.0132775	1.16	0.244	-.0105668	.0414799
havmil	.0154293	.016452	0.94	0.348	-.016816	.0476745
avgcumdosew2	-.0557184	.2274565	-0.24	0.806	-.501525	.3900881
bf1	-.1915136	.1848361	-1.04	0.300	-.5537857	.1707584
bf4	-1.014161	.384844	-2.64	0.008	-1.768442	-.2598809
bf2	.0009651	.0003217	3.00	0.003	.0003345	.0015957
bf4m	.5255255	.2920885	1.80	0.072	-.0469573	1.098008
bf5m	-.0090927	.0046394	-1.96	0.050	-.0181857	3.32e-07
bf7m	.0026491	.0014384	1.84	0.066	-.0001701	.0054684
bf8	-.0000651	.0001057	-0.62	0.538	-.0002723	.0001421
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.1424239	.1725233	0.83	0.409	-.1957155	.4805633
bf22	-.0003108	.0003594	-0.86	0.387	-.0010152	.0003936
bf29	0	(omitted)				
bf30	-.0023793	.0008117	-2.93	0.003	-.0039701	-.0007885

bf40	.9125294	.4548855	2.01	0.045	.0209702	1.804089
deaw2	-.6840264	.6025074	-1.14	0.256	-1.864919	.4968663
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	1.109415	.6826211	1.63	0.104	-.2284975	2.447328
movew2	1.822244	1.095619	1.66	0.096	-.3251288	3.969618
illw2	-.4132514	.5817296	-0.71	0.477	-1.55342	.7269176
shfamw2	.0127979	.0115841	1.10	0.269	-.0099065	.0355022
shhlw2	.0134786	.0158032	0.85	0.394	-.0174951	.0444522
shjobw2	-.038737	.0177181	-2.19	0.029	-.0734639	-.0040101
shrelaw2	-.0185842	.0149559	-1.24	0.214	-.0478973	.0107288
suprtw2	.013763	.0125463	1.10	0.273	-.0108273	.0383533
suchrw2	-.0155904	.0122501	-1.27	0.203	-.0396002	.0084195
havmilsq	-.000036	.0000355	-1.01	0.312	-.0001056	.0000337
_cons	-17.72332	9.218306	-1.92	0.055	-35.79086	.3442328

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	24	8	32
-	14	163	177
Total	38	171	209

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2vacatn != 0

Sensitivity	$\Pr(+ D)$	63.16%
Specificity	$\Pr(- \sim D)$	95.32%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	92.09%

False + rate for true ~D	$\Pr(+ \sim D)$	4.68%
False - rate for true D	$\Pr(- D)$	36.84%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	7.91%

Correctly classified	89.47%
----------------------	--------

Logistic model for HP2vacatn, goodness-of-fit test

```

      number of observations =      209
number of covariate patterns =      209
      Pearson chi2(169) =      254.11
      Prob > chi2 =      0.0000

```

Measures of Fit for **logistic** of **HP2vacatn**

```

Log-Lik Intercept Only:      -99.095      Log-Lik Full Model:      -47.603
D(153):                      95.206      LR(39):                  102.984
                               Prob > LR:      0.000
McFadden's R2:               0.520      McFadden's Adj R2:      -0.045
Maximum Likelihood R2:       0.389      Cragg & Uhler's R2:     0.635
McKelvey and Zavoina's R2:   0.876      Efron's R2:             0.535
Variance of y*:              26.488      Variance of error:      3.290
Count R2:                    0.895      Adj Count R2:           0.421
AIC:                         0.991      AIC*n:                  207.206
BIC:                         -722.171     BIC':                   105.367
Full main model for HP2vacatn for wave= 2

```

chunk 2 H1 test:Gender= 2 model Wave = 2 for HP2vacatn

```

i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: bf15m != 0 predicts failure perfectly
      bf15m dropped and 12 obs not used

```

```

note: sepaw2 != 0 predicts failure perfectly
      sepaw2 dropped and 7 obs not used

```

```

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf17 omitted because of collinearity

```

```

Logistic regression                                Number of obs   =      343
                                                    LR chi2(50)     =      113.11
                                                    Prob > chi2      =      0.0000
Log likelihood = -105.52458                        Pseudo R2       =      0.3489

```

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0854752	.0223994	3.82	0.000	.0415731	.1293772
_Ieduc_2	-13.44949	933.6235	-0.01	0.989	-1843.318	1816.419
_Ieduc_3	-13.23035	933.6235	-0.01	0.989	-1843.099	1816.638
_Ieduc_4	-11.35201	933.6237	-0.01	0.990	-1841.221	1818.517
_Ieduc_5	-12.71553	933.6236	-0.01	0.989	-1842.584	1817.153
_Ieduc_6	-12.77592	933.6235	-0.01	0.989	-1842.644	1817.093
_Ieduc_7	-13.29025	933.6257	-0.01	0.989	-1843.163	1816.582
_Ieduc_8	0 (omitted)					
occlw2	-1.13677	2.279208	-0.50	0.618	-5.603935	3.330396

occ2w2	-.2856297	2.305316	-0.12	0.901	-4.803966	4.232706
occ3w2	-.216915	2.29482	-0.09	0.925	-4.714679	4.280849
occ4w2	-.6834035	2.371062	-0.29	0.773	-5.330599	3.963792
occ5w2	-1.371419	2.630896	-0.52	0.602	-6.52788	3.785042
occ6w2	.0514808	2.451681	0.02	0.983	-4.753725	4.856686
occ7w2	-.181635	2.248007	-0.08	0.936	-4.587648	4.224378
occ8w2	.8447418	2.549831	0.33	0.740	-4.152835	5.842319
marrw21	-.3962422	1.357576	-0.29	0.770	-3.057042	2.264558
marrw22	-.7030307	1.344505	-0.52	0.601	-3.338211	1.93215
marrw23	-.2946063	.8362364	-0.35	0.725	-1.933599	1.344387
marrw25	-.3847231	1.312392	-0.29	0.769	-2.956964	2.187518
marrw26	0	(omitted)				
inclw2	-.1652405	2.308326	-0.07	0.943	-4.689477	4.358996
inc2w2	.5715205	2.259629	0.25	0.800	-3.857271	5.000312
inc3w2	.4239257	2.273462	0.19	0.852	-4.031977	4.879829
inc4w2	-.1023194	2.63109	-0.04	0.969	-5.25916	5.054522
radhlw2	.0311839	.0092957	3.35	0.001	.0129647	.0494031
havmil	.0003102	.0031015	0.10	0.920	-.0057687	.006389
avgcumdosew2	.0845928	.134995	0.63	0.531	-.1799926	.3491782
bf1	-.0293287	.036543	-0.80	0.422	-.1009517	.0422942
bf4	-.0358912	.2239004	-0.16	0.873	-.474728	.4029456
bf2	.0000573	.0001382	0.41	0.678	-.0002135	.0003281
bf4m	-.0145732	.2099542	-0.07	0.945	-.4260759	.3969296
bf5m	-.0005729	.0016599	-0.35	0.730	-.0038263	.0026805
bf7m	-.0009478	.0006252	-1.52	0.130	-.0021731	.0002775
bf8	-.0000327	.0000408	-0.80	0.422	-.0001126	.0000472
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0039961	.0309743	0.13	0.897	-.0567124	.0647046
bf22	.0000865	.0001546	0.56	0.576	-.0002165	.0003895
bf29	.0000586	.0000394	1.49	0.137	-.0000187	.000136
bf30	-.0003297	.0003684	-0.89	0.371	-.0010518	.0003924
bf40	-.198659	.1714101	-1.16	0.246	-.5346167	.1372987
deaw2	.2948234	.2283214	1.29	0.197	-.1526784	.7423251
dvcew2	1.552638	1.538913	1.01	0.313	-1.463576	4.568851
sepaw2	0	(omitted)				
accdw2	-.6724358	.784314	-0.86	0.391	-2.209663	.8647914
movew2	-.2536718	.8260112	-0.31	0.759	-1.872624	1.36528
illw2	.1943909	.2307856	0.84	0.400	-.2579405	.6467223
shfamw2	.0107227	.0072538	1.48	0.139	-.0034944	.0249399
shhlw2	.0100533	.0078834	1.28	0.202	-.0053979	.0255045
shjobw2	-.0092742	.0068673	-1.35	0.177	-.0227339	.0041855
shrelaw2	-.0224847	.0085804	-2.62	0.009	-.039302	-.0056674
suprtw2	-.0043934	.0060874	-0.72	0.470	-.0163245	.0075377
suchrw2	.0021142	.0069953	0.30	0.762	-.0115964	.0158248
havmilsq	-6.39e-07	2.42e-06	-0.26	0.792	-5.38e-06	4.10e-06
_cons	8.078046	933.628	0.01	0.993	-1821.799	1837.955

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	30	11	41
-	32	270	302
Total	62	281	343

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2vacatn != 0

Sensitivity	$\Pr(+ D)$	48.39%
Specificity	$\Pr(- \sim D)$	96.09%
Positive predictive value	$\Pr(D +)$	73.17%
Negative predictive value	$\Pr(\sim D -)$	89.40%
False + rate for true ~D	$\Pr(+ \sim D)$	3.91%
False - rate for true D	$\Pr(- D)$	51.61%
False + rate for classified +	$\Pr(\sim D +)$	26.83%
False - rate for classified -	$\Pr(D -)$	10.60%
Correctly classified		87.46%

Logistic model for HP2vacatn, goodness-of-fit test

```

      number of observations =      343
number of covariate patterns =      343
      Pearson chi2(292) =      331.68
              Prob > chi2 =      0.0548
  
```

Measures of Fit for **logistic** of HP2vacatn

Log-Lik Intercept Only:	-162.082	Log-Lik Full Model:	-105.525
D(287):	211.049	LR(50):	113.114
		Prob > LR:	0.000
McFadden's R2:	0.349	McFadden's Adj R2:	0.003
Maximum Likelihood R2:	0.281	Cragg & Uhler's R2:	0.460
McKelvey and Zavoina's R2:	0.590	Efron's R2:	0.377
Variance of y*:	8.031	Variance of error:	3.290
Count R2:	0.875	Adj Count R2:	0.306
AIC:	0.942	AIC*n:	323.049
BIC:	-1464.379	BIC':	178.773

```

142 .
143 . title4 "trimming male models of dose and HP2work relationship in wave 2 "

```

```

trimming male models of dose and HP2work relationship in wave 2

```

```

144 . * male models
145 .     forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      3. di as input "Gender =1 HP2work model"
      4. di _skip(5)
      5.     logit HP2work age inclw2-inc4w2 bf2 bf4  bf5m bf30 bf40 illw`j' /
> //
>     shhlw`j' radhlw2 havmilsq ///
>     avgcumdosew`j' if gender==1
      6.         estat class
      7.         estat gof
      8.         fitstat
      9. }
Gender =1 HP2work model

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -142.40034
Iteration 2:  log likelihood = -139.93804
Iteration 3:  log likelihood = -139.91728
Iteration 4:  log likelihood = -139.91728

```

Logistic regression	Number of obs	=	340
	LR chi2(15)	=	65.91
	Prob > chi2	=	0.0000
Log likelihood = -139.91728	Pseudo R2	=	0.1906

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0011282	.0148134	0.08	0.939	-.0279056	.030162
inclw2	-.9128308	1.006103	-0.91	0.364	-2.884756	1.059095
inc2w2	.2695533	.6709232	0.40	0.688	-1.045432	1.584539
inc3w2	.7986152	.6627163	1.21	0.228	-.5002849	2.097515
inc4w2	-.2811072	1.2809	-0.22	0.826	-2.791626	2.229412
bf2	.0000321	.0000932	0.34	0.730	-.0001506	.0002148
bf4	-.1434674	.0383586	-3.74	0.000	-.2186488	-.0682859
bf5m	-.0001776	.0008906	-0.20	0.842	-.0019232	.0015679
bf30	-.0001426	.0003057	-0.47	0.641	-.0007418	.0004566
bf40	.3375085	.0997566	3.38	0.001	.1419893	.5330278
illw2	-.0213359	.267186	-0.08	0.936	-.5450108	.502339
shhlw2	.0011092	.0043627	0.25	0.799	-.0074416	.00966

radhlw2	.000307	.0058685	0.05	0.958	-.011195	.011809
havmilsq	2.49e-08	1.65e-06	0.02	0.988	-3.21e-06	3.26e-06
avgcumdosew2	.0233352	.0524776	0.44	0.657	-.0795191	.1261894
_cons	-1.06417	1.235654	-0.86	0.389	-3.486007	1.357667

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	19	15	34
-	51	255	306
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	27.14%
Specificity	$\Pr(- \sim D)$	94.44%
Positive predictive value	$\Pr(D +)$	55.88%
Negative predictive value	$\Pr(\sim D -)$	83.33%

False + rate for true ~D	$\Pr(+ \sim D)$	5.56%
False - rate for true D	$\Pr(- D)$	72.86%
False + rate for classified +	$\Pr(\sim D +)$	44.12%
False - rate for classified -	$\Pr(D -)$	16.67%

Correctly classified	80.59%
----------------------	--------

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    336
    Pearson chi2(320) =    291.79
        Prob > chi2 =    0.8693

```

Measures of Fit for **logit** of **HP2work**

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-139.917
D(324):	279.835	LR(15):	65.911
		Prob > LR:	0.000
McFadden's R2:	0.191	McFadden's Adj R2:	0.098
Maximum Likelihood R2:	0.176	Cragg & Uhler's R2:	0.276
McKelvey and Zavoina's R2:	0.292	Efron's R2:	0.182
Variance of y*:	4.649	Variance of error:	3.290
Count R2:	0.806	Adj Count R2:	0.057
AIC:	0.917	AIC*n:	311.835
BIC:	-1608.744	BIC':	21.523

```

146 .
147 .
148 . forvalues j=2/2 {
      2. title4 "trimmed HP2work main effects models wave `j' for H1 part 2 with d
> ose ns"
      3. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      4. di as input "Gender = male HP2work model"
      5.
149 . set more off
      6. forvalues j=2/2 {
      7.             logistic HP2work age bf4 illw`j' shhlw`j' havmilsq ///
>             avgcumdosew`j' if gender==1, coef nolog
      8.             estat class
      9.             estat gof
     10.             fitstat
     11. }
     12. }

```

```
trimmed HP2work main effects models wave 2 for H1 part 2 with dose ns
```

```
Gender = male HP2work model
```

Logistic regression	Number of obs	=	340
	LR chi2(6)	=	46.77
	Prob > chi2	=	0.0000
Log likelihood = -149.49038	Pseudo R2	=	0.1353

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0127019	.0133613	0.95	0.342	-.0134858	.0388895
bf4	-.1397142	.0305029	-4.58	0.000	-.1994988	-.0799296
illw2	.2410569	.2214219	1.09	0.276	-.192922	.6750358
shhlw2	.0043743	.0038731	1.13	0.259	-.0032168	.0119654
havmilsq	2.84e-07	1.53e-06	0.19	0.852	-2.71e-06	3.28e-06
avgcumdosew2	.0173789	.0498005	0.35	0.727	-.0802284	.1149862
_cons	-.7234318	.9036114	-0.80	0.423	-2.494478	1.047614

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	15	13	28
-	55	257	312
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	21.43%
Specificity	$\Pr(- \sim D)$	95.19%
Positive predictive value	$\Pr(D +)$	53.57%
Negative predictive value	$\Pr(\sim D -)$	82.37%
False + rate for true ~D	$\Pr(+ \sim D)$	4.81%
False - rate for true D	$\Pr(- D)$	78.57%
False + rate for classified +	$\Pr(\sim D +)$	46.43%
False - rate for classified -	$\Pr(D -)$	17.63%
Correctly classified		80.00%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    325
Pearson chi2(318) =      310.55
Prob > chi2 =      0.6069

```

Measures of Fit for **logistic** of **HP2work**

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-149.490
D(333):	298.981	LR(6):	46.765
		Prob > LR:	0.000
McFadden's R2:	0.135	McFadden's Adj R2:	0.095
Maximum Likelihood R2:	0.129	Cragg & Uhler's R2:	0.201
McKelvey and Zavoina's R2:	0.196	Efron's R2:	0.134
Variance of y*:	4.094	Variance of error:	3.290
Count R2:	0.800	Adj Count R2:	0.029
AIC:	0.921	AIC*n:	312.981
BIC:	-1642.058	BIC':	-11.791

```
150 .
151 . title4 "Simultaneous trimming"
```

Simultaneous trimming

```
152 . forvalues j=2/2 {
      2.          logistic HP2work age bf8 illw`j' shhlw`j' ///
>          avgcumdosew`j' if gender==1, coef nolog
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }
```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	26.93
	Prob > chi2	=	0.0001
Log likelihood = -159.40747	Pseudo R2	=	0.0779

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0348108	.0120851	2.88	0.004	.0111245	.0584972
bf8	-.0000289	.0000207	-1.40	0.163	-.0000694	.0000117
illw2	.4876542	.2119789	2.30	0.021	.0721831	.9031252
shhlw2	.0088288	.0036112	2.44	0.014	.0017511	.0159066
avgcumdosew2	.0118366	.0475514	0.25	0.803	-.0813624	.1050355
_cons	-3.658274	.6492228	-5.63	0.000	-4.930727	-2.385821

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	6	5	11
-	64	265	329
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	8.57%
Specificity	$\Pr(- \sim D)$	98.15%
Positive predictive value	$\Pr(D +)$	54.55%
Negative predictive value	$\Pr(\sim D -)$	80.55%
False + rate for true ~D	$\Pr(+ \sim D)$	1.85%
False - rate for true D	$\Pr(- D)$	91.43%
False + rate for classified +	$\Pr(\sim D +)$	45.45%
False - rate for classified -	$\Pr(D -)$	19.45%
Correctly classified		79.71%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    311
    Pearson chi2(305) =    333.90
        Prob > chi2 =      0.1226

```

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-159.407
D(334):	318.815	LR(5):	26.931
		Prob > LR:	0.000
McFadden's R2:	0.078	McFadden's Adj R2:	0.043
Maximum Likelihood R2:	0.076	Cragg & Uhler's R2:	0.119
McKelvey and Zavoina's R2:	0.136	Efron's R2:	0.088
Variance of y*:	3.807	Variance of error:	3.290
Count R2:	0.797	Adj Count R2:	0.014
AIC:	0.973	AIC*n:	330.815
BIC:	-1628.053	BIC':	2.214

```

153 . // HP2work for men washes out    no dose impact
154 .
155 . scalar SigDoseWkFw2 = "no"

156 .
157 .
158 . des bf8

```

variable name	storage type	display format	value label	variable label
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m

```

159 . * male sign main effects in main effects model: 4- age, bf8, illw2 shjobw2
160 . * male main effects model avgcumdosew2 was not signif.
161 . * male hp2wk w2 mediators: age illw2 ageXillw2 bf8
162 . * female signif main effects in main effects model
163 . * female hp2wk w2 mediators: radhlw2 age bf1 bf4 bf4m
164 . * hypothnuym pt dv wave gender signif
165 .
166 .
167 . title4 " 1. Summary matrix construction Paid employment partition: first two
> rows"

```

```

1. Summary matrix construction Paid employment partition: first two rows

```

```

168 .
169 .     matrix define HP2wkMw2 = J(1,8, 0)

170 .     matrix define HP2wkFw2 = J(1,8, 0)

171 . matrix colnames HP2wkMw2=  hypnum ptnum wave gender medsig numMA sig numModsi
> g numMed

172 . matrix colnames HP2wkFw2=  hypnum ptnum wave gender medsig numMA sig numModsi
> g numMed

```

```

173 .      matrix rownames HP2wkMw2 = workM
174 .      matrix rownames HP2wkFw2 = workF
175 .      matrix define HP2wkMw2= (1, 2, 3, 1, 0 ,4, 0, 4 )
176 .      matrix define HP2wkFw2= (1, 2, 3, 2, 0, 1, 0, 6 )
177 .
178 .      matrix define H1pt2w2 = (HP2wkMw2 \ HP2wkFw2)
179 .      matrix colnames H1pt2w2 =  hypnum ptnum wave  medsig numMASig numModsig
    > numMed
180 .      matrix rownames H1pt2w2 = HP2wkMw2 WHP2wkFw2
181 .      matlist H1pt2w2

```

		hypnum	ptnum	wave	medsig	numMASig	numModsi
> g	numMed	numMed					
>							
	HP2wkMw2	1	2	3	1	0	
> 4	0	4					
	WHP2wkFw2	1	2	3	2	0	
> 1	0	6					

```

182 .
183 . scalar SigDoseWKMw2 = "no"
184 . scalar MainEfffwkMw2 = "workM: age  bf8  illw2  shjobw2"
185 .
186 . scalar list `MainEfffwkMw2'
    wkMedMw2 = bf8 age illw2
    VactnMedFw2 = age illw2 radhlw2
    VactnMedMw2 = age illw2
    VacatnModFw2 = none
    MainEffVactnFw2 = age radhlw2 deaw2
    SigDoseVactnFw2 = no
    vactnModMw2 = none
    MainEffVactnMw2 = age bf7m radhlw2
    SigDoseVactnMw2 = no
    sxLifeMedFw2 = age bf4 bf4m
    sxLifeMedMw2 = age illw2
    InthbModFw2 = none
    MainEffInthbFw2 = age radhlw2 bf4
    SigdoseInthbFw2 = no
    InthbMw2 = none

```

```

MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
sxlifeMedMw2 = age illw2
sxlifeModFw2 = none
MainEffsxlifeFw2 = age radhlw2 bf4 bf4m shrelaw2 shfamw2
SigDoseSxlifeFw2 = no
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
MainEffsxlifeMw2 = age bf4 illw2 radhlw2
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf1 bf4 dvcew2 bf7m
ProbsocMedFw2 = age radhlw2
ProbsocMedMw2 = age
ProbsocModFw2 = none
MainEffProbSocFw2 = age radhlw2 illw2 Shrelaw2 avgcumodsew2
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
MainEffPrbsocMw2 = age radhlw2 shjobw2
hmcareMedFw2 = age illw2
hmcareMedMw2 = age illw2
hmcareModFw2 = none
SigDoseWKFw2 = 0
SigdoseHmcareFw2 = no
hmcareModMw2 = none
MainEffhmcareMw2 = none
SigDoseHmcareMw2 = no
    wkMedFw2 = radhlw2 age bf40 bf4m bf1
    wkModFw2 = none
    wkModMw2 = none
MainEffwkFw2 = age
MainEffwkMw2 = workM: age bf8 illw2 shjobw2
SigDoseWKMw2 = no
SigDoseWkFw2 = no
hmcrMedFw1 = age icdxcnt shjobw1 bf4 BSIIsoma WHPpain WHPsleep WHPel
hmcrMedMw1 = age
MainEffhmcrFw1 = illw1 age
SigDosehmcrFw1 = no
hmcrModMw1 = none
MainEffhmcrMw1 = age shjobw1
SigDosehmcrMw1 = no

```

```

    wkMedFw1 = age b4
MainEffwkFw1 = age
MainEffwkMw1 = age
    wkMedMw1 = bf40
    WkMedMw1 = none
    WkModFw1 = none
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
    medsigFw1 =          1
prbsocnumMA sig =          8

187 .
188 . * moderator construction
189 . * none used because basic dose work relationship washes out
190 .
191 . sem(avgcumdosew2->bf4)(bf4->hp2work) ///
    > (avgcumdosew2->bf4m)(bf4m->hp2work)(avgcumdosew2->hp2work) if gender==2, n
    > ocapslatent

Endogenous variables

Observed:  bf4 hp2work bf4m

Exogenous variables

Observed:  avgcumdosew2

Fitting target model:

Iteration 0:  log likelihood = -3065.5103
Iteration 1:  log likelihood = -3065.5103

Structural equation model                                Number of obs      =      363
Estimation method  = ml
Log likelihood      = -3065.5103

```

```

> _____
               OIM
             Coef.   Std. Err.      z    P>|z|     [95% Conf. Inter
> val]
_____
Structural
  bf4 <-
    avgcumdosew2 |   -.595012   .1955294   -3.04   0.002   -.9782426   -.211
> 7813
    _cons |   11.02048   .321487   34.28   0.000   10.39037   11.6
> 5058
_____
> _____
  hp2work <-
    bf4 |   -.1104133   .0240718   -4.59   0.000   -.1575931   -.063
> 2334
    bf4m |   .0772012   .0220571    3.50   0.000    .03397    .120
> 4324
    avgcumdosew2 |   .0267414   .0155054    1.72   0.085   -.0036486    .057
> 1315
    _cons |   -.022371   .1624855   -0.14   0.890   -.3408367    .296
> 0947
_____
> _____
  bf4m <-
    avgcumdosew2 |   -.599311   .2133886   -2.81   0.005   -1.017545   -.181
> 0771
    _cons |   18.83424   .3508508   53.68   0.000   18.14659   19.
> 5219
_____
> _____
Variance
    e.bf4 |   26.38663   1.958599                22.81402   30.5
> 1869
    e.hp2work |   .1612644   .0119702                .13943    .186
> 5179
    e.bf4m |   31.42693   2.332725                27.17189   36.3
> 4829
_____
> _____
LR test of model vs. saturated: chi2(1)    =   1284.49, Prob > chi2 = 0.0000

```

192 . estat teffects, standardize

Direct effects

		Coef.	OIM Std. Err.	z	P> z	Std. C
> oef.						
> Structural						
bf4 <-						
avgcumdosew2		-.595012	.1955294	-3.04	0.002	-.157
> 7212						
> Structural						
hp2work <-						
bf4		-.1104133	.0240718	-4.59	0.000	-.699
> 4476						
bf4m		.0772012	.0220571	3.50	0.000	.532
> 7398						
avgcumdosew2		.0267414	.0155054	1.72	0.085	.044
> 9038						
> Structural						
bf4m <-						
avgcumdosew2		-.599311	.2133886	-2.81	0.005	-.145
> 8343						
> Structural						
hp2work <-						
bf4						

Indirect effects

		Coef.	OIM Std. Err.	z	P> z	Std. C
> oef.						
> Structural						
bf4 <-						
avgcumdosew2		0	(no path)			
> 0						
> Structural						
hp2work <-						
bf4		0	(no path)			

```

> 0
      bf4m | 0 (no path)
> 0
      avgcumdosew2 | .0194297 .0272807 0.71 0.476 .03
> 2626
-----
> 
      bf4m <-
      avgcumdosew2 | 0 (no path)
> 0
-----
> 

```

Total effects

```

> 
      Coef.      OIM      z      P>|z|      Std. C
> oef.
-----
> 
Structural
      bf4 <-
      avgcumdosew2 | -.595012 .1955294 -3.04 0.002 -.157
> 7212
-----
> 
      hp2work <-
      bf4 | -.1104133 .0240718 -4.59 0.000 -.699
> 4476
      bf4m | .0772012 .0220571 3.50 0.000 .532
> 7398
      avgcumdosew2 | .0461711 .031163 1.48 0.138 .077
> 5298
-----
> 
      bf4m <-
      avgcumdosew2 | -.599311 .2133886 -2.81 0.005 -.145
> 8343
-----
> 

```

```

193 .
194 .
195 .
196 . title4 "testing female hp2work main effects for hypothesis 1 pt 2 wave 2"
-----
testing female hp2work main effects for hypothesis 1 pt 2 wave 2
-----

197 . * Dose work relationship washes out for males in wave 2 also
198 . cap gen hp2hmcare=HP2hmcare

199 . set more off

200 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      3. di as input "For females HP2work on wave 2 with dose ns"
      4.       des age occ1w`j'-occ8w`j' inc1w`j'-inc4w`j' avgcumdosew`j' bf8 /
> //
>       marrw`j'1-marrw`j'6 `w2bf'
      5.       logistic HP2work marrw`j'3-marrw`j'6 age havmilsq ///
>       avgcumdosew2 bf8 illw`j' shjobw`j' suprtw`j' if gender==2, c
> oef nolog
      6.       estat gof
      7.       estat class
      8.       fitstat
      9.       }
For females HP2work on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996

inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf17	float	%9.0g		bf17 = max(0, 20 - ecprw3) * bf15m
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf29	float	%9.0g		bf29 = max(0, 18 - CSsocspt) * bf8
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

note: marrw24 != 0 predicts success perfectly
marrw24 dropped and 1 obs not used

Logistic regression

Log likelihood = **-180.79074**

Number of obs	=	362
LR chi2(10)	=	48.81
Prob > chi2	=	0.0000
Pseudo R2	=	0.1189

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
marrw23	.3465168	.4485933	0.77	0.440	-.53271	1.225743
marrw24	0	(omitted)				
marrw25	.1476199	.8212357	0.18	0.857	-1.461973	1.757212
marrw26	1.010731	.7069238	1.43	0.153	-.3748139	2.396276
age	.0569149	.0131729	4.32	0.000	.0310966	.0827332
havmilsq	-8.40e-07	1.31e-06	-0.64	0.520	-3.40e-06	1.72e-06
avgcumdosew2	.112931	.0849282	1.33	0.184	-.0535252	.2793872
bf8	-8.51e-07	.0000122	-0.07	0.944	-.0000247	.000023
illw2	.2083243	.1431057	1.46	0.145	-.0721576	.4888063
shjobw2	-.0000502	.0033727	-0.01	0.988	-.0066606	.0065603
suprtw2	.0007776	.0033741	0.23	0.818	-.0058355	.0073907
_cons	-4.607688	.7503726	-6.14	0.000	-6.078391	-3.136985

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      362
number of covariate patterns =    360
    Pearson chi2(349) =    381.32
        Prob > chi2 =      0.1127

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	21	7	28
-	71	263	334
Total	92	270	362

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	22.83%
Specificity	$\Pr(- \sim D)$	97.41%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	78.74%

False + rate for true ~D	$\Pr(+ \sim D)$	2.59%
False - rate for true D	$\Pr(- D)$	77.17%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	21.26%

Correctly classified 78.45%

Measures of Fit for **logistic** of **HP2work**

Log-Lik Intercept Only:	-205.197	Log-Lik Full Model:	-180.791
D(350):	361.581	LR(10):	48.812
		Prob > LR:	0.000
McFadden's R2:	0.119	McFadden's Adj R2:	0.060
Maximum Likelihood R2:	0.126	Cragg & Uhler's R2:	0.186
McKelvey and Zavoina's R2:	0.242	Efron's R2:	0.149
Variance of y*:	4.341	Variance of error:	3.290
Count R2:	0.785	Adj Count R2:	0.152
AIC:	1.065	AIC*n:	385.581
BIC:	-1700.494	BIC':	10.104

```

201 .
202 .
203 . // female wave 2 homcare washes out
204 .
205 .
206 .
207 . scalar MainEffwkFw2 = "age"

208 . scalar SigDoseWKFW2 = 0

209 .
210 .
211 .
212 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3. set more off
      4. di as input "For females HP2work on wave 2 with dose ns"
      5.      des age occ1w`j' - occ8w`j' inc1w`j' - inc4w`j' avgcumdosew`j' bf8 /
      > //
      >      marrw`j'1 - marrw`j'6 `w2bf'
      6.      logistic HP2work marrw`j'3 - marrw`j'6 age havmilsq ///
      >      avgcumdosew2 bf8 illw`j' shjobw`j' suprtw`j' if gender==1, c
      > oef nolog
      7.      estat gof
      8.      estat class
      9.      fitstat
      10.     }
For females HP2work on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2

```

bf17          float   %9.0g          bf17 = max(0, 20 - ecprw3) *
          bf15m
bf20          float   %9.0g          bf20 = max(0, kzchorn -
          2.53946E-006)
bf22          float   %9.0g          bf22 = max(0, icdxcnt -
          1.01635E-007) * bf7m
bf29          float   %9.0g          bf29 = max(0, 18 - CSsocspt) *
          bf8
bf30          float   %9.0g          bf30 = max(0, neiwl - 85) * bf20
bf40          float   %9.0g          bf40 = max(0, icdxcnt -
          1.01635E-007)

```

note: marrw24 != 0 predicts failure perfectly
marrw24 dropped and 3 obs not used

```

Logistic regression                      Number of obs   =       337
                                         LR chi2(10)      =       28.86
                                         Prob > chi2      =       0.0013
Log likelihood = -157.74569              Pseudo R2       =       0.0838

```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
marrw23	-.4766426	.3747451	-1.27	0.203	-1.21113	.2578444
marrw24	0 (omitted)					
marrw25	.4073573	.955349	0.43	0.670	-1.465092	2.279807
marrw26	-.9721074	1.293416	-0.75	0.452	-3.507156	1.562941
age	.0477474	.0139539	3.42	0.001	.0203982	.0750965
havmilsq	-2.10e-07	1.49e-06	-0.14	0.888	-3.12e-06	2.70e-06
avgcumdosew2	.0155478	.048524	0.32	0.749	-.0795575	.1106532
bf8	-.0000302	.0000209	-1.45	0.148	-.0000712	.0000107
illw2	.5115257	.2184297	2.34	0.019	.0834114	.9396399
shjobw2	.0088647	.0037067	2.39	0.017	.0015997	.0161296
suprtw2	-.0044167	.0036236	-1.22	0.223	-.0115188	.0026855
_cons	-3.748494	.6958591	-5.39	0.000	-5.112352	-2.384635

Logistic model for HP2work, goodness-of-fit test

```

number of observations =       337
number of covariate patterns =     332
Pearson chi2(321) =     336.79
Prob > chi2 =       0.2612

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	6	3	9
-	64	264	328
Total	70	267	337

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	8.57%
Specificity	$\Pr(- \sim D)$	98.88%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	80.49%
False + rate for true ~D	$\Pr(+ \sim D)$	1.12%
False - rate for true D	$\Pr(- D)$	91.43%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	19.51%
Correctly classified		80.12%

Measures of Fit for **logistic** of **HP2work**

Log-Lik Intercept Only:	-172.178	Log-Lik Full Model:	-157.746
D(325):	315.491	LR(10):	28.864
		Prob > LR:	0.001
McFadden's R2:	0.084	McFadden's Adj R2:	0.014
Maximum Likelihood R2:	0.082	Cragg & Uhler's R2:	0.128
McKelvey and Zavoina's R2:	0.142	Efron's R2:	0.099
Variance of y*:	3.835	Variance of error:	3.290
Count R2:	0.801	Adj Count R2:	0.043
AIC:	1.007	AIC*n:	339.491
BIC:	-1576.036	BIC':	29.336

```

213 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      3. set more off
      4. di as input "For females trimmed HP2work on wave 2 with dose ns"
      5.       des age occ1w`j' -occ8w`j' inc1w`j' -inc4w`j' avgcumdosew`j' bf8 /
> //
>       marrw`j'1-marrw`j'6 `w2bf'
      6.       logistic HP2work age ///
>       avgcumdosew2 bf8 illw`j' shjobw`j' radhlw`j' if gender==1, c
> oef nolog
      7.       estat gof
      8.       estat class
      9.       fitstat
     10.       }
For females trimmed HP2work on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single

```

marrw22      byte    %8.0g      marrw2==2. cohabitating
marrw23      byte    %8.0g      marrw2==3. married
marrw24      byte    %8.0g      marrw2==4. separated
marrw25      byte    %8.0g      marrw2==5. divorced
marrw26      byte    %8.0g      marrw2==6. widowed
bf1          float   %9.0g      bf1 = max(0, kzchorn - 40)
bf4          float   %9.0g      bf4 = max(0, 24 - BSIsoma)
bf2          float   %9.0g      bf2 = max(0, efradw3 -
                                1.61252E-006) * bf1
bf4m         float   %9.0g      bf4m = max(0, 32 - BSIsoma)
bf5m         float   %9.0g      bf5m = max(0, ecprw3 - 75) *
                                bf4m
bf7m         float   %9.0g      bf7m = max(0, radtlw3 -
                                2.12558E-007) * bf4m
bf8          float   %9.0g      bf8 = max(0, radtlw3 - 40) *
                                bf5m
bf15m        float   %9.0g      bf15m = max(0, 1 - icdxcnt) * bf2
bf17         float   %9.0g      bf17 = max(0, 20 - ecprw3) *
                                bf15m
bf20         float   %9.0g      bf20 = max(0, kzchorn -
                                2.53946E-006)
bf22         float   %9.0g      bf22 = max(0, icdxcnt -
                                1.01635E-007) * bf7m
bf29         float   %9.0g      bf29 = max(0, 18 - CSsocspt) *
                                bf8
bf30         float   %9.0g      bf30 = max(0, neiwl - 85) * bf20
bf40         float   %9.0g      bf40 = max(0, icdxcnt -
                                1.01635E-007)

```

Logistic regression

```

Number of obs    =      340
LR chi2(6)       =      34.24
Prob > chi2      =      0.0000
Pseudo R2       =      0.0990

```

Log likelihood = **-155.75258**

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0279967	.0125982	2.22	0.026	.0033047	.0526886
avgcumdosew2	.0093245	.0489486	0.19	0.849	-.0866129	.1052619
bf8	-.0000433	.0000214	-2.03	0.043	-.0000852	-1.44e-06
illw2	.503088	.2180574	2.31	0.021	.0757033	.9304727
shjobw2	.0054505	.0037374	1.46	0.145	-.0018746	.0127756
radhlw2	.0133173	.0044637	2.98	0.003	.0045685	.022066
_cons	-3.81568	.6836898	-5.58	0.000	-5.155688	-2.475673

Logistic model for HP2work, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      332
      Pearson chi2(325) =      343.93
          Prob > chi2 =      0.2252

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	6	5	11
-	64	265	329
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	8.57%
Specificity	$\Pr(- \sim D)$	98.15%
Positive predictive value	$\Pr(D +)$	54.55%
Negative predictive value	$\Pr(\sim D -)$	80.55%
False + rate for true ~D	$\Pr(+ \sim D)$	1.85%
False - rate for true D	$\Pr(- D)$	91.43%
False + rate for classified +	$\Pr(\sim D +)$	45.45%
False - rate for classified -	$\Pr(D -)$	19.45%
Correctly classified		79.71%

Measures of Fit for **logistic** of **HP2work**

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-155.753
D(333):	311.505	LR(6):	34.241
		Prob > LR:	0.000
McFadden's R2:	0.099	McFadden's Adj R2:	0.059
Maximum Likelihood R2:	0.096	Cragg & Uhler's R2:	0.150
McKelvey and Zavoina's R2:	0.170	Efron's R2:	0.114
Variance of y*:	3.963	Variance of error:	3.290
Count R2:	0.797	Adj Count R2:	0.014
AIC:	0.957	AIC*n:	325.505
BIC:	-1629.534	BIC':	0.733

```

214 .
215 . // female trimmed dose work washes out with does not signif.
216 .
217 .
218 .
219 .
220 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      3. set more off
      4. di as input "Full females HPprobsoc on wave 2 with dose ns"
      5.          des age occ1w`j' -occ8w`j' incl1w`j' -inc4w`j' avgcumdosew`j' bf8 /
> //
>          marrw`j'1 -marrw`j'6 radhlw`j' `w2bf'
      6.          logistic HP2probsoc marrw`j'3 -marrw`j'6 age havmilsq radhlw2 //
> /
>          avgcumdosew2 bf8 illw`j' shjobw`j' suprtw`j' if gender==1, c
> oef nolog
      7.          estat gof
      8.          estat class
      9.          fitstat
     10.          }
Full females HPprobsoc on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
incl1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996

inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
radhlw2	double	%8.0g		how much believed personal health is affected by radiation in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf17	float	%9.0g		bf17 = max(0, 20 - ecprw3) * bf15m
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf29	float	%9.0g		bf29 = max(0, 18 - CSsocspt) * bf8
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

note: marrw24 != 0 predicts failure perfectly
marrw24 dropped and 3 obs not used

note: marrw26 != 0 predicts failure perfectly
marrw26 dropped and 4 obs not used

Logistic regression

Number of obs = 333

LR chi2(10) = 62.55

Prob > chi2 = 0.0000

Pseudo R2 = 0.2517

Log likelihood = -92.970187

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
marrw23	-.3736488	.5239634	-0.71	0.476	-1.400598	.6533007
marrw24	0	(omitted)				
marrw25	.3178572	1.386011	0.23	0.819	-2.398675	3.034389
marrw26	0	(omitted)				
age	.068219	.0199083	3.43	0.001	.0291995	.1072385
havmilsq	-1.61e-06	5.43e-06	-0.30	0.767	-.0000122	9.03e-06
radhlw2	.0237245	.0062836	3.78	0.000	.0114089	.0360402
avgcumdosew2	.0249392	.0537004	0.46	0.642	-.0803117	.1301901
bf8	-.0000369	.0000244	-1.51	0.130	-.0000846	.0000109
illw2	.4654847	.2879266	1.62	0.106	-.098841	1.02981
shjobw2	.013417	.0052952	2.53	0.011	.0030386	.0237954
suprtw2	.0027116	.0050363	0.54	0.590	-.0071593	.0125825
_cons	-7.790191	1.174345	-6.63	0.000	-10.09186	-5.488517

Logistic model for HP2probsoc, goodness-of-fit test

number of observations = 333
 number of covariate patterns = 331
 Pearson chi2(320) = 376.50
 Prob > chi2 = 0.0162

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	11	4	15
-	30	288	318
Total	41	292	333

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	26.83%
Specificity	$\Pr(- \sim D)$	98.63%
Positive predictive value	$\Pr(D +)$	73.33%
Negative predictive value	$\Pr(\sim D -)$	90.57%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.37%
False - rate for true D	$\Pr(- D)$	73.17%
False + rate for classified +	$\Pr(\sim D +)$	26.67%
False - rate for classified -	$\Pr(D -)$	9.43%
Correctly classified		89.79%

Measures of Fit for **logistic** of **HP2probsoc**

Log-Lik Intercept Only:	-124.243	Log-Lik Full Model:	-92.970
D(320):	185.940	LR(10):	62.545
		Prob > LR:	0.000
McFadden's R2:	0.252	McFadden's Adj R2:	0.147
Maximum Likelihood R2:	0.171	Cragg & Uhler's R2:	0.326
McKelvey and Zavoina's R2:	0.420	Efron's R2:	0.243
Variance of y*:	5.673	Variance of error:	3.290
Count R2:	0.898	Adj Count R2:	0.171
AIC:	0.636	AIC*n:	211.940
BIC:	-1672.665	BIC':	-4.464

```

221 .
222 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3. set more off
      4. di as input "females trimmed HP2probsoc on wave 2 with dose ns"
      5.      des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' bf8 /
      > //
      >      marrw`j'1-marrw`j'6 `w2bf'
      6.      logistic HP2probsoc age ///
      >      avgcumdosew2 bf8 illw`j' shjobw`j' radhlw`j' if gender==1, c
      > oef nolog
      7.      estat gof
      8.      estat class
      9.      fitstat
      10.     }
      females trimmed HP2probsoc on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2

```

bf17      float   %9.0g      bf17 = max(0, 20 - ecprw3) *
                                bf15m
bf20      float   %9.0g      bf20 = max(0, kzchorn -
                                2.53946E-006)
bf22      float   %9.0g      bf22 = max(0, icdxcnt -
                                1.01635E-007) * bf7m
bf29      float   %9.0g      bf29 = max(0, 18 - CSsocspt) *
                                bf8
bf30      float   %9.0g      bf30 = max(0, neiwl - 85) * bf20
bf40      float   %9.0g      bf40 = max(0, icdxcnt -
                                1.01635E-007)

```

```

Logistic regression              Number of obs   =       340
                                LR chi2(6)       =       60.41
                                Prob > chi2       =       0.0000
Log likelihood = -94.948223      Pseudo R2    =       0.2413

```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0592362	.0176148	3.36	0.001	.0247118	.0937607
avgcumdosew2	.0315514	.0525591	0.60	0.548	-.0714626	.1345653
bf8	-.0000332	.0000239	-1.39	0.165	-.0000801	.0000136
illw2	.5251102	.2757549	1.90	0.057	-.0153594	1.06558
shjobw2	.0135312	.0051744	2.62	0.009	.0033897	.0236728
radhlw2	.0242757	.006237	3.89	0.000	.0120514	.0365
_cons	-7.543673	1.131417	-6.67	0.000	-9.76121	-5.326137

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =       340
number of covariate patterns =     332
Pearson chi2(325) =     382.40
Prob > chi2 =       0.0155

```

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	12	3	15
-	29	296	325
Total	41	299	340

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	29.27%
Specificity	$\Pr(- \sim D)$	99.00%
Positive predictive value	$\Pr(D +)$	80.00%
Negative predictive value	$\Pr(\sim D -)$	91.08%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.00%
False - rate for true D	$\Pr(- D)$	70.73%
False + rate for classified +	$\Pr(\sim D +)$	20.00%
False - rate for classified -	$\Pr(D -)$	8.92%
Correctly classified		90.59%

Measures of Fit for **logistic** of **HP2probsoc**

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-94.948
D(333):	189.896	LR(6):	60.408
		Prob > LR:	0.000
McFadden's R2:	0.241	McFadden's Adj R2:	0.185
Maximum Likelihood R2:	0.163	Cragg & Uhler's R2:	0.312
McKelvey and Zavoina's R2:	0.420	Efron's R2:	0.235
Variance of y*:	5.669	Variance of error:	3.290
Count R2:	0.906	Adj Count R2:	0.220
AIC:	0.600	AIC*n:	203.896
BIC:	-1751.142	BIC':	-25.435

```

223 .
224 . // female trimmed dose work washes out with does not signif.
225 .
226 .
227 .
228 .
229 .
230 .

```

231 . des bf8

variable name	storage type	display format	value label	variable label
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m

232 . title4 "bf8 is a male mediator of paid employment"

bf8 is a male mediator of paid employment

233 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
> 0

234 . foreach var in `w2bf'{
 2. glm `var' avgcumdosew2 if gender==1, family(gaussian) link(identity)
 3. glm hp2work `var' illw2 avgcumdosew2 if gender==1, family(binomial) ///
 > irls scale(dev) link(probit)
 4. }

Iteration 0: log likelihood = **-1551.9176**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	542.9132
Deviance	= 183504.6626	(1/df) Deviance	=	542.9132
Pearson	= 183504.6626	(1/df) Pearson	=	542.9132
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	9.140692
Log likelihood	= -1551.917557	<u>BIC</u>	=	181534.5

bf1	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	-.0294245	.5053831	-0.06	0.954	-1.019957	.9611082
_cons	32.06654	1.353933	23.68	0.000	29.41288	34.7202

Iteration 1: deviance = **327.3468**
 Iteration 2: deviance = **326.8667**
 Iteration 3: deviance = **326.8661**
 Iteration 4: deviance = **326.8661**

```

Generalized linear models                                No. of obs      =       340
Optimization      : ML Fisher scoring                 Residual df     =       336
                  (IRLS EIM)                          Scale parameter =         1
Deviance          =   326.8660563                    (1/df) Deviance =   .9728156
Pearson           =   340.1753181                    (1/df) Pearson  =   1.012427

Variance function: V(u) = u*(1-u)                  [Bernoulli]
Link function     : g(u) = invnorm(u)              [Probit]

                                                    BIC              =   -1631.66

```

hp2work	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf1	.0109044	.0035032	3.11	0.002	.0040382	.0177705
illw2	.2657677	.1244152	2.14	0.033	.0219184	.509617
avgcumdosew2	.0146157	.0285488	0.51	0.609	-.041339	.0705704
_cons	-1.302985	.1496632	-8.71	0.000	-1.59632	-1.009651

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-1027.1225**

```

Generalized linear models                                No. of obs      =       340
Optimization      : ML                                Residual df     =       338
                                                        Scale parameter =   24.7771
Deviance          =   8374.659221                    (1/df) Deviance =   24.7771
Pearson           =   8374.659221                    (1/df) Pearson  =   24.7771

Variance function: V(u) = 1                          [Gaussian]
Link function     : g(u) = u                          [Identity]

Log likelihood    = -1027.122509

                                                    AIC              =   6.053662
                                                    BIC              =   6404.476

```

bf4	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2447701	.1784427
_cons	12.52896	.2892393	43.32	0.000	11.96206	13.09586

Iteration 1: deviance = 300.9022
 Iteration 2: deviance = 299.8184
 Iteration 3: deviance = 299.8108
 Iteration 4: deviance = 299.8108
 Iteration 5: deviance = 299.8108

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	336
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 299.8108296	(1/df) Deviance	=	.8922941
Pearson	= 319.1468848	(1/df) Pearson	=	.9498419

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1658.715

hp2work	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.0960279	.0152223	-6.31	0.000	-.125863	-.0661928
illw2	.1615525	.1227138	1.32	0.188	-.0789623	.4020672
avgcumdosew2	.0143706	.0276919	0.52	0.604	-.0399044	.0686457
_cons	.2173252	.204472	1.06	0.288	-.1834325	.6180829

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -3110.6399

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	5209030
Deviance	= 1760652206	(1/df) Deviance	=	5209030
Pearson	= 1760652206	(1/df) Pearson	=	5209030

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]

		<u>AIC</u>	=	18.30965
Log likelihood	= -3110.639872	<u>BIC</u>	=	1.76e+09

bf2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-36.03645	49.50328	-0.73	0.467	-133.0611	60.9882
_cons	1976.708	132.6205	14.91	0.000	1716.777	2236.64

Iteration 1: deviance = **326.2564**
Iteration 2: deviance = **326.0185**
Iteration 3: deviance = **326.0184**
Iteration 4: deviance = **326.0184**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 326.0184207	(1/df) Deviance	=	.9702929
Pearson = 340.5103126	(1/df) Pearson	=	1.013424

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1632.507**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf2	.0001126	.0000342	3.29	0.001	.0000456	.0001797
illw2	.2301304	.1264315	1.82	0.069	-.0176708	.4779317
avgcumdosew2	.0207807	.0278478	0.75	0.456	-.0338	.0753614
_cons	-1.166294	.1149488	-10.15	0.000	-1.391589	-.9409983

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-1060.7791**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	30.20174
Deviance = 10208.18969	(1/df) Deviance	=	30.20174
Pearson = 10208.18969	(1/df) Pearson	=	30.20174

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

	<u>AIC</u>	=	6.251642
Log likelihood = -1060.779096	<u>BIC</u>	=	8238.006

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0266037	.1191987	-0.22	0.823	-.2602289	.2070215
_cons	20.34324	.3193362	63.70	0.000	19.71735	20.96913

Iteration 1: deviance = 303.3546
Iteration 2: deviance = 302.5908
Iteration 3: deviance = 302.587
Iteration 4: deviance = 302.587
Iteration 5: deviance = 302.587

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	336
Deviance = 302.5870341	Scale parameter	=	1
Pearson = 319.7148309	(1/df) Deviance	=	.9005566
	(1/df) Pearson	=	.9515322

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1655.939

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4m	-.0822373	.0137721	-5.97	0.000	-.1092302	-.0552444
illw2	.1770621	.1226767	1.44	0.149	-.0633798	.4175039
avgcumdosew2	.0150542	.0276105	0.55	0.586	-.0390613	.0691697
_cons	.694465	.2897107	2.40	0.017	.1266424	1.262288

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -2273.2523

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
Deviance = 12776789.76	Scale parameter	=	37801.15
Pearson = 12776789.76	(1/df) Deviance	=	37801.15
	(1/df) Pearson	=	37801.15

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

Log likelihood	= -2273.252279	<u>AIC</u>	= 13.38384
		<u>BIC</u>	= 1.28e+07

	OIM					
bf5m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	9.243905	4.217043	2.19	0.028	.9786526	17.50916
_cons	104.6228	11.29756	9.26	0.000	82.47996	126.7656

```
Iteration 1: deviance = 336.3745
Iteration 2: deviance = 336.2755
Iteration 3: deviance = 336.2754
Iteration 4: deviance = 336.2754
```

```
Generalized linear models
Optimization      : ML Fisher scoring
                   (IRLS EIM)
Deviance          = 336.2754021
Pearson           = 339.5058665
```

Variance function: $V(u) = u \cdot (1-u)$
Link function : $g(u) = \text{invnorm}(u)$

$$\text{BTC} = -1622.25$$

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf5m	-.0001044	.000414	-0.25	0.801	-.0009159	.000707
illw2	.3706764	.1252132	2.96	0.003	.1252631	.6160898
avgcumdosew2	.0147823	.0283632	0.52	0.602	-.0408084	.0703731
_cons	-.9460378	.0985679	-9.60	0.000	-1.139227	-.7528483

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -2733.8869

Generalized linear models
Optimization : ML

```
Deviance      = 191952095.6
Pearson       = 191952095.6
```

Variance function: $V(u) = 1$
Link function : $g(u) = u$

Log likelihood	= -2733.886934	<u>AIC</u>	= 16.09345
		<u>BIC</u>	= 1.92e+08

	OIM					
bf7m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	9.152801	16.34533	0.56	0.576	-22.88345	41.18905
_cons	1025.425	43.78952	23.42	0.000	939.5992	1111.251

```
Iteration 1:    deviance = 336.2763
Iteration 2:    deviance = 336.1772
Iteration 3:    deviance = 336.1772
Iteration 4:    deviance = 336.1772
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 336.177176	(1/df) Deviance	=	1.000527
Pearson = 339.9627414	(1/df) Pearson	=	1.011794

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1622.349

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf7m	-.0000423	.000105	-0.40	0.687	-.0002481	.0001634
illw2	.3607427	.1214759	2.97	0.003	.1226542	.5988312
avgcumdosew2	.014265	.0281752	0.51	0.613	-.0409575	.0694874
_cons	-.910979	.1415067	-6.44	0.000	-1.188327	-.633631

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -3529.9433

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	6.14e+07
Deviance = 2.07423e+10	(1/df) Deviance	=	6.14e+07
Pearson = 2.07423e+10	(1/df) Pearson	=	6.14e+07

Variance function: $\mathbf{V(u)} = 1$ [Gaussian]
Link function : $\mathbf{g(u)} = u$ [Identity]

Log likelihood	= -3529.943345	<u>AIC</u>	= 20.77614
		<u>BIC</u>	= 2.07e+10

	OIM					
bf8	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	357.2422	169.9126	2.10	0.036	24.2195	690.2648
_cons	2822.831	455.2	6.20	0.000	1930.655	3715.006

```
Iteration 1:    deviance = 335.4034
Iteration 2:    deviance = 335.2271
Iteration 3:    deviance = 335.2265
Iteration 4:    deviance = 335.2265
Iteration 5:    deviance = 335.2265
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	336
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 335.2264779	(1/df) Deviance	=	.9976979
Pearson	= 338.675469	(1/df) Pearson	=	1.007963

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1623.299

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf8	-.0000115	.0000109	-1.05	0.292	-.0000329	9.89e-06
illw2	.3835488	.1226954	3.13	0.002	.1430703	.6240273
avgcumdosew2	.0178965	.0281831	0.64	0.525	-.0373414	.0731343
_cons	-.9311558	.0948074	-9.82	0.000	-1.116975	-.7453367

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-2696.8707**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	456784.9
Deviance = 154393311.2	(1/df) Deviance	=	456784.9
Pearson = 154393311.2	(1/df) Pearson	=	456784.9

[Gaussian]
[Identity]

<u>AIC</u>	=	15.87571
<u>BIC</u>	=	1.54e+08

	OIM					
bf15m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-3.877137	14.65924	-0.26	0.791	-32.60872	24.85444
_cons	115.2001	39.27245	2.93	0.003	38.22751	192.1727

```
Iteration 1:    deviance = 336.3366
Iteration 2:    deviance = 336.2425
Iteration 3:    deviance = 336.2425
Iteration 4:    deviance = 336.2425
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 336.2424662	(1/df) Deviance	=	1.000722
Pearson = 339.8130547	(1/df) Pearson	=	1.011348

Variance function: $V(u) = u \cdot (1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1622.283

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf15m	.0000349	.0001107	0.32	0.752	-.000182	.0002518
illw2	.3640012	.1216115	2.99	0.003	.1256471	.6023553
avgcumdosew2	.0139566	.0282099	0.49	0.621	-.0413337	.0692469
_cons	-.9590254	.0937715	-10.23	0.000	-1.142814	-.7752366

(Standard errors scaled using square root of deviance-based dispersion.)

```
Iteration 0:  log likelihood = -3469.0038
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	4.29e+07
Deviance = 1.44936e+10	(1/df) Deviance	=	4.29e+07
Pearson = 1.44936e+10	(1/df) Pearson	=	4.29e+07

[Gaussian]
[Identity]

<u>AIC</u>	=	20.41767
<u>BIC</u>	=	1.45e+10

	OIM					
bf17	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-16.67211	142.0317	-0.12	0.907	-295.0491	261.7049
_cons	429.2726	380.5063	1.13	0.259	-316.5061	1175.051

Iteration 1:	deviance =	336.1233
Iteration 2:	deviance =	335.855
Iteration 3:	deviance =	335.7482
Iteration 4:	deviance =	335.4893
Iteration 5:	deviance =	335.046
Iteration 6:	deviance =	334.8623
Iteration 7:	deviance =	334.7646
Iteration 8:	deviance =	334.7046
Iteration 9:	deviance =	334.6492
Iteration 10:	deviance =	334.5367
Iteration 11:	deviance =	334.466
Iteration 12:	deviance =	334.4424
Iteration 13:	deviance =	334.4338
Iteration 14:	deviance =	334.4305
Iteration 15:	deviance =	334.429
Iteration 16:	deviance =	334.4282
Iteration 17:	deviance =	334.4278
Iteration 18:	deviance =	334.4276
Iteration 19:	deviance =	334.4274
Iteration 20:	deviance =	334.4273
Iteration 21:	deviance =	334.4272
Iteration 22:	deviance =	334.4271
Iteration 23:	deviance =	334.4271
Iteration 24:	deviance =	334.4271
Iteration 25:	deviance =	334.427
Iteration 26:	deviance =	334.427
Iteration 27:	deviance =	334.427
Iteration 28:	deviance =	334.4269
Iteration 29:	deviance =	334.4269
Iteration 30:	deviance =	334.4269
Iteration 31:	deviance =	334.4269
Iteration 32:	deviance =	334.4269
Iteration 33:	deviance =	334.4269
Iteration 34:	deviance =	334.4269
Iteration 35:	deviance =	334.4269

```

Iteration 36: deviance = 334.4269
Iteration 37: deviance = 334.4269
Iteration 38: deviance = 334.4268
Iteration 39: deviance = 334.4268
Iteration 40: deviance = 334.4268
Iteration 41: deviance = 334.4268
Iteration 42: deviance = 334.4268
Iteration 43: deviance = 334.4268
Iteration 44: deviance = 334.4268
Iteration 45: deviance = 334.4268
Iteration 46: deviance = 334.4268
Iteration 47: deviance = 334.4268
Iteration 48: deviance = 334.4268
Iteration 49: deviance = 334.4268
Iteration 50: deviance = 334.4268
Iteration 51: deviance = 334.4268
Iteration 52: deviance = 334.4268
Iteration 53: deviance = 334.4268
Iteration 54: deviance = 334.4268
Iteration 55: deviance = 334.4268
Iteration 56: deviance = 334.4268
Iteration 57: deviance = 334.4268
Iteration 58: deviance = 334.4268
Iteration 59: deviance = 334.4268
Iteration 60: deviance = 334.4268
Iteration 61: deviance = 334.4268
Iteration 62: deviance = 334.4268
Iteration 63: deviance = 334.4268
Iteration 64: deviance = 334.4268
Iteration 65: deviance = 334.4268
Iteration 66: deviance = 334.4268
Iteration 67: deviance = 334.4268
Iteration 68: deviance = 334.4268

```

Generalized linear models

```

Optimization      : ML Fisher scoring
                   (IRLS EIM)
Deviance          = 334.426778
Pearson           = 334.5406031

```

```

No. of obs       = 340
Residual df      = 336
Scale parameter  = 1
(1/df) Deviance  = .9953178
(1/df) Pearson   = .9956566

```

```

Variance function: V(u) = u*(1-u)
Link function     : g(u) = invnorm(u)

```

```

[Bernoulli]
[Probit]

```

```

BIC               = -1624.099

```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf17	-.0063351	.0141649	-0.45	0.655	-.0340978	.0214276
illw2	.3553446	.1212371	2.93	0.003	.1177242	.5929649
avgcumdosew2	.0135183	.02812	0.48	0.631	-.0415959	.0686325
_cons	-.9421698	.0926941	-10.16	0.000	-1.123847	-.7604927

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-1596.6381**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	706.2799
Deviance = 238722.6207	(1/df) Deviance	=	706.2799
Pearson = 238722.6207	(1/df) Pearson	=	706.2799
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.403754
Log likelihood = -1596.638134	<u>BIC</u>	=	236752.4

bf20	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.1996497	.5764265	-0.35	0.729	-1.329425	.9301255
_cons	70.37734	1.54426	45.57	0.000	67.35065	73.40404

Iteration 1: deviance = **326.4244**
Iteration 2: deviance = **325.6691**
Iteration 3: deviance = **325.6663**
Iteration 4: deviance = **325.6663**
Iteration 5: deviance = **325.6663**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 325.6663467	(1/df) Deviance	=	.9692451
Pearson = 338.4324666	(1/df) Pearson	=	1.007239
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		

BIC = -1632.859

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf20	.0104867	.0032097	3.27	0.001	.0041958	.0167776
illw2	.2668849	.1239534	2.15	0.031	.0239406	.5098291
avgcumdosew2	.0159959	.0289453	0.55	0.581	-.0407358	.0727275
_cons	-1.696899	.2514028	-6.75	0.000	-2.189639	-1.204158

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -3143.8431

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	6332576
Deviance = 2140410669	(1/df) Deviance	=	6332576
Pearson = 2140410669	(1/df) Pearson	=	6332576

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

	AIC	=	18.50496
Log likelihood = -3143.84315	BIC	=	2.14e+09

bf22	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	69.44601	54.58153	1.27	0.203	-37.53183	176.4239
_cons	2129.507	146.2252	14.56	0.000	1842.911	2416.103

Iteration 1: deviance = 329.663
Iteration 2: deviance = 329.5329
Iteration 3: deviance = 329.5327
Iteration 4: deviance = 329.5327

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	336
	Scale parameter	=	1
Deviance = 329.5326856	(1/df) Deviance	=	.980752
Pearson = 336.2324364	(1/df) Pearson	=	1.000692

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1628.993

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf22	.0000783	.0000296	2.64	0.008	.0000202	.0001364
illw2	.3005113	.1241463	2.42	0.015	.0571889	.5438337
avgcumdosew2	.0091767	.0283699	0.32	0.746	-.0464273	.0647808
_cons	-1.120001	.1128358	-9.93	0.000	-1.341155	-.8988465

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -3683.6132

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1.52e+08
Deviance = 5.12192e+10	(1/df) Deviance	=	1.52e+08
Pearson = 5.12192e+10	(1/df) Pearson	=	1.52e+08

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

	AIC	=	21.68008
Log likelihood = -3683.613157	BIC	=	5.12e+10

bf29	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	82.80099	267.0015	0.31	0.756	-440.5124	606.1144
_cons	1325.352	715.3035	1.85	0.064	-76.61736	2727.321

Iteration 1: deviance = 336.3754
Iteration 2: deviance = 336.2738
Iteration 3: deviance = 336.2737
Iteration 4: deviance = 336.2737

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 336.273687	(1/df) Deviance	=	1.000815
Pearson = 339.164143	(1/df) Pearson	=	1.009417

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1622.252

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf29	1.48e-06	5.82e-06	0.25	0.799	-9.92e-06	.0000129
illw2	.3622929	.1215962	2.98	0.003	.1239688	.600617
avgcumdosew2	.0137461	.028224	0.49	0.626	-.0415719	.0690641
_cons	-.9567327	.092818	-10.31	0.000	-1.138653	-.7748128

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -2661.1745

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	370270.9
Deviance = 125151569.5	(1/df) Deviance	=	370270.9
Pearson = 125151569.5	(1/df) Pearson	=	370270.9

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

	AIC	=	15.66573
Log likelihood = -2661.174486	BIC	=	1.25e+08

bf30	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-9.387797	13.19822	-0.71	0.477	-35.25583	16.48024
_cons	497.7068	35.35834	14.08	0.000	428.4057	567.0079

Iteration 1: deviance = 331.3314
Iteration 2: deviance = 331.1891
Iteration 3: deviance = 331.1888
Iteration 4: deviance = 331.1888

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 331.1888247	(1/df) Deviance	=	.985681
Pearson = 342.2972093	(1/df) Pearson	=	1.018742

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1627.337

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf30	.0002835	.0001242	2.28	0.022	.0000401	.0005269
illw2	.3537185	.1220211	2.90	0.004	.1145615	.5928754
avgcumdosew2	.0172486	.0281673	0.61	0.540	-.0379583	.0724554
_cons	-1.105489	.1160104	-9.53	0.000	-1.332866	-.8781133

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -659.07396

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	2.843195
Deviance = 960.9998238	(1/df) Deviance	=	2.843195
Pearson = 960.9998238	(1/df) Pearson	=	2.843195

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

	AIC	=	3.88867
Log likelihood = -659.0739647	BIC	=	-1009.184

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.0482004	.0365729	1.32	0.188	-.0234811	.1198818
_cons	2.097753	.0979795	21.41	0.000	1.905716	2.289789

Iteration 1: deviance = 315.0711
Iteration 2: deviance = 314.451
Iteration 3: deviance = 314.4494
Iteration 4: deviance = 314.4494

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 314.4493978	(1/df) Deviance	=	.9358613
Pearson = 332.2461013	(1/df) Pearson	=	.9888277

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1644.076

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.2308417	.0484278	4.77	0.000	.1359249	.3257585
illw2	.1331906	.1291807	1.03	0.303	-.1199989	.3863801
avgcumdosew2	.0062786	.0280086	0.22	0.823	-.0486172	.0611743
_cons	-1.427269	.1387712	-10.29	0.000	-1.699256	-1.155283

(Standard errors scaled using square root of deviance-based dispersion.)

```

235 .
236 . **** male mediators of dose paid employment: bf8, age, illw2 ageXillw2
237 . scalar wkMedMw2 = "bf8 age illw2 "

238 .
239 . title4 "Female mediator models for dose-paid employment"

```

Female mediator models for dose-paid employment

```

240 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = -1791.2233

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1137.567
Deviance = 410661.5604	(1/df) Deviance	=	1137.567
Pearson = 410661.5604	(1/df) Pearson	=	1137.567

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	9.880018
Log likelihood = -1791.223306	<u>BIC</u>	=	408533.7

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	3.302288	1.283833	2.57	0.010	.7860214	5.818555
_cons	56.95167	2.110863	26.98	0.000	52.81445	61.08888

```
241 . glm hp2work radhlw2 if gender==2, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 395.8837
Iteration 2:  deviance = 395.5308
Iteration 3:  deviance = 395.5307
Iteration 4:  deviance = 395.5307
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 395.5307336	(1/df) Deviance	=	1.095653
Pearson = 363.4160364	(1/df) Pearson	=	1.006693

Variance function: V(u) = u*(1-u)	[Bernoulli]
Link function : g(u) = invnorm(u)	[Probit]

BIC = -1732.349

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0090691	.0023064	3.93	0.000	.0045487	.0135895
_cons	-1.229859	.1685308	-7.30	0.000	-1.560173	-.8995443

(Standard errors scaled using square root of deviance-based dispersion.)

```
242 . glm age avgcumdosew2 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -1406.9403
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.9184
Deviance = 49427.52828	(1/df) Deviance	=	136.9184
Pearson = 49427.52828	(1/df) Pearson	=	136.9184

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271	<u>BIC</u>	=	47299.65

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

243 . glm hp2work age if gender==2, fam(binomial) irls scale(dev) link(probit)

Iteration 1: deviance = **372.7391**
Iteration 2: deviance = **372.3711**
Iteration 3: deviance = **372.3711**
Iteration 4: deviance = **372.3711**

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 372.3710546	(1/df) Deviance	=	1.031499
Pearson = 375.1783727	(1/df) Pearson	=	1.039275

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1755.508**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0398718	.0066503	6.00	0.000	.0268375	.052906
_cons	-2.722762	.3594297	-7.58	0.000	-3.427231	-2.018292

(Standard errors scaled using square root of deviance-based dispersion.)

244 . glm illw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity)

Iteration 0: log likelihood = **-463.51524**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.756881
Deviance = 273.2340487	(1/df) Deviance	=	.756881
Pearson = 273.2340487	(1/df) Pearson	=	.756881

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood	= -463.5152411	<u>AIC</u>	= 2.564822
		<u>BIC</u>	= -1854.645

	OIM					
illw2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1249912	.0331157	3.77	0.000	.0600856	.1898968
_cons	.301285	.0544484	5.53	0.000	.194568	.4080019

```
245 . glm hp2work illw2 if gender==2, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 405.7435
Iteration 2:    deviance = 405.3085
Iteration 3:    deviance = 405.3081
Iteration 4:    deviance = 405.3081
Iteration 5:    deviance = 405.3081
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 405.3080692	(1/df) Deviance	=	1.122737
Pearson = 363.1923247	(1/df) Pearson	=	1.006073

Variance function: $V(u) = u(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1722.571

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.2093544	.0854065	2.45	0.014	.0419606	.3767481
_cons	-.7522712	.0853534	-8.81	0.000	-.9195607	-.5849817

(Standard errors scaled using square root of deviance-based dispersion.)

```

246 .
247 .
248 . cap gen illw2Xd2=illw2*avgcumdosew2

249 .
250 . * interaction of illw2Xd is not a mediator
251 . glm illw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity) nolog

```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.756881
Deviance = 273.2340487	(1/df) Deviance	=	.756881
Pearson = 273.2340487	(1/df) Pearson	=	.756881

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	2.564822
Log likelihood = -463.5152411	<u>BIC</u>	=	-1854.645

illw2	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	.1249912	.0331157	3.77	0.000	.0600856	.1898968
_cons	.301285	.0544484	5.53	0.000	.194568	.4080019

```

252 . glm hp2work illw2Xd2 illw2 avgcumdosew2 if gender==2, fam(binomial) ///
> nolog irls scale(dev) link(probit)

```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.8217749	(1/df) Deviance	=	1.116495
Pearson = 360.6634088	(1/df) Pearson	=	1.004633

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1715.269
--	-----	---	-----------

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2Xd2	-.0002555	.0352447	-0.01	0.994	-.0693338	.0688228
illw2	.1843288	.1001774	1.84	0.066	-.0120152	.3806729
avgcumdosew2	.1074757	.0718444	1.50	0.135	-.0333367	.2482882
_cons	-.8405461	.1053904	-7.98	0.000	-1.047107	-.6339848

(Standard errors scaled using square root of deviance-based dispersion.)

```

253 .
254 .
255 .
256 . **** Basis function mediators of paid employment
257 . ** female b4 b4m b40
258 .
259 . title4 "bf8 is a male mediator of paid employment"

```

```

bf8 is a male mediator of paid employment

```

```

260 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0
261 . foreach var in `w2bf'{
    2. glm `var' avgcumdosew2 if gender==2, family(gaussian) link(identity)
    3. glm hp2work `var' avgcumdosew2 if gender==2, family(binomial) irls scale
    > (dev) link(probit)
    4. }

```

Iteration 0: log likelihood = **-1648.0584**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	516.905
Deviance = 186602.7154	(1/df) Deviance	=	516.905
Pearson = 186602.7154	(1/df) Pearson	=	516.905
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.091231
Log likelihood = -1648.05836	<u>BIC</u>	=	184474.8

bf1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.592699	.8654173	1.84	0.066	-.1034879	3.288886
_cons	37.79953	1.422908	26.56	0.000	35.01068	40.58837

Iteration 1: deviance = **400.85**
Iteration 2: deviance = **400.4115**
Iteration 3: deviance = **400.4114**
Iteration 4: deviance = **400.4114**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.4114259	(1/df) Deviance	=	1.112254
Pearson = 362.4247002	(1/df) Pearson	=	1.006735

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1721.574**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf1	.0079775	.0034614	2.30	0.021	.0011932	.0147618
avgcumdosew2	.1139711	.0531295	2.15	0.032	.0098392	.2181029
_cons	-1.08756	.1662101	-6.54	0.000	-1.413326	-.7617939

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-1109.0983**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.53281
Deviance = 9578.344971	(1/df) Deviance	=	26.53281
Pearson = 9578.344971	(1/df) Pearson	=	26.53281

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -1109.098281	<u>AIC</u>	=	6.121754
	<u>BIC</u>	=	7450.466

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.595012	.1960703	-3.03	0.002	-.9793027	-.2107212
_cons	11.02048	.3223763	34.19	0.000	10.38863	11.65232

Iteration 1: deviance = 368.2526
Iteration 2: deviance = 367.9545
Iteration 3: deviance = 367.9542
Iteration 4: deviance = 367.9542

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 367.9541653	(1/df) Deviance	=	1.022095
Pearson = 355.981786	(1/df) Pearson	=	.9888383

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1754.031

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.0878252	.0146171	-6.01	0.000	-.1164742	-.0591762
avgcumdosew2	.0839548	.051694	1.62	0.104	-.0173635	.1852731
_cons	.1183858	.1696362	0.70	0.485	-.2140951	.4508667

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -3335.9882

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	5653290
Deviance = 2040837774	(1/df) Deviance	=	5653290
Pearson = 2040837774	(1/df) Pearson	=	5653290

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

Log likelihood = -3335.988235	<u>AIC</u>	=	18.39112
	<u>BIC</u>	=	2.04e+09

bf2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-6.46457	90.50464	-0.07	0.943	-183.8504	170.9213
_cons	2475.004	148.8066	16.63	0.000	2183.349	2766.66

Iteration 1: deviance = **400.9948**
Iteration 2: deviance = **400.598**
Iteration 3: deviance = **400.598**
Iteration 4: deviance = **400.598**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.5979742	(1/df) Deviance	=	1.112772
Pearson = 362.9767308	(1/df) Pearson	=	1.008269

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1721.387**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf2	.0000727	.0000317	2.29	0.022	.0000106	.0001349
avgcumdosew2	.1275153	.0528818	2.41	0.016	.0238688	.2311617
_cons	-.9638935	.1245337	-7.74	0.000	-1.207975	-.719812

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-1140.8259**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	31.60104
Deviance = 11407.97484	(1/df) Deviance	=	31.60104
Pearson = 11407.97484	(1/df) Pearson	=	31.60104

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -1140.825904	<u>AIC</u>	=	6.296561
	<u>BIC</u>	=	9280.095

bf5m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	13.38431	8.434936	1.59	0.113	-3.147864	29.91648
_cons	147.9804	13.86862	10.67	0.000	120.7984	175.1624

Iteration 1: deviance = **406.9626**
Iteration 2: deviance = **406.4247**
Iteration 3: deviance = **406.4246**
Iteration 4: deviance = **406.4246**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 406.4245618	(1/df) Deviance	=	1.128957
Pearson = 362.4207333	(1/df) Pearson	=	1.006724

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1715.56**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf5m	.0000409	.0003437	0.12	0.905	-.0006328	.0007146
avgcumdosew2	.1250263	.0533787	2.34	0.019	.020406	.2296465
_cons	-.7796998	.1041776	-7.48	0.000	-.9838841	-.5755154

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-2919.8439**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	570884.5
Deviance = 206089311.1	(1/df) Deviance	=	570884.5
Pearson = 206089311.1	(1/df) Pearson	=	570884.5

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -2919.843936	<u>AIC</u>	=	16.09831
	<u>BIC</u>	=	2.06e+08

bf7m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-14.75682	28.76036	-0.51	0.608	-71.12609	41.61245
_cons	1193.681	47.28742	25.24	0.000	1101	1286.363

Iteration 1: deviance = **406.5017**
Iteration 2: deviance = **405.9725**
Iteration 3: deviance = **405.9723**
Iteration 4: deviance = **405.9723**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 405.9722985	(1/df) Deviance	=	1.127701
Pearson = 362.2389826	(1/df) Pearson	=	1.006219

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1716.013**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf7m	-.0000668	.0001013	-0.66	0.509	-.0002652	.0001317
avgcumdosew2	.1244811	.0531995	2.34	0.019	.020212	.2287502
_cons	-.6947121	.1494363	-4.65	0.000	-.9876019	-.4018223

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-3888.9836**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.19e+08
Deviance = 4.29556e+10	(1/df) Deviance	=	1.19e+08
Pearson = 4.29556e+10	(1/df) Pearson	=	1.19e+08

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

AIC = **21.43793**
BIC = **4.30e+10**

Log likelihood = **-3888.983569**

bf15m	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	-20.7721	24.75663	-0.84	0.401	-69.29421	27.75	
_cons	118.713	40.70454	2.92	0.004	38.93359	198.4925	

```

Iteration 1:  deviance = 403.5605
Iteration 2:  deviance = 401.8807
Iteration 3:  deviance = 401.3347
Iteration 4:  deviance = 400.9492
Iteration 5:  deviance = 400.5446
Iteration 6:  deviance = 400.2059
Iteration 7:  deviance = 400.0413
Iteration 8:  deviance = 399.9425
Iteration 9:  deviance = 399.8645
Iteration 10: deviance = 399.8166
Iteration 11: deviance = 399.8
Iteration 12: deviance = 399.7944
Iteration 13: deviance = 399.7924
Iteration 14: deviance = 399.7917
Iteration 15: deviance = 399.7914
Iteration 16: deviance = 399.7913
Iteration 17: deviance = 399.7912
Iteration 18: deviance = 399.7912
Iteration 19: deviance = 399.7912
Iteration 20: deviance = 399.7912
Iteration 21: deviance = 399.7912
Iteration 22: deviance = 399.7912
Iteration 23: deviance = 399.7912
Iteration 24: deviance = 399.7912
Iteration 25: deviance = 399.7912
Iteration 26: deviance = 399.7912
Iteration 27: deviance = 399.7912
Iteration 28: deviance = 399.7912
Iteration 29: deviance = 399.7912

```

```

Generalized linear models
Optimization      : MQL Fisher scoring
                   (IRLS EIM)
Deviance          = 399.7911696
Pearson           = 350.5970313

```

```

No. of obs       = 363
Residual df      = 360
Scale parameter  = 1
(1/df) Deviance = 1.110531
(1/df) Pearson  = .9738806

```

```

Variance function: V(u) = u*(1-u)
Link function     : g(u) = invnorm(u)

```

```

[Bernoulli]
[Probit]

```

```

BIC = -1722.194

```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf15m	-.0186941	.1404434	-0.13	0.894	-.293958	.2565699
avgcumdosew2	.1198992	.0526195	2.28	0.023	.0167668	.2230316
_cons	-.7426095	.0909405	-8.17	0.000	-.9208497	-.5643693

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-3826.3245**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	8.43e+07
Deviance = 3.04151e+10	(1/df) Deviance	=	8.43e+07
Pearson = 3.04151e+10	(1/df) Pearson	=	8.43e+07

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	21.0927
Log likelihood = -3826.324541	<u>BIC</u>	=	3.04e+10

bf17	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-273.4502	349.3904	-0.78	0.434	-958.2427	411.3423
_cons	1275.196	574.4633	2.22	0.026	149.269	2401.124

Iteration 1: deviance = **405.2053**
Iteration 2: deviance = **404.0203**
Iteration 3: deviance = **403.6855**
Iteration 4: deviance = **403.4175**
Iteration 5: deviance = **403.1159**
Iteration 6: deviance = **402.9417**
Iteration 7: deviance = **402.8368**
Iteration 8: deviance = **402.7416**
Iteration 9: deviance = **402.6786**
Iteration 10: deviance = **402.6575**
Iteration 11: deviance = **402.6503**
Iteration 12: deviance = **402.6478**
Iteration 13: deviance = **402.647**
Iteration 14: deviance = **402.6466**
Iteration 15: deviance = **402.6465**
Iteration 16: deviance = **402.6465**
Iteration 17: deviance = **402.6465**

Iteration 18: deviance = 402.6464
 Iteration 19: deviance = 402.6464
 Iteration 20: deviance = 402.6464
 Iteration 21: deviance = 402.6464
 Iteration 22: deviance = 402.6464
 Iteration 23: deviance = 402.6464
 Iteration 24: deviance = 402.6464
 Iteration 25: deviance = 402.6464

Generalized linear models
 Optimization : **ML Fisher scoring**
 (**IRLS EIM**)
 Deviance = 402.6464206
 Pearson = 355.5597944

No. of obs = 363
 Residual df = 360
 Scale parameter = 1
 (1/df) Deviance = 1.118462
 (1/df) Pearson = .9876661

Variance function: $V(u) = u*(1-u)$
 Link function : $g(u) = \text{invnorm}(u)$

[**Bernoulli**]
 [**Probit**]

BIC = -1719.339

hp2work	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf17	-.0009496	.0098579	-0.10	0.923	-.0202707	.0183715
avgcumdosew2	.1218174	.0528492	2.30	0.021	.0182348	.2253999
_cons	-.755413	.0909044	-8.31	0.000	-.9335823	-.5772436

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = -1709.1559

Generalized linear models
 Optimization : **ML**
 Deviance = 261283.9058
 Pearson = 261283.9058

No. of obs = 363
 Residual df = 361
 Scale parameter = 723.7781
 (1/df) Deviance = 723.7781
 (1/df) Pearson = 723.7781

Variance function: $V(u) = 1$
 Link function : $g(u) = u$

[**Gaussian**]
 [**Identity**]

Log likelihood = -1709.155932

AIC = 9.427856
BIC = 259156

bf20	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.580896	1.024054	1.54	0.123	-.4262136	3.588005
_cons	75.9561	1.683737	45.11	0.000	72.65604	79.25616

Iteration 1: deviance = **400.9593**
Iteration 2: deviance = **400.4773**
Iteration 3: deviance = **400.4772**
Iteration 4: deviance = **400.4772**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.4771542	(1/df) Deviance	=	1.112437
Pearson = 362.8420021	(1/df) Pearson	=	1.007894

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1721.508**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf20	.0068438	.0030242	2.26	0.024	.0009166	.012771
avgcumdosew2	.1159481	.0531408	2.18	0.029	.011794	.2201022
_cons	-1.306413	.2554428	-5.11	0.000	-1.807072	-.8057543

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-3441.897**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.01e+07
Deviance = 3657865066	(1/df) Deviance	=	1.01e+07
Pearson = 3657865066	(1/df) Pearson	=	1.01e+07

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -3441.896981	<u>AIC</u>	=	18.97464
	<u>BIC</u>	=	3.66e+09

bf22	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	220.8529	121.1659	1.82	0.068	-16.62788	458.3337
_cons	3140.533	199.2195	15.76	0.000	2750.07	3530.996

Iteration 1: deviance = **405.124**
Iteration 2: deviance = **404.6331**
Iteration 3: deviance = **404.6329**
Iteration 4: deviance = **404.6329**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 404.6329168	(1/df) Deviance	=	1.12398
Pearson = 360.9276967	(1/df) Pearson	=	1.002577

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1717.352**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf22	.0000304	.0000232	1.31	0.191	-.0000151	.0000759
avgcumdosew2	.1199526	.0533515	2.25	0.025	.0153855	.2245196
_cons	-.8734808	.1187957	-7.35	0.000	-1.106316	-.6406455

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-3484.9777**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.28e+07
Deviance = 4637795801	(1/df) Deviance	=	1.28e+07
Pearson = 4637795801	(1/df) Pearson	=	1.28e+07

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -3484.977739	<u>AIC</u>	=	19.212
	<u>BIC</u>	=	4.64e+09

bf29	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	52.50345	136.4339	0.38	0.700	-214.9022	319.909
_cons	267.0292	224.323	1.19	0.234	-172.6358	706.6941

Iteration 1: deviance = **406.0224**
Iteration 2: deviance = **405.5022**
Iteration 3: deviance = **405.5021**
Iteration 4: deviance = **405.5021**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 405.5020775	(1/df) Deviance	=	1.126395
Pearson = 362.236176	(1/df) Pearson	=	1.006212

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1716.483**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf29	.0000177	.0000198	0.89	0.371	-.0000211	.0000564
avgcumdosew2	.1248052	.0530425	2.35	0.019	.0208439	.2287666
_cons	-.7795525	.0909171	-8.57	0.000	-.9577467	-.6013582

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-2855.8596**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	401278.8
Deviance = 144861628.9	(1/df) Deviance	=	401278.8
Pearson = 144861628.9	(1/df) Pearson	=	401278.8

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -2855.859629	<u>AIC</u>	=	15.74578
	<u>BIC</u>	=	1.45e+08

bf30	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	58.2065	24.11256	2.41	0.016	10.94675	105.4662
_cons	476.5581	39.64556	12.02	0.000	398.8542	554.2619

Iteration 1: deviance = **404.5558**
Iteration 2: deviance = **404.0864**
Iteration 3: deviance = **404.0863**
Iteration 4: deviance = **404.0863**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 404.0863003	(1/df) Deviance	=	1.122462
Pearson = 361.7532879	(1/df) Pearson	=	1.00487

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1717.899**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf30	.0001722	.0001187	1.45	0.147	-.0000605	.0004048
avgcumdosew2	.116572	.0537488	2.17	0.030	.0112264	.2219177
_cons	-.8607769	.1094838	-7.86	0.000	-1.075361	-.6461925

(Standard errors scaled using square root of deviance-based dispersion.)

Iteration 0: log likelihood = **-818.51169**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	5.351378
Deviance = 1931.847477	(1/df) Deviance	=	5.351378
Pearson = 1931.847477	(1/df) Pearson	=	5.351378

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

Log likelihood = -818.5116931	<u>AIC</u>	=	4.520726
	<u>BIC</u>	=	-196.0319

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1794903	.0880548	2.04	0.042	.0069061	.3520745
_cons	3.004543	.1447786	20.75	0.000	2.720783	3.288304

Iteration 1: deviance = 400.9844
Iteration 2: deviance = 400.6024
Iteration 3: deviance = 400.6022
Iteration 4: deviance = 400.6022

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.6022459	(1/df) Deviance	=	1.112784
Pearson = 359.7424008	(1/df) Pearson	=	.9992844

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1721.383

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.0741875	.0318129	2.33	0.020	.0118353	.1365397
avgcumdosew2	.1139391	.0533719	2.13	0.033	.009332	.2185461
_cons	-1.008205	.1365187	-7.39	0.000	-1.275776	-.740633

(Standard errors scaled using square root of deviance-based dispersion.)

```
262 . * Saving mediators as scalars for Dose=work relationship
263 . **** female mediators of dose-paid employment: radhlw2, age,b40, bf4m, bf4,
> bf1
```

```

264 . scalar wkMedFw2 = "radhlw2 age bf40 bf4m bf1"

265 . scalar list
      wkMedMw2 = bf8 age illw2
VactnMedFw2 = age illw2 radhlw2
VactnMedMw2 = age illw2
VacatnModFw2 = none
MainEffVactnFw2 = age radhlw2 deaw2
SigDoseVactnFw2 = no
vactnModMw2 = none
MainEffVactnMw2 = age bf7m radhlw2
SigDoseVactnMw2 = no
sxLifeMedFw2 = age bf4 bf4m
sxLifeMedMw2 = age illw2
InthbModFw2 = none
MainEffInthbFw2 = age radhlw2 bf4
SigDoseInthbFw2 = no
      InthbMw2 = none
MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
sxlifeMedMw2 = age illw2
sxlifeModFw2 = none
MainEffsxlifeFw2 = age radhlw2 bf4 bf4m shrelaw2 shfamw2
SigDoseSxlifeFw2 = no
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
MainEffsxlifeMw2 = age bf4 illw2 radhlw2
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf1 bf4 dvcew2 bf7m
ProbsocMedFw2 = age radhlw2
ProbsocMedMw2 = age
ProbsocModFw2 = none
MainEffProbSocFw2 = age radhlw2 illw2 Shrelaw2 avgcumodsew2
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
MainEffPrbsocMw2 = age radhlw2 shjobw2
hmcareMedFw2 = age illw2
hmcareMedMw2 = age illw2
hmcareModFw2 = none
SigDoseWKFw2 = 0

```

```

SigdoseHmcareFw2 = no
hmcareModMw2 = none
MainEffhmcareMw2 = none
SigDoseHmcareMw2 = no
    wkMedFw2 = radhlw2 age bf40 bf4m bf1
    wkModFw2 = none
    wkModMw2 = none
MainEffwkFw2 = age
MainEffwkMw2 = workM: age bf8 illw2 shjobw2
SigDoseWKMw2 = no
SigDoseWkFw2 = no
hmcrMedFw1 = age icdxcnt shjobw1 bf4 BSIIsoma WHPpain WHPsleep WHPel
hmcrMedMw1 = age
MainEffhmcrFw1 = illw1 age
SigDosehmcrFw1 = no
hmcrModMw1 = none
MainEffhmcrMw1 = age shjobw1
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
MainEffwkFw1 = age
MainEffwkMw1 = age
    wkMedMw1 = bf40
    WkMedMw1 = none
    WkModFw1 = none
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
    medsigFw1 = 1
    prbsocnumMA sig = 8

```

```

266 .
267 . set linesize 100

268 .

```

```

269 . *****
    > ****
270 . ***** We summarize the main effects models that were supposed to be signif
    > icant
271 . *****
    > ****
272 . set linesize 100

273 . est clear

274 .
275 .
276 .     * work
277 . forvalues j=2/2 {
    2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
    > bf40
    3. set more off
    4. di as input "For females trimmed HP2work on wave 2 with dose ns"
    5.         des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' bf8 /
    > //
    >         marrw`j'1-marrw`j'6 `w2bf'
    6.         logistic HP2work age ///
    >             avgcumdosew2 bf8 illw`j' shjobw`j' radhlw`j' if gender==1, c
    > oef nolog
    7.
278 . eststo paidwk
    8.         }
    For females trimmed HP2work on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
incl1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996

inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf17	float	%9.0g		bf17 = max(0, 20 - ecprw3) * bf15m
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf29	float	%9.0g		bf29 = max(0, 18 - CSsocspt) * bf8
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Logistic regression

Log likelihood = **-155.75258**

Number of obs	=	340
LR chi2(6)	=	34.24
Prob > chi2	=	0.0000
Pseudo R2	=	0.0990

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0279967	.0125982	2.22	0.026	.0033047	.0526886
avgcumdosew2	.0093245	.0489486	0.19	0.849	-.0866129	.1052619
bf8	-.0000433	.0000214	-2.03	0.043	-.0000852	-1.44e-06
illw2	.503088	.2180574	2.31	0.021	.0757033	.9304727
shjobw2	.0054505	.0037374	1.46	0.145	-.0018746	.0127756
radhlw2	.0133173	.0044637	2.98	0.003	.0045685	.022066
_cons	-3.81568	.6836898	-5.58	0.000	-5.155688	-2.475673

```

279 .
280 .
281 . * social life
282 . forvalues j=2/2 {
      2. set more off
      3. di as input "females trimmed HP2probsoc on wave 2 with dose ns"
      4.      des age occ1w`j'-occ8w`j' inc1w`j'-inc4w`j' avgcumdosew`j' bf8 /
> //
>      marrw`j'1-marrw`j'6 `w2bf'
      5.      logistic HP2probsoc age ///
>      avgcumdosew2 bf8 illw`j' shjobw`j' radhlw`j' if gender==1, c
> oef nolog
      6. eststo socprobs
      7.      }
females trimmed HP2probsoc on wave 2 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for

inc3w2	double	%15.0g	LABJ	basic neccessities in 1996 Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf17	float	%9.0g		bf17 = max(0, 20 - ecprw3) * bf15m
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf29	float	%9.0g		bf29 = max(0, 18 - CSsocspt) * bf8
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)
Logistic regression				Number of obs = 340
				LR chi2(6) = 60.41
				Prob > chi2 = 0.0000
Log likelihood = -94.948223				Pseudo R2 = 0.2413


```

286 . * male models
287 .     forvalues j=2/2 {
      2. set more off
      3. di as input  "trimmed HP2sexlife main effects models wave 1 for H1 part 2
> with dose ns"
      4. di as input  "wave 2 male dose avgcumdosew`j' main effect not signif"
      5.     logit HP2sexlife age  bf4  illw`j' ///
>     avgcumdosew`j' radhlw`j' if gender==1
      6.
288 .     eststo sexlife
      7. }
trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose ns
wave 2 male dose avgcumdosew2 main effect not signif

```

```

Iteration 0:  log likelihood = -171.51396
Iteration 1:  log likelihood = -121.56573
Iteration 2:  log likelihood = -115.51071
Iteration 3:  log likelihood = -115.37175
Iteration 4:  log likelihood = -115.3714
Iteration 5:  log likelihood = -115.3714

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	112.29
	Prob > chi2	=	0.0000
Log likelihood = -115.3714	Pseudo R2	=	0.3273

HP2sexlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0668709	.0154805	4.32	0.000	.0365295	.0972122
bf4	-.1650598	.0368511	-4.48	0.000	-.2372867	-.0928329
illw2	.3077459	.2454954	1.25	0.210	-.1734162	.788908
avgcumdosew2	.0621309	.0473611	1.31	0.190	-.0306951	.1549569
radhlw2	.010562	.0054615	1.93	0.053	-.0001422	.0212663
_cons	-3.881348	1.050876	-3.69	0.000	-5.941027	-1.82167

```

289 .
290 .
291 .
292 .
293 .
294 . * inthob
295 .
296 . forvalues j=2/2 {
      2. set more off
      3.
297 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
298 .   foreach var in HP2inthob {
      5.       forvalues k=2/2 {
      6.         local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      7.
299 . di as input "trimmed main model for `var' for wave= `j' "
      8. di _skip(4)
      9. di as input "chunk 8 H1 test:Gender= `k' model Wave = `j' for `e(depva
      > r)' "
      10. di _skip(4)
      11. title "Full Nottingham Part 2 subscale models for male and then females"
      12. di as input "Model for gender==`k' and wave == `j'"
      13. di _skip(2)
      14.       logit `var' age ///
      >               avgcumdosew`j' bf4 bf30 ///
      >               shrelaw`j' suprtw`j' ///
      >               radhlw2 if gender==2, difficult iterate(50) nolog
      15.
300 .           eststo inthobbies
      16. }
      17. }
      18. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished


```
> *
*****
> *
```

Model for gender==2 and wave == 2

```
Logistic regression                                Number of obs   =       363
                                                    LR chi2(7)      =      101.28
                                                    Prob > chi2     =       0.0000
Log likelihood = -121.47255                      Pseudo R2       =       0.2942
```

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0729699	.016233	4.50	0.000	.0411537	.104786
avgcumdosew2	.0713471	.0870475	0.82	0.412	-.0992629	.2419571
bf4	-.12277	.0348875	-3.52	0.000	-.1911482	-.0543918
bf30	.0005237	.0002568	2.04	0.041	.0000204	.001027
shrelaw2	-.0121549	.0056037	-2.17	0.030	-.0231379	-.001172
suprtw2	-.0103307	.0040941	-2.52	0.012	-.018355	-.0023065
radhlw2	.0119091	.0056652	2.10	0.036	.0008055	.0230128
_cons	-4.716583	1.190104	-3.96	0.000	-7.049144	-2.384021

```
301 .
302 .
303 .
304 . * vacation plans
305 .
306 . di _skip(1)

307 . di as input "For females trimmed vacation plans model on wave2 and d2 is not
> signif "
For females trimmed vacation plans model on wave2 and d2 is not signif
```

```
308 . di _skip(1)
```

```
309 . logistic hp2vacatn age deaw2 shjobw2 bf7m havmil ///
> radhlw2 avgcumdosew2 if ///
> gender==2, coef nolog
```

```
Logistic regression                                Number of obs   =       363
                                                    LR chi2(7)      =       76.69
                                                    Prob > chi2     =       0.0000
Log likelihood = -129.17206                        Pseudo R2       =       0.2289
```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.079348	.0155749	5.09	0.000	.0488217	.1098742
deaw2	.1646231	.1715933	0.96	0.337	-.1716935	.5009397
shjobw2	-.0056137	.0041432	-1.35	0.175	-.0137341	.0025068
bf7m	-.0006133	.00025	-2.45	0.014	-.0011032	-.0001234
havmil	-.0001958	.0011139	-0.18	0.860	-.0023791	.0019875
radhlw2	.0233367	.005861	3.98	0.000	.0118494	.034824
avgcumdosew2	.0651649	.0909818	0.72	0.474	-.1131561	.243486
_cons	-6.606305	1.018983	-6.48	0.000	-8.603475	-4.609135

```
310 . eststo vacatn
```

```
311 .
312 .
313 . estout *, cells(b(star fmt(%9.3f)) se(par) t p) ///
> stats(r2_p bic N, fmt(%9.3f %9.0g) ) ///
> legend collabels(none) varlabels(_cons Constant) ///
> mlabels(workw2 socprobsw2 sexlifew2 inthobw2 vactnw2) ///
> title("main effects regression coefficients"
> ///
> "of reconstructed dose for females in wave 2")
```

```
main effects regression coefficients of reconstructed dose for females in wave
> 2
```

	workw2	socprobsw2	sexlifew2	inthobw2
vactnw2				
age	0.028*	0.059***	0.067***	0.073***
	0.079***			

	(0.013)	(0.018)	(0.015)	(0.016)
> (0.016)				
	2.222	3.363	4.320	4.495
> 5.095				
	0.026	0.001	0.000	0.000
> 0.000				
avgcumdosew2	0.009	0.032	0.062	0.071
> 0.065				
	(0.049)	(0.053)	(0.047)	(0.087)
> (0.091)				
	0.190	0.600	1.312	0.820
> 0.716				
	0.849	0.548	0.190	0.412
> 0.474				
bf8	-0.000*	-0.000		
>				
	(0.000)	(0.000)		
>				
	-2.028	-1.389		
>				
	0.043	0.165		
>				
illw2	0.503*	0.525	0.308	
>				
	(0.218)	(0.276)	(0.245)	
>				
	2.307	1.904	1.254	
>				
	0.021	0.057	0.210	
>				
shjobw2	0.005	0.014**		
> -0.006				
	(0.004)	(0.005)		
> (0.004)				
	1.458	2.615		
> -1.355				
	0.145	0.009		
> 0.175				
radhlw2	0.013**	0.024***	0.011	0.012*
> 0.023***				
	(0.004)	(0.006)	(0.005)	(0.006)
> (0.006)				
	2.983	3.892	1.934	2.102
> 3.982				
	0.003	0.000	0.053	0.036
> 0.000				
bf4			-0.165***	-0.123***
>				
			(0.037)	(0.035)

>		-4.479	-3.519
>		0.000	0.000
>			0.001*
bf30			
>			(0.000)
>			2.039
>			0.041
>			-0.012*
shrelaw2			
>			(0.006)
>			-2.169
>			0.030
>			-0.010*
suprtw2			
>			(0.004)
>			-2.523
>			0.012
>			
deaw2			
>	0.165		
>	(0.172)		
>	0.959		
>	0.337		
bf7m			
>	-0.001*		
>	(0.000)		
>	-2.454		
>	0.014		
havmil			
>	-0.000		
>	(0.001)		

```

>      -0.176

>      0.860
Constant      -3.816***      -7.544***      -3.881***      -4.717***
>      -6.606***
              (0.684)      (1.131)      (1.051)      (1.190)
>      (1.019)
              -5.581      -6.667      -3.693      -3.963
>      -6.483
              0.000      0.000      0.000      0.000
>      0.000

```

```

> -----
r2_p          0.099          0.241          0.327          0.294
>      0.229
bic          352.3078      230.6991      265.7165      290.1003
>      305.4993
N            340          340          340          363
>      363

```

```

> -----
* p<0.05, ** p<0.01, *** p<0.001

```

```

314 .
315 .
316 .
317 .
318 .
319 .
320 .
321 .
322 . *XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
> xxxx
323 . *----- Chunk 3      Dose=> hp2hmcare impact for males and females
324 . *XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
> xxxx

```

```

325 .
326 . title "2. wave 2 part2 H1: dose home care relationship " ///
    > " wave 2 Dose - HP2home care Main effects identification"

*****
> *
*****
> *
*****
> *
*****
2. wave 2 part2 H1: dose home care relationship
> *
***** wave 2 Dose - HP2home care Main effects identification
> *
*****
> *
*****
> *
***** 1 Jul 2012 15:01:08
> *
*****
> *
*****

327 .
328 . * review of general model for men and women
329 .
330 . forvalues j=2/2 {
    2. set more off
    3.
331 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
    > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
    4.

```

```

332 .   foreach var in HP2hmcare {
      5.
333 .       forvalues k=1/2 {
      6.   local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf3
> 0 bf40
      7.   title "chunk 3 H1 test pt 2 :Gender= `k' model Wave = `j' for `e(de
> pvar)' "
      8.               di _skip(4)
      9.
334 .
335 .       xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
>           marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
> //
>           radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>           deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>           illw2 shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' such
> rw`j' ///
>           havmilsq if gender==`k', coef nolog difficult iterate(50)
      10.               estat class
      11.               estat gof
      12.               fitstat
      13. }
      14. }
      15. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 44 obs not used

note: bf17 != 0 predicts failure perfectly
bf17 dropped and 3 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 6 obs not used

note: _Ieduc_7 omitted because of collinearity

Logistic regression	Number of obs	=	270
	LR chi2(49)	=	112.39
	Prob > chi2	=	0.0000
Log likelihood = -98.319474	Pseudo R2	=	0.3637

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0339056	.0231493	1.46	0.143	-.0114661	.0792774
_Ieduc_2	-4.046801	2.06481	-1.96	0.050	-8.093754	.0001521
_Ieduc_3	-2.332961	1.654719	-1.41	0.159	-5.576151	.9102284
_Ieduc_4	0	(omitted)				
_Ieduc_5	-2.109138	1.662617	-1.27	0.205	-5.367807	1.149531
_Ieduc_6	-2.575578	1.598895	-1.61	0.107	-5.709355	.5581988
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	.2791915	3.076664	0.09	0.928	-5.750959	6.309342
occ2w2	-.2043325	3.082144	-0.07	0.947	-6.245223	5.836559
occ3w2	.5280791	3.097215	0.17	0.865	-5.542352	6.59851
occ4w2	.3530379	3.103258	0.11	0.909	-5.729235	6.435311
occ5w2	1.030726	3.128223	0.33	0.742	-5.100479	7.161931
occ6w2	1.834194	3.454783	0.53	0.595	-4.937056	8.605444
occ7w2	.6310877	3.205439	0.20	0.844	-5.651457	6.913633
occ8w2	0	(omitted)				
marrw21	-1.774375	1.681557	-1.06	0.291	-5.070167	1.521417
marrw22	-3.603201	2.051956	-1.76	0.079	-7.624961	.4185589
marrw23	-3.822298	1.717545	-2.23	0.026	-7.188624	-.4559723
marrw25	-.1941937	2.536946	-0.08	0.939	-5.166517	4.77813
marrw26	-3.213845	2.602626	-1.23	0.217	-8.314899	1.887208
inclw2	2.821191	3.187221	0.89	0.376	-3.425647	9.068029
inc2w2	2.680447	3.109489	0.86	0.389	-3.41404	8.774935
inc3w2	2.9859	3.107015	0.96	0.337	-3.103737	9.075536
inc4w2	1.060877	3.414563	0.31	0.756	-5.631544	7.753298
radhlw2	.0009802	.0078741	0.12	0.901	-.0144527	.0164132
havmil	.0033106	.008219	0.40	0.687	-.0127982	.0194195
avgcumdosew2	-.0408898	.0892564	-0.46	0.647	-.2158292	.1340496
bf1	-.0224294	.0411105	-0.55	0.585	-.1030045	.0581457
bf4	-.1579765	.2337949	-0.68	0.499	-.616206	.300253

bf2	.0000992	.0001626	0.61	0.542	-.0002196	.000418
bf4m	-.1739281	.2154639	-0.81	0.420	-.5962296	.2483734
bf5m	.0006314	.0017487	0.36	0.718	-.002796	.0040589
bf7m	.0005115	.000594	0.86	0.389	-.0006527	.0016757
bf8	-.0000403	.0000473	-0.85	0.394	-.0001331	.0000525
bf15m	-.0001301	.0003714	-0.35	0.726	-.000858	.0005979
bf17	0	(omitted)				
bf20	.0027387	.0345917	0.08	0.937	-.0650597	.0705372
bf22	-.0000529	.0001896	-0.28	0.780	-.0004245	.0003187
bf29	2.63e-06	.0000221	0.12	0.905	-.0000407	.0000459
bf30	-.0002608	.0004218	-0.62	0.536	-.0010875	.0005659
bf40	.3296594	.2457937	1.34	0.180	-.1520874	.8114062
deaw2	.0069355	.3395872	0.02	0.984	-.6586432	.6725142
dvcew2	-.8346564	3.597118	-0.23	0.817	-7.884878	6.215565
sepaw2	0	(omitted)				
accdw2	.1481124	.4606844	0.32	0.748	-.7548124	1.051037
movew2	.2192344	.5237343	0.42	0.676	-.807266	1.245735
illw2	-.2794365	.3922624	-0.71	0.476	-1.048257	.4893838
shfamw2	-.0130582	.0087013	-1.50	0.133	-.0301125	.0039961
shhlw2	-.0041104	.0095817	-0.43	0.668	-.0228901	.0146694
shjobw2	.0000993	.009716	0.01	0.992	-.0189438	.0191423
shrelaw2	.0041598	.0074695	0.56	0.578	-.0104802	.0187997
suprtw2	.0129457	.0070817	1.83	0.068	-.0009342	.0268256
suchrw2	-.0024472	.0063512	-0.39	0.700	-.0148953	.010001
havmilsq	-8.45e-06	.000015	-0.56	0.573	-.0000379	.000021
_cons	3.897935	3.960914	0.98	0.325	-3.865314	11.66118

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	41	17	58
-	29	183	212
Total	70	200	270

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	58.57%
Specificity	$\Pr(- \sim D)$	91.50%
Positive predictive value	$\Pr(D +)$	70.69%
Negative predictive value	$\Pr(\sim D -)$	86.32%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	8.50%
False - rate for true D	$\Pr(- D)$	41.43%
False + rate for classified +	$\Pr(\sim D +)$	29.31%
False - rate for classified -	$\Pr(D -)$	13.68%
Correctly classified		82.96%

Logistic model for HP2hmcare, goodness-of-fit test

```

      number of observations =      270
number of covariate patterns =      270
      Pearson chi2(220) =      227.64
              Prob > chi2 =      0.3476
  
```

Measures of Fit for **logistic** of HP2hmcare

Log-Lik Intercept Only:	-154.516	Log-Lik Full Model:	-98.319
D(214):	196.639	LR(49):	112.393
		Prob > LR:	0.000
McFadden's R2:	0.364	McFadden's Adj R2:	0.001
Maximum Likelihood R2:	0.340	Cragg & Uhler's R2:	0.500
McKelvey and Zavoina's R2:	0.594	Efron's R2:	0.390
Variance of y*:	8.112	Variance of error:	3.290
Count R2:	0.830	Adj Count R2:	0.343
AIC:	1.143	AIC*n:	308.639
BIC:	-1001.423	BIC':	161.930

```

*****
> *
*****
> *
*****
> *
***** chunk 3 H1 test pt 2 :Gender= 2 model Wave = 2 for HP2hmcare *****
> *
*****
> *
*****
> *
***** 1 Jul 2012 15:01:10 *****
> *
*****
> *
*****
> *

```

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
note: bf29 != 0 predicts success perfectly
 bf29 dropped and 4 obs not used

note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
convergence not achieved

Logistic regression	Number of obs	=	358
	LR chi2(51)	=	177.21
	Prob > chi2	=	0.0000
Log likelihood = -139.72732	Pseudo R2	=	0.3881

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0689184	.0184884	3.73	0.000	.0326818	.105155
_Ieduc_2	-17.33023	2.370203	-7.31	0.000	-21.97575	-12.68472
_Ieduc_3	-17.85228	2.271622	-7.86	0.000	-22.30458	-13.39998
_Ieduc_4	-16.22367	2.322199	-6.99	0.000	-20.7751	-11.67225
_Ieduc_5	-17.51753	2.330541	-7.52	0.000	-22.0853	-12.94975
_Ieduc_6	-18.46499	2.320848	-7.96	0.000	-23.01377	-13.91621
_Ieduc_7	-17.72595	3.034199	-5.84	0.000	-23.67287	-11.77903
_Ieduc_8	0	(omitted)				
occ1w2	-2.066459	1.51974	-1.36	0.174	-5.045095	.9121779
occ2w2	-2.243078	1.553998	-1.44	0.149	-5.288858	.8027026

occ3w2	-1.29392	1.568233	-0.83	0.409	-4.367601	1.77976
occ4w2	-3.169244	1.685231	-1.88	0.060	-6.472236	.1337472
occ5w2	-4.174961	1.966604	-2.12	0.034	-8.029433	-.3204881
occ6w2	-5.016961	2.033875	-2.47	0.014	-9.003283	-1.030639
occ7w2	-1.338521	1.557092	-0.86	0.390	-4.390365	1.713323
occ8w2	.0102882	1.823109	0.01	0.995	-3.56294	3.583517
marrw21	-.4364242	1.195764	-0.36	0.715	-2.780078	1.907229
marrw22	.2779117	1.516808	0.18	0.855	-2.694977	3.2508
marrw23	1.982364	.8407589	2.36	0.018	.3345069	3.630221
marrw25	.7265557	1.247315	0.58	0.560	-1.718137	3.171248
marrw26	0	(omitted)				
inclw2	2.1918	1.615301	1.36	0.175	-.9741308	5.357731
inc2w2	3.722591	1.551917	2.40	0.016	.6808895	6.764292
inc3w2	3.205652	1.561296	2.05	0.040	.1455678	6.265737
inc4w2	3.577016	1.917029	1.87	0.062	-.1802924	7.334325
radhlw2	-.0017814	.0069396	-0.26	0.797	-.0153829	.01182
havmil	.0004744	.0029523	0.16	0.872	-.005312	.0062609
avgcumdosew2	-.232422	.1275125	-1.82	0.068	-.4823419	.017498
bf1	-.0155252	.0283044	-0.55	0.583	-.0710008	.0399503
bf4	-.6331543	.2104116	-3.01	0.003	-1.045553	-.2207551
bf2	.0002047	.0001148	1.78	0.075	-.0000203	.0004296
bf4m	.369727	.1901433	1.94	0.052	-.0029469	.742401
bf5m	-.0009929	.001436	-0.69	0.489	-.0038073	.0018215
bf7m	.0003779	.0005084	0.74	0.457	-.0006186	.0013744
bf8	-5.36e-07	.0000355	-0.02	0.988	-.0000702	.0000691
bf15m	-.0123361	.496536	-0.02	0.980	-.9855287	.9608566
bf17	.0006265	.0248268	0.03	0.980	-.0480332	.0492861
bf20	-.0134138	.0231788	-0.58	0.563	-.0588434	.0320158
bf22	-.0000815	.0001207	-0.67	0.500	-.000318	.0001551
bf29	0	(omitted)				
bf30	-.0000914	.0002999	-0.30	0.760	-.0006791	.0004963
bf40	.1554702	.1284498	1.21	0.226	-.0962868	.4072271
deaw2	.7476902	.2584678	2.89	0.004	.2411026	1.254278
dvcew2	1.232183	1.276036	0.97	0.334	-1.268802	3.733168
sepaw2	-1.82805	1.829743	-1.00	0.318	-5.41428	1.75818
accdw2	-.7440138	.5452818	-1.36	0.172	-1.812746	.3247189
movew2	-.5229006	.4948092	-1.06	0.291	-1.492709	.4469077
illw2	-.1315546	.1759029	-0.75	0.455	-.4763179	.2132087
shfamw2	-.0038201	.0062872	-0.61	0.543	-.0161429	.0085027
shhlw2	-.0093005	.0066582	-1.40	0.162	-.0223502	.0037493
shjobw2	.0003285	.005919	0.06	0.956	-.0112724	.0119295
shrelaw2	-.0125743	.0072115	-1.74	0.081	-.0267086	.00156
suprtw2	-.0093988	.0049637	-1.89	0.058	-.0191275	.0003299
suchrw2	.0039959	.0055359	0.72	0.470	-.0068542	.0148461
havmilsq	-6.92e-07	2.48e-06	-0.28	0.780	-5.56e-06	4.18e-06
_cons	12.62346	.	.	.	.	.

Note: 4 failures and 0 successes completely determined.
Warning: convergence not achieved

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	86	29	115
-	34	209	243
Total	120	238	358

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	71.67%
Specificity	$\Pr(- \sim D)$	87.82%
Positive predictive value	$\Pr(D +)$	74.78%
Negative predictive value	$\Pr(\sim D -)$	86.01%

False + rate for true ~D	$\Pr(+ \sim D)$	12.18%
False - rate for true D	$\Pr(- D)$	28.33%
False + rate for classified +	$\Pr(\sim D +)$	25.22%
False - rate for classified -	$\Pr(D -)$	13.99%

Correctly classified	82.40%
----------------------	---------------

Logistic model for HP2hmcare, goodness-of-fit test

number of observations =	358
number of covariate patterns =	358
Pearson chi2(305) =	382.80
Prob > chi2 =	0.0016

Measures of Fit for **logistic** of HP2hmcare

Log-Lik Intercept Only:	-228.331	Log-Lik Full Model:	-139.727
D(302):	279.455	LR(51):	177.208
		Prob > LR:	0.000
McFadden's R2:	0.388	McFadden's Adj R2:	0.143
Maximum Likelihood R2:	0.390	Cragg & Uhler's R2:	0.542
McKelvey and Zavoina's R2:	0.930	Efron's R2:	0.437
Variance of y*:	47.071	Variance of error:	3.290
Count R2:	0.824	Adj Count R2:	0.475
AIC:	1.093	AIC*n:	391.455
BIC:	-1496.466	BIC':	122.699

```

336 .
337 .   title4 "Male Main effects model for dose=> homcare wave 2"

```

Male Main effects model for dose=> homcare wave 2

```

338 .   logit hp2hmcare age radhlw2 avgcumdosew2 bf4 bf4m bf40 if gender==1

```

```

Iteration 0:   log likelihood = -172.87291
Iteration 1:   log likelihood = -133.32556
Iteration 2:   log likelihood = -130.68368
Iteration 3:   log likelihood = -130.58803
Iteration 4:   log likelihood = -130.58773
Iteration 5:   log likelihood = -130.58773

```

Logistic regression	Number of obs	=	340
	LR chi2(6)	=	84.57
	Prob > chi2	=	0.0000
Log likelihood = -130.58773	Pseudo R2	=	0.2446

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0212175	.0144823	1.47	0.143	-.0071673	.0496022
radhlw2	.0004287	.0051507	0.08	0.934	-.0096666	.0105239
avgcumdosew2	.0002129	.0577761	0.00	0.997	-.1130262	.113452
bf4	-.0235753	.2097912	-0.11	0.911	-.4347586	.3876079
bf4m	-.1707442	.1936458	-0.88	0.378	-.5502831	.2087946
bf40	.141308	.0923159	1.53	0.126	-.0396278	.3222439
_cons	.6763131	1.703403	0.40	0.691	-2.662295	4.014921

```

339 .
340 .
341 .   // male main effects dose-work model washes out
342 .
343 .   di as input "Male trimmed model for dose-home care impact in wv 3: dose not
> signif"
Male trimmed model for dose-home care impact in wv 3: dose not signif

```

```

344 . di as input " male dose is not signif as main effect in dose - homecare impa
    > ct "
    male dose is not signif as main effect in dose - homecare impact

345 . di as input " no male moderate interactions for dose-homecare impact"
    no male moderate interactions for dose-homecare impact

346 .
347 . scalar SigDoseHmcareMw2 = "no"

348 . scalar MainEffhmcareMw2= "none"

349 . scalar list
    wkMedMw2 = bf8 age illw2
    VactnMedFw2 = age illw2 radhlw2
    VactnMedMw2 = age illw2
    VacatnModFw2 = none
    MainEffVactnFw2 = age radhlw2 deaw2
    SigDoseVactnFw2 = no
    vactnModMw2 = none
    MainEffVactnMw2 = age bf7m radhlw2
    SigDoseVactnMw2 = no
    sxLifeMedFw2 = age bf4 bf4m
    sxLifeMedMw2 = age illw2
    InthbModFw2 = none
    MainEffInthbFw2 = age radhlw2 bf4
    SigdoseInthbFw2 = no
    InthbMw2 = none
    MainEffInthbMw2 = age radhlw2 shfamw2
    SigDoseInthbMw2 = no
    sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
    sxlifeMedMw2 = age illw2
    sxlifeModFw2 = none
    MainEffsxlifeFw2 = age radhlw2 bf4 bf4m shrelaw2 shfamw2
    SigDoseSxlifeFw2 = no
    sxlifeModMw2 = none
    SigDosesxlifeMw2 = no
    MainEffsxlifeMw2 = age bf4 illw2 radhlw2
    PrbfmhmMedFw2 = age bf4
    PrbfmhmMedMw2 = age
    PrbfmhmModFw2 = none
    MainEffPrbfmhmFw2 = age bf4 bf40
    SigDosePrbfmhmFw2 = no
    PrbfmhmModw2 = none
    SigDosePrbfmhmMw2 = no
    SigDosePrbfhmMw2 = no
    MainEffPrbfhmMw2 = bf1 bf4 dvcew2 bf7m
    ProbsocMedFw2 = age radhlw2
    ProbsocMedMw2 = age

```

```

ProbsocModFw2 = none
MainEffProbSocFw2 = age radhlw2 illw2 Shrelaw2 avgcumodsew2
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
MainEffPrbsocMw2 = age radhlw2 shjobw2
hmcareMedFw2 = age illw2
hmcareMedMw2 = age illw2
hmcareModFw2 = none
SigDoseWKFw2 = 0
SigdoseHmcareFw2 = no
hmcareModMw2 = none
MainEffhmcareMw2 = none
SigDoseHmcareMw2 = no
    wkMedFw2 = radhlw2 age bf40 bf4m bf1
    wkModFw2 = none
    wkModMw2 = none
MainEfffwkFw2 = age
MainEfffwkMw2 = workM: age bf8 illw2 shjobw2
SigDoseWKMw2 = no
SigDoseWkFw2 = no
hmcrMedFw1 = age icdxcnt shjobw1 bf4 BSIsoma WHPpain WHPsleep WHPel
hmcrMedMw1 = age
MainEffhmcrFw1 = illw1 age
SigDosehmcrFw1 = no
hmcrModMw1 = none
MainEffhmcrMw1 = age shjobw1
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
MainEfffwkFw1 = age
MainEfffwkMw1 = age
    wkMedMw1 = bf40
    WkMedMw1 = none
    WkModFw1 = none
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
    medsigFw1 = 1
prbsocnumMASig = 8

```

```

350 .
351 . title4 "male main effect plus interaction model"

```

```
male main effect plus interaction model
```

```

352 . logit hp2hmcare age radhlw2 avgcumdosew2 ageXd3 illw2 if gender==1

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -151.63199
Iteration 2:  log likelihood = -150.23873
Iteration 3:  log likelihood = -150.14009
Iteration 4:  log likelihood = -150.13472
Iteration 5:  log likelihood = -150.13471

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	45.48
	Prob > chi2	=	0.0000
Log likelihood = -150.13471	Pseudo R2	=	0.1315

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0283791	.0164052	1.73	0.084	-.0037745	.0605327
radhlw2	.0154894	.0043054	3.60	0.000	.007051	.0239279
avgcumdosew2	-1.218369	1.156272	-1.05	0.292	-3.48462	1.047882
ageXd3	.0170005	.0151684	1.12	0.262	-.012729	.0467301
illw2	.3201382	.2199825	1.46	0.146	-.1110197	.751296
_cons	-3.730027	.9027785	-4.13	0.000	-5.49944	-1.960613

```

353 . cap gen radhlw2Xillw2 = radhlw2*illw2

```

```

354 . cap drop radhlw2Xd1

```

```

355 . cap gen radhlw2Xd3 = radhlw2*avgcumdosew2

```

```

356 . cap drop illw2Xd1

357 . cap gen illw2Xd3 = illw2*avgcumdosew2

358 .
359 .
360 . * there are no significant moderators for male dose=hmcare relationship
361 . scalar hmcareModMw2 = "none"

362 .
363 . *----- Male moderator tests for Dose-Hmcare in wave 2: -----
> -----
364 .
365 . title "Dose-home care impact relationship reveals no male moderators"

*****
> *
*****
> *
***** ****
> *
***** ****
> *
***** Dose-home care impact relationship reveals no male moderators ****
> *
***** ****
> *
***** ****
> *
***** 1 Jul 2012 15:01:15 ****
> *
*****
> *
*****
> *

```

```

366 . logit hp2hmcare radhlw2 avgcumdosew2 illw2 radhlw2Xillw2 radhlw2Xd3 illw2Xd3
> ///
> if gender==1, nolog

```

```

Logistic regression                                Number of obs   =       340
                                                    LR chi2(6)      =       34.02
                                                    Prob > chi2     =       0.0000
Log likelihood = -155.8647                        Pseudo R2       =       0.0984

```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
hp2hmcare						
radhlw2	.0124854	.006471	1.93	0.054	-.0001976	.025168
avgcumdosew2	-.6591079	.694783	-0.95	0.343	-2.020858	.702641
illw2	-.0271833	.4678058	-0.06	0.954	-.9440659	.889699
radhlw2Xillw2	.0076663	.0070763	1.08	0.279	-.006203	.021535
radhlw2Xd3	.0069713	.0070473	0.99	0.323	-.0068412	.020783
illw2Xd3	.0895034	.2486877	0.36	0.719	-.3979155	.576922
_cons	-2.001833	.530832	-3.77	0.000	-3.042245	-.961421

```

367 .
368 . fitstat

```

Measures of Fit for **logit** of **hp2hmcare**

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-155.865
D(333):	311.729	LR(6):	34.016
		Prob > LR:	0.000
McFadden's R2:	0.098	McFadden's Adj R2:	0.058
Maximum Likelihood R2:	0.095	Cragg & Uhler's R2:	0.149
McKelvey and Zavoina's R2:	0.259	Efron's R2:	0.109
Variance of y*:	4.438	Variance of error:	3.290
Count R2:	0.806	Adj Count R2:	0.057
AIC:	0.958	AIC*n:	325.729
BIC:	-1629.309	BIC':	0.957

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
testing female moderators for hp2hmcare
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:01:16
> *
*****
> *
*****
> *
*****

```

```
373 . * Dose work relationship for females in wave 2 washes out also
374 . set more off
```

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376 . }

For females hp2hmcare on wave 1 with dose ns

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m = max(0, 1 - icdxcnt) * bf2
bf17	float	%9.0g		bf17 = max(0, 20 - ecprw3) * bf15m
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf29	float	%9.0g		bf29 = max(0, 18 - CSsocspt) * bf8
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)
Logistic regression				Number of obs = 363
				LR chi2(8) = 60.77
				Prob > chi2 = 0.0000
Log likelihood = -176.17616				Pseudo R2 = 0.1471

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0605771	.012257	4.94	0.000	.0365537	.0846004
havmilsq	-6.47e-07	1.17e-06	-0.55	0.579	-2.93e-06	1.64e-06
radhlw2	.0108128	.0042449	2.55	0.011	.0024929	.0191327
avgcumdosew2	.1024263	.084282	1.22	0.224	-.0627633	.2676159
shhlw2	.0099394	.0048118	2.07	0.039	.0005085	.0193703
shjobw2	-.00289	.0045988	-0.63	0.530	-.0119035	.0061234
shrelaw2	-.0105367	.0047951	-2.20	0.028	-.019935	-.0011384
suprtw2	.0029696	.0033321	0.89	0.373	-.0035611	.0095003
_cons	-5.319428	.7716311	-6.89	0.000	-6.831797	-3.807059

```

377 .
378 . scalar SigdoseHmcareFw2="no"

379 .
380 . * capturing significant vars to test as moderators
381 . local cn4: colnames(e(b))

382 . di "`cn4'"
      age havmilsq radhlw2 avgcumdosew2 shhlw2 shjobw2 shrelaw2 suprtw2 _cons

383 . local leng4 = length( "`cn4'")

384 . di `leng4'
      71

385 . local leng4b `leng4'-6

386 . di `leng3b'

387 . local nuvlist4 = substr("`cn4'",4,`leng4b')

388 . di "`nuvlist4'"
      havmilsq radhlw2 avgcumdosew2 shhlw2 shjobw2 shrelaw2 suprtw2 _c

```

```

389 . local rhsvars4 = "`nuvlist4'"
390 . local nuvlist4= "`nuvlist4'"
391 . local nuvlist4= substr("`cn4'",1,`leng4b')
392 . di "`nuvlist4'"
    age havmilsq radhlw2 avgcumdosew2 shhlw2 shjobw2 shrelaw2 suprtw2
393 .
394 . cap gen shhlw2Xd3 = shhlw2*avgcumdosew2
395 .
396 . title "No sig female moderators for dose-hmcare impact are found here"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****    No sig female moderators for dose-hmcare impact are found here    *****
> *
*****
> *
*****
> *
*****
> *
*****    1 Jul 2012    15:01:18    *****
> *
*****
> *
*****
> *

```

```
Iteration 0: log likelihood = -233.72859
Iteration 1: log likelihood = -195.05719
Iteration 2: log likelihood = -194.19863
Iteration 3: log likelihood = -194.19128
Iteration 4: log likelihood = -194.19128
```

```
Number of obs    =      363
LR chi2(5)       =      79.07
Prob > chi2      =      0.0000
Pseudo R2       =      0.1692
```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.084796	.0149038	5.69	0.000	.0555851	.1140068
shhlw2	-.000082	.004448	-0.02	0.985	-.0087999	.0086358
avgcumdosew2	-.7437036	.8125992	-0.92	0.360	-2.336369	.8489616
ageXd3	.0110146	.0113714	0.97	0.333	-.0112729	.033302
shhlw2Xd3	-.0030423	.0040693	-0.75	0.455	-.011018	.0049333
_cons	-4.921691	.7788456	-6.32	0.000	-6.448201	-3.395182

```
398 .
399 . set more off

400 . *----- Mediator relationships for home care are tested below: -----
    > ----
401 . title "Mediator relationships of Dose - home care impact are tested"
```

```
*****
> *
*****
> *
*****
> *
*****
> *
***** Mediator relationships of Dose - home care impact are tested *****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
```

```
> *
*****
> *
```

```
402 . forvalues k=1/2 {
      2. forvalues j=2/2 {
      3. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      4. di _skip(2)
      5. di as input "Trimmed gender=`k' hp2hmcare impact of dose in wave `j' "
      6. des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' `w2bf'
      7. sw, pr(.1): logistic hp2hmcare age havmilsq ///
> avgcumdosew2 ageXd3 illw`j' shjobw`j' suprtw`j' if gender==`k', coef nol
> og
      8. estat gof
      9. estat class
     10. fitstat
     11. }
     12. }
```

Trimmed gender=1 hp2hmcare impact of dose in wave 2

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
incl1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996

```

inc4w2          double %15.0g      LABJ      Income allows to comfortably
                                                afford luxury items in 1996
avgcumdosew2    double %8.0g
bf1             float %9.0g         bf1 = max(0, kzchorn - 40)
bf4             float %9.0g         bf4 = max(0, 24 - BSIsoma)
bf2             float %9.0g         bf2 = max(0, efradw3 -
                                   1.61252E-006) * bf1
bf4m            float %9.0g         bf4m = max(0, 32 - BSIsoma)
bf5m            float %9.0g         bf5m = max(0, ecprw3 - 75) *
                                   bf4m
bf7m            float %9.0g         bf7m = max(0, radtlw3 -
                                   2.12558E-007) * bf4m
bf8             float %9.0g         bf8 = max(0, radtlw3 - 40) *
                                   bf5m
bf15m           float %9.0g         bf15m = max(0, 1 - icdxcnt) * bf2
bf17            float %9.0g         bf17 = max(0, 20 - ecprw3) *
                                   bf15m
bf20            float %9.0g         bf20 = max(0, kzchorn -
                                   2.53946E-006)
bf22            float %9.0g         bf22 = max(0, icdxcnt -
                                   1.01635E-007) * bf7m
bf29            float %9.0g         bf29 = max(0, 18 - CSsocspt) *
                                   bf8
bf30            float %9.0g         bf30 = max(0, neiwl - 85) * bf20
bf40            float %9.0g         bf40 = max(0, icdxcnt -
                                   1.01635E-007)

```

```

begin with full model
p = 0.4827 >= 0.1000 removing havmilsq
p = 0.4147 >= 0.1000 removing suprtw2
p = 0.2849 >= 0.1000 removing shjobw2
p = 0.2522 >= 0.1000 removing avgcumdosew2
p = 0.9715 >= 0.1000 removing ageXd3

```

Logistic regression

```

Number of obs   =      340
LR chi2(2)      =      28.54
Prob > chi2     =      0.0000
Pseudo R2      =      0.0826

```

Log likelihood = -158.60117

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0538093	.0119121	4.52	0.000	.030462	.0771566
illw2	.347449	.2097345	1.66	0.098	-.063623	.7585211
_cons	-4.244759	.6492495	-6.54	0.000	-5.517264	-2.972253

Logistic model for hp2hmcare, goodness-of-fit test

```
number of observations =      340
number of covariate patterns =    91
Pearson chi2(88) =      90.18
Prob > chi2 =      0.4155
```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	3	2	5
-	67	268	335
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	4.29%
Specificity	$\Pr(- \sim D)$	99.26%
Positive predictive value	$\Pr(D +)$	60.00%
Negative predictive value	$\Pr(\sim D -)$	80.00%
False + rate for true ~D	$\Pr(+ \sim D)$	0.74%
False - rate for true D	$\Pr(- D)$	95.71%
False + rate for classified +	$\Pr(\sim D +)$	40.00%
False - rate for classified -	$\Pr(D -)$	20.00%
Correctly classified		79.71%

Measures of Fit for logistic of hp2hmcare

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-158.601
D(337):	317.202	LR(2):	28.543
		Prob > LR:	0.000
McFadden's R2:	0.083	McFadden's Adj R2:	0.065
Maximum Likelihood R2:	0.081	Cragg & Uhler's R2:	0.126
McKelvey and Zavoina's R2:	0.140	Efron's R2:	0.094
Variance of y*:	3.826	Variance of error:	3.290
Count R2:	0.797	Adj Count R2:	0.014
AIC:	0.951	AIC*n:	323.202
BIC:	-1647.152	BIC':	-16.886

Trimmed gender=2 hp2hmcare impact of dose in wave 2

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w2	double	%15.0g	LABJ	profess executive administration in 1996
occ2w2	double	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	double	%15.0g	LABJ	service occup protective services in 1996
occ4w2	double	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	double	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	double	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	double	%15.0g	LABJ	student in 1996
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf2	float	%9.0g		bf2 = max(0, efradw3 - 1.61252E-006) * bf1
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
bf7m	float	%9.0g		bf7m = max(0, radtlw3 - 2.12558E-007) * bf4m
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf17	float	%9.0g		bf17 = max(0, 20 - ecprw3) * bf15m
bf20	float	%9.0g		bf20 = max(0, kzchorn - 2.53946E-006)
bf22	float	%9.0g		bf22 = max(0, icdxcnt - 1.01635E-007) * bf7m
bf29	float	%9.0g		bf29 = max(0, 18 - CSsocspt) * bf8

```

bf30          float   %9.0g          bf30 = max(0, neiwl - 85) * bf20
bf40          float   %9.0g          bf40 = max(0, icdxcnt -
                                     1.01635E-007)

```

```

begin with full model
p = 0.7388 >= 0.1000 removing suprtw2
p = 0.7127 >= 0.1000 removing illw2
p = 0.7000 >= 0.1000 removing shjobw2
p = 0.4326 >= 0.1000 removing havmilsq
p = 0.4184 >= 0.1000 removing ageXd3
p = 0.1321 >= 0.1000 removing avgcumdosew2

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(1)      =       74.63
                                                    Prob > chi2     =       0.0000
Log likelihood = -196.41342                      Pseudo R2      =       0.1597

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0907219	.0119185	7.61	0.000	.0673621	.1140817
_cons	-5.350036	.6457493	-8.29	0.000	-6.615682	-4.084391

Logistic model for hp2hmcare, goodness-of-fit test

```

number of observations =       363
number of covariate patterns =     49
Pearson chi2(47) =     39.93
Prob > chi2 =     0.7580

```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	62	33	95
-	63	205	268
Total	125	238	363

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	49.60%
Specificity	$\Pr(- \sim D)$	86.13%
Positive predictive value	$\Pr(D +)$	65.26%
Negative predictive value	$\Pr(\sim D -)$	76.49%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	13.87%
False - rate for true D	$\Pr(- D)$	50.40%
False + rate for classified +	$\Pr(\sim D +)$	34.74%
False - rate for classified -	$\Pr(D -)$	23.51%
Correctly classified		73.55%

Measures of Fit for **logistic** of **hp2hmcare**

Log-Lik Intercept Only:	-233.729	Log-Lik Full Model:	-196.413
D(361):	392.827	LR(1):	74.630
		Prob > LR:	0.000
McFadden's R2:	0.160	McFadden's Adj R2:	0.151
Maximum Likelihood R2:	0.186	Cragg & Uhler's R2:	0.257
McKelvey and Zavoina's R2:	0.261	Efron's R2:	0.204
Variance of y*:	4.449	Variance of error:	3.290
Count R2:	0.736	Adj Count R2:	0.232
AIC:	1.093	AIC*n:	396.827
BIC:	-1735.053	BIC':	-68.736

```

403 .
404 . scalar hmcareModFw2 = "none"

405 .
406 .
407 .
408 . * age and illw2 are a female mediators of dose - home care impact
409 .

```

```

410 . * age is a male and female mediator with impact on home care
411 . glm age avgcumdosew2 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```

412 . glm hp2hmcare age if gender==1, fam(binomial) irls scale(dev) link(probit)

```

Iteration 1: deviance = **320.8295**
 Iteration 2: deviance = **320.0337**
 Iteration 3: deviance = **320.0328**
 Iteration 4: deviance = **320.0328**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 320.0327771	(1/df) Deviance	=	.9468425
Pearson = 341.699231	(1/df) Pearson	=	1.010944
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	<u>BIC</u>	=	-1650.151

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.032545	.0064212	5.07	0.000	.0199596	.0451304
_cons	-2.483665	.3435565	-7.23	0.000	-3.157023	-1.810306

(Standard errors scaled using square root of deviance-based dispersion.)

413 .

414 . glm age avgcumdosew2 if gender==2, fam(gaussian) link(identity)

Iteration 0: log likelihood = **-1406.9403**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.9184
Deviance = 49427.52828	(1/df) Deviance	=	136.9184
Pearson = 49427.52828	(1/df) Pearson	=	136.9184
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		

	<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271	<u>BIC</u>	=	47299.65

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

415 . glm hp2hmcare age if gender==2 , fam(binomial) irls scale(dev) link(probit)

Iteration 1: deviance = **393.7958**
Iteration 2: deviance = **393.6955**
Iteration 3: deviance = **393.6955**
Iteration 4: deviance = **393.6955**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 393.6954976	(1/df) Deviance	=	1.090569
Pearson = 375.4421438	(1/df) Pearson	=	1.040006

[Bernoulli]
[Probit]

BIC = -1734.184

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0533501	.0069587	7.67	0.000	.0397113	.0669889
_cons	-3.144653	.3710751	-8.47	0.000	-3.871946	-2.417359

(Standard errors scaled using square root of deviance-based dispersion.)

```
416 .
417 .
418 . * illw2 is a male mediator wrt dose home care impact
419 . glm illw2 avgcumdosew2 if gender==1, fam(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -303.59609
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988

Variance function: $\mathbf{V}(\mathbf{u}) = 1$ [Gaussian]
Link function : $\mathbf{g}(\mathbf{u}) = \mathbf{u}$ [Identity]

Log likelihood	= -303.5960853	<u>AIC</u>	= 1.797624
		<u>BIC</u>	= -1851.445

	OIM					
illw2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.0085423	.0128556	0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406	7.96	0.000	.2066336	.3416382

```
420 . glm hp2hmcare illw2 if gender==1, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =   338.889
Iteration 2:  deviance =   338.7479
Iteration 3:  deviance =   338.7478
Iteration 4:  deviance =   338.7478
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  MQL Fisher scoring  Residual df    =       338
                    (IRLS EIM)          Scale parameter =         1
Deviance          =   338.7478085        (1/df) Deviance =   1.002212
Pearson           =   338.1071125        (1/df) Pearson  =   1.000317
```

```
Variance function: V(u) = u*(1-u)      [Bernoulli]
Link function      : g(u) = invnorm(u)  [Probit]
```

```
BIC                                     = -1631.436
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.3223509	.1214283	2.65	0.008	.0843558	.560346
_cons	-.926217	.0878912	-10.54	0.000	-1.098481	-.7539535

(Standard errors scaled using square root of deviance-based dispersion.)

```
421 .
```

```
422 . glm illw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -463.51524
```

```
Generalized linear models          No. of obs      =       363
Optimization      :  ML            Residual df    =       361
Scale parameter =   .756881
Deviance          =   273.2340487    (1/df) Deviance =   .756881
Pearson           =   273.2340487    (1/df) Pearson  =   .756881
```

```
Variance function: V(u) = 1          [Gaussian]
Link function      : g(u) = u        [Identity]
```

```
Log likelihood    = -463.5152411      AIC               =   2.564822
                                         BIC               = -1854.645
```

illw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1249912	.0331157	3.77	0.000	.0600856	.1898968
_cons	.301285	.0544484	5.53	0.000	.194568	.4080019

423 . glm hp2hmcare illw2 if gender==2, fam(binomial) irls scale(dev) link(probit)

Iteration 1: deviance = 466.1156
Iteration 2: deviance = 465.4957
Iteration 3: deviance = 465.4956
Iteration 4: deviance = 465.4956

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 465.4955997	(1/df) Deviance	=	1.289461
Pearson = 362.823507	(1/df) Pearson	=	1.005051

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1662.384

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.1070451	.0863777	1.24	0.215	-.0622522	.2763423
_cons	-.4461214	.0854256	-5.22	0.000	-.6135525	-.2786904

(Standard errors scaled using square root of deviance-based dispersion.)

424 .
425 .

```

426 .
427 . scalar hmcareMedMw2 = "age illw2"

428 . scalar hmcareMedFw2 = "age illw2"

429 . scalar list
      wkMedMw2 = bf8 age illw2
VactnMedFw2 = age illw2 radhlw2
VactnMedMw2 = age illw2
VacatnModFw2 = none
MainEffVactnFw2 = age radhlw2 deaw2
SigDoseVactnFw2 = no
vactnModMw2 = none
MainEffVactnMw2 = age bf7m radhlw2
SigDoseVactnMw2 = no
sxLifeMedFw2 = age bf4 bf4m
sxLifeMedMw2 = age illw2
InthbModFw2 = none
MainEffInthbFw2 = age radhlw2 bf4
SigDoseInthbFw2 = no
  InthbMw2 = none
MainEffInthbMw2 = age radhlw2 shfamw2
SigDoseInthbMw2 = no
sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
sxlifeMedMw2 = age illw2
sxlifeModFw2 = none
MainEffsxlifeFw2 = age radhlw2 bf4 bf4m shrelaw2 shfamw2
SigDoseSxlifeFw2 = no
sxlifeModMw2 = none
SigDosesxlifeMw2 = no
MainEffsxlifeMw2 = age bf4 illw2 radhlw2
PrbfmhmMedFw2 = age bf4
PrbfmhmMedMw2 = age
PrbfmhmModFw2 = none
MainEffPrbfmhmFw2 = age bf4 bf40
SigDosePrbfmhmFw2 = no
PrbfmhmModw2 = none
SigDosePrbfmhmMw2 = no
SigDosePrbfhmMw2 = no
MainEffPrbfhmMw2 = bf1 bf4 dvcew2 bf7m
ProbsocMedFw2 = age radhlw2
ProbsocMedMw2 = age
ProbsocModFw2 = none
MainEffProbSocFw2 = age radhlw2 illw2 Shrelaw2 avgcumodsew2
SigDoseProbsocFw2 = yes
ProbSocModMw2 = none
SigDoseProbsocMw2 = no
MainEffPrbsocMw2 = age radhlw2 shjobw2
hmcareMedFw2 = age illw2

```

```

hmcareMedMw2 = age illw2
hmcareModFw2 = none
SigDoseWKFW2 = 0
SigdoseHmcareFw2 = no
hmcareModMw2 = none
MainEffhmcareMw2 = none
SigDoseHmcareMw2 = no
    wkMedFw2 = radhlw2 age bf40 bf4m bf1
    wkModFw2 = none
    wkModMw2 = none
MainEffwkFw2 = age
MainEffwkMw2 = workM: age bf8 illw2 shjobw2
SigDoseWKMW2 = no
SigDoseWkFw2 = no
hmcrMedFw1 = age icdxcnt shjobw1 bf4 BSIsoma WHPpain WHPsleep WHPel
hmcrMedMw1 = age
MainEffhmcrFw1 = illw1 age
SigDosehmcrFw1 = no
hmcrModMw1 = none
MainEffhmcrMw1 = age shjobw1
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
MainEffwkFw1 = age
MainEffwkMw1 = age
    wkMedMw1 = bf40
    WkMedMw1 = none
    WkModFw1 = none
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
    medsigFw1 = 1
prbsocnumMASig = 8

```

430 .

```

431 . * conclusion "age & illw2 are main effects as possible male & female mediato
    > rs"
432 . * conclusion title "their interaction is not a mediator"
433 .
434 .
435 .
436 .
437 . * Other non-signif test results for mediators of the dose-homecare impact
438 .
439 . glm illw2Xd3 illw2 avgcumdosew2 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-561.33689**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	1.604749
Deviance = 540.8004038	(1/df) Deviance	=	1.604749
Pearson = 540.8004038	(1/df) Pearson	=	1.604749

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	3.319629
Log likelihood = -561.3368924	<u>BIC</u>	=	-1423.554

illw2Xd3	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw2	.6995256	.1162537	6.02	0.000	.4716726	.9273787
avgcumdosew2	.5560421	.0274943	20.22	0.000	.5021543	.6099299
_cons	-.4073759	.0802126	-5.08	0.000	-.5645897	-.2501622

```

440 . glm hp2hmcare illw2Xd3 illw2 avgcumdosew2 if gender==1, fam(binomial) ///
    > irls scale(dev) link(probit)

```

Iteration 1: deviance = **338.5042**
Iteration 2: deviance = **338.3318**
Iteration 3: deviance = **338.3296**
Iteration 4: deviance = **338.3295**
Iteration 5: deviance = **338.3295**
Iteration 6: deviance = **338.3295**

```

Generalized linear models                      No. of obs      =       340
Optimization      : ML Fisher scoring         Residual df      =       336
                  (IRLS EIM)                 Scale parameter =         1
Deviance          =   338.3295375             (1/df) Deviance =   1.006933
Pearson           =   337.9090682             (1/df) Pearson  =   1.005682

Variance function: V(u) = u*(1-u)           [Bernoulli]
Link function     : g(u) = invnorm(u)       [Probit]

BIC = -1620.196

```

hp2hmcare	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw2Xd3	.043344	.0744303	0.58	0.560	-.1025368	.1892247
illw2	.2934865	.1303698	2.25	0.024	.0379663	.5490066
avgcumdosew2	-.02475	.0655641	-0.38	0.706	-.1532532	.1037532
_cons	-.9097069	.1011012	-9.00	0.000	-1.107862	-.7115522

(Standard errors scaled using square root of deviance-based dispersion.)

```
441 . glm illw2Xd3 illw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0: log likelihood = -802.15873
```

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                       Residual df      =       360
                                                Scale parameter =   4.903891
Deviance          =   1765.400887             (1/df) Deviance =   4.903891
Pearson           =   1765.400887             (1/df) Pearson  =   4.903891

Variance function: V(u) = 1                 [Gaussian]
Link function     : g(u) = u                 [Identity]

Log likelihood    = -802.1587263             AIC          =   4.436136
                                                BIC          = -356.5841

```

illw2Xd3	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw2	1.477942	.1339686	11.03	0.000	1.215369	1.740516
avgcumdosew2	1.48752	.0859399	17.31	0.000	1.319081	1.655959
_cons	-1.335179	.1443511	-9.25	0.000	-1.618101	-1.052256

```

442 . glm hp2hmcare illw2Xd3 illw2 avgcumdosew2 if gender==2, fam(binomial) ///
>      irls scale(dev) link(probit)

```

```

Iteration 1:  deviance = 463.5448
Iteration 2:  deviance = 462.9346
Iteration 3:  deviance = 462.934
Iteration 4:  deviance = 462.934
Iteration 5:  deviance = 462.934

```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 462.93402	(1/df) Deviance	=	1.28951
Pearson = 361.7870308	(1/df) Pearson	=	1.007763

Variance function: $V(u) = u*(1-u)$ [**Bernoulli**]
Link function : $g(u) = \text{invnorm}(u)$ [**Probit**]

BIC = -1653.157

hp2hmcare	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw2Xd3	-.0539164	.0417648	-1.29	0.197	-.1357739	.0279411
illw2	.1869825	.1045198	1.79	0.074	-.0178725	.3918376
avgcumdosew2	.0522197	.0762058	0.69	0.493	-.097141	.2015804
_cons	-.4961458	.106924	-4.64	0.000	-.7057129	-.2865786

(Standard errors scaled using square root of deviance-based dispersion.)

```

443 .
444 .
445 . glm havmilsq avgcumdosew2 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = -4357.4808

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	7.98e+09
Deviance = 2.69740e+12	(1/df) Deviance	=	7.98e+09
Pearson = 2.69740e+12	(1/df) Pearson	=	7.98e+09

Variance function: $V(u) = 1$ [**Gaussian**]
Link function : $g(u) = u$ [**Identity**]

	<u>AIC</u>	=	25.644
Log likelihood = -4357.480823	<u>BIC</u>	=	2.70e+12

havamilsq	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-1562.571	1937.625	-0.81	0.420	-5360.246	2235.104
_cons	18476.58	5190.943	3.56	0.000	8302.515	28650.64

```
446 . glm hp2hmcare havmilsq if gender==1, fam(binomial) irls scale(dev) link(prob
> it)
```

```
Iteration 1:  deviance = 345.527
Iteration 2:  deviance = 345.1721
Iteration 3:  deviance = 345.1646
Iteration 4:  deviance = 345.1644
Iteration 5:  deviance = 345.1644
Iteration 6:  deviance = 345.1644
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 345.1644251	(1/df) Deviance	=	1.021197
Pearson = 339.1838387	(1/df) Pearson	=	1.003502

```
Variance function: V(u) = u*(1-u)      [Bernoulli]
Link function      : g(u) = invnorm(u)  [Probit]
```

```
BIC = -1625.019
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
havamilsq	-9.19e-07	1.39e-06	-0.66	0.509	-3.65e-06	1.81e-06
_cons	-.8078353	.0797621	-10.13	0.000	-.9641661	-.6515045

(Standard errors scaled using square root of deviance-based dispersion.)

```
447 . glm havmilsq avgcumdosew2 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0: log likelihood = -5315.5316
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	3.08e+11
Deviance = 1.11295e+14	(1/df) Deviance	=	3.08e+11
Pearson = 1.11295e+14	(1/df) Pearson	=	3.08e+11

Variance function: $V(u) = 1$ [Gaussian]
Link function : $g(u) = u$ [Identity]

	AIC	=	29.29769
Log likelihood = -5315.53158	BIC	=	1.11e+14

havamilsq	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-2103.378	21135.06	-0.10	0.921	-43527.34	39320.58
_cons	62705.69	34750	1.80	0.071	-5403.056	130814.4

```
448 . glm hp2hmcare havmilsq if gender==2, fam(binomial) irls scale(dev) link(prob > it)
```

```
Iteration 1: deviance = 466.1751
Iteration 2: deviance = 465.0334
Iteration 3: deviance = 464.73
Iteration 4: deviance = 464.6076
Iteration 5: deviance = 464.5797
Iteration 6: deviance = 464.5779
Iteration 7: deviance = 464.5779
Iteration 8: deviance = 464.5779
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 464.5778963	(1/df) Deviance	=	1.286919
Pearson = 360.2475414	(1/df) Pearson	=	.9979156

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC	=	-1663.302
-----	---	-----------

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
havmilsq	-7.46e-07	1.04e-06	-0.72	0.475	-2.79e-06	1.30e-06
_cons	-.3815177	.0787742	-4.84	0.000	-.5359124	-.227123

(Standard errors scaled using square root of deviance-based dispersion.)

449 .

450 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaussian) link(identity)

Iteration 0: log likelihood = **-1693.4076**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.972986
Log likelihood = -1693.407647	<u>BIC</u>	=	419831.3

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

451 . glm hp2hmcare radhlw2 if gender==1, fam(binomial) irls scale(dev) link(probi
> t)

Iteration 1: deviance = **320.2142**
Iteration 2: deviance = **319.4143**
Iteration 3: deviance = **319.4134**
Iteration 4: deviance = **319.4134**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 319.4134212	(1/df) Deviance	=	.9450101
Pearson = 343.7631942	(1/df) Pearson	=	1.017051

Variance function: $V(u) = u*(1-u)$
 Link function : $g(u) = \text{invnorm}(u)$

[Bernoulli]
 [Probit]

BIC = -1650.77

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0113273	.0022041	5.14	0.000	.0070074	.0156472
_cons	-1.415444	.1449647	-9.76	0.000	-1.69957	-1.131318

(Standard errors scaled using square root of deviance-based dispersion.)

452 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaussian) link(identity)

Iteration 0: log likelihood = -1791.2233

Generalized linear models
 Optimization : ML

No. of obs = 363
 Residual df = 361
 Scale parameter = 1137.567
 (1/df) Deviance = 1137.567
 (1/df) Pearson = 1137.567

Deviance = 410661.5604
 Pearson = 410661.5604

Variance function: $V(u) = 1$
 Link function : $g(u) = u$

[Gaussian]
 [Identity]

Log likelihood = -1791.223306

AIC = 9.880018
 BIC = 408533.7

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	3.302288	1.283833	2.57	0.010	.7860214	5.818555
_cons	56.95167	2.110863	26.98	0.000	52.81445	61.08888

```
453 . glm hp2hmcare radhlw2 if gender==2, fam(binomial) irls scale(dev) link(probi
> t)
```

```
Iteration 1:  deviance =  465.9397
Iteration 2:  deviance =  465.344
Iteration 3:  deviance =  465.3439
Iteration 4:  deviance =  465.3439
```

```
Generalized linear models                               No. of obs      =       363
Optimization      :  MQL Fisher scoring                 Residual df     =       361
                   (IRLS EIM)                           Scale parameter =        1
Deviance          =  465.3438602                       (1/df) Deviance =  1.289041
Pearson           =  362.9626143                       (1/df) Pearson  =  1.005437
```

```
Variance function: V(u) = u*(1-u)                     [Bernoulli]
Link function     : g(u) = invnorm(u)                  [Probit]
```

```
BIC = -1662.536
```

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
radhlw2	.0029148	.0022776	1.28	0.201	-.0015493	.0073789
_cons	-.5772317	.1586961	-3.64	0.000	-.8882703	-.266193

(Standard errors scaled using square root of deviance-based dispersion.)

```
454 .
455 . title4 "*----- summary matrix construction for dose home care"
```

```
*----- summary matrix construction for dose home care
```

```
456 .
457 . matrix define HP2hmcrMw2 = J(1,8, 0)
```

```

458 .      matrix define HP2hmcFw2 = J(1,8, 0)

459 . matrix colnames HP2hmcMw2=  hypnum ptnum wave gender medsig numMA sig numMod
    > sig ///
    >      numMed

460 . matrix colnames HP2hmcFw2=  hypnum ptnum wave gender medsig numMA sig numMod
    > sig ///
    >      numMed

461 .      matrix rownames HP2hmcMw2 = hmcareM

462 .      matrix rownames HP2hmcFw2 = hmcareF

463 .      matrix define HP2hmcFw2= (1, 2, 3, 2, 0 ,2, 0 , 2 )

464 .      matrix define HP2hmcMw2= (1, 2, 3, 1, 0 , 4, 0 , 2 )

465 .      matrix define H1pt2w2 = (HP2wkMw2 \ HP2wkFw2 \ HP2hmcMw2 \HP2hmcFw
    > 2)

466 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMA sig numM
    > odsig numMed

467 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMA sig numM
    > odsig numMed

468 .      matrix rownames H1pt2w2 = HP2wkMw2 WHP2wkFw2 HP2hmcMw2 HP2hmcFw2

469 .      matlist H1pt2w2

```

		hypnum	ptnum	wave	gender	medsig	numMA sig
> g	numMod sig						
>							
	HP2wkMw2	1	2	3	1	0	
> 4	0						
	WHP2wkFw2	1	2	3	2	0	
> 1	0						
	HP2hmcMw2	1	2	3	1	0	
> 4	0						
	HP2hmcFw2	1	2	3	2	0	
> 2	0						

	numMed
HP2wkMw2	4
WHP2wkFw2	6
HP2hmcrMw2	2
HP2hmcrFw2	2

```

470 .
471 . * see scalar list for names of variables
472 .
473 .
474 . * X * missing the number of main effects in the trimmed models
475 .
476 . ////////////////////////////////////////
> *----- Chunk 4   Dose prob soc impact relationship HP2probsoc
477 . *-----
> ----
478 . *           General model for all part 2 of Nottingham Health Profile
479 .
480 . title " 3. wave 2 part2    H1: Test of hypothesis 1 Part 2 "

*****
> *
*****
> *
*****                               ****
> *
*****                               ****
> *
*****          3. wave 2 part2    H1: Test of hypothesis 1 Part 2          ****
> *
*****                               ****
> *
*****                               ****
> *
*****                                1 Jul 2012      15:02:07      ****
> *
*****
> *
*****
> *
```

```
481 . title " wave 2 Dose - HP2probsoc Main effects identification"
```

```
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```

```
482 . forvalues j=2/2 {
      2. set more off
      3.
483 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
484 .   foreach var in HP2probsoc {
      5.       forvalues k=1/2 {
      6.         di as input "Full main model for `var' for wave= `j' "
      7.         di _skip(4)
      8.         di as input  "chunk 4 H1 test:Gender= `k'  model Wave = `j' for `e(depva
      > r)' "
      9.         di _skip(4)
     10.         title "Full Nottingham Part 2 subscale models for male and then females"
     11.
```

```

485 .      xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
>          marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
> //
>          radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>          deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>          illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
> chrw`j' ///
>          havmilsq if gender==`k', coef nolog difficult iterate(50)
12.          estat class
13.          estat gof
14.          fitstat
15. }
16. }
17. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly
marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly
marrw26 dropped and 1 obs not used

note: inc4w2 != 0 predicts failure perfectly
inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 14 obs not used

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 5 obs not used

note: marrw25 != 0 predicts success perfectly
marrw25 dropped and 1 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	217
	LR chi2(40)	=	113.21
	Prob > chi2	=	0.0000
Log likelihood = -47.096671	Pseudo R2	=	0.5459

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1159429	.0419803	2.76	0.006	.0336631	.1982228
_Ieduc_2	-.0479004	1.407174	-0.03	0.973	-2.80591	2.710109
_Ieduc_3	-.8284731	.7880615	-1.05	0.293	-2.373045	.716099
_Ieduc_4	0	(omitted)				
_Ieduc_5	.2454375	1.100079	0.22	0.823	-1.910677	2.401552
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occl1w2	-1.3725	16.54078	-0.08	0.934	-33.79183	31.04683
occ2w2	-1.244674	16.53791	-0.08	0.940	-33.65838	31.16903
occ3w2	-.7835828	16.55903	-0.05	0.962	-33.23868	31.67152
occ4w2	-3.862736	16.57719	-0.23	0.816	-36.35344	28.62797
occ5w2	-2.775301	16.58962	-0.17	0.867	-35.29036	29.73976
occ6w2	0	(omitted)				

occ7w2	0	(omitted)				
occ8w2	0	(omitted)				
marrw21	12.58162	1075.856	0.01	0.991	-2096.057	2121.22
marrw22	0	(omitted)				
marrw23	10.03646	1075.856	0.01	0.993	-2098.602	2118.675
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inclw2	.0757099	16.62358	0.00	0.996	-32.50591	32.65733
inc2w2	2.619578	16.55703	0.16	0.874	-29.83159	35.07075
inc3w2	4.14916	16.572	0.25	0.802	-28.33137	36.62969
inc4w2	0	(omitted)				
radhlw2	.0130005	.0142344	0.91	0.361	-.0148985	.0408995
havmil	-.002818	.0090337	-0.31	0.755	-.0205238	.0148877
avgcumdosew2	.0114306	.0823526	0.14	0.890	-.1499776	.1728387
bf1	.0037783	.0642153	0.06	0.953	-.1220814	.129638
bf4	.016836	.3033169	0.06	0.956	-.5776542	.6113261
bf2	.0006302	.0003126	2.02	0.044	.0000175	.0012428
bf4m	-.5319968	.2823116	-1.88	0.060	-1.085317	.0213237
bf5m	.0058806	.0028091	2.09	0.036	.0003749	.0113862
bf7m	.0013216	.0011466	1.15	0.249	-.0009257	.0035688
bf8	-.0001829	.0000911	-2.01	0.045	-.0003616	-4.31e-06
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0241214	.0536769	-0.45	0.653	-.1293262	.0810833
bf22	.0004188	.0002855	1.47	0.142	-.0001407	.0009783
bf29	-.000073	.0001017	-0.72	0.473	-.0002723	.0001263
bf30	-.0016782	.0007996	-2.10	0.036	-.0032455	-.000111
bf40	-.1773534	.3453449	-0.51	0.608	-.854217	.4995102
deaw2	-.7039739	.7523846	-0.94	0.349	-2.178621	.7706728
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.0469037	.8655378	-0.05	0.957	-1.743327	1.649519
movew2	1.585081	.8835966	1.79	0.073	-.1467362	3.316899
illw2	-.6496621	.6161215	-1.05	0.292	-1.857238	.5579138
shfamw2	-.0160373	.0116025	-1.38	0.167	-.0387778	.0067033
shhlw2	-.0105176	.0138341	-0.76	0.447	-.0376321	.0165968
shjobw2	.0250231	.0129193	1.94	0.053	-.0002983	.0503445
shrelaw2	-.0217826	.0114409	-1.90	0.057	-.0442063	.0006412
suprtw2	.0083099	.0108445	0.77	0.444	-.012945	.0295648
suchrw2	.0212997	.0111718	1.91	0.057	-.0005966	.0431959
havmilsq	6.25e-06	.0000101	0.62	0.537	-.0000136	.0000261
_cons	-13.61182	1075.864	-0.01	0.990	-2122.266	2095.042

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	26	4	30
-	14	173	187
Total	40	177	217

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	65.00%
Specificity	$\Pr(- \sim D)$	97.74%
Positive predictive value	$\Pr(D +)$	86.67%
Negative predictive value	$\Pr(\sim D -)$	92.51%
False + rate for true ~D	$\Pr(+ \sim D)$	2.26%
False - rate for true D	$\Pr(- D)$	35.00%
False + rate for classified +	$\Pr(\sim D +)$	13.33%
False - rate for classified -	$\Pr(D -)$	7.49%
Correctly classified		91.71%

Logistic model for HP2probsoc, goodness-of-fit test

```

      number of observations =      217
number of covariate patterns =      217
      Pearson chi2(176) =      158.28
          Prob > chi2 =      0.8270

```

Measures of Fit for **logistic** of HP2probsoc

Log-Lik Intercept Only:	-103.704	Log-Lik Full Model:	-47.097
D(161):	94.193	LR(40):	113.215
		Prob > LR:	0.000
McFadden's R2:	0.546	McFadden's Adj R2:	0.006
Maximum Likelihood R2:	0.407	Cragg & Uhler's R2:	0.660
McKelvey and Zavoina's R2:	0.840	Efron's R2:	0.562
Variance of y*:	20.586	Variance of error:	3.290
Count R2:	0.917	Adj Count R2:	0.550
AIC:	0.950	AIC*n:	206.193
BIC:	-771.970	BIC':	101.981

Full main model for HP2probsoc for wave= 2

chunk 4 H1 test:Gender= 2 model Wave = 2 for HP2probsoc

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1034919	.0270041	3.83	0.000	.0505648	.1564191
_Ieduc_2	-13.17654	1236.407	-0.01	0.991	-2436.49	2410.137
_Ieduc_3	-13.38577	1236.407	-0.01	0.991	-2436.699	2409.928
_Ieduc_4	-12.54323	1236.407	-0.01	0.992	-2435.857	2410.771
_Ieduc_5	-12.47221	1236.407	-0.01	0.992	-2435.786	2410.842
_Ieduc_6	-13.80248	1236.407	-0.01	0.991	-2437.116	2409.511
_Ieduc_7	-15.17121	1236.497	-0.01	0.990	-2438.662	2408.319
_Ieduc_8	0	(omitted)				
occ1w2	-1.147886	3.571925	-0.32	0.748	-8.14873	5.852957
occ2w2	-1.271517	3.611241	-0.35	0.725	-8.349419	5.806385
occ3w2	.2117582	3.586153	0.06	0.953	-6.816973	7.24049
occ4w2	-1.534382	3.689834	-0.42	0.678	-8.766324	5.69756
occ5w2	-2.414751	3.8284	-0.63	0.528	-9.918277	5.088775
occ6w2	0	(omitted)				
occ7w2	-.6787306	3.585162	-0.19	0.850	-7.70552	6.348058
occ8w2	2.909649	3.844529	0.76	0.449	-4.625489	10.44479
marrw21	-1.181403	1.729099	-0.68	0.494	-4.570375	2.207569
marrw22	1.066113	1.762045	0.61	0.545	-2.387432	4.519658
marrw23	.6150888	.9283649	0.66	0.508	-1.204473	2.434651
marrw25	.4424041	1.311023	0.34	0.736	-2.127154	3.011962
marrw26	0	(omitted)				
inclw2	.302891	3.591795	0.08	0.933	-6.736898	7.34268
inc2w2	1.142371	3.560505	0.32	0.748	-5.836091	8.120833
inc3w2	.8314334	3.569583	0.23	0.816	-6.164821	7.827688
inc4w2	.0290561	3.848853	0.01	0.994	-7.514557	7.57267
radhlw2	.0111407	.0096438	1.16	0.248	-.0077607	.0300422
havmil	.0005515	.0077361	0.07	0.943	-.0146109	.0157139
avgcumdosew2	.546822	.23001	2.38	0.017	.0960107	.9976333
bf1	.0275412	.0390831	0.70	0.481	-.0490602	.1041427
bf4	-.4078914	.2433269	-1.68	0.094	-.8848033	.0690205
bf2	.0001427	.0001416	1.01	0.314	-.0001349	.0004204
bf4m	.1372093	.2260724	0.61	0.544	-.3058844	.5803031
bf5m	-.0016005	.0026021	-0.62	0.538	-.0067005	.0034995
bf7m	.0002743	.0007319	0.37	0.708	-.0011601	.0017087
bf8	.0000233	.0000548	0.42	0.671	-.0000841	.0001306
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.04615	.0319322	-1.45	0.148	-.1087361	.016436
bf22	9.68e-06	.0001672	0.06	0.954	-.000318	.0003374
bf29	-.0000266	.0000488	-0.54	0.586	-.0001221	.000069
bf30	.0001087	.0003798	0.29	0.775	-.0006357	.0008531
bf40	-.0077229	.1716746	-0.04	0.964	-.344199	.3287532
deaw2	-.0328171	.2515674	-0.13	0.896	-.5258803	.460246
dvcew2	1.645199	1.729548	0.95	0.341	-1.744652	5.03505
sepaw2	-.787699	2.185185	-0.36	0.718	-5.070584	3.495186
accdw2	-.7482691	.7741464	-0.97	0.334	-2.265568	.7690299

movew2	-.1983887	.9882329	-0.20	0.841	-2.13529	1.738512
illw2	.037099	.2627647	0.14	0.888	-.4779104	.5521084
shfamw2	-.0189411	.0086476	-2.19	0.028	-.03589	-.0019922
shhlw2	.0013266	.0086367	0.15	0.878	-.0156011	.0182542
shjobw2	-.0022444	.0078272	-0.29	0.774	-.0175855	.0130966
shrelaw2	-.0057107	.0089259	-0.64	0.522	-.0232051	.0117837
suprtw2	.0019185	.0068705	0.28	0.780	-.0115475	.0153845
suchrw2	-.0030114	.0077253	-0.39	0.697	-.0181526	.0121298
havmilsq	-5.64e-06	.0000161	-0.35	0.725	-.0000371	.0000258
_cons	8.438379	1236.411	0.01	0.995	-2414.883	2431.76

Note: 2 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	52	13	65
-	21	255	276
Total	73	268	341

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	71.23%
Specificity	$\Pr(- \sim D)$	95.15%
Positive predictive value	$\Pr(D +)$	80.00%
Negative predictive value	$\Pr(\sim D -)$	92.39%

False + rate for true ~D	$\Pr(+ \sim D)$	4.85%
False - rate for true D	$\Pr(- D)$	28.77%
False + rate for classified +	$\Pr(\sim D +)$	20.00%
False - rate for classified -	$\Pr(D -)$	7.61%

Correctly classified	90.03%
----------------------	--------

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	341
number of covariate patterns =	341
Pearson $\chi^2(290)$ =	351.64
Prob > χ^2 =	0.0077

Measures of Fit for **logistic** of **HP2probsoc**

Log-Lik Intercept Only:	-177.084	Log-Lik Full Model:	-89.934
D(285):	179.869	LR(50):	174.299
		Prob > LR:	0.000
McFadden's R2:	0.492	McFadden's Adj R2:	0.176
Maximum Likelihood R2:	0.400	Cragg & Uhler's R2:	0.619
McKelvey and Zavoina's R2:	0.858	Efron's R2:	0.531
Variance of y*:	23.160	Variance of error:	3.290
Count R2:	0.900	Adj Count R2:	0.534
AIC:	0.856	AIC*n:	291.869
BIC:	-1482.218	BIC':	117.295

```

486 .
487 . *-----Chunk 4 dose3 social problem impact-----no sig dose main effe
    > ct--
488 . title4 "Chunk 4 trimmed models of dose and HP2work relationship in wave 2"
    _____
    Chunk 4 trimmed models of dose and HP2work relationship in wave 2
    _____

489 . * male models
490 . set more off

491 .      forvalues j=2/2 {
    2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
    > bf40
    3. title3 "trimmed HP2probsoc main effects models wave 2 for H1 part 2 with
    > dose ns"
    4. title "wave 2 dose HP2probsoc relationship but avgcumdosew`j': Dose not s
    > ignif"
    5. xi:logit HP2probsoc age i.educ radhlw2 accdw`j' bf8 shjobw`j' suchrw2 ha
    > vmilsg ///
    >      avgcumdosew`j' if gender==1
    6.                  estat class
    7.                  estat gof
    8.                  fitstat
    9. }
    _____

title3 : trimmed HP2probsoc main effects models wave 2 for H1 part 2 with dose
> ns
1 Jul 2012
15:02:10
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2395 variables and 703 obser
> vations

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****wave 2 dose HP2probsoc relationship but avgcumdosew2: Dose not signif****
> *
*****
> *
*****
> *
*****
1 Jul 2012    15:02:10    ****
> *
*****
> *
*****
> *

```

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: _Ieduc_4 != 0 predicts failure perfectly
 _Ieduc_4 dropped and 14 obs not used

note: _Ieduc_7 != 0 predicts failure perfectly
 _Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
 _Ieduc_8 dropped and 2 obs not used

note: _Ieduc_6 omitted because of collinearity

```

Iteration 0:  log likelihood = -122.49818
Iteration 1:  log likelihood = -97.278367
Iteration 2:  log likelihood = -91.419426
Iteration 3:  log likelihood = -91.263695
Iteration 4:  log likelihood = -91.263586
Iteration 5:  log likelihood = -91.263586

```

Logistic regression	Number of obs	=	320
	LR chi2(11)	=	62.47
	Prob > chi2	=	0.0000
Log likelihood = -91.263586	Pseudo R2	=	0.2550

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0708065	.0177532	3.99	0.000	.0360108	.1056021
_Ieduc_2	.0385275	.9109987	0.04	0.966	-1.746997	1.824052
_Ieduc_3	-.5726249	.461212	-1.24	0.214	-1.476584	.3313341
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.2324702	.5513297	-0.42	0.673	-1.313057	.8481161
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
radhlw2	.0254018	.006594	3.85	0.000	.0124778	.0383257
accdw2	-.5083029	.6480971	-0.78	0.433	-1.77855	.7619441
bf8	-.0000267	.0000244	-1.09	0.274	-.0000745	.0000212
shjobw2	.0157373	.0055054	2.86	0.004	.0049469	.0265278
suchrw2	.00109	.0046549	0.23	0.815	-.0080334	.0102134
havmilsq	-1.25e-06	5.36e-06	-0.23	0.815	-.0000118	9.25e-06
avgcumdosew2	.0268182	.0517674	0.52	0.604	-.0746441	.1282805
_cons	-7.869049	1.225988	-6.42	0.000	-10.27194	-5.466157

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	12	2	14
-	29	277	306
Total	41	279	320

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	29.27%
Specificity	$\Pr(- \sim D)$	99.28%
Positive predictive value	$\Pr(D +)$	85.71%
Negative predictive value	$\Pr(\sim D -)$	90.52%
False + rate for true ~D	$\Pr(+ \sim D)$	0.72%
False - rate for true D	$\Pr(- D)$	70.73%
False + rate for classified +	$\Pr(\sim D +)$	14.29%
False - rate for classified -	$\Pr(D -)$	9.48%
Correctly classified		90.31%

Logistic model for HP2probsoc, goodness-of-fit test

```
number of observations =      320
number of covariate patterns =    317
Pearson chi2(305) =    353.85
Prob > chi2 =    0.0282
```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-122.498	Log-Lik Full Model:	-91.264
D(304):	182.527	LR(11):	62.469
		Prob > LR:	0.000
McFadden's R2:	0.255	McFadden's Adj R2:	0.124
Maximum Likelihood R2:	0.177	Cragg & Uhler's R2:	0.332
McKelvey and Zavoina's R2:	0.447	Efron's R2:	0.255
Variance of y*:	5.948	Variance of error:	3.290
Count R2:	0.903	Adj Count R2:	0.244
AIC:	0.670	AIC*n:	214.527
BIC:	-1571.042	BIC':	0.982

```
492 .
493 .
494 . forvalues j=2/2 {
      2. title "trimmed HP2probsoc main effects models wave `j'" " for H1 part 2 w
> ith dose ns"
      3. title2 "Wave `j' dose HP2work relationship but avgcumdosew`j': Dose not si
> gnif"
      4. }
```

```
*****
> *
*****
> *
*****
> *
*****
trimmed HP2probsoc main effects models wave 2
> *
*****
for H1 part 2 with dose ns
> *
*****
> *
*****
1 Jul 2012    15:02:12    *****
> *
```



```
> *
*****
> *
```

```
Iteration 0: log likelihood = -125.15243
Iteration 1: log likelihood = -102.49803
Iteration 2: log likelihood = -97.612007
Iteration 3: log likelihood = -97.514638
Iteration 4: log likelihood = -97.514623
Iteration 5: log likelihood = -97.514623
```

```
Logistic regression                                Number of obs   =          340
                                                    LR chi2(4)      =          55.28
                                                    Prob > chi2     =          0.0000
Log likelihood = -97.514623                        Pseudo R2      =          0.2208
```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0650468	.0171243	3.80	0.000	.0314838	.0986098
avgcumdosew2	.0250528	.0516618	0.48	0.628	-.0762025	.1263081
radhlw2	.0217043	.0059664	3.64	0.000	.0100104	.0333982
shjobw2	.0153749	.0050929	3.02	0.003	.0053929	.0253569
_cons	-7.726421	1.13381	-6.81	0.000	-9.948647	-5.504194

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	9	1	10
-	32	298	330
Total	41	299	340

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	21.95%
Specificity	$\Pr(- \sim D)$	99.67%
Positive predictive value	$\Pr(D +)$	90.00%
Negative predictive value	$\Pr(\sim D -)$	90.30%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	0.33%
False - rate for true D	$\Pr(- D)$	78.05%
False + rate for classified +	$\Pr(\sim D +)$	10.00%
False - rate for classified -	$\Pr(D -)$	9.70%
Correctly classified		90.29%

Logistic model for HP2probsoc, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      327
      Pearson chi2(322) =      384.78
              Prob > chi2 =      0.0093
  
```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-97.515
D(335):	195.029	LR(4):	55.276
		Prob > LR:	0.000
McFadden's R2:	0.221	McFadden's Adj R2:	0.181
Maximum Likelihood R2:	0.150	Cragg & Uhler's R2:	0.288
McKelvey and Zavoina's R2:	0.411	Efron's R2:	0.210
Variance of y*:	5.584	Variance of error:	3.290
Count R2:	0.903	Adj Count R2:	0.195
AIC:	0.603	AIC*n:	205.029
BIC:	-1757.668	BIC':	-31.960

```

499 .
500 . scalar MainEffPrbsocMw2 = "age radhlw2 shjobw2"

501 .
502 .
503 . forvalues j=2/2 {
      2.  logit HP2probsoc age  radhlw2 shjobw`j'  ///
>      avgcumdosew`j'  ///
>      shjobw2Xd3 if gender==1
      3.
      4.
      5.
      6. }

```

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -102.40367
Iteration 2:  log likelihood = -97.802085
Iteration 3:  log likelihood = -96.367187
Iteration 4:  log likelihood = -96.245667
Iteration 5:  log likelihood = -96.239265
Iteration 6:  log likelihood = -96.239247
Iteration 7:  log likelihood = -96.239247

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	57.83
	Prob > chi2	=	0.0000
Log likelihood = -96.239247	Pseudo R2	=	0.2310

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0645913	.0169521	3.81	0.000	.0313658	.0978168
radhlw2	.0222475	.0060296	3.69	0.000	.0104297	.0340653
shjobw2	.0092759	.0068028	1.36	0.173	-.0040574	.0226091
avgcumdosew2	-.7357041	.6602672	-1.11	0.265	-2.029804	.5583958
shjobw2Xd3	.0081692	.0068728	1.19	0.235	-.0053013	.0216397
_cons	-7.172995	1.201125	-5.97	0.000	-9.527157	-4.818833

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	10	2	12
-	31	297	328
Total	41	299	340

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	24.39%
Specificity	$\Pr(- \sim D)$	99.33%
Positive predictive value	$\Pr(D +)$	83.33%
Negative predictive value	$\Pr(\sim D -)$	90.55%
False + rate for true ~D	$\Pr(+ \sim D)$	0.67%
False - rate for true D	$\Pr(- D)$	75.61%
False + rate for classified +	$\Pr(\sim D +)$	16.67%
False - rate for classified -	$\Pr(D -)$	9.45%
Correctly classified		90.29%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    327
    Pearson chi2(321) =    353.15
        Prob > chi2 =      0.1047

```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-96.239
D(334):	192.478	LR(5):	57.826
		Prob > LR:	0.000
McFadden's R2:	0.231	McFadden's Adj R2:	0.183
Maximum Likelihood R2:	0.156	Cragg & Uhler's R2:	0.300
McKelvey and Zavoina's R2:	0.495	Efron's R2:	0.219
Variance of y*:	6.518	Variance of error:	3.290
Count R2:	0.903	Adj Count R2:	0.195
AIC:	0.601	AIC*n:	204.478
BIC:	-1754.389	BIC':	-28.682

```

504 . scalar SigDoseProbsocMw2 = "no"

505 . * xx no signific radhlw3 by dose effect
506 . * xx for males no signif dose social problem effect
507 . * xx for males no significant moderator in dose social problem effect
508 . scalar ProbSocModMw2 = "none"

509 .
510 .
511 . *****
> ****
512 . * female dose social problems wave 2 models
513 .
514 . forvalues j=2/2 {
      2. set more off
      3. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      4. title3 "partly trimmed HP2probsoc main effects models wave 2 for H1 part
> 2 with dose ns"
      5. title "wave 2 dose HP2probsoc relationship but avgcumdosew`j': Dose signi
> f here"
      6. logit HP2probsoc age radhlw2 accdw`j' sepaw`j' illw`j' shjobw`j' ////
> shrelaw`j' suchrw2 havmilsq avgcumdosew`j' if gender==2, nolog
      7. estat class
      8. estat gof
      9. fitstat
    10. }

```

```

title3 : partly trimmed HP2probsoc main effects models wave 2 for H1 part 2 wi
> th dose ns
1 Jul 2012
15:02:14
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2397 variables and 703 obser
> vations

```


Classified	True		Total
	D	~D	
+	37	11	48
-	37	278	315
Total	74	289	363

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	50.00%
Specificity	$\Pr(- \sim D)$	96.19%
Positive predictive value	$\Pr(D +)$	77.08%
Negative predictive value	$\Pr(\sim D -)$	88.25%
False + rate for true ~D	$\Pr(+ \sim D)$	3.81%
False - rate for true D	$\Pr(- D)$	50.00%
False + rate for classified +	$\Pr(\sim D +)$	22.92%
False - rate for classified -	$\Pr(D -)$	11.75%
Correctly classified		86.78%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      363
number of covariate patterns =    362
    Pearson chi2(351) =    479.72
        Prob > chi2 =      0.0000

```

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-183.570	Log-Lik Full Model:	-121.038
D(352):	242.077	LR(10):	125.064
		Prob > LR:	0.000
McFadden's R2:	0.341	McFadden's Adj R2:	0.281
Maximum Likelihood R2:	0.291	Cragg & Uhler's R2:	0.458
McKelvey and Zavoina's R2:	0.831	Efron's R2:	0.386
Variance of y*:	19.413	Variance of error:	3.290
Count R2:	0.868	Adj Count R2:	0.351
AIC:	0.727	AIC*n:	264.077
BIC:	-1832.753	BIC':	-66.120

```

515 .
516 . scalar SigDoseProbsocFw2 = "yes"

517 . scalar MainEffProbSocFw2 = "age radhlw2 illw2 Shrelaw2 avgcumodsew2"

518 .
519 . * trimmed female model with basis functions
520 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      3. title "trimmed HP2probsoc main effects models wave 2 for H1 part 2 " "Dos
> e is signif Females"
      4. title "wave 2 dose HP2probsoc relationship but avgcumdosew`j':"
      5. title "Dose is signif but this trimming is too path dependent"
      6. sw, pr(.1): logit HP2probsoc age radhlw2 illw`j' `w2bf' ///
> shrelaw`j' avgcumdosew`j' if gender==2
      7.          estat class
      8.          estat gof
      9.          fitstat
     10. }

*****
> *
*****
> *
*****
> *
*****
> *
***** trimmed HP2probsoc main effects models wave 2 for H1 part 2 *****
> *
***** Dose is signif Females *****
> *
*****
> *
*****
> *
***** 1 Jul 2012 15:02:16 *****
> *
*****
> *
*****
> *

```


note: bf15m dropped because of estimability
 note: bf17 dropped because of estimability
 note: o.bf15m dropped because of estimability
 note: o.bf17 dropped because of estimability
 note: 12 obs. dropped because of estimability

begin with full model

p = **0.9612** >= 0.1000 removing **bf40**
 p = **0.9509** >= 0.1000 removing **bf29**
 p = **0.7921** >= 0.1000 removing **illw2**
 p = **0.7993** >= 0.1000 removing **bf8**
 p = **0.6044** >= 0.1000 removing **bf22**
 p = **0.5736** >= 0.1000 removing **bf2**
 p = **0.5392** >= 0.1000 removing **bf30**
 p = **0.3501** >= 0.1000 removing **bf7m**
 p = **0.2282** >= 0.1000 removing **bf5m**
 p = **0.2737** >= 0.1000 removing **bf1**
 p = **0.2645** >= 0.1000 removing **bf20**
 p = **0.2181** >= 0.1000 removing **bf4m**

Logistic regression

Number of obs = **351**
 LR chi2(5) = **143.75**
 Prob > chi2 = **0.0000**
 Pseudo R2 = **0.3976**

Log likelihood = **-108.90897**

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0962607	.0184725	5.21	0.000	.0600553	.1324662
radhlw2	.0145499	.005748	2.53	0.011	.003284	.0258158
avgcumdosew2	.4041686	.1517163	2.66	0.008	.1068102	.7015271
shrelaw2	-.0146954	.0058729	-2.50	0.012	-.0262061	-.0031847
bf4	-.1767354	.0368357	-4.80	0.000	-.2489321	-.1045388
_cons	-6.140261	1.256194	-4.89	0.000	-8.602356	-3.678166

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	45	10	55
-	29	267	296
Total	74	277	351

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	60.81%
Specificity	$\Pr(- \sim D)$	96.39%
Positive predictive value	$\Pr(D +)$	81.82%
Negative predictive value	$\Pr(\sim D -)$	90.20%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	3.61%
False - rate for true D	$\Pr(- D)$	39.19%
False + rate for classified +	$\Pr(\sim D +)$	18.18%
False - rate for classified -	$\Pr(D -)$	9.80%
Correctly classified		88.89%

Logistic model for HP2probsoc, goodness-of-fit test

```

      number of observations =      351
number of covariate patterns =      350
      Pearson chi2(344) =      405.23
          Prob > chi2 =      0.0127
  
```

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-180.782	Log-Lik Full Model:	-108.909
D(345):	217.818	LR(5):	143.747
		Prob > LR:	0.000
McFadden's R2:	0.398	McFadden's Adj R2:	0.364
Maximum Likelihood R2:	0.336	Cragg & Uhler's R2:	0.523
McKelvey and Zavoina's R2:	0.578	Efron's R2:	0.445
Variance of y*:	7.801	Variance of error:	3.290
Count R2:	0.889	Adj Count R2:	0.473
AIC:	0.655	AIC*n:	229.818
BIC:	-1804.153	BIC':	-114.443

```

521 .
522 .
523 . * trimmed female model with basis functions
524 . forvalues j=2/2 {
      2. set more off
      3. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      4. title "partly trimmed HP2probsoc main effects models wave 2 for H1 part 2
> " "Dose is signif Females"
      5. title "wave 2 dose HP2probsoc relationship but avgcumdosew`j':"
      6. title "Dose is not signif when fully trimmed "
      7. title "Dose significance is too path dependent to be stable"
      8. logit HP2probsoc age radhlw2 illw`j' `w2bf' ///
> shrelaw`j' avgcumdosew`j' if gender==2, nolog
      9.          estat class
     10.          estat gof
     11.          fitstat
     12. }

```

```

*****
> *
*****
> *
*****
> *
*****partly trimmed HP2probsoc main effects models wave 2 for H1 part 2 *****
> *
*****          Dose is signif Females          *****
> *
*****
> *
*****
> *
*****          1 Jul 2012    15:02:35    *****
> *
*****
> *
*****
> *

```


bf29	-2.02e-06	.0000345	-0.06	0.953	-.0000697	.0000656
bf30	.0001996	.0003187	0.63	0.531	-.0004251	.0008243
bf40	.0074913	.1539797	0.05	0.961	-.2943034	.309286
shrelaw2	-.0131188	.0063308	-2.07	0.038	-.025527	-.0007106
avgcumdosew2	.4534463	.1712457	2.65	0.008	.1178109	.7890817
_cons	-5.944128	2.135376	-2.78	0.005	-10.12939	-1.758869

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	47	12	59
-	27	265	292
Total	74	277	351

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	63.51%
Specificity	$\Pr(- \sim D)$	95.67%
Positive predictive value	$\Pr(D +)$	79.66%
Negative predictive value	$\Pr(\sim D -)$	90.75%
False + rate for true ~D	$\Pr(+ \sim D)$	4.33%
False - rate for true D	$\Pr(- D)$	36.49%
False + rate for classified +	$\Pr(\sim D +)$	20.34%
False - rate for classified -	$\Pr(D -)$	9.25%
Correctly classified		88.89%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      351
number of covariate patterns =    351
    Pearson chi2(333) =    432.31
        Prob > chi2 =      0.0002

```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-180.782	Log-Lik Full Model:	-105.149
D(331):	210.297	LR(17):	151.267
		Prob > LR:	0.000
McFadden's R2:	0.418	McFadden's Adj R2:	0.308
Maximum Likelihood R2:	0.350	Cragg & Uhler's R2:	0.544
McKelvey and Zavoina's R2:	0.610	Efron's R2:	0.465
Variance of y*:	8.437	Variance of error:	3.290
Count R2:	0.889	Adj Count R2:	0.473
AIC:	0.713	AIC*n:	250.297
BIC:	-1729.623	BIC':	-51.634

```

525 .
526 .
527 . * trimmed female model with basis functions
528 . forvalues j=2/2 {
      2. set more off
      3. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      4. title "fully trimmed HP2probsoc main effects models wave 2 for H1 part 2
      > " "Dose is not signif for Females"
      5. title "wave 2 dose HP2probsoc relationship but avgcumdosew`j':"
      6. title "Dose is not signif "
      7. logit HP2probsoc age radhlw2    b4 ////
      > shrelaw`j' avgcumdosew`j' if gender==2, nolog
      8.          estat class
      9.          estat gof
     10.          fitstat
     11. }

```

```

*****
> *
*****
> *
*****
> *
***** fully trimmed HP2probsoc main effects models wave 2 for H1 part 2 *****
> *
*****          Dose is not signif for Females          *****
> *
*****
> *
*****
> *
*****          1 Jul 2012    15:02:36    *****
> *
*****

```

```
> *
*****
> *

*****
> *
***** ****
> *
***** ****
> *
***** wave 2 dose HP2probsoc relationship but avgcumdosew2: ****
> *
***** ****
> *
***** ****
> *
***** 1 Jul 2012 15:02:36 ****
> *
*****
> *
*****
> *
***** Dose is not signif ****
> *
***** ****
> *
***** 1 Jul 2012 15:02:36 ****
> *
*****
```

```
*****
> *
```

```
Logistic regression                                Number of obs   =       363
                                                    LR chi2(5)      =      121.71
                                                    Prob > chi2     =       0.0000
Log likelihood = -122.71719                        Pseudo R2      =       0.3315
```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.111496	.0203766	5.47	0.000	.0715586	.1514333
radhlw2	.0196292	.0053673	3.66	0.000	.0091095	.030149
b4Xd3	.0068784	.0106999	0.64	0.520	-.0140931	.0278498
shrelaw2	-.0088391	.0053365	-1.66	0.098	-.0192985	.0016202
avgcumdosew2	-.0685999	.7594291	-0.09	0.928	-1.557053	1.419854
_cons	-9.015948	1.232733	-7.31	0.000	-11.43206	-6.599837

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	38	10	48
-	36	279	315
Total	74	289	363

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	51.35%
Specificity	$\Pr(- \sim D)$	96.54%
Positive predictive value	$\Pr(D +)$	79.17%
Negative predictive value	$\Pr(\sim D -)$	88.57%
False + rate for true ~D	$\Pr(+ \sim D)$	3.46%
False - rate for true D	$\Pr(- D)$	48.65%
False + rate for classified +	$\Pr(\sim D +)$	20.83%
False - rate for classified -	$\Pr(D -)$	11.43%
Correctly classified		87.33%

Logistic model for HP2probsoc, goodness-of-fit test

```
number of observations =      363
number of covariate patterns =    357
    Pearson chi2(351) =    464.33
        Prob > chi2 =      0.0000
```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-183.570	Log-Lik Full Model:	-122.717
D(357):	245.434	LR(5):	121.706
		Prob > LR:	0.000
McFadden's R2:	0.331	McFadden's Adj R2:	0.299
Maximum Likelihood R2:	0.285	Cragg & Uhler's R2:	0.448
McKelvey and Zavoina's R2:	0.521	Efron's R2:	0.377
Variance of y*:	6.863	Variance of error:	3.290
Count R2:	0.873	Adj Count R2:	0.378
AIC:	0.709	AIC*n:	257.434
BIC:	-1858.867	BIC':	-92.234

```
529 .
530 .
531 .
532 .
533 .
534 .
535 . foreach var in b4 shrelaw2 {
      2. cap gen `var'Xd3 = age*avgcumdosew2
      3. }

536 .
537 . * testing the female moderator model with basis functions
538 . forvalues j=2/2 {
      2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3. title "trimmed HP2socprob main effects  wv 3 for Hyp1 pt 2" "dose is sign
      > if for females"
      4. title "wave 2 dose HP2socprob relationship but avgcumdosew`j'" " Dose is
      > signif for females"
      5. title "problem is that stepwise backward is too path dependent" "and shou
      > ld be checked by simultaneous trim"
      6. sw, pr(.1): logit HP2probsoc age radhlw2 illw`j' `w2bf' ///
      > shrelaw`j' avgcumdosew`j' b4Xd3 ///
      > if gender==2
      7. estat class
      8. estat gof
      9. fitstat
     10. }
```


Logistic regression

Number of obs = 351

LR chi2(5) = 144.26

Prob > chi2 = 0.0000

Log likelihood = -108.65463

Pseudo R2 = 0.3990

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0909062	.018443	4.93	0.000	.0547586	.1270537
radhlw2	.0146177	.0057691	2.53	0.011	.0033105	.025925
shrelaw2	-.0146099	.0058727	-2.49	0.013	-.0261202	-.0030996
b4Xd3	.005736	.0020674	2.77	0.006	.0016839	.009788
bf4	-.1769505	.0368092	-4.81	0.000	-.2490952	-.1048059
_cons	-5.869429	1.246027	-4.71	0.000	-8.311597	-3.427261

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	45	9	54
-	29	268	297
Total	74	277	351

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	60.81%
Specificity	$\Pr(- \sim D)$	96.75%
Positive predictive value	$\Pr(D +)$	83.33%
Negative predictive value	$\Pr(\sim D -)$	90.24%

False + rate for true ~D	$\Pr(+ \sim D)$	3.25%
False - rate for true D	$\Pr(- D)$	39.19%
False + rate for classified +	$\Pr(\sim D +)$	16.67%
False - rate for classified -	$\Pr(D -)$	9.76%

Correctly classified	89.17%
----------------------	--------

Logistic model for HP2probsoc, goodness-of-fit test

```

        number of observations =      351
number of covariate patterns =      350
        Pearson chi2(344) =      405.40
        Prob > chi2 =      0.0126

```

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-180.782	Log-Lik Full Model:	-108.655
D(345):	217.309	LR(5):	144.255
		Prob > LR:	0.000
McFadden's R2:	0.399	McFadden's Adj R2:	0.366
Maximum Likelihood R2:	0.337	Cragg & Uhler's R2:	0.524
McKelvey and Zavoina's R2:	0.579	Efron's R2:	0.447
Variance of y*:	7.808	Variance of error:	3.290
Count R2:	0.892	Adj Count R2:	0.486
AIC:	0.653	AIC*n:	229.309
BIC:	-1804.662	BIC':	-114.951

```

539 .
540 . scalar ProbsocModFw2 = "none"

541 .
542 . title4 " testing for male and female dose probsoc mediators"

```

```

testing for male and female dose probsoc mediators

```

```

543 . * Male mediator dose social problem response models
544 .
545 .
546 .
547 . // age is a male mediator
548 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

```

Iteration 0:  log likelihood = -1330.6004

```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	147.6853
Deviance	= 49917.64009	(1/df) Deviance	=	147.6853
Pearson	= 49917.64009	(1/df) Pearson	=	147.6853
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]
		<u>AIC</u>	=	7.838826
Log likelihood	= -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

549 . glm HP2probsoc age if gender==1, fam(bin) irls link(probit) scale(dev)

Iteration 1: deviance = **230.0069**
Iteration 2: deviance = **223.5454**
Iteration 3: deviance = **223.2469**
Iteration 4: deviance = **223.2456**
Iteration 5: deviance = **223.2456**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 223.2456447	(1/df) Deviance	=	.6604901
Pearson = 331.0340472	(1/df) Pearson	=	.9793907

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1746.938**

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0392343	.0064286	6.10	0.000	.0266344	.0518342
_cons	-3.234772	.3587306	-9.02	0.000	-3.937871	-2.531673

(Standard errors scaled using square root of deviance-based dispersion.)

550 .

```
551 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1693.4076
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	1247.933
Deviance	= 421801.4584	(1/df) Deviance	=	1247.933
Pearson	= 421801.4584	(1/df) Pearson	=	1247.933

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	9.972986
Log likelihood = -1693.407647	<u>BIC</u>	=	419831.3

radhlw2	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128	
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522	

```
552 . glm HP2probsoc radhlw2 if gender==1,fam(bin) irls link(probit) scale(dev)
```

```
Iteration 1: deviance = 226.5911
Iteration 2: deviance = 218.8478
Iteration 3: deviance = 218.3822
Iteration 4: deviance = 218.3787
Iteration 5: deviance = 218.3787
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 218.378733	(1/df) Deviance	=	.6460909
Pearson	= 326.2667817	(1/df) Pearson	=	.9652863

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1751.805
--	-----	---	-----------

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0149459	.0022581	6.62	0.000	.0105201	.0193717
_cons	-2.034921	.1640547	-12.40	0.000	-2.356462	-1.71338

(Standard errors scaled using square root of deviance-based dispersion.)

553 .

554 . glm shjobw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1730.3274**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1550.634
Deviance = 524114.2615	(1/df) Deviance	=	1550.634
Pearson = 524114.2615	(1/df) Pearson	=	1550.634
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	10.19016
Log likelihood = -1730.327396	<u>BIC</u>	=	522144.1

shjobw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.7146559	.8541028	0.84	0.403	-.9593549	2.388667
_cons	49.09491	2.288162	21.46	0.000	44.61019	53.57962

555 . glm HP2probsoc shjobw2 if gender==1,fam(bin) irls link(probit) scale(dev)

Iteration 1: deviance = **241.5668**
Iteration 2: deviance = **238.4954**
Iteration 3: deviance = **238.438**
Iteration 4: deviance = **238.438**
Iteration 5: deviance = **238.438**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 238.4379517	(1/df) Deviance	=	.7054377
Pearson = 344.7520389	(1/df) Pearson	=	1.019976

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1731.746

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw2	.0079142	.0019981	3.96	0.000	.003998	.0118303
_cons	-1.622345	.1436613	-11.29	0.000	-1.903915	-1.340774

(Standard errors scaled using square root of deviance-based dispersion.)

556 .
 557 . // shjobw2Xd3 is almost significant but not quite
 558 . glm radhlw2 shjobw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1684.8126

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	1189.928
Deviance = 401005.7796	(1/df) Deviance	=	1189.928
Pearson = 401005.7796	(1/df) Pearson	=	1189.928

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]
 Log likelihood = -1684.812637
 AIC = 9.92831
 BIC = 399041.4

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw2	.1991928	.0476483	4.18	0.000	.1058038	.2925817
avgcumdosew2	1.078018	.7489714	1.44	0.150	-.3899386	2.545975
_cons	35.85263	3.080591	11.64	0.000	29.81478	41.89047

```

559 . glm HP2probsoc shjobw2 avgcumdosew2 shjobw2Xd3 if gender==1,fam(bin) ///
> irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 238.9844
Iteration 2: deviance = 235.7842
Iteration 3: deviance = 235.5578
Iteration 4: deviance = 235.4233
Iteration 5: deviance = 235.4108
Iteration 6: deviance = 235.4106
Iteration 7: deviance = 235.4106
Iteration 8: deviance = 235.4106

```

```

Generalized linear models                                No. of obs      =       340
Optimization      : ML Fisher scoring                  Residual df     =       336
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 235.4106098                        (1/df) Deviance =  .7006268
Pearson           = 342.9227819                        (1/df) Pearson  = 1.020604

```

```

Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                 [Probit]

```

```

BIC = -1723.115

```

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
shjobw2	.005567	.0027192	2.05	0.041	.0002374	.0108965
avgcumdosew2	-.2189419	.2705013	-0.81	0.418	-.7491148	.311231
shjobw2Xd3	.002944	.0028701	1.03	0.305	-.0026813	.0085693
_cons	-1.466051	.2263255	-6.48	0.000	-1.909641	-1.022461

(Standard errors scaled using square root of deviance-based dispersion.)

```

560 .
561 . scalar ProbsocMedMw2 = "age"

```

```

562 .
563 . * female mediator tests
564 .
565 . // age is a female mediator
566 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.9403**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.9184
Deviance = 49427.52828	(1/df) Deviance	=	136.9184
Pearson = 49427.52828	(1/df) Pearson	=	136.9184

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271	<u>BIC</u>	=	47299.65

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

```

567 . glm HP2probsoc age if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **289.3253**
Iteration 2: deviance = **280.9528**
Iteration 3: deviance = **280.5176**
Iteration 4: deviance = **280.5162**
Iteration 5: deviance = **280.5162**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 280.5161869	(1/df) Deviance	=	.7770531
Pearson = 406.2926804	(1/df) Pearson	=	1.125464

Variance function: **V(u) = u*(1-u)** [Bernoulli]
Link function : **g(u) = invnorm(u)** [Probit]

	BIC	=	-1847.363
--	------------	---	------------------

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0683554	.007474	9.15	0.000	.0537067	.083004
_cons	-4.505136	.424587	-10.61	0.000	-5.337311	-3.672961

(Standard errors scaled using square root of deviance-based dispersion.)

```

568 .
569 . // radhlw2 is a female mediator
570 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = -1791.2233

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1137.567
Deviance = 410661.5604	(1/df) Deviance	=	1137.567
Pearson = 410661.5604	(1/df) Pearson	=	1137.567

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	AIC	=	9.880018
Log likelihood = -1791.223306	BIC	=	408533.7

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	3.302288	1.283833	2.57	0.010	.7860214	5.818555
_cons	56.95167	2.110863	26.98	0.000	52.81445	61.08888

```

571 . glm HP2probsoc radhlw2 if gender==2,fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 335.706
Iteration 2: deviance = 333.7569
Iteration 3: deviance = 333.7467
Iteration 4: deviance = 333.7467
Iteration 5: deviance = 333.7467

```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 333.7467432	(1/df) Deviance	=	.9245062
Pearson = 373.5069806	(1/df) Pearson	=	1.034645

Variance function: $V(u) = u*(1-u)$
 Link function : $g(u) = \text{invnorm}(u)$

[Bernoulli]
 [Probit]

BIC = -1794.133

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0135849	.002393	5.68	0.000	.0088947	.0182751
_cons	-1.729418	.1840212	-9.40	0.000	-2.090093	-1.368743

(Standard errors scaled using square root of deviance-based dispersion.)

572 .

573 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1027.1225

Generalized linear models

Optimization : ML

No. of obs = 340

Residual df = 338

Scale parameter = 24.7771

Deviance = 8374.659221

(1/df) Deviance = 24.7771

Pearson = 8374.659221

(1/df) Pearson = 24.7771

Variance function: $V(u) = 1$

[Gaussian]

Link function : $g(u) = u$

[Identity]

Log likelihood = -1027.122509

AIC = 6.053662

BIC = 6404.476

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2447701	.1784427
_cons	12.52896	.2892393	43.32	0.000	11.96206	13.09586

```
574 . glm HP2probsoc bf4 if gender==1,fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 194.8196
Iteration 2:  deviance = 182.741
Iteration 3:  deviance = 181.7875
Iteration 4:  deviance = 181.7753
Iteration 5:  deviance = 181.7753
Iteration 6:  deviance = 181.7753
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 181.7752898	(1/df) Deviance	=	.5377967
Pearson = 293.1088357	(1/df) Pearson	=	.8671859

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

BIC = -1788.408

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.1440261	.0137935	-10.44	0.000	-.1710608	-.1169913
_cons	.3344471	.1497689	2.23	0.026	.0409054	.6279887

(Standard errors scaled using square root of deviance-based dispersion.)

```
575 .
576 .
577 . scalar ProbsocMedFw2 = "age radhlw2"

578 .
579 . title4 "summary matrix for dose Hp2probsoc impact in wave 2"
```

summary matrix for dose Hp2probsoc impact in wave 2

```

580 . * male hp2spM w2 mediators: age
581 . * dose is not significant main effect for males
582 . * female hp2spF w2 mediators: age radhlw2
583 . * dose is not sig main effect for males
584 .
585 . scalar SigDoseProbsocMw2 = "no"

586 .
587 .     matrix define HP2spMw2 = J(1,8, 0)

588 .     matrix define HP2spFw2 = J(1,8, 0)

589 . matrix colnames HP2spMw2=  hypnum ptnum wave gender medsig numMAsig numModsi
    > g numMed

590 . matrix colnames HP2spFw2=  hypnum ptnum wave gender medsig numMAsig numModsi
    > g numMed

591 .     matrix define HP2spFw2= (1, 2, 3, 2, 1, 5, 5, 2 )

592 .     matrix define HP2spMw2= (1, 2, 3, 1, 0, 2, 0, 1 )

593 .     matrix rowname HP2spMw2 = HP2spMw2

594 .     matrix rowname HP2spFw2 = HP2spFw2

595 .     matlist HP2spMw2

```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	HP2spMw2	1	2	3	1	0	
> 2	0						
		c8					
	HP2spMw2	1					

```
596 .      matlist HP2spFw2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	HP2spFw2	1	2	3	2	1	
> 5	5						
		c8					
	HP2spFw2	2					

```
597 .      matrix define H1pt2w2 = ( HP2wkMw2 \ HP2wkFw2 \ HP2hmcMw2 \ HP2hmc
> Fw2 \ HP2spMw2 \ HP2spFw2 )
```

```
598 .
```

```
599 .      matlist H1pt2w2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 1	0						
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 2	0						
	HP2spMw2	1	2	3	1	0	
> 2	0						
	HP2spFw2	1	2	3	2	1	
> 5	5						
		c8					
	r1	4					
	r1	6					
	r1	2					
	r1	2					
	HP2spMw2	1					
	HP2spFw2	2					

```

600 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMA sig numM
      > odsig numMed

```

```

601 .      matrix rownames H1pt2w2 =  HP2wkMw2 HP2wkFw2 HP2hmcrMw2 HP2hmcrFw2 HP2s
      > ocprbMw2 HP2socprbFw2

```

```

602 .      matlist H1pt2w2

```

		hypnum	ptnum	wave	gender	medsig	numMA sig
> g numModsig							
>							
	HP2wkMw2	1	2	3	1	0	
> 4	0						
	HP2wkFw2	1	2	3	2	0	
> 1	0						
	HP2hmcrMw2	1	2	3	1	0	
> 4	0						
	HP2hmcrFw2	1	2	3	2	0	
> 2	0						
	HP2socprbMw2	1	2	3	1	0	
> 2	0						
	HP2socprbFw2	1	2	3	2	1	
> 5	5						

		numMed
	HP2wkMw2	4
	HP2wkFw2	6
	HP2hmcrMw2	2
	HP2hmcrFw2	2
	HP2socprbMw2	1
	HP2socprbFw2	2

```

603 .
604 .
605 . *xx significant dose effect for females

```

```

606 . scalar ProbsocModFw2 = "none"

607 . *xx no female moderators for Dose Social problem impact relationship
608 . scalar list
      wkMedMw2 = bf8 age illw2
      VactnMedFw2 = age illw2 radhlw2
      VactnMedMw2 = age illw2
      VacatnModFw2 = none
      MainEffVactnFw2 = age radhlw2 deaw2
      SigDoseVactnFw2 = no
      vactnModMw2 = none
      MainEffVactnMw2 = age bf7m radhlw2
      SigDoseVactnMw2 = no
      sxLifeMedFw2 = age bf4 bf4m
      sxLifeMedMw2 = age illw2
      InthbModFw2 = none
      MainEffInthbFw2 = age radhlw2 bf4
      SigdoseInthbFw2 = no
      InthbMw2 = none
      MainEffInthbMw2 = age radhlw2 shfamw2
      SigDoseInthbMw2 = no
      sxlifeMedFw2 = age illw2 radhlw2 bf4 bf4m
      sxlifeMedMw2 = age illw2
      sxlifeModFw2 = none
      MainEffsxlifeFw2 = age radhlw2 bf4 bf4m shrelaw2 shfamw2
      SigDoseSxlifeFw2 = no
      sxlifeModMw2 = none
      SigDosesxlifeMw2 = no
      MainEffsxlifeMw2 = age bf4 illw2 radhlw2
      PrbfmhmMedFw2 = age bf4
      PrbfmhmMedMw2 = age
      PrbfmhmModFw2 = none
      MainEffPrbfmhmFw2 = age bf4 bf40
      SigDosePrbfmhmFw2 = no
      PrbfmhmModw2 = none
      SigDosePrbfmhmMw2 = no
      SigDosePrbfhmMw2 = no
      MainEffPrbfhmMw2 = bf1 bf4 dvcew2 bf7m
      ProbsocMedFw2 = age radhlw2
      ProbsocMedMw2 = age
      ProbsocModFw2 = none
      MainEffProbSocFw2 = age radhlw2 illw2 Shrelaw2 avgcumodsew2
      SigDoseProbsocFw2 = yes
      ProbSocModMw2 = none
      SigDoseProbsocMw2 = no
      MainEffPrbsocMw2 = age radhlw2 shjobw2
      hmcareMedFw2 = age illw2
      hmcareMedMw2 = age illw2
      hmcareModFw2 = none

```

```

SigDoseWKFw2 = 0
SigdoseHmcareFw2 = no
hmcareModMw2 = none
MainEffhmcareMw2 = none
SigDoseHmcareMw2 = no
    wkMedFw2 = radhlw2 age bf40 bf4m bf1
    wkModFw2 = none
    wkModMw2 = none
MainEffwkFw2 = age
MainEffwkMw2 = workM: age bf8 illw2 shjobw2
SigDoseWKMw2 = no
SigDoseWkFw2 = no
hmcrMedFw1 = age icdxcnt shjobw1 bf4 BSIsoma WHPpain WHPsleep WHPel
hmcrMedMw1 = age
MainEffhmcrFw1 = illw1 age
SigDosehmcrFw1 = no
hmcrModMw1 = none
MainEffhmcrMw1 = age shjobw1
SigDosehmcrMw1 = no
    wkMedFw1 = age b4
MainEffwkFw1 = age
MainEffwkMw1 = age
    wkMedMw1 = bf40
    WkMedMw1 = none
    WkModFw1 = none
    WKModMw1 = none
SigDoseWkMw1 = no
SigDoseWkFw1 = no
SigDoseFw1 = no
    wkModFw1 = none
    wkModMw1 = none
    medsigFw1 = 1
prbsocnumMAsig = 8

```

```

609 .
610 . *----- Chunk 5    Dose => Problems with the Family at home Impact
611 . * this washes out in the trimmed models

```



```

618 . di as input "Full main model for `var' for wave= `j' "
      8. di _skip(4)
      9. di as input "chunk 5 H1 test:Gender= `k' model Wave = `j' for `e(depva
> r)' "
     10. di _skip(4)
     11. title "Full Nottingham Part 2 subscale models for male and then females"
     12.
619 .      xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
>          marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
> //
>          radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>          deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>          illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
> chrw`j' ///
>          havmilsq if gender==`k', coef nolog difficult iterate(50)
     13.          estat class
     14.          estat gof
     15.          fitstat
     16. }
     17. }
     18. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inclw2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings

			in 1996
inc4w2	double	%15.0g	LABJ Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g	bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g	bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g	bf9 = max(0, 30 - shhlw1)
bf11	float	%9.0g	bf11 = max(0, 20 - sufamw1)
bf4m	float	%9.0g	bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g	bf15m = max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g	bf30 = max(0, neiw1 - 85) * bf20
bf40	float	%9.0g	bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2pbfhm for wave= 2

chunk 5 H1 test:Gender= 1 model Wave = 2 for HP2probsoc

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
*****  
Full Nottingham Part 2 subscale models for male and then females  
> *  
*****  
*****  
*****  
*****  
*****  
1 Jul 2012      15:03:18  
> *  
*****  
> *  
*****  
> *
```

```
i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
note: _Ieduc_2 != 0 predicts failure perfectly
      _Ieduc_2 dropped and 10 obs not used

note: _Ieduc_4 != 0 predicts failure perfectly
      Ieduc 4 dropped and 13 obs not used
```

note: _Ieduc_7 != 0 predicts failure perfectly
_Ieduc_7 dropped and 4 obs not used

note: _Ieduc_8 != 0 predicts failure perfectly
_Ieduc_8 dropped and 2 obs not used

note: occ5w2 != 0 predicts failure perfectly
occ5w2 dropped and 17 obs not used

note: occ6w2 != 0 predicts failure perfectly
occ6w2 dropped and 5 obs not used

note: occ8w2 != 0 predicts failure perfectly
occ8w2 dropped and 44 obs not used

note: marrw22 != 0 predicts failure perfectly
marrw22 dropped and 7 obs not used

note: marrw26 != 0 predicts failure perfectly
marrw26 dropped and 3 obs not used

note: inclw2 != 0 predicts failure perfectly
inclw2 dropped and 13 obs not used

note: inc4w2 != 0 predicts failure perfectly
inc4w2 dropped and 10 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 12 obs not used

note: bf29 != 0 predicts failure perfectly
bf29 dropped and 4 obs not used

note: dvcew2 != 0 predicts failure perfectly
dvcew2 dropped and 4 obs not used

note: marrw25 != 0 predicts success perfectly
marrw25 dropped and 1 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 1 obs not used

note: _Ieduc_6 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression

Number of obs = 188

LR chi2(37) = 54.88

Prob > chi2 = 0.0294

Pseudo R2 = 0.4169

Log likelihood = -38.373257

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0444593	.0428518	1.04	0.299	-.0395286	.1284472
_Ieduc_2	0	(omitted)				
_Ieduc_3	-1.216759	1.079528	-1.13	0.260	-3.332594	.8990769
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.8969887	1.218662	-0.74	0.462	-3.285522	1.491544
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w2	-.1675434	7.199614	-0.02	0.981	-14.27853	13.94344
occ2w2	-.7756164	7.209263	-0.11	0.914	-14.90551	13.35428
occ3w2	1.02351	7.214423	0.14	0.887	-13.1165	15.16352
occ4w2	1.180132	7.249556	0.16	0.871	-13.02874	15.389
occ5w2	0	(omitted)				
occ6w2	0	(omitted)				
occ7w2	-1.331976	7.411247	-0.18	0.857	-15.85775	13.1938
occ8w2	0	(omitted)				
marrw21	11.23886	2191.219	0.01	0.996	-4283.471	4305.948
marrw22	0	(omitted)				
marrw23	11.19426	2191.219	0.01	0.996	-4283.515	4305.904
marrw25	0	(omitted)				
marrw26	0	(omitted)				
inclw2	0	(omitted)				
inc2w2	1.591635	7.274442	0.22	0.827	-12.66601	15.84928
inc3w2	2.001132	7.228455	0.28	0.782	-12.16638	16.16864
inc4w2	0	(omitted)				
radhlw2	.0450707	.0190833	2.36	0.018	.0076681	.0824733
havmil	-.0149705	.0133639	-1.12	0.263	-.0411632	.0112223
avgcumdosew2	-.0788123	.3549706	-0.22	0.824	-.7745419	.6169173
bf1	-.1607809	.1318246	-1.22	0.223	-.4191523	.0975906
bf4	-.2790034	.3019344	-0.92	0.355	-.8707839	.3127772
bf2	.0006459	.0003574	1.81	0.071	-.0000546	.0013465
bf4m	.1083622	.270079	0.40	0.688	-.4209828	.6377072
bf5m	.0014293	.004266	0.34	0.738	-.0069319	.0097905
bf7m	.0014124	.0012328	1.15	0.252	-.0010038	.0038286
bf8	-.0000455	.0000891	-0.51	0.610	-.0002201	.0001291
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0990519	.1141451	0.87	0.386	-.1246683	.3227721
bf22	.0000324	.0003377	0.10	0.924	-.0006295	.0006943
bf29	0	(omitted)				
bf30	-.0005162	.0007544	-0.68	0.494	-.0019949	.0009625

bf40	-.3427693	.4881552	-0.70	0.483	-1.299536	.6139973
deaw2	1.277518	.6289072	2.03	0.042	.0448826	2.510153
dvcew2	0	(omitted)				
sepaw2	0	(omitted)				
accdw2	-.8756107	1.266217	-0.69	0.489	-3.35735	1.606128
movew2	.2828439	1.570553	0.18	0.857	-2.795383	3.36107
illw2	1.383819	.6666357	2.08	0.038	.0772372	2.690401
shfamw2	-.0048065	.0139543	-0.34	0.731	-.0321564	.0225433
shhlw2	-.0126567	.0158426	-0.80	0.424	-.0437076	.0183942
shjobw2	.0113436	.0152838	0.74	0.458	-.018612	.0412992
shrelaw2	-.0154518	.0162014	-0.95	0.340	-.047206	.0163025
suprtw2	-.0271504	.0129849	-2.09	0.037	-.0526003	-.0017006
suchrw2	.0166833	.0117501	1.42	0.156	-.0063465	.039713
havmilsq	.0000156	.0000131	1.19	0.234	-.00001	.0000412
_cons	-21.58182	2191.227	-0.01	0.992	-4316.307	4273.143

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	8	4	12
-	13	163	176
Total	21	167	188

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	38.10%
Specificity	$\Pr(- \sim D)$	97.60%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	92.61%
False + rate for true ~D	$\Pr(+ \sim D)$	2.40%
False - rate for true D	$\Pr(- D)$	61.90%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	7.39%
Correctly classified		90.96%

Logistic model for HP2pbfhm, goodness-of-fit test

note: marrw22 != 0 predicts failure perfectly
marrw22 dropped and 8 obs not used

note: inc4w2 != 0 predicts failure perfectly
inc4w2 dropped and 9 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 12 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 5 obs not used

note: movew2 != 0 predicts failure perfectly
movew2 dropped and 37 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw26 omitted because of collinearity

note: bf17 omitted because of collinearity

convergence not achieved

Logistic regression

Number of obs = 282

LR chi2(45) = 115.64

Prob > chi2 = 0.0000

Pseudo R2 = 0.4551

Log likelihood = -69.237721

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0573216	.0276334	2.07	0.038	.0031611	.1114822
_Ieduc_2	24.79783	5.419934	4.58	0.000	14.17495	35.4207
_Ieduc_3	25.40648	5.405293	4.70	0.000	14.8123	36.00065
_Ieduc_4	26.0435	5.498915	4.74	0.000	15.26582	36.82117
_Ieduc_5	25.99152	5.477282	4.75	0.000	15.25625	36.7268
_Ieduc_6	25.22458	5.399044	4.67	0.000	14.64265	35.80651
_Ieduc_7	24.91381	.	.	.	.	.
_Ieduc_8	0	(omitted)				
occ1w2	.1268694	2.741862	0.05	0.963	-5.247082	5.50082
occ2w2	-2.180454	2.943693	-0.74	0.459	-7.949987	3.589079
occ3w2	.8729362	2.776498	0.31	0.753	-4.568899	6.314772
occ4w2	-1.353704	2.942107	-0.46	0.645	-7.120128	4.41272
occ5w2	2.7416	3.183927	0.86	0.389	-3.498782	8.981982
occ6w2	0	(omitted)				
occ7w2	1.723368	2.749238	0.63	0.531	-3.66504	7.111775
occ8w2	1.071406	3.004006	0.36	0.721	-4.816337	6.959149
marrw21	1.363708	1.652619	0.83	0.409	-1.875365	4.602781
marrw22	0	(omitted)				
marrw23	.3462148	1.088773	0.32	0.750	-1.78774	2.48017
marrw25	1.049262	1.686487	0.62	0.534	-2.256193	4.354717
marrw26	0	(omitted)				

inclw2	-.4454501	2.822154	-0.16	0.875	-5.976771	5.085871
inc2w2	1.223562	2.740806	0.45	0.655	-4.148319	6.595444
inc3w2	.8897543	2.773723	0.32	0.748	-4.546642	6.326151
inc4w2	0	(omitted)				
radhlw2	.0162494	.0128872	1.26	0.207	-.0090091	.0415079
havmil	.0034284	.0174028	0.20	0.844	-.0306804	.0375372
avgcumdosew2	.2841701	.2286177	1.24	0.214	-.1639122	.7322525
bf1	-.0034211	.0428716	-0.08	0.936	-.0874479	.0806057
bf4	-.5482161	.2947147	-1.86	0.063	-1.125846	.0294141
bf2	.0001496	.0001782	0.84	0.401	-.0001996	.0004989
bf4m	.2436517	.2745867	0.89	0.375	-.2945285	.7818318
bf5m	-.0026475	.0036526	-0.72	0.469	-.0098065	.0045114
bf7m	-.0008652	.0008476	-1.02	0.307	-.0025264	.000796
bf8	.0000586	.0000741	0.79	0.429	-.0000867	.0002038
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0232359	.0348214	-0.67	0.505	-.0914845	.0450127
bf22	.0000587	.0002121	0.28	0.782	-.0003569	.0004744
bf29	.0000275	.0000434	0.63	0.527	-.0000576	.0001126
bf30	.0000875	.0005016	0.17	0.862	-.0008956	.0010706
bf40	-.3662342	.2446561	-1.50	0.134	-.8457514	.1132829
deaw2	.0470792	.2393731	0.20	0.844	-.4220834	.5162419
dvcew2	-1.779925	2.445695	-0.73	0.467	-6.573399	3.013549
sepaw2	0	(omitted)				
accdw2	-2.474844	1.428768	-1.73	0.083	-5.275177	.3254891
movew2	0	(omitted)				
illw2	-.2222062	.2628556	-0.85	0.398	-.7373938	.2929813
shfamw2	.0141915	.0093043	1.53	0.127	-.0040446	.0324276
shhlw2	.0087578	.0103731	0.84	0.399	-.0115731	.0290887
shjobw2	-.0066068	.0093228	-0.71	0.479	-.0248791	.0116655
shrelaw2	-.0301632	.0120406	-2.51	0.012	-.0537624	-.0065641
suprtw2	-.0125721	.0077017	-1.63	0.103	-.0276672	.002523
suchrw2	-.0060097	.0083821	-0.72	0.473	-.0224384	.010419
havmilsq	-.0000291	.000055	-0.53	0.597	-.0001368	.0000787
_cons	-27.59558	6.62482	-4.17	0.000	-40.57999	-14.61117

Note: 3 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	29	7	36
-	18	228	246
Total	47	235	282

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	61.70%
Specificity	$\Pr(- \sim D)$	97.02%
Positive predictive value	$\Pr(D +)$	80.56%
Negative predictive value	$\Pr(\sim D -)$	92.68%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	2.98%
False - rate for true D	$\Pr(- D)$	38.30%
False + rate for classified +	$\Pr(\sim D +)$	19.44%
False - rate for classified -	$\Pr(D -)$	7.32%
Correctly classified		91.13%

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	282
number of covariate patterns =	282
Pearson $\chi^2(235)$ =	241.50
Prob > χ^2 =	0.3715

Measures of Fit for logistic of HP2pbfhm

Log-Lik Intercept Only:	-127.058	Log-Lik Full Model:	-69.238
D(226):	138.475	LR(45):	115.641
		Prob > LR:	0.000
McFadden's R2:	0.455	McFadden's Adj R2:	0.014
Maximum Likelihood R2:	0.336	Cragg & Uhler's R2:	0.566
McKelvey and Zavoina's R2:	0.950	Efron's R2:	0.475
Variance of y*:	65.351	Variance of error:	3.290
Count R2:	0.911	Adj Count R2:	0.468
AIC:	0.888	AIC*n:	250.475
BIC:	-1136.596	BIC':	138.245

```

620 .
621 .
622 . title "Partly Trimmed male wave 2  Dose => Problems with Family at home mode
> ls"

```

```

*****
> *
*****
> *
*****
> *
*****Partly Trimmed male wave 2  Dose => Problems with Family at home models**
> ***
*****
> *
*****
> *
*****
1 Jul 2012    15:03:22    ****
> *
*****
> *
*****
> *

```

```

623 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
> 0

```

```

624 . logit HP2pbfhm age sepaw2 dvcew2 radhlw2 avgcumdosew2 suprtw2 ///
>   havmilsq illw2 `w2bf' if gender==1, iterate(50)

```

```

note: sepaw2 != 0 predicts failure perfectly
      sepaw2 dropped and 6 obs not used

```

```

note: dvcew2 != 0 predicts failure perfectly
      dvcew2 dropped and 4 obs not used

```

```

note: bf15m != 0 predicts failure perfectly
      bf15m dropped and 20 obs not used

```

```

note: bf29 != 0 predicts failure perfectly
      bf29 dropped and 8 obs not used

```

note: bf17 omitted because of collinearity
Iteration 0: log likelihood = **-78.804936**
Iteration 1: log likelihood = **-67.490685**
Iteration 2: log likelihood = **-61.940594**
Iteration 3: log likelihood = **-61.733617**
Iteration 4: log likelihood = **-61.732595**
Iteration 5: log likelihood = **-61.732594**

Logistic regression

Number of obs = **302**
LR chi2(17) = **34.14**
Prob > chi2 = **0.0080**
Pseudo R2 = **0.2166**

Log likelihood = **-61.732594**

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0292956	.0235579	1.24	0.214	-.016877	.0754681
sepaw2	0	(omitted)				
dvcew2	0	(omitted)				
radhlw2	.0182205	.0109536	1.66	0.096	-.0032483	.0396892
avgcumdosew2	-.090545	.2561457	-0.35	0.724	-.5925814	.4114914
suprtw2	-.0052645	.0059622	-0.88	0.377	-.0169502	.0064212
havmilsq	-1.61e-06	7.15e-06	-0.23	0.822	-.0000156	.0000124
illw2	.7307941	.4092131	1.79	0.074	-.0712488	1.532837
bf1	-.0825023	.0733724	-1.12	0.261	-.2263094	.0613049
bf4	-.1790987	.2180029	-0.82	0.411	-.6063764	.2481791
bf2	.0002682	.0002153	1.25	0.213	-.0001537	.0006901
bf4m	.0150156	.1990066	0.08	0.940	-.3750301	.4050613
bf5m	.0001665	.0028981	0.06	0.954	-.0055136	.0058466
bf7m	.0013857	.000794	1.75	0.081	-.0001704	.0029419
bf8	-.0000382	.0000618	-0.62	0.537	-.0001593	.0000829
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0450852	.0634467	0.71	0.477	-.0792681	.1694385
bf22	-.0000253	.0002352	-0.11	0.914	-.0004863	.0004357
bf29	0	(omitted)				
bf30	-.0003567	.0004856	-0.73	0.463	-.0013085	.0005951
bf40	-.229251	.3317905	-0.69	0.490	-.8795485	.4210465
_cons	-5.211948	3.446845	-1.51	0.131	-11.96764	1.543744

```

625 .
626 . estat class

```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	1	1
-	22	279	301
Total	22	280	302

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	0.00%
Specificity	$\Pr(- \sim D)$	99.64%
Positive predictive value	$\Pr(D +)$	0.00%
Negative predictive value	$\Pr(\sim D -)$	92.69%
False + rate for true ~D	$\Pr(+ \sim D)$	0.36%
False - rate for true D	$\Pr(- D)$	100.00%
False + rate for classified +	$\Pr(\sim D +)$	100.00%
False - rate for classified -	$\Pr(D -)$	7.31%
Correctly classified		92.38%

```

627 . estat gof

```

Logistic model for HP2pbfhm, goodness-of-fit test

```

      number of observations =      302
number of covariate patterns =      301
      Pearson chi2(283) =     231.95
          Prob > chi2 =       0.9882

```

```
628 . fitstat
```

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-78.805	Log-Lik Full Model:	-61.733
D(279):	123.465	LR(17):	34.145
		Prob > LR:	0.008
McFadden's R2:	0.217	McFadden's Adj R2:	-0.075
Maximum Likelihood R2:	0.107	Cragg & Uhler's R2:	0.263
McKelvey and Zavoina's R2:	0.433	Efron's R2:	0.127
Variance of y*:	5.806	Variance of error:	3.290
Count R2:	0.924	Adj Count R2:	-0.045
AIC:	0.561	AIC*n:	169.465
BIC:	-1469.744	BIC':	62.933

```
629 .
630 . title "fully Trimmed male main effects wv 3" " Dose => Problems with Family
    > at home models"
```

```
*****  
> *  
*****  
> *  
*****  
> *  
*****  
> *  
*****  
  
fully Trimmed male main effects wv 3  
  
> *  
*****  
Dose => Problems with Family at home models  
  
> *  
*****  
  
> *  
*****  
  
1 Jul 2012      15:03:24    ***  
  
> *  
*****  
  
> *
```

```
631 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0
```

```
632 . sw, pr(.1):logit HP2pbfhm age sepaw2 dvcew2 radhlw2 avgcumdosew2 suprtw2 ///
    > havmilsq illw2 `w2bf' if gender==1, iterate(50)
note: sepaw2 dropped because of estimability
note: dvcew2 dropped because of estimability
note: bf15m dropped because of estimability
note: bf17 dropped because of estimability
note: bf29 dropped because of estimability
note: o.sepaw2 dropped because of estimability
note: o.dvcew2 dropped because of estimability
note: o.bf15m dropped because of estimability
note: o.bf17 dropped because of estimability
note: o.bf29 dropped because of estimability
note: 38 obs. dropped because of estimability
begin with full model
p = 0.9542 >= 0.1000 removing bf5m
p = 0.9265 >= 0.1000 removing bf4m
p = 0.9130 >= 0.1000 removing bf22
p = 0.8252 >= 0.1000 removing havmilsq
p = 0.7278 >= 0.1000 removing avgcumdosew2
p = 0.4697 >= 0.1000 removing bf20
p = 0.4787 >= 0.1000 removing bf30
p = 0.3553 >= 0.1000 removing bf8
p = 0.3688 >= 0.1000 removing suprtw2
p = 0.3130 >= 0.1000 removing age
p = 0.3217 >= 0.1000 removing bf40
p = 0.2872 >= 0.1000 removing bf2
p = 0.1449 >= 0.1000 removing bf1
p = 0.2454 >= 0.1000 removing radhlw2
p = 0.1939 >= 0.1000 removing illw2
```

Logistic regression	Number of obs	=	302
	LR chi2(2)	=	22.57
	Prob > chi2	=	0.0000
Log likelihood = -67.522012	Pseudo R2	=	0.1432

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.2376169	.0586559	-4.05	0.000	-.3525804	-.1226534
bf7m	.0012872	.0004582	2.81	0.005	.0003891	.0021853
_cons	-1.530756	.4468865	-3.43	0.001	-2.406637	-.6548742

```
633 .
634 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	22	280	302
Total	22	280	302

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	0.00%
Specificity	$\Pr(- \sim D)$	100.00%
Positive predictive value	$\Pr(D +)$	.%
Negative predictive value	$\Pr(\sim D -)$	92.72%
False + rate for true ~D	$\Pr(+ \sim D)$	0.00%
False - rate for true D	$\Pr(- D)$	100.00%
False + rate for classified +	$\Pr(\sim D +)$	.%
False - rate for classified -	$\Pr(D -)$	7.28%
Correctly classified		92.72%

```
635 . estat gof
```

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      302
number of covariate patterns =    117
    Pearson chi2(114) =    146.75
        Prob > chi2 =      0.0210
```

636 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-78.805	Log-Lik Full Model:	-67.522
D(299):	135.044	LR(2):	22.566
		Prob > LR:	0.000
McFadden's R2:	0.143	McFadden's Adj R2:	0.105
Maximum Likelihood R2:	0.072	Cragg & Uhler's R2:	0.177
McKelvey and Zavoina's R2:	0.333	Efron's R2:	0.089
Variance of y*:	4.936	Variance of error:	3.290
Count R2:	0.927	Adj Count R2:	0.000
AIC:	0.467	AIC*n:	141.044
BIC:	-1572.374	BIC':	-11.145

637 .

638 . scalar MainEffPrbfhmMw2 = "bf1 bf4 dvcew2 bf7m"

639 . scalar SigDosePrbfhmMw2 = "no"

640 . // construction of moderators for male model

641 .

```
642 . foreach var in bf1 bf4 dvcew2 bf2 bf7m {  
    2.  cap gen `var'Xd3 = `var'*avgcumdosew2  
    3.  }
```

643 .

644 .

645 .

646 .

```
647 . *****  
> **
```

648 . *-----chunk 6 continued -testing moderators and none found for males

```
649 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4  
> 0
```

650 .

```
651 .  
652 . title "fully Trimmed male main effects wv 3" ///  
    > "Dose => Problems with Family at home models"  
  
*****  
> *  
*****  
> *  
***** ****  
> *  
***** ****  
> *  
***** fully Trimmed male main effects wv 3 ****  
> *  
***** Dose => Problems with Family at home models ****  
> *  
***** ****  
> *  
***** ****  
> *  
***** 1 Jul 2012 15:03:48 ****  
> *  
*****  
> *  
*****  
> *  
*****  
  
653 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4  
    > 0  
  
654 . sw, pr(.1):logit HP2pbfhm age sepaw2 dvcew2 radhlw2 avgcumdosew2 suprtw2 ///  
    > havmilsq illw2 `w2bf' bf1Xd3 bf4Xd3 bf2Xd3 bf7mXd3 dvcew2Xd3 if ///  
    > gender==1, iterate(50)  
note: sepaw2 dropped because of estimability  
note: dvcew2 dropped because of estimability  
note: bf15m dropped because of estimability  
note: bf17 dropped because of estimability  
note: bf29 dropped because of estimability  
note: dvcew2Xd3 dropped because of estimability  
note: o.sepaw2 dropped because of estimability  
note: o.dvcew2 dropped because of estimability  
note: o.bf15m dropped because of estimability  
note: o.bf17 dropped because of estimability  
note: o.bf29 dropped because of estimability  
note: o.dvcew2Xd3 dropped because of estimability  
note: 38 obs. dropped because of estimability
```

```

begin with full model
p = 0.9625 >= 0.1000 removing bf22
p = 0.9571 >= 0.1000 removing bf4m
p = 0.8570 >= 0.1000 removing bf5m
p = 0.8130 >= 0.1000 removing havmilsq
p = 0.7588 >= 0.1000 removing bf2Xd3
p = 0.6682 >= 0.1000 removing bf7mXd3
p = 0.7871 >= 0.1000 removing bf1Xd3
p = 0.4970 >= 0.1000 removing avgcumdosew2
p = 0.7875 >= 0.1000 removing bf4Xd3
p = 0.4697 >= 0.1000 removing bf20
p = 0.4787 >= 0.1000 removing bf30
p = 0.3553 >= 0.1000 removing bf8
p = 0.3688 >= 0.1000 removing suprtw2
p = 0.3130 >= 0.1000 removing age
p = 0.3217 >= 0.1000 removing bf40
p = 0.2872 >= 0.1000 removing bf2
p = 0.1449 >= 0.1000 removing bf1
p = 0.2454 >= 0.1000 removing radhlw2
p = 0.1939 >= 0.1000 removing illw2

```

Logistic regression

```

Number of obs   =      302
LR chi2(2)      =      22.57
Prob > chi2     =      0.0000
Pseudo R2      =      0.1432

```

Log likelihood = -67.522012

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.2376169	.0586559	-4.05	0.000	-.3525804	-.1226534
bf7m	.0012872	.0004582	2.81	0.005	.0003891	.0021853
_cons	-1.530756	.4468865	-3.43	0.001	-2.406637	-.6548742

655 .

656 . estat class

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	22	280	302
Total	22	280	302

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	0.00%
Specificity	$\Pr(- \sim D)$	100.00%
Positive predictive value	$\Pr(D +)$	.%
Negative predictive value	$\Pr(\sim D -)$	92.72%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	0.00%
False - rate for true D	$\Pr(- D)$	100.00%
False + rate for classified +	$\Pr(\sim D +)$	.%
False - rate for classified -	$\Pr(D -)$	7.28%
Correctly classified		92.72%

657 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	302
number of covariate patterns =	117
Pearson $\chi^2(114)$ =	146.75
Prob > χ^2 =	0.0210

658 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-78.805	Log-Lik Full Model:	-67.522
D(299):	135.044	LR(2):	22.566
		Prob > LR:	0.000
McFadden's R2:	0.143	McFadden's Adj R2:	0.105
Maximum Likelihood R2:	0.072	Cragg & Uhler's R2:	0.177
McKelvey and Zavoina's R2:	0.333	Efron's R2:	0.089
Variance of y*:	4.936	Variance of error:	3.290
Count R2:	0.927	Adj Count R2:	0.000
AIC:	0.467	AIC*n:	141.044
BIC:	-1572.374	BIC':	-11.145

```

659 .
660 . scalar SigDosePrbfmhmMw2 = "no"

661 . scalar PrbfmhmModw2 = "none"

662 .
663 . * 3 main effects signif    no main effect for dose    for males
664 .
665 .
666 . *****
> *****
667 . title4 "Chunk 6    continued -testing meditors for females"

```

```

Chunk 6    continued -testing meditors for females

```

```

668 . title4 "Partly Trimmed female wave 2"    "Dose => Problems with Family at home
>    models"

```

```

Partly Trimmed female wave 2 Dose => Problems with Family at home models

```

```

669 . local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
> 0

670 . logit HP2pbfhm age sepaw2 dvcew2 radhlw2 avgcumdosew2 bf4 bf8 bf40 ///
>    shrelaw2 suchrw2 suprtw2 ///
>    havmilsq illw2 `w2bf' if gender==2, iterate(50)

note: sepaw2 != 0 predicts failure perfectly
      sepaw2 dropped and 8 obs not used

note: bf15m != 0 predicts failure perfectly
      bf15m dropped and 11 obs not used

note: bf4 omitted because of collinearity
note: bf8 omitted because of collinearity
note: bf17 omitted because of collinearity
note: bf40 omitted because of collinearity
Iteration 0:    log likelihood = -137.18535
Iteration 1:    log likelihood = -103.93355
Iteration 2:    log likelihood = -95.703442
Iteration 3:    log likelihood = -95.15807
Iteration 4:    log likelihood = -94.770663
Iteration 5:    log likelihood = -94.32988
Iteration 6:    log likelihood = -94.321437
Iteration 7:    log likelihood = -94.321422
Iteration 8:    log likelihood = -94.321422

```

Logistic regression

Number of obs = 344

LR chi2(21) = 85.73

Prob > chi2 = 0.0000

Pseudo R2 = 0.3125

Log likelihood = -94.321422

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0495582	.0188768	2.63	0.009	.0125605	.086556
sepaw2	0	(omitted)				
dvcew2	.1260682	1.324676	0.10	0.924	-2.470249	2.722386
radhlw2	.0105681	.0093019	1.14	0.256	-.0076632	.0287993
avgcumdosew2	.0737234	.1141614	0.65	0.518	-.1500289	.2974756
bf4	-.4430413	.2263763	-1.96	0.050	-.8867306	.000648
bf8	.0000574	.0000561	1.02	0.306	-.0000524	.0001673
bf40	-.1754276	.1875146	-0.94	0.350	-.5429494	.1920941
shrelaw2	-.0156329	.0070882	-2.21	0.027	-.0295256	-.0017402
suchrw2	-.0041523	.0059924	-0.69	0.488	-.0158972	.0075927
suprtw2	-.007471	.0054359	-1.37	0.169	-.0181252	.0031831
havmilsq	-.000013	.0000109	-1.19	0.233	-.0000344	8.39e-06
illw2	-.0615734	.1862759	-0.33	0.741	-.4266675	.3035207
bf1	.007936	.0350726	0.23	0.821	-.060805	.0766769
bf4	0	(omitted)				
bf2	-.0000527	.0001277	-0.41	0.680	-.0003031	.0001977
bf4m	.1913739	.2129046	0.90	0.369	-.2259115	.6086594
bf5m	-.0025742	.0029442	-0.87	0.382	-.0083446	.0031963
bf7m	-.0002656	.0006721	-0.40	0.693	-.0015828	.0010516
bf8	0	(omitted)				
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0160588	.0276726	-0.58	0.562	-.0702962	.0381785
bf22	.0000785	.0001703	0.46	0.645	-.0002554	.0004124
bf29	.000024	.0000382	0.63	0.529	-.0000508	.0000989
bf30	-.0003425	.0003633	-0.94	0.346	-.0010546	.0003696
bf40	0	(omitted)				
_cons	-1.808076	2.335383	-0.77	0.439	-6.385343	2.76919

Note: 3 failures and 0 successes completely determined.

```
671 .
672 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	17	8	25
-	30	289	319
Total	47	297	344

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	36.17%
Specificity	$\Pr(- \sim D)$	97.31%
Positive predictive value	$\Pr(D +)$	68.00%
Negative predictive value	$\Pr(\sim D -)$	90.60%
False + rate for true ~D	$\Pr(+ \sim D)$	2.69%
False - rate for true D	$\Pr(- D)$	63.83%
False + rate for classified +	$\Pr(\sim D +)$	32.00%
False - rate for classified -	$\Pr(D -)$	9.40%
Correctly classified		88.95%

```
673 . estat gof
```

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      344
number of covariate patterns =    344
    Pearson chi2(322) =    324.25
        Prob > chi2 =    0.4544
```

674 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-137.185	Log-Lik Full Model:	-94.321
D(316):	188.643	LR(21):	85.728
		Prob > LR:	0.000
McFadden's R2:	0.312	McFadden's Adj R2:	0.108
Maximum Likelihood R2:	0.221	Cragg & Uhler's R2:	0.401
McKelvey and Zavoina's R2:	0.947	Efron's R2:	0.303
Variance of y*:	61.833	Variance of error:	3.290
Count R2:	0.890	Adj Count R2:	0.191
AIC:	0.711	AIC*n:	244.643
BIC:	-1657.000	BIC':	36.926

675 .

676 . *-----Chunk 6 continued -testing meditors for females

677 . title "More partly female Trimmed wave 2" "Dose => Problems with Family at
> home models"

```
*****
> *
*****
> *
*****
> *
*****
> *
*****
More partly female Trimmed wave 2
> *
*****
Dose => Problems with Family at home models
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:04:19
> *
*****
> *
*****
> *
```

```
678 . local w2bf bf1 bf4 bf2 bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf40
```

```
679 . logit HP2pbfhm age bf4 bf40 if gender==2, iterate(50)
```

```
Iteration 0: log likelihood = -139.89675
Iteration 1: log likelihood = -112.36921
Iteration 2: log likelihood = -106.24923
Iteration 3: log likelihood = -106.12137
Iteration 4: log likelihood = -106.12091
Iteration 5: log likelihood = -106.12091
```

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(3)      =          67.55
                                                    Prob > chi2     =          0.0000
Log likelihood = -106.12091                      Pseudo R2       =          0.2414
```

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0636233	.017269	3.68	0.000	.0297767	.0974699
bf4	-.2029758	.0392585	-5.17	0.000	-.2799211	-.1260305
bf40	-.1942568	.091411	-2.13	0.034	-.373419	-.0150946
_cons	-3.085643	1.113267	-2.77	0.006	-5.267607	-.9036792

```
680 .
```

```
681 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	12	3	15
-	35	313	348
Total	47	316	363

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	25.53%
Specificity	$\Pr(- \sim D)$	99.05%
Positive predictive value	$\Pr(D +)$	80.00%
Negative predictive value	$\Pr(\sim D -)$	89.94%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	0.95%
False - rate for true D	$\Pr(- D)$	74.47%
False + rate for classified +	$\Pr(\sim D +)$	20.00%
False - rate for classified -	$\Pr(D -)$	10.06%
Correctly classified		89.53%

682 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	363
number of covariate patterns =	341
Pearson chi2(337) =	366.00
Prob > chi2 =	0.1331

683 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-139.897	Log-Lik Full Model:	-106.121
D(359):	212.242	LR(3):	67.552
		Prob > LR:	0.000
McFadden's R2:	0.241	McFadden's Adj R2:	0.213
Maximum Likelihood R2:	0.170	Cragg & Uhler's R2:	0.316
McKelvey and Zavoina's R2:	0.399	Efron's R2:	0.224
Variance of y*:	5.470	Variance of error:	3.290
Count R2:	0.895	Adj Count R2:	0.191
AIC:	0.607	AIC*n:	220.242
BIC:	-1903.849	BIC':	-49.868

```

684 .
685 . scalar SigDosePrbfmhmFw2 = "no"

686 . scalar MainEffPrbfmhmFw2 = "age bf4 bf40"

687 . * 3 significant main effects for females
688 . * no significant main effect for dose
689 .
690 . * constructing moderators
691 .
692 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd3 = `var'*avgcumdosew2
      3. }

693 .
694 .
695 . *- testing female moderator effects:  no moderator effects for females
696 .
697 . sw, pr(.1): logit HP2pbfhm age bf4 bf40 ageXd3 bf4Xd3 bf40Xd3 if gender==2,
      > iterate(50)

                                begin with full model
p = 0.7256 >= 0.1000  removing bf4Xd3
p = 0.5514 >= 0.1000  removing bf40

```

Logistic regression	Number of obs	=	363
	LR chi2(4)	=	69.05
	Prob > chi2	=	0.0000
Log likelihood = -105.37103	Pseudo R2	=	0.2468

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0553962	.0175151	3.16	0.002	.0210671	.0897253
bf4	-.1901097	.0380586	-5.00	0.000	-.2647032	-.1155163
bf40Xd3	-.1318421	.0668537	-1.97	0.049	-.262873	-.0008113
ageXd3	.0078148	.0040047	1.95	0.051	-.0000342	.0156639
_cons	-3.363212	1.084085	-3.10	0.002	-5.487979	-1.238446

698 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations = **363**
number of covariate patterns = **359**
Pearson chi2(**354**) = **358.75**
Prob > chi2 = **0.4197**

699 . estat class

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	12	4	16
-	35	312	347
Total	47	316	363

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	25.53%
Specificity	$\Pr(- \sim D)$	98.73%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	89.91%

False + rate for true ~D	$\Pr(+ \sim D)$	1.27%
False - rate for true D	$\Pr(- D)$	74.47%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	10.09%

Correctly classified		89.26%
----------------------	--	---------------

700 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-139.897	Log-Lik Full Model:	-105.371
D(358):	210.742	LR(4):	69.051
		Prob > LR:	0.000
McFadden's R2:	0.247	McFadden's Adj R2:	0.211
Maximum Likelihood R2:	0.173	Cragg & Uhler's R2:	0.322
McKelvey and Zavoina's R2:	0.417	Efron's R2:	0.228
Variance of y*:	5.645	Variance of error:	3.290
Count R2:	0.893	Adj Count R2:	0.170
AIC:	0.608	AIC*n:	220.742
BIC:	-1899.454	BIC':	-45.474

701 .

702 . scalar PrbfmhmModFw2="none"

703 .

704 . *****
> ****

705 . *-----Chunk 6 continued testing mediating effects for Problems with fami
> ly

706 . * at home

707 .

708 . * age is a mediating effect for males for Dose=> problems with family at hom
> e

709 . des bf4 bf40

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

710 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	147.6853
Deviance	= 49917.64009	(1/df) Deviance	=	147.6853
Pearson	= 49917.64009	(1/df) Pearson	=	147.6853
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]

Log likelihood	=	-1330.6004	<u>AIC</u>	=	7.838826
			<u>BIC</u>	=	47947.46

	OIM					
age	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
711 . glm HP2pbfhm age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 163.1004
Iteration 2:    deviance = 152.8997
Iteration 3:    deviance = 151.9532
Iteration 4:    deviance = 151.9347
Iteration 5:    deviance = 151.9347
Iteration 6:    deviance = 151.9347
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 151.9346518	(1/df) Deviance	=	.4495108
Pearson = 324.8005072	(1/df) Pearson	=	.9609482

Variance function: $V(u) = u(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1818.249

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0296385	.0061334	4.83	0.000	.0176173	.0416597
_cons	-3.073816	.3430721	-8.96	0.000	-3.746225	-2.401407

(Standard errors scaled using square root of deviance-based dispersion.)

```
712 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1027.1225
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	24.7771
Deviance = 8374.659221	(1/df) Deviance	=	24.7771
Pearson = 8374.659221	(1/df) Pearson	=	24.7771

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	6.053662
Log likelihood = -1027.122509	<u>BIC</u>	=	6404.476

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2447701	.1784427
_cons	12.52896	.2892393	43.32	0.000	11.96206	13.09586

```
713 . glm HP2pbfhm bf4 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 160.0024
Iteration 2: deviance = 148.9095
Iteration 3: deviance = 148.0472
Iteration 4: deviance = 148.0358
Iteration 5: deviance = 148.0358
Iteration 6: deviance = 148.0358
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 148.0358223	(1/df) Deviance	=	.4379758
Pearson = 318.8927909	(1/df) Pearson	=	.9434698

Variance function: V(u) = u*(1-u)	[Bernoulli]
Link function : g(u) = invnorm(u)	[Probit]

	BIC	=	-1822.148
--	-----	---	-----------

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.0752171	.0127773	-5.89	0.000	-.1002602	-.0501741
_cons	-.6910419	.1483563	-4.66	0.000	-.9818149	-.400269

(Standard errors scaled using square root of deviance-based dispersion.)

```

714 .
715 . * age is a mediating effect for females for Dose=> Problems with family at h
    > ome
716 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.9403**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.9184
Deviance = 49427.52828	(1/df) Deviance	=	136.9184
Pearson = 49427.52828	(1/df) Pearson	=	136.9184

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271	<u>BIC</u>	=	47299.65

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

```

717 . glm HP2pbfhm age if gender==2, fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 252.4902
Iteration 2: deviance = 245.4181
Iteration 3: deviance = 245.1325
Iteration 4: deviance = 245.1321
Iteration 5: deviance = 245.1321

```

```

Generalized linear models                      No. of obs      =       363
Optimization      : MQL Fisher scoring      Residual df     =       361
                  (IRLS EIM)                Scale parameter =         1
Deviance          =   245.1320769          (1/df) Deviance =   .6790362
Pearson           =   382.7456824          (1/df) Pearson  =   1.060237

Variance function: V(u) = u*(1-u)          [Bernoulli]
Link function     : g(u) = invnorm(u)      [Probit]

                                          BIC              = -1882.747

```

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.043836	.0066445	6.60	0.000	.030813	.056859
_cons	-3.477625	.3761287	-9.25	0.000	-4.214824	-2.740426

(Standard errors scaled using square root of deviance-based dispersion.)

```

718 .
719 . * bf4 is a mediating effect for females for Dose=> Problems with family at ho
    > me
720 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1109.0983**

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                      Residual df     =       361
                                          Scale parameter =   26.53281
Deviance          =   9578.344971          (1/df) Deviance =   26.53281
Pearson           =   9578.344971          (1/df) Pearson  =   26.53281

Variance function: V(u) = 1                [Gaussian]
Link function     : g(u) = u                [Identity]

                                          AIC              =   6.121754
Log likelihood    = -1109.098281          BIC              =   7450.466

```

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.595012	.1960703	-3.03	0.002	-.9793027	-.2107212
_cons	11.02048	.3223763	34.19	0.000	10.38863	11.65232

```
721 . glm HP2pbfhm bf4 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 240.0481
Iteration 2: deviance = 229.4916
Iteration 3: deviance = 228.6166
Iteration 4: deviance = 228.5986
Iteration 5: deviance = 228.5985
Iteration 6: deviance = 228.5985
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML Fisher scoring                 Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 228.5985175                        (1/df) Deviance =  .6332369
Pearson           = 299.6186696                        (1/df) Pearson  =  .8299686
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function      : g(u) = invnorm(u)                [Probit]
```

```
BIC = -1899.281
```

HP2pbfhm	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.1229375	.0145262	-8.46	0.000	-.1514083	-.0944667
_cons	-.0739521	.1322299	-0.56	0.576	-.3331179	.1852138

(Standard errors scaled using square root of deviance-based dispersion.)

```
722 .
```

```
723 .
```

```
724 . glm bf40 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -818.51169
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML                                   Residual df     =       361
Scale parameter = 5.351378
Deviance          = 1931.847477                        (1/df) Deviance = 5.351378
Pearson           = 1931.847477                        (1/df) Pearson  = 5.351378
```

```
Variance function: V(u) = 1                            [Gaussian]
Link function      : g(u) = u                            [Identity]
```

```
Log likelihood    = -818.5116931                        AIC              = 4.520726
                                                           BIC              = -196.0319
```

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1794903	.0880548	2.04	0.042	.0069061	.3520745
_cons	3.004543	.1447786	20.75	0.000	2.720783	3.288304

```
725 . glm HP2pbfhm bf40 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 280.0603
Iteration 2: deviance = 279.7443
Iteration 3: deviance = 279.7441
Iteration 4: deviance = 279.7441
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML Fisher scoring                 Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 279.7440687                        (1/df) Deviance =  .7749143
Pearson           = 362.9453702                        (1/df) Pearson  = 1.005389
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                 [Probit]
```

```
BIC = -1848.135
```

HP2pbfhm	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.0081494	.0313367	0.26	0.795	-.0532693	.0695682
_cons	-1.154869	.1244365	-9.28	0.000	-1.398761	-.9109783

(Standard errors scaled using square root of deviance-based dispersion.)

```
726 .
```

```
727 . scalar PrbfmhmMedMw2 = "age"
```

```

728 . scalar PrbfmhmMedFw2 = "age bf4"

729 .
730 . title4 " Summary of dose=problems with family at home  mediating effects "

```

```

Summary of dose=problems with family at home  mediating effects

```

```

731 . * males mediators age 1
732 . * females mediators age and BSIsoma rescaled (bf4) 2
733 .
734 .     matrix define HP2prbfamMw2 = J(1,8, 0)

735 .         matrix define HP2prbfamFw2 = J(1,8, 0)

736 . matrix colnames HP2prbfamMw2 =  hypnum ptnum wave gender medsig numMA sig num
    > Modsig numMed

737 .         matrix colnames HP2prbfamFw2=  hypnum ptnum wave gender medsig numMA
    > sig numModsig numMed

738 .     matrix define HP2prbfamMw2= (1, 2, 3, 1, 0, 5, 0, 1 )

739 .         matrix define HP2prbfamFw2= (1, 2, 3, 2, 0, 2, 2, 2)

740 .         matrix rowname HP2prbfamMw2 = HP2prbfamM

741 .         matrix rowname HP2prbfamFw2 = HP2prbfamF

742 .         matlist HP2prbfamMw2

```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
HP2prbfamM		1	2	3	1	0	
> 5	0						

	c8
HP2prbfamM	1

```
743 .      matlist HP2prbfamFw2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	HP2prbfamF	1	2	3	2	0	
> 2	2						
		c8					
	HP2prbfamF	2					

```
744 .      matrix define H1pt2w2 = ( HP2wkMw2 \ HP2wkFw2 \ HP2hmcrMw2 \ HP2hmcr
> Fw2 \ HP2spMw2 \ HP2spFw2 \ HP2prbfamMw2 \ HP2prbfamFw2 )
```

```
745 .
```

```
746 .      matlist H1pt2w2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 1	0						
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 2	0						
	HP2spMw2	1	2	3	1	0	
> 2	0						
	HP2spFw2	1	2	3	2	1	
> 5	5						
	HP2prbfamM	1	2	3	1	0	
> 5	0						
	HP2prbfamF	1	2	3	2	0	
> 2	2						

	c8
r1	4
r1	6
r1	2
r1	2
HP2spMw2	1
HP2spFw2	2
HP2prbfamM	1
HP2prbfamF	2

```
747 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
748 .      matrix rownames H1pt2w2 =  HP2wkMw2 HP2wkFw2 HP2hmcrMw2 HP2hmcrFw2 HP2p
> rbfhmMw2 HP2prbfhmFw2
```

```
749 .      matlist H1pt2w2
```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g	numModsig						
>							
	HP2wkMw2	1	2	3	1	0	
> 4	0						
	HP2wkFw2	1	2	3	2	0	
> 1	0						
	HP2hmcrMw2	1	2	3	1	0	
> 4	0						
	HP2hmcrFw2	1	2	3	2	0	
> 2	0						
	HP2prbfhmMw2	1	2	3	1	0	
> 2	0						
	HP2prbfhmFw2	1	2	3	2	1	
> 5	5						
	HP2prbfhmFw2	1	2	3	1	0	
> 5	0						
	HP2prbfhmFw2	1	2	3	2	0	
> 2	2						

	numMed
HP2wkMw2	4
HP2wkFw2	6
HP2hmcrMw2	2
HP2hmcrFw2	2
HP2prbfhmMw2	1
HP2prbfhmFw2	2
HP2prbfhmFw2	1
HP2prbfhmFw2	2

```

750 .
751 .
752 . *-----
> ----
753 . *****
> ****
754 . *-----Chunk 7   Dose==> problems with sex life impact
755 . * Chunk 7   General model for all part 2 of Nottingham Health Profile
756 . * washes out for men
757 . * female main effects wash out in trimmed model
758 . title "5. wave 2 part2 H1: Test of hypothesis 1 with Male and Female Respon
> dents" ///
>      " wave 2 Main effects Dose=> sexlife impact identification"

*****
> *
*****
> *
*****
> *
*****
> *
*****5. wave 2 part2 H1: Test of hypothesis 1 with Male and Female Respondent
> s*****
*****      wave 2 Main effects Dose=> sexlife impact identification      ****
> *
*****
> *
*****
> *
*****
> *
*****      1 Jul 2012      15:04:41      ****
> *
*****
> *
*****
> *

```

```

759 . forvalues j=2/2 {
      2. set more off
      3.
760 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
761 .   foreach var in HP2sxlife {
      5.       forvalues k=2/2 {
      6.   local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      7.   title "Full Nottingham Part 2 subscale models for male & females" ///
      >   "Full main model for `var' for wave= `j' " ///
      >   "chunk 7 H1 test:Gender= `k' model Wave = `j' for `e(depvar)' "
      8.   di _skip(4)
      9.
762 . di _skip(4)
      10.
763 .
764 .   xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
      >   marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
      > //
      >   radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
      >   deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
      >   illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
      > chrw`j' ///
      >   havmilsq radhlw2 if gender==`k', coef nolog difficult iter
      > ate(50)
      11.           estat class
      12.           estat gof
      13.           fitstat
      14. }
      15. }
      16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished

educ7	byte	%8.0g		specialist/master's degree
marrw21	byte	%8.0g		educ==7. doctor of science/phd
marrw22	byte	%8.0g		marrw2==1. single
marrw23	byte	%8.0g		marrw2==2. cohabitating
marrw24	byte	%8.0g		marrw2==3. married
marrw25	byte	%8.0g		marrw2==4. separated
marrw26	byte	%8.0g		marrw2==5. divorced
inclw2	double	%15.0g	LABJ	marrw2==6. widowed
				Income is not sufficient for
				basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for
				basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics
				plus extra purchases/savings
				in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably
				afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt -
				1.01635E-007)

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
Full Nottingham Part 2 subscale models for male & females
> *
*****
Full main model for HP2sxlife for wave= 2
> *
*****
chunk 7 H1 test:Gender= 2 model Wave = 2 for HP2pbfhm
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:04:41
> *
*****

```

```
> *
*****
> *
```

```
i.educ          _Ieduc_1-8          (naturally coded; _Ieduc_1 omitted)
note: bf15m != 0 predicts failure perfectly
      bf15m dropped and 12 obs not used
```

```
note: bf29 != 0 predicts success perfectly
      bf29 dropped and 4 obs not used
```

```
note: _Ieduc_8 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf17 omitted because of collinearity
note: radhlw2 omitted because of collinearity
```

```
Logistic regression                                Number of obs   =          346
                                                    LR chi2(50)      =          172.45
                                                    Prob > chi2      =          0.0000
Log likelihood = -111.04151                        Pseudo R2       =          0.4371
```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1025465	.0220099	4.66	0.000	.0594079	.145685
_Ieduc_2	-15.48089	5580.75	-0.00	0.998	-10953.55	10922.59
_Ieduc_3	-13.96022	5580.75	-0.00	0.998	-10952.03	10924.11
_Ieduc_4	-13.71505	5580.75	-0.00	0.998	-10951.78	10924.35
_Ieduc_5	-14.90906	5580.75	-0.00	0.998	-10952.98	10923.16
_Ieduc_6	-14.036	5580.75	-0.00	0.998	-10952.1	10924.03
_Ieduc_7	-14.35246	5580.751	-0.00	0.998	-10952.42	10923.72
_Ieduc_8	0	(omitted)				
occ1w2	-1.981003	1.626317	-1.22	0.223	-5.168525	1.20652
occ2w2	-1.199181	1.677697	-0.71	0.475	-4.487407	2.089044
occ3w2	-.7937582	1.670584	-0.48	0.635	-4.068042	2.480526
occ4w2	-.8102305	1.76353	-0.46	0.646	-4.266686	2.646225
occ5w2	-.5056346	1.89785	-0.27	0.790	-4.225353	3.214084
occ6w2	-1.645496	1.931022	-0.85	0.394	-5.430229	2.139237
occ7w2	-1.288749	1.611028	-0.80	0.424	-4.446306	1.868809
occ8w2	-.2492981	1.896994	-0.13	0.895	-3.967338	3.468742
marrw21	-.8001566	1.260909	-0.63	0.526	-3.271493	1.67118
marrw22	-.5650635	1.458662	-0.39	0.698	-3.423989	2.293861
marrw23	-1.064868	.8865967	-1.20	0.230	-2.802566	.6728293
marrw25	-2.27112	1.443829	-1.57	0.116	-5.100972	.5587328
marrw26	0	(omitted)				
inclw2	.5165366	1.706152	0.30	0.762	-2.82746	3.860533

inc2w2	.9386295	1.604285	0.59	0.558	-2.205712	4.082971
inc3w2	-.0514022	1.646264	-0.03	0.975	-3.27802	3.175215
inc4w2	.0543252	2.074029	0.03	0.979	-4.010697	4.119348
radhlw2	.0162077	.0081749	1.98	0.047	.0001852	.0322303
havmil	-.0014745	.0033419	-0.44	0.659	-.0080244	.0050754
avgcumdosew2	.1675129	.1251712	1.34	0.181	-.0778182	.412844
bf1	-.0006699	.0354295	-0.02	0.985	-.0701104	.0687707
bf4	-.6290339	.2665349	-2.36	0.018	-1.151433	-.1066351
bf2	.0000625	.000131	0.48	0.633	-.0001943	.0003193
bf4m	.4940985	.2505491	1.97	0.049	.0030312	.9851658
bf5m	-.002308	.0018303	-1.26	0.207	-.0058953	.0012792
bf7m	.00018	.0006254	0.29	0.773	-.0010457	.0014058
bf8	6.11e-06	.0000425	0.14	0.886	-.0000772	.0000894
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0009967	.0290168	-0.03	0.973	-.0578686	.0558752
bf22	-.0001321	.0001453	-0.91	0.363	-.0004169	.0001527
bf29	0	(omitted)				
bf30	-.0003317	.0003532	-0.94	0.348	-.001024	.0003605
bf40	.149372	.145042	1.03	0.303	-.1349052	.4336491
deaw2	.0989356	.2231863	0.44	0.658	-.3385014	.5363726
dvcew2	-14.61462	1422.458	-0.01	0.992	-2802.582	2773.353
sepaw2	13.19252	1422.46	0.01	0.993	-2774.778	2801.163
accdw2	-.3607593	.7071147	-0.51	0.610	-1.746679	1.02516
movew2	.2363995	.5198633	0.45	0.649	-.7825137	1.255313
illw2	.5572231	.2374511	2.35	0.019	.0918274	1.022619
shfamw2	.001878	.0072955	0.26	0.797	-.0124209	.0161768
shhlw2	.0092925	.0072946	1.27	0.203	-.0050046	.0235896
shjobw2	-.0069643	.0067203	-1.04	0.300	-.0201358	.0062073
shrelaw2	-.0169606	.0081044	-2.09	0.036	-.032845	-.0010762
suprtw2	-.0129953	.0058047	-2.24	0.025	-.0243723	-.0016183
suchrw2	.0118245	.0068566	1.72	0.085	-.0016142	.0252632
havmilsq	-6.39e-08	2.74e-06	-0.02	0.981	-5.43e-06	5.30e-06
radhlw2	0	(omitted)				
_cons	5.841436	5580.75	0.00	0.999	-10932.23	10943.91

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2sxlif

Classified	True		Total
	D	~D	
+	57	17	74
-	32	240	272
Total	89	257	346

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2sxlife $\neq 0$

Sensitivity	$\Pr(+ D)$	64.04%
Specificity	$\Pr(- \sim D)$	93.39%
Positive predictive value	$\Pr(D +)$	77.03%
Negative predictive value	$\Pr(\sim D -)$	88.24%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	6.61%
False - rate for true D	$\Pr(- D)$	35.96%
False + rate for classified +	$\Pr(\sim D +)$	22.97%
False - rate for classified -	$\Pr(D -)$	11.76%
Correctly classified		85.84%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	346
number of covariate patterns =	346
Pearson $\chi^2(295)$ =	312.67
Prob > χ^2 =	0.2294

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-197.267	Log-Lik Full Model:	-111.042
D(289):	222.083	LR(50):	172.450
		Prob > LR:	0.000
McFadden's R2:	0.437	McFadden's Adj R2:	0.148
Maximum Likelihood R2:	0.393	Cragg & Uhler's R2:	0.577
McKelvey and Zavoina's R2:	0.765	Efron's R2:	0.477
Variance of y*:	14.018	Variance of error:	3.290
Count R2:	0.858	Adj Count R2:	0.449
AIC:	0.971	AIC*n:	336.083
BIC:	-1467.538	BIC':	119.872

```

765 . // full model washes out
766 .
767 . title "5. wave 2 part2 H1: Test of hypothesis 1 with Male and Female Respon
> dents" ///
> " wave 2 Main effects Dose=> sexlife impact identification"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****5. wave 2 part2 H1: Test of hypothesis 1 with Male and Female Respondent
> s*****
***** wave 2 Main effects Dose=> sexlife impact identification *****
> *
*****
> *
*****
> *
*****
> *
***** 1 Jul 2012 15:04:43 *****
> *
*****
> *
*****
> *

```

```

768 . forvalues j=2/2 {
      2. set more off
      3.
769 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
> bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.

```

```

770 .   foreach var in HP2sxlife {
      5.       forvalues k=2/2 {
      6. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      7. title "Full Nottingham Part 2 subscale models for male & females" ///
> "Full main model for `var' for wave= `j' " ///
> "chunk 7 H1 test:Gender= `k' model Wave = `j' for `e(depvar)' "
      8. di _skip(4)
      9.
771 . di _skip(4)
      10.
772 .
773 .   xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
>       marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
> //
>       radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>       deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>       illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
> chrw`j' ///
>       havmilsq radhlw2 if gender==`k', coef nolog difficult iter
> ate(50)
      11.               estat class
      12.               estat gof
      13.               fitstat
      14. }
      15. }
      16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed

inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9 = max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11 = max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m = max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

```

*****
> *
*****
> *
*****
> *
*****
Full Nottingham Part 2 subscale models for male & females
> *
*****
Full main model for HP2sxlife for wave= 2
> *
*****
chunk 7 H1 test:Gender= 2 model Wave = 2 for HP2sxlife
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:04:43
> *
*****
> *
*****
> *

```

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
 note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 12 obs not used

note: bf29 != 0 predicts success perfectly
 bf29 dropped and 4 obs not used

note: _Ieduc_8 omitted because of collinearity
 note: marrw26 omitted because of collinearity
 note: bf17 omitted because of collinearity
 note: radhlw2 omitted because of collinearity

Logistic regression	Number of obs	=	346
	LR chi2(50)	=	172.45
	Prob > chi2	=	0.0000
Log likelihood = -111.04151	Pseudo R2	=	0.4371

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1025465	.0220099	4.66	0.000	.0594079	.145685
_Ieduc_2	-15.48089	5580.75	-0.00	0.998	-10953.55	10922.59
_Ieduc_3	-13.96022	5580.75	-0.00	0.998	-10952.03	10924.11
_Ieduc_4	-13.71505	5580.75	-0.00	0.998	-10951.78	10924.35
_Ieduc_5	-14.90906	5580.75	-0.00	0.998	-10952.98	10923.16
_Ieduc_6	-14.036	5580.75	-0.00	0.998	-10952.1	10924.03
_Ieduc_7	-14.35246	5580.751	-0.00	0.998	-10952.42	10923.72
_Ieduc_8	0	(omitted)				
occ1w2	-1.981003	1.626317	-1.22	0.223	-5.168525	1.20652
occ2w2	-1.199181	1.677697	-0.71	0.475	-4.487407	2.089044
occ3w2	-.7937582	1.670584	-0.48	0.635	-4.068042	2.480526
occ4w2	-.8102305	1.76353	-0.46	0.646	-4.266686	2.646225
occ5w2	-.5056346	1.89785	-0.27	0.790	-4.225353	3.214084
occ6w2	-1.645496	1.931022	-0.85	0.394	-5.430229	2.139237
occ7w2	-1.288749	1.611028	-0.80	0.424	-4.446306	1.868809
occ8w2	-.2492981	1.896994	-0.13	0.895	-3.967338	3.468742
marrw21	-.8001566	1.260909	-0.63	0.526	-3.271493	1.67118
marrw22	-.5650635	1.458662	-0.39	0.698	-3.423989	2.293861
marrw23	-1.064868	.8865967	-1.20	0.230	-2.802566	.6728293
marrw25	-2.27112	1.443829	-1.57	0.116	-5.100972	.5587328
marrw26	0	(omitted)				
inc1w2	.5165366	1.706152	0.30	0.762	-2.82746	3.860533
inc2w2	.9386295	1.604285	0.59	0.558	-2.205712	4.082971
inc3w2	-.0514022	1.646264	-0.03	0.975	-3.27802	3.175215
inc4w2	.0543252	2.074029	0.03	0.979	-4.010697	4.119348
radhlw2	.0162077	.0081749	1.98	0.047	.0001852	.0322303
havmil	-.0014745	.0033419	-0.44	0.659	-.0080244	.0050754

avgcumdosew2	.1675129	.1251712	1.34	0.181	-.0778182	.412844
bf1	-.0006699	.0354295	-0.02	0.985	-.0701104	.0687707
bf4	-.6290339	.2665349	-2.36	0.018	-1.151433	-.1066351
bf2	.0000625	.000131	0.48	0.633	-.0001943	.0003193
bf4m	.4940985	.2505491	1.97	0.049	.0030312	.9851658
bf5m	-.002308	.0018303	-1.26	0.207	-.0058953	.0012792
bf7m	.00018	.0006254	0.29	0.773	-.0010457	.0014058
bf8	6.11e-06	.0000425	0.14	0.886	-.0000772	.0000894
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0009967	.0290168	-0.03	0.973	-.0578686	.0558752
bf22	-.0001321	.0001453	-0.91	0.363	-.0004169	.0001527
bf29	0	(omitted)				
bf30	-.0003317	.0003532	-0.94	0.348	-.001024	.0003605
bf40	.149372	.145042	1.03	0.303	-.1349052	.4336491
deaw2	.0989356	.2231863	0.44	0.658	-.3385014	.5363726
dvcew2	-14.61462	1422.458	-0.01	0.992	-2802.582	2773.353
sepaw2	13.19252	1422.46	0.01	0.993	-2774.778	2801.163
accdw2	-.3607593	.7071147	-0.51	0.610	-1.746679	1.02516
movew2	.2363995	.5198633	0.45	0.649	-.7825137	1.255313
illw2	.5572231	.2374511	2.35	0.019	.0918274	1.022619
shfamw2	.001878	.0072955	0.26	0.797	-.0124209	.0161768
shhlw2	.0092925	.0072946	1.27	0.203	-.0050046	.0235896
shjobw2	-.0069643	.0067203	-1.04	0.300	-.0201358	.0062073
shrelaw2	-.0169606	.0081044	-2.09	0.036	-.032845	-.0010762
suprtw2	-.0129953	.0058047	-2.24	0.025	-.0243723	-.0016183
suchrw2	.0118245	.0068566	1.72	0.085	-.0016142	.0252632
havmilsq	-6.39e-08	2.74e-06	-0.02	0.981	-5.43e-06	5.30e-06
radhlw2	0	(omitted)				
_cons	5.841436	5580.75	0.00	0.999	-10932.23	10943.91

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	57	17	74
-	32	240	272
Total	89	257	346

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2sxlife $\neq 0$

Sensitivity	$\Pr(+ D)$	64.04%
Specificity	$\Pr(- \sim D)$	93.39%
Positive predictive value	$\Pr(D +)$	77.03%
Negative predictive value	$\Pr(\sim D -)$	88.24%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	6.61%
False - rate for true D	$\Pr(- D)$	35.96%
False + rate for classified +	$\Pr(\sim D +)$	22.97%
False - rate for classified -	$\Pr(D -)$	11.76%
Correctly classified		85.84%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	346
number of covariate patterns =	346
Pearson $\chi^2(295)$ =	312.67
Prob > χ^2 =	0.2294

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-197.267	Log-Lik Full Model:	-111.042
D(289):	222.083	LR(50):	172.450
		Prob > LR:	0.000
McFadden's R2:	0.437	McFadden's Adj R2:	0.148
Maximum Likelihood R2:	0.393	Cragg & Uhler's R2:	0.577
McKelvey and Zavoina's R2:	0.765	Efron's R2:	0.477
Variance of y*:	14.018	Variance of error:	3.290
Count R2:	0.858	Adj Count R2:	0.449
AIC:	0.971	AIC*n:	336.083
BIC:	-1467.538	BIC':	119.872

```

774 .
775 . *-----Chunk 7 female dose2 => sex life impact-----
776 . * wash out in the trimmed model
777 . title "Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave
> 2"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave 2**
> ***
*****
> *
*****
> *
*****
1 Jul 2012 15:04:44
> *
*****
> *
*****
> *

```

```

778 . * male models
779 . forvalues j=2/2 {
2. di as input "trimmed HP2sexlife main effects models wave 1 for H1 part 2
> with dose ns"
3. di as input "wave 2 male dose avgcumdosew`j' main effect not signif"
4. logit HP2sxlife age marrw21-marrw26 bf4 bf4m dvcew`j' illw`j' shh
> lw`j' ///
> havmilsq shrelaw`j' suchrw2 ///
> avgcumdosew`j' radhlw`j' if gender==1
5. estat class
6. estat gof
7. fitstat
8. }
trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose ns
wave 2 male dose avgcumdosew2 main effect not signif

note: marrw22 != 0 predicts failure perfectly
marrw22 dropped and 11 obs not used

```

note: marrw24 != 0 predicts failure perfectly
 marrw24 dropped and 3 obs not used

note: dvcew2 != 0 predicts failure perfectly
 dvcew2 dropped and 8 obs not used

Iteration 0: log likelihood = **-166.08818**
 Iteration 1: log likelihood = **-113.32233**
 Iteration 2: log likelihood = **-107.02172**
 Iteration 3: log likelihood = **-106.73421**
 Iteration 4: log likelihood = **-106.72877**
 Iteration 5: log likelihood = **-106.72753**
 Iteration 6: log likelihood = **-106.72723**
 Iteration 7: log likelihood = **-106.72717**
 Iteration 8: log likelihood = **-106.72716**

Logistic regression

Number of obs = **317**
 LR chi2(14) = **118.72**
 Prob > chi2 = **0.0000**
 Pseudo R2 = **0.3574**

Log likelihood = **-106.72716**

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0644457	.0181912	3.54	0.000	.0287916	.1000998
marrw21	8.652724	607.7898	0.01	0.989	-1182.593	1199.899
marrw22	0	(omitted)				
marrw23	8.99536	607.7899	0.01	0.988	-1182.251	1200.242
marrw24	0	(omitted)				
marrw25	10.60048	607.791	0.02	0.986	-1180.648	1201.849
marrw26	8.365677	607.7915	0.01	0.989	-1182.884	1199.615
bf4	-.2024234	.1925354	-1.05	0.293	-.5797859	.174939
bf4m	.0200376	.172285	0.12	0.907	-.3176348	.35771
dvcew2	0	(omitted)				
illw2	.3945351	.2569746	1.54	0.125	-.1091258	.8981961
shhlw2	.0030985	.0058298	0.53	0.595	-.0083277	.0145248
havmilsq	-2.23e-06	4.62e-06	-0.48	0.630	-.0000113	6.84e-06
shrelaw2	-.010479	.006183	-1.69	0.090	-.0225974	.0016394
suchrw2	.0070631	.0045745	1.54	0.123	-.0019027	.0160288
avgcumdosew2	.0643464	.0493461	1.30	0.192	-.0323701	.161063
radhlw2	.0146535	.0060343	2.43	0.015	.0028265	.0264806
_cons	-13.11105	607.7916	-0.02	0.983	-1204.361	1178.139

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	35	15	50
-	34	233	267
Total	69	248	317

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	50.72%
Specificity	$\Pr(- \sim D)$	93.95%
Positive predictive value	$\Pr(D +)$	70.00%
Negative predictive value	$\Pr(\sim D -)$	87.27%
False + rate for true ~D	$\Pr(+ \sim D)$	6.05%
False - rate for true D	$\Pr(- D)$	49.28%
False + rate for classified +	$\Pr(\sim D +)$	30.00%
False - rate for classified -	$\Pr(D -)$	12.73%
Correctly classified		84.54%

Logistic model for HP2sxlife, goodness-of-fit test

```

      number of observations =      317
number of covariate patterns =      312
      Pearson chi2(297) =      255.20
              Prob > chi2 =      0.9621

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-166.088	Log-Lik Full Model:	-106.727
D(299):	213.454	LR(14):	118.722
		Prob > LR:	0.000
McFadden's R2:	0.357	McFadden's Adj R2:	0.249
Maximum Likelihood R2:	0.312	Cragg & Uhler's R2:	0.481
McKelvey and Zavoina's R2:	0.539	Efron's R2:	0.374
Variance of y*:	7.131	Variance of error:	3.290
Count R2:	0.845	Adj Count R2:	0.290
AIC:	0.787	AIC*n:	249.454
BIC:	-1508.457	BIC':	-38.097

Logistic regression

Number of obs = 340

LR chi2(5) = 112.29

Prob > chi2 = 0.0000

Log likelihood = -115.3714

Pseudo R2 = 0.3273

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0668709	.0154805	4.32	0.000	.0365295	.0972122
bf4	-.1650598	.0368511	-4.48	0.000	-.2372867	-.0928329
illw2	.3077459	.2454954	1.25	0.210	-.1734162	.788908
avgcumdosew2	.0621309	.0473611	1.31	0.190	-.0306951	.1549569
radhlw2	.010562	.0054615	1.93	0.053	-.0001422	.0212663
_cons	-3.881348	1.050876	-3.69	0.000	-5.941027	-1.82167

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	32	15	47
-	37	256	293
Total	69	271	340

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	46.38%
Specificity	$\Pr(- \sim D)$	94.46%
Positive predictive value	$\Pr(D +)$	68.09%
Negative predictive value	$\Pr(\sim D -)$	87.37%

False + rate for true ~D	$\Pr(+ \sim D)$	5.54%
False - rate for true D	$\Pr(- D)$	53.62%
False + rate for classified +	$\Pr(\sim D +)$	31.91%
False - rate for classified -	$\Pr(D -)$	12.63%

Correctly classified	84.71%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

```

        number of observations =      340
number of covariate patterns =      330
        Pearson chi2(324) =      287.38
            Prob > chi2 =      0.9292

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-115.371
D(334):	230.743	LR(5):	112.285
		Prob > LR:	0.000
McFadden's R2:	0.327	McFadden's Adj R2:	0.292
Maximum Likelihood R2:	0.281	Cragg & Uhler's R2:	0.443
McKelvey and Zavoina's R2:	0.462	Efron's R2:	0.344
Variance of y*:	6.119	Variance of error:	3.290
Count R2:	0.847	Adj Count R2:	0.246
AIC:	0.714	AIC*n:	242.743
BIC:	-1716.125	BIC':	-83.140

```

783 .
784 . * sex life washes out
785 .
786 .
787 . scalar MainEffsxlifeMw2 = "age bf4 illw2 radhlw2"

788 . scalar SigDosesxlifeMw2 = "no"

789 .
790 .
791 . forvalues j=2/2 {
      2. title "trimmed HP2sxlife main effects models wave `j' for H1 part 2 with
> dose ns"
      3. title2 "Wave `j' dose HPsxlife relationship but avgcumdosew`j': Dose not s
> ignif"
      4. }

*****
> *
*****
> *
*****
> *
*****trimmed HP2sxlife main effects models wave 2 for H1 part 2 with dose ns**
> ***
*****
> *
*****

```

```

> *
*****                               1 Jul 2012    15:04:47    ****
> *
*****
> *
*****
> *

```

```

title2: Wave `j dose HPsxlife relationship but avgcumdosew2: Dose not signif
              Date and time:   1 Jul 2012    15:04:47
              Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/Hltests/hlpt2
              Stata data file: chwide1jul2012.dta  h
> as 2399 variables and 703 observations

```

```

Wave `j dose HPsxlife relationship but avgcumdosew2: Dose not signif

```

```

792 .
793 .
794 . cap gen radhlw2Xd3 = radhlw2*avgcumdosew2

795 .
796 . set more off

797 . des bf4

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```

798 . forvalues j=2/2 {
      2.           sw, pr(.1):logistic HP2sxlife age bf4 illw`j' ///
>           avgcumdosew`j' radhlw`j' ageXd3 radhlw2Xd3 illw2Xd3 if gende
> r==1, coef nolog
      3.           estat class
      4.           estat gof
      5.           fitstat
      6. }

              begin with full model
p = 0.6505 >= 0.1000 removing avgcumdosew2
p = 0.4079 >= 0.1000 removing illw2Xd3

```

Logistic regression

Number of obs = 340

LR chi2(6) = 121.14

Prob > chi2 = 0.0000

Pseudo R2 = 0.3531

Log likelihood = -110.94454

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0529331	.0169001	3.13	0.002	.0198095	.0860566
bf4	-.1653141	.0375369	-4.40	0.000	-.2388852	-.0917431
illw2	.4168743	.2517861	1.66	0.098	-.0766174	.9103659
radhlw2Xd3	-.0118911	.0064749	-1.84	0.066	-.0245816	.0007994
radhlw2	.0203277	.0073575	2.76	0.006	.0059072	.0347481
ageXd3	.0144933	.0077512	1.87	0.062	-.0006989	.0296854
_cons	-3.925242	1.078928	-3.64	0.000	-6.039901	-1.810582

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	33	11	44
-	36	260	296
Total	69	271	340

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	47.83%
Specificity	$\Pr(- \sim D)$	95.94%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	87.84%
False + rate for true ~D	$\Pr(+ \sim D)$	4.06%
False - rate for true D	$\Pr(- D)$	52.17%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	12.16%
Correctly classified		86.18%

Logistic model for HP2sxlife, goodness-of-fit test

Measures of Fit for **logistic** of **HP2sxl**life

```

799 .
800 . scalar sxlifeModMw2 = "none"

801 . *xx male moderators: no main significant dose effect
802 . *xx no male moderators for sexlife impact
803 .
804 .
805 . * female models
806 . *-----Chunk 7 dose3 moderator => sex life impact-----
> -
807 . di as input "chunk 7  female wave=3"
    chunk 7  female wave=3

808 . title "Chunk 7 trimmed female model:" "dose and HP2sxlife relationship in wa
> ve 2"

```



```

*****
> *
*****
1 Jul 2012    15:04:53    *****
> *
*****
> *
*****
> *

```

```

809 . * female models
810 .       forvalues j=2/2 {
      2.
811 . set more off
      3. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      4. title "trimmed HP2sexlife main effects models" "wave 2 for H1 part 2 with
> dose ns"
      5. title "wave 2 dose HP2sexlife relationship" "avgcumdosew`j' Dose not sign
> if"
      6.       logit HP2sxlife age marrw21-marrw26  radhlw`j' bf4 bf4m    ///
>       shfamw`j' shrelaw`j' avgcumdosew`j'  if gender==2
      7.               estat class
      8.               estat gof
      9.               fitstat
     10. }

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

note: marrw24 omitted because of collinearity
 note: marrw26 omitted because of collinearity
 Iteration 0: log likelihood = **-206.26609**
 Iteration 1: log likelihood = **-143.57745**
 Iteration 2: log likelihood = **-138.68519**
 Iteration 3: log likelihood = **-138.62333**
 Iteration 4: log likelihood = **-138.62326**
 Iteration 5: log likelihood = **-138.62326**

Logistic regression

Number of obs = **362**
 LR chi2(11) = **135.29**
 Prob > chi2 = **0.0000**
 Pseudo R2 = **0.3279**

Log likelihood = **-138.62326**

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.076392	.0165292	4.62	0.000	.0439954	.1087886
marrw21	-.5305645	.8871345	-0.60	0.550	-2.269316	1.208187
marrw22	.2470266	1.206929	0.20	0.838	-2.11851	2.612563
marrw23	-.9086585	.7011467	-1.30	0.195	-2.282881	.4655638
marrw24	0 (omitted)					
marrw25	-1.473965	1.020033	-1.45	0.148	-3.473194	.525263
marrw26	0 (omitted)					
radhlw2	.0078658	.0048473	1.62	0.105	-.0016346	.0173663
bf4	-.6041323	.1886755	-3.20	0.001	-.9739294	-.2343351
bf4m	.40554	.1714694	2.37	0.018	.0694661	.7416139
shfamw2	-.0013231	.0052527	-0.25	0.801	-.0116181	.008972
shrelaw2	-.0119535	.0060123	-1.99	0.047	-.0237374	-.0001695
avgcumdosew2	.185182	.1129898	1.64	0.101	-.0362739	.4066379
_cons	-6.005196	1.747399	-3.44	0.001	-9.430035	-2.580358

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	53	20	73
-	40	249	289
Total	93	269	362

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2sxlife $\neq 0$

Sensitivity	$\Pr(+ D)$	56.99%
Specificity	$\Pr(- \sim D)$	92.57%
Positive predictive value	$\Pr(D +)$	72.60%
Negative predictive value	$\Pr(\sim D -)$	86.16%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	7.43%
False - rate for true D	$\Pr(- D)$	43.01%
False + rate for classified +	$\Pr(\sim D +)$	27.40%
False - rate for classified -	$\Pr(D -)$	13.84%
Correctly classified		83.43%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations = **362**
 number of covariate patterns = **361**
 Pearson $\chi^2(349)$ = **408.71**
 Prob > χ^2 = **0.0151**

Measures of Fit for **logit** of HP2sxlife

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-138.623
D(348):	277.247	LR(11):	135.286
		Prob > LR:	0.000
McFadden's R2:	0.328	McFadden's Adj R2:	0.260
Maximum Likelihood R2:	0.312	Cragg & Uhler's R2:	0.459
McKelvey and Zavoina's R2:	0.482	Efron's R2:	0.384
Variance of y*:	6.352	Variance of error:	3.290
Count R2:	0.834	Adj Count R2:	0.355
AIC:	0.843	AIC*n:	305.247
BIC:	-1773.046	BIC':	-70.478

```

812 . scalar SigDoseSxlifeFw2 = "no"

813 . scalar MainEffsxlifeFw2 = "age marrw23 radhlw2 bf4 bf4m shrelaw2"

814 . *----- constructing possible moderators
815 .
816 .     foreach var in marrw21 marrw22 marrw23 marrw24 marrw25 marrw26 ///
>         bf4 bf4m shfamw2 shrelaw2 radhlw2 {
    2.         cap gen `var'Xd3 = `var'*avgcumdosew2
    3.         }

817 .
818 . title "Chunk 7 trimmed female model:" "dose and HP2sxlife relationship in wa
> ve 2"

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****          Chunk 7 trimmed female model:          ****
> *
*****          dose and HP2sxlife relationship in wave 2          ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****          1 Jul 2012    15:04:54    ****
> *
*****
> *
*****
> *

```

```

819 . * female models
820 .         forvalues j=2/2 {
      2.
821 . set more off
      3. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      4. title "trimmed HP2sexlife main effects models" "wave 2 for H1 part 2 with
> dose ns"
      5. title "wave 2 dose HP2sexlife relationship" "avgcumdosew`j' Dose not sign
> if"
      6.         logit HP2sxlife age marrw21-marrw26   radhlw`j' bf4 bf4m   ///
>         shfamw`j' shrelaw`j' avgcumdosew`j'   ageXd3 marrw21Xd3 marrw22Xd3
>         ///
>         marrw23Xd3 marrw24Xd3 marrw25Xd3 bf4Xd3 bf4mXd3 shrelaw2Xd3 ///
>         if gender==2
      7.                 estat class
      8.                 estat gof
      9.                 fitstat
10. }

```

	storage	display	value	
variable name	type	format	label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
trimmed HP2sexlife main effects models
> *
*****
wave 2 for H1 part 2 with dose ns
> *
*****
> *
*****

```

```
note: marrw24 omitted because of collinearity
note: marrw26 omitted because of collinearity
note: marrw24Xd3 omitted because of collinearity
Iteration 0:    log likelihood = -206.26609
Iteration 1:    log likelihood = -141.90135
Iteration 2:    log likelihood = -137.13734
Iteration 3:    log likelihood = -137.05422
Iteration 4:    log likelihood = -137.05402
Iteration 5:    log likelihood = -137.05402
```

Logistic regression

Number of obs = 362

LR chi2(19) = 138.42

Prob > chi2 = 0.0000

Log likelihood = -137.05402

Pseudo R2 = 0.3355

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0771657	.0249115	3.10	0.002	.02834	.1259913
marrw21	-1.451767	1.441353	-1.01	0.314	-4.276767	1.373234
marrw22	.0685249	1.464872	0.05	0.963	-2.802572	2.939622
marrw23	-1.092581	.9071979	-1.20	0.228	-2.870657	.6854937
marrw24	0	(omitted)				
marrw25	-1.837988	1.514456	-1.21	0.225	-4.806268	1.130292
marrw26	0	(omitted)				
radhlw2	.0079384	.0048969	1.62	0.105	-.0016593	.0175361
bf4	-.363408	.3781896	-0.96	0.337	-1.104646	.3778301
bf4m	.2325195	.3434991	0.68	0.498	-.4407264	.9057654
shfamw2	-.0007843	.0054412	-0.14	0.885	-.011449	.0098803
shrelaw2	-.0124226	.0061868	-2.01	0.045	-.0245484	-.0002967
avgcumdosew2	-1.023812	3.170547	-0.32	0.747	-7.23797	5.190346
ageXd3	.0002661	.0332903	0.01	0.994	-.0649818	.0655139
marrw21Xd3	1.328931	1.506104	0.88	0.378	-1.622979	4.28084
marrw22Xd3	.1769697	.9861833	0.18	0.858	-1.755914	2.109853
marrw23Xd3	.2926788	.7754937	0.38	0.706	-1.227261	1.812619
marrw24Xd3	0	(omitted)				
marrw25Xd3	.2934835	.9361317	0.31	0.754	-1.541301	2.128268
bf4Xd3	-.2172939	.2938598	-0.74	0.460	-.7932486	.3586608
bf4mXd3	.14997	.2614038	0.57	0.566	-.362372	.6623121
shrelaw2Xd3	.0002655	.0431225	0.01	0.995	-.084253	.084784
_cons	-5.03786	3.098692	-1.63	0.104	-11.11118	1.035465

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	55	20	75
-	38	249	287
Total	93	269	362

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2sxlife $\neq 0$

Sensitivity	$\Pr(+ D)$	59.14%
Specificity	$\Pr(- \sim D)$	92.57%
Positive predictive value	$\Pr(D +)$	73.33%
Negative predictive value	$\Pr(\sim D -)$	86.76%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	7.43%
False - rate for true D	$\Pr(- D)$	40.86%
False + rate for classified +	$\Pr(\sim D +)$	26.67%
False - rate for classified -	$\Pr(D -)$	13.24%
Correctly classified		83.98%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	362
number of covariate patterns =	361
Pearson $\chi^2(341)$ =	404.96
Prob > χ^2 =	0.0097

Measures of Fit for **logit** of HP2sxlife

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-137.054
D(339):	274.108	LR(19):	138.424
		Prob > LR:	0.000
McFadden's R ² :	0.336	McFadden's Adj R ² :	0.224
Maximum Likelihood R ² :	0.318	Cragg & Uhler's R ² :	0.467
McKelvey and Zavoina's R ² :	0.494	Efron's R ² :	0.389
Variance of y*:	6.498	Variance of error:	3.290
Count R ² :	0.840	Adj Count R ² :	0.376
AIC:	0.884	AIC*n:	320.108
BIC:	-1723.159	BIC':	-26.483

```

822 . scalar sxlifeModFw2="none"

823 .
824 .
825 .
826 .
827 . *----- testing female moderators
828 . title "partly trimmed female moderator model of dose & HP2sxlife relationshi
    > p in wv 3"

*****
> *
*****
> *
*****
> *
*****
> *
*****partly trimmed female moderator model of dose & HP2sxlife relationship in
> wv 3*****
*****
> *
*****
> *
*****
1 Jul 2012    15:04:56    ****
> *
*****
> *
*****
> *

829 . * male models
830 .     forvalues j=2/2 {
    2. set more off
    3. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
    4. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
    5. title "wave 2 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
    6.     logit HP2sxlife age marrw21-marrw26 radhlw`j' bf4 bf4m    ///
>     shfamw`j' shrelaw`j' avgcumdosew`j' marrw21Xd3 marrw22Xd3 ///
>     marrw23Xd3 marrw24Xd3 marrw25Xd3 marrw26Xd3 radhlw`j'Xd3 ///
>     bf4Xd3 shfamw2Xd3 shrelaw2Xd3 if gender==2
    7.         estat class
    8.         estat gof
    9.         fitstat

```

```
10. }
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```
title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
1 Jul 2012
15:04:56
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2406 variables and 703 obser
> vations
```

```
*****
> *
*****
> *
*****
> *
*****
> *
*****wave 2 dose HP2sexlife relationship but avgcumdosew2: Dose not signif****
> *
*****
> *
*****
> *
*****
> *
*****1 Jul 201215:04:56****
> *
*****
> *
*****
> *
```

note: marrw24 omitted because of collinearity
 note: marrw26 omitted because of collinearity
 note: marrw24Xd3 omitted because of collinearity
 note: marrw26Xd3 omitted because of collinearity

Iteration 0: log likelihood = **-206.26609**
 Iteration 1: log likelihood = **-142.57705**
 Iteration 2: log likelihood = **-137.51325**
 Iteration 3: log likelihood = **-137.42461**
 Iteration 4: log likelihood = **-137.42437**
 Iteration 5: log likelihood = **-137.42437**

Logistic regression	Number of obs	=	362
	LR chi2(19)	=	137.68
	Prob > chi2	=	0.0000
Log likelihood = -137.42437	Pseudo R2	=	0.3338

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0881857	.0228618	3.86	0.000	.0433774	.132994
marrw21	-1.190817	1.437325	-0.83	0.407	-4.007921	1.626288
marrw22	.0152843	1.480232	0.01	0.992	-2.885916	2.916485
marrw23	-1.100839	.8999384	-1.22	0.221	-2.864686	.6630077
marrw24	0	(omitted)				
marrw25	-1.714881	1.480971	-1.16	0.247	-4.61753	1.187768
marrw26	0	(omitted)				
radhlw2	.0059255	.0058476	1.01	0.311	-.0055355	.0173866
bf4	-.5647269	.1952268	-2.89	0.004	-.9473645	-.1820894
bf4m	.4033962	.174148	2.32	0.021	.0620723	.7447201
shfamw2	.0021518	.0065354	0.33	0.742	-.0106573	.0149608
shrelaw2	-.0127936	.0062133	-2.06	0.039	-.0249714	-.0006158
avgcumdosew2	1.042177	1.610695	0.65	0.518	-2.114727	4.199082
marrw21Xd3	1.083118	1.522783	0.71	0.477	-1.901481	4.067718
marrw22Xd3	.3220928	1.102342	0.29	0.770	-1.838458	2.482644
marrw23Xd3	.394904	.7698412	0.51	0.608	-1.113957	1.903765
marrw24Xd3	0	(omitted)				
marrw25Xd3	.3165762	.9106048	0.35	0.728	-1.468176	2.101329
marrw26Xd3	0	(omitted)				
radhlw2Xd3	.0024173	.0037617	0.64	0.520	-.0049555	.00979
bf4Xd3	-.0361335	.046891	-0.77	0.441	-.1280381	.0557711
shfamw2Xd3	-.0034656	.0052445	-0.66	0.509	-.0137447	.0068135
shrelaw2Xd3	-.0162686	.0222527	-0.73	0.465	-.0598831	.0273459
_cons	-6.710013	2.18777	-3.07	0.002	-10.99796	-2.422062

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	54	19	73
-	39	250	289
Total	93	269	362

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	58.06%
Specificity	$\Pr(- \sim D)$	92.94%
Positive predictive value	$\Pr(D +)$	73.97%
Negative predictive value	$\Pr(\sim D -)$	86.51%

False + rate for true ~D	$\Pr(+ \sim D)$	7.06%
False - rate for true D	$\Pr(- D)$	41.94%
False + rate for classified +	$\Pr(\sim D +)$	26.03%
False - rate for classified -	$\Pr(D -)$	13.49%

Correctly classified	83.98%
----------------------	---------------

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	362
number of covariate patterns =	361
Pearson chi2(341) =	404.20
Prob > chi2 =	0.0104

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-137.424
D(338):	274.849	LR(19):	137.683
		Prob > LR:	0.000
McFadden's R2:	0.334	McFadden's Adj R2:	0.217
Maximum Likelihood R2:	0.316	Cragg & Uhler's R2:	0.465
McKelvey and Zavoina's R2:	0.497	Efron's R2:	0.388
Variance of y*:	6.546	Variance of error:	3.290
Count R2:	0.840	Adj Count R2:	0.376
AIC:	0.892	AIC*n:	322.849
BIC:	-1716.527	BIC':	-25.742


```

834 .
835 . * female models
836 .       forvalues j=2/2 {
      2. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      3. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
      4. title "wave 2 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      5.       logit HP2sxlife age  radhlw`j' bf4 bf4m   ///
>       shrelaw2 shfamw`j'  avgcumdosew`j'   ///
>       shrelaw2Xd3 if gender==2
      6.               estat class
      7.               estat gof
      8.               fitstat
      9. }

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```

title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
  1 Jul 2012
15:04:58
computer  Macintosh (Intel 64-bit)
folder   /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file  chwideljul2012.dta  currently has  2406  variables and  703  obser
> vations

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****wave 2 dose HP2sexlife relationship but avgcumdosew2: Dose not signif****
> *
*****
> *
*****
> *
*****
1 Jul 2012    15:04:58    ****
> *
*****
> *
*****
> *

```

```

Iteration 0:  log likelihood = -206.26609
Iteration 1:  log likelihood = -145.82764
Iteration 2:  log likelihood =  -140.338
Iteration 3:  log likelihood = -140.1844
Iteration 4:  log likelihood = -140.1838
Iteration 5:  log likelihood = -140.1838

```

```

Logistic regression              Number of obs   =       362
                                LR chi2(8)       =       132.16
                                Prob > chi2       =       0.0000
Log likelihood = -140.1838      Pseudo R2      =       0.3204

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.086161	.0187529	4.59	0.000	.049406	.122916
radhlw2	.0086327	.004785	1.80	0.071	-.0007457	.018011
bf4	-.5633458	.1891523	-2.98	0.003	-.9340774	-.1926141
bf4m	.3743527	.1732499	2.16	0.031	.0347891	.7139163
shrelaw2	-.0122309	.0059271	-2.06	0.039	-.0238478	-.000614
shfamw2	-.0009006	.0051781	-0.17	0.862	-.0110495	.0092484
avgcumdosew2	.9067215	.7875706	1.15	0.250	-.6368885	2.450332
shrelaw2Xd3	-.0126027	.0132428	-0.95	0.341	-.0385582	.0133527
_cons	-7.277228	1.721919	-4.23	0.000	-10.65213	-3.902329

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	52	22	74
-	41	247	288
Total	93	269	362

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	55.91%
Specificity	$\Pr(- \sim D)$	91.82%
Positive predictive value	$\Pr(D +)$	70.27%
Negative predictive value	$\Pr(\sim D -)$	85.76%
False + rate for true ~D	$\Pr(+ \sim D)$	8.18%
False - rate for true D	$\Pr(- D)$	44.09%
False + rate for classified +	$\Pr(\sim D +)$	29.73%
False - rate for classified -	$\Pr(D -)$	14.24%
Correctly classified		82.60%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations = **362**
 number of covariate patterns = **361**
 Pearson chi2(352) = **405.41**
 Prob > chi2 = **0.0259**

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-140.184
D(353):	280.368	LR(8):	132.165
		Prob > LR:	0.000
McFadden's R2:	0.320	McFadden's Adj R2:	0.277
Maximum Likelihood R2:	0.306	Cragg & Uhler's R2:	0.450
McKelvey and Zavoina's R2:	0.479	Efron's R2:	0.373
Variance of y*:	6.317	Variance of error:	3.290
Count R2:	0.826	Adj Count R2:	0.323
AIC:	0.824	AIC*n:	298.368
BIC:	-1799.383	BIC':	-85.031

```

837 . * female models
838 .       forvalues j=2/2 {
      2. des bf4 bf4m shfamw2 shrelaw2 avgcumdosew2
      3. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
      4. title "wave 2 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      5.       logit HP2sxlife age  radhlw`j' bf4 bf4m   ///
>       shrelaw2 shfamw`j'   ///
>       if gender==2
      6.               estat class
      7.               estat gof
      8.               fitstat
      9. }

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996
avgcumdosew2	double	%8.0g		Average mean dose CS1337 in mGy for wave 2

```

title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
  1 Jul 2012
15:04:59
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2406 variables and 703 obser
> vations

```

```
Iteration 0:    log likelihood = -206.26609
Iteration 1:    log likelihood = -147.80582
Iteration 2:    log likelihood = -142.56802
Iteration 3:    log likelihood = -142.50325
Iteration 4:    log likelihood = -142.50319
Iteration 5:    log likelihood = -142.50319
```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0773867	.0151879	5.10	0.000	.0476189	.1071545
radhlw2	.0092803	.0047101	1.97	0.049	.0000487	.0185119
bf4	-.5791652	.1890895	-3.06	0.002	-.9497739	-.2085566
bf4m	.3860275	.1731752	2.23	0.026	.0466104	.7254445
shrelaw2	-.0111587	.0058224	-1.92	0.055	-.0225703	.000253
shfamw2	-.0012219	.005072	-0.24	0.810	-.0111628	.008719
_cons	-6.703691	1.604696	-4.18	0.000	-9.848837	-3.558545



Classified	True		Total
	D	~D	
+	49	23	72
-	44	246	290
Total	93	269	362

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	52.69%
Specificity	$\Pr(- \sim D)$	91.45%
Positive predictive value	$\Pr(D +)$	68.06%
Negative predictive value	$\Pr(\sim D -)$	84.83%
False + rate for true ~D	$\Pr(+ \sim D)$	8.55%
False - rate for true D	$\Pr(- D)$	47.31%
False + rate for classified +	$\Pr(\sim D +)$	31.94%
False - rate for classified -	$\Pr(D -)$	15.17%
Correctly classified		81.49%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      362
number of covariate patterns =    357
    Pearson chi2(350) =    401.39
        Prob > chi2 =      0.0301

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-142.503
D(355):	285.006	LR(6):	127.526
		Prob > LR:	0.000
McFadden's R2:	0.309	McFadden's Adj R2:	0.275
Maximum Likelihood R2:	0.297	Cragg & Uhler's R2:	0.437
McKelvey and Zavoina's R2:	0.465	Efron's R2:	0.360
Variance of y*:	6.146	Variance of error:	3.290
Count R2:	0.815	Adj Count R2:	0.280
AIC:	0.826	AIC*n:	299.006
BIC:	-1806.527	BIC':	-92.176

```

839 .
840 . scalar MainEffsxlifeFw2 = "age radhlw2 bf4 bf4m shrelaw2 shfamw2"

841 . scalar SigDoseSxlifeFw2="no"

842 . * xx female main effects model: no sign dose main effect
843 . * xx 6 signif main effects
844 . * xx no moderator effects significant
845 .
846 . *----- mediator models for Dose => sexlife impact
847 .
848 . di as input "testing possible sex life mediator effects for males"
      testing possible sex life mediator effects for males

849 .
850 . * age is a mediating effect for males for Dose=> sex life for men
851 . des bf4 bf4m

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```

852 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew2	.5832314	.2635871		2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562		68.85	0.000	47.23729	50.00537

```
853 . glm HP2sxlife age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =    287.05
Iteration 2:  deviance =   282.9134
Iteration 3:  deviance =   282.8157
Iteration 4:  deviance =   282.8156
Iteration 5:  deviance =   282.8156
```

```
Generalized linear models                      No. of obs      =       340
Optimization      :  MQL Fisher scoring        Residual df      =       338
                  (IRLS EIM)                  Scale parameter =         1
Deviance          =   282.8156218              (1/df) Deviance =   .8367326
Pearson           =   327.5643783              (1/df) Pearson  =   .9691254
```

```
Variance function: V(u) = u*(1-u)             [Bernoulli]
Link function     : g(u) = invnorm(u)          [Probit]
```

```
BIC = -1687.368
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0532907	.0067666	7.88	0.000	.0400283	.0665531
_cons	-3.620299	.3741324	-9.68	0.000	-4.353585	-2.887013

(Standard errors scaled using square root of deviance-based dispersion.)

```
854 .
855 . * illness is a mediating effect for males = > sex life for men
856 . des illw2
```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```
857 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:   log likelihood = -303.59609
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
avgcumdosew2	.0085423	.0128556	0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406	7.96	0.000	.2066336	.3416382

```
858 . glm HP2sxlife illw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:   deviance = 327.4086
Iteration 2:   deviance = 327.3702
Iteration 3:   deviance = 327.3699
Iteration 4:   deviance = 327.3699
Iteration 5:   deviance = 327.3699
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 327.36992	(1/df) Deviance	=	.9685501
Pearson = 335.9738293	(1/df) Pearson	=	.9940054

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1642.814
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.4754044	.1211711	3.92	0.000	.2379134	.7128953
_cons	-.9963884	.0886054	-11.25	0.000	-1.170052	-.822725

(Standard errors scaled using square root of deviance-based dispersion.)

```
859 .
860 . des radhlw2
```

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		how much believed personal health is affected by radiation in 1996

```
861 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1693.4076**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	9.972986
Log likelihood = -1693.407647	<u>BIC</u>	=	419831.3

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

```
862 . glm HP2sxlife radhlw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 299.0301
Iteration 2:  deviance = 296.5897
Iteration 3:  deviance = 296.5625
Iteration 4:  deviance = 296.5625
Iteration 5:  deviance = 296.5625
```

```
Generalized linear models                      No. of obs      =       340
Optimization      :  MQL Fisher scoring        Residual df     =       338
                  (IRLS EIM)                  Scale parameter =         1
Deviance          = 296.5625078                (1/df) Deviance =  .8774039
Pearson           = 336.752315                 (1/df) Pearson  =  .9963086
```

```
Variance function: V(u) = u*(1-u)             [Bernoulli]
Link function      : g(u) = invnorm(u)         [Probit]
```

```
BIC = -1673.621
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0156386	.0022528	6.94	0.000	.0112232	.020054
_cons	-1.687381	.1543913	-10.93	0.000	-1.989983	-1.38478

(Standard errors scaled using square root of deviance-based dispersion.)

```
863 .
864 .
865 . des bf4
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
866 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1027.1225
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	24.7771
Deviance = 8374.659221	(1/df) Deviance	=	24.7771
Pearson = 8374.659221	(1/df) Pearson	=	24.7771

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	6.053662
Log likelihood = -1027.122509	<u>BIC</u>	=	6404.476

bf4	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2447701	.1784427	
_cons	12.52896	.2892393	43.32	0.000	11.96206	13.09586	

```
867 . glm HP2sxlife bf4 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 265.0595
Iteration 2: deviance = 261.6959
Iteration 3: deviance = 261.6273
Iteration 4: deviance = 261.6271
Iteration 5: deviance = 261.6271
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 261.6270836	(1/df) Deviance	=	.7740446
Pearson = 301.9171445	(1/df) Pearson	=	.893246

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1708.557
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1431725	.0149643	-9.57	0.000	-.172502	-.1138431
_cons	.7780696	.180124	4.32	0.000	.425033	1.131106

(Standard errors scaled using square root of deviance-based dispersion.)

868 .
869 . des bf4m

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

870 . glm bf4m avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1060.7791**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	30.20174
Deviance = 10208.18969	(1/df) Deviance	=	30.20174
Pearson = 10208.18969	(1/df) Pearson	=	30.20174

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	6.251642
Log likelihood = -1060.779096	<u>BIC</u>	=	8238.006

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0266037	.1191987	-0.22	0.823	-.2602289	.2070215
_cons	20.34324	.3193362	63.70	0.000	19.71735	20.96913

```
871 . glm HP2sxlife bf4m if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 266.1375
Iteration 2:  deviance = 263.3205
Iteration 3:  deviance = 263.273
Iteration 4:  deviance = 263.2729
Iteration 5:  deviance = 263.2729
```

```
Generalized linear models                               No. of obs      =       340
Optimization      : ML Fisher scoring                 Residual df     =       338
                   (IRLS EIM)                          Scale parameter =        1
Deviance          = 263.2728985                        (1/df) Deviance =  .7789139
Pearson           = 303.0162706                        (1/df) Pearson  =  .8964978
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                 [Probit]
```

```
BIC = -1706.911
```

HP2sxlife	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4m	-.1287243	.0140303	-9.17	0.000	-.1562231	-.1012255
_cons	1.624944	.276779	5.87	0.000	1.082468	2.167421

(Standard errors scaled using square root of deviance-based dispersion.)

```
872 .
873 .
874 . * age is a mediating effect for females for Dose=> sex life for women
875 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1406.9403
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML                                   Residual df     =       361
Deviance          = 49427.52828                        Scale parameter = 136.9184
Pearson           = 49427.52828                        (1/df) Deviance = 136.9184
                                                         (1/df) Pearson  = 136.9184
```

```
Variance function: V(u) = 1                            [Gaussian]
Link function     : g(u) = u                             [Identity]
```

```
Log likelihood    = -1406.940271                        AIC              = 7.762756
                                                         BIC              = 47299.65
```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

876 . glm HP2sxlife age if gender==2, fam(bin) irls scale(dev) link(probit)

Iteration 1: deviance = **336.5251**
Iteration 2: deviance = **333.7638**
Iteration 3: deviance = **333.7326**
Iteration 4: deviance = **333.7326**
Iteration 5: deviance = **333.7326**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 333.7325644	(1/df) Deviance	=	.9244669
Pearson = 379.4384762	(1/df) Pearson	=	1.051076

Variance function: **V(u) = u*(1-u)** [**Bernoulli**]
Link function : **g(u) = invnorm(u)** [**Probit**]

BIC = **-1794.147**

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0606116	.0071416	8.49	0.000	.0466144	.0746088
_cons	-3.838422	.3937027	-9.75	0.000	-4.610065	-3.066779

(Standard errors scaled using square root of deviance-based dispersion.)

877 .

```

878 . * illness is a mediating effect for females = > sex life for men
879 . des illw2

```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```

880 . glm illw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-463.51524**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	.756881
Deviance = 273.2340487	(1/df) Deviance	=	.756881
Pearson = 273.2340487	(1/df) Pearson	=	.756881

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	2.564822
Log likelihood = -463.5152411	<u>BIC</u>	=	-1854.645

illw2	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew2	.1249912	.0331157		3.77	0.000	.0600856	.1898968
_cons	.301285	.0544484		5.53	0.000	.194568	.4080019

```

881 . glm HP2sxlife illw2 if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **388.6886**
 Iteration 2: deviance = **388.2329**
 Iteration 3: deviance = **388.2328**
 Iteration 4: deviance = **388.2328**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	361
	Scale parameter	=	1
Deviance = 388.2327887	(1/df) Deviance	=	1.075437
Pearson = 359.7775997	(1/df) Pearson	=	.9966138

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1739.647

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.4442672	.0949037	4.68	0.000	.2582594	.630275
_cons	-.8535276	.0872416	-9.78	0.000	-1.024518	-.6825372

(Standard errors scaled using square root of deviance-based dispersion.)

882 .
 883 . des radhlw2

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		how much believed personal health is affected by radiation in 1996

884 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1791.2233

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1137.567
Deviance = 410661.5604	(1/df) Deviance	=	1137.567
Pearson = 410661.5604	(1/df) Pearson	=	1137.567

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]

	AIC	=	9.880018
Log likelihood = -1791.223306	BIC	=	408533.7

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	3.302288	1.283833	2.57	0.010	.7860214	5.818555
_cons	56.95167	2.110863	26.98	0.000	52.81445	61.08888

```
885 . glm HP2sxlife radhlw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 390.2214
Iteration 2:  deviance = 389.9357
Iteration 3:  deviance = 389.9356
Iteration 4:  deviance = 389.9356
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  MQL Fisher scoring                 Residual df     =       361
                  (IRLS EIM)                           Scale parameter =        1
Deviance          = 389.935535                         (1/df) Deviance = 1.080154
Pearson           = 370.7850434                         (1/df) Pearson  = 1.027105
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                 [Probit]
```

```
BIC = -1737.944
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0108547	.0023275	4.66	0.000	.0062929	.0154166
_cons	-1.340315	.1718732	-7.80	0.000	-1.67718	-1.003449

(Standard errors scaled using square root of deviance-based dispersion.)

```
886 .
887 . des bf4 // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
888 . * bf4 is a meditating effect for females for Dose=> sex life for women
889 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1109.0983
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  ML                                 Residual df     =       361
Deviance          = 9578.344971                         Scale parameter = 26.53281
Pearson           = 9578.344971                         (1/df) Deviance = 26.53281
                                                         (1/df) Pearson  = 26.53281
```

```
Variance function: V(u) = 1                    [Gaussian]
Link function     : g(u) = u                    [Identity]
```

Log likelihood	= -1109.098281	<u>AIC</u>	= 6.121754
		<u>BIC</u>	= 7450.466

	OIM					
bf4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.595012	.1960703	-3.03	0.002	-.9793027	-.2107212
_cons	11.02048	.3223763	34.19	0.000	10.38863	11.65232

```
890 . glm HP2sxlife bf4 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 344.0399
Iteration 2:    deviance = 342.6827
Iteration 3:    deviance = 342.6686
Iteration 4:    deviance = 342.6686
Iteration 5:    deviance = 342.6686
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 342.6686152	(1/df) Deviance	=	.9492205
Pearson = 336.3540555	(1/df) Pearson	=	.9317287

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]

BIC = -1785.211

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1230087	.0148291	-8.30	0.000	-.1520732	-.0939442
_cons	.5134392	.1542351	3.33	0.001	.211144	.8157344

(Standard errors scaled using square root of deviance-based dispersion.)

```

891 .
892 . des bf4m // soma recentered

```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```

893 . * bf4m is a possible mediating effect for female sex life
894 . glm bf4m avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1140.8259**

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
Deviance	= 11407.97484	Scale parameter	=	31.60104
Pearson	= 11407.97484	(1/df) Deviance	=	31.60104
		(1/df) Pearson	=	31.60104
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	6.296561
Log likelihood	= -1140.825904	<u>BIC</u>	=	9280.095

bf4m	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	-.599311	.2139789	-2.80	0.005	-1.018702	-.1799202	
_cons	18.83424	.3518214	53.53	0.000	18.14469	19.5238	

```

895 . glm HP2sxlife bf4m if gender==2, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **356.1451**
 Iteration 2: deviance = **355.6209**
 Iteration 3: deviance = **355.6178**
 Iteration 4: deviance = **355.6178**
 Iteration 5: deviance = **355.6178**

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	361
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 355.6178202	(1/df) Deviance	=	.9850909
Pearson	= 340.0032816	(1/df) Pearson	=	.9418373

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1772.262

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4m	-.0990193	.0135516	-7.31	0.000	-.12558	-.0724586
_cons	1.063679	.244399	4.35	0.000	.584666	1.542693

(Standard errors scaled using square root of deviance-based dispersion.)

896 .
 897 . des shfamw2

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

898 . glm shfamw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1804.1821

Generalized linear models	No. of obs	=	362
Optimization : ML	Residual df	=	360
	Scale parameter	=	1255.79
Deviance = 452084.3956	(1/df) Deviance	=	1255.79
Pearson = 452084.3956	(1/df) Pearson	=	1255.79

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]

Log likelihood = -1804.182119
 AIC = 9.978907
 BIC = 449963.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.6648412	1.349346	0.49	0.622	-1.979828	3.30951
_cons	33.6876	2.218839	15.18	0.000	29.33876	38.03645

```
899 . glm HP2sxlife shfamw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 411.7925
Iteration 2:  deviance = 411.1829
Iteration 3:  deviance = 411.1826
Iteration 4:  deviance = 411.1826
```

Generalized linear models	No. of obs	=	362
Optimization : ML Fisher scoring	Residual df	=	360
(IRLS EIM)	Scale parameter	=	1
Deviance = 411.1826472	(1/df) Deviance	=	1.142174
Pearson = 361.8999919	(1/df) Pearson	=	1.005278

Variance function: $V(u) = u*(1-u)$ [**Bernoulli**]
Link function : $g(u) = \text{invnorm}(u)$ [**Probit**]

BIC = -1709.809

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	-.0023803	.0021918	-1.09	0.277	-.0066761	.0019156
_cons	-.5736929	.1047839	-5.48	0.000	-.7790656	-.3683202

(Standard errors scaled using square root of deviance-based dispersion.)

```
900 .
901 . des shrelaw2
```

variable name	storage type	display format	value label	variable label
shrelaw2	double	%8.0g		Percentage of strains and hassles related to relationships in 1996

```
902 . glm shrelaw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1767.2727
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	996.9369
Deviance = 359894.211	(1/df) Deviance	=	996.9369
Pearson = 359894.211	(1/df) Pearson	=	996.9369

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	9.748059
Log likelihood = -1767.272695	<u>BIC</u>	=	357766.3

shrelaw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.945314	1.20186	1.62	0.106	-.4102891	4.300917
_cons	22.64351	1.976084	11.46	0.000	18.77046	26.51657

```
903 . glm HP2sxlife shrelaw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 415.0412
Iteration 2: deviance = 414.406
Iteration 3: deviance = 414.4058
Iteration 4: deviance = 414.4058
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 414.4057989	(1/df) Deviance	=	1.147939
Pearson = 362.9721983	(1/df) Pearson	=	1.005463

Variance function: V(u) = u*(1-u)	[Bernoulli]
Link function : g(u) = invnorm(u)	[Probit]

	<u>BIC</u>	=	-1713.474
--	------------	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw2	-.0020918	.0024591	-0.85	0.395	-.0069114	.0027279
_cons	-.5970179	.0953785	-6.26	0.000	-.7839564	-.4100794

(Standard errors scaled using square root of deviance-based dispersion.)

```

904 .
905 .
906 .
907 . *xx summary of mediating effects: age and illness mediate sex life for men
908 . * age illness radhlw2 bf4 bf4m (soma) medi
    > ate sex life for women
909 .
910 . scalar sxlifeMedMw2 = "age illw2"

911 . scalar sxlifeMedFw2 = "age illw2 radhlw2 bf4 bf4m"

912 . title4 "5. summary matrix contstruction for dose -> sexlife impact"
-----
5. summary matrix contstruction for dose -> sexlife impact
-----

913 .
914 . matrix define HP2sxlifeMw2 = J(1,8, 0)

915 . matrix define HP2sxlifeFw2 = J(1,8, 0)

916 . matrix colnames HP2sxlifeMw2 = hypnum ptnum wave gender medsig numMA sig num
    > Modsig numMed

917 . matrix colnames HP2sxlifeFw2 = hypnum ptnum wave gender medsig numM
    > Asig numModsig numMed

918 . matrix define HP2sxlifeMw2 = (1, 2, 3, 1, 0, 4, 0, 2 )

```

```
919 .      matrix define HP2sxlifefw2 = (1, 2, 3, 2, 1, 6, 0, 5)
```

```
920 .      matrix rowname HP2sxlifefw2 = HP2sxlifefw2
```

```
921 .      matrix rowname HP2sxlifefw2 = HP2sxlifefw2
```

```
922 .      matlist HP2sxlifefw2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
HP2sxlifefw2		1	2	3	1	0	
> 4	0						
		c8					
HP2sxlifefw2		2					

```
923 .      matlist HP2sxlifefw2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
HP2sxlifefw2		1	2	3	2	1	
> 6	0						
		c8					
HP2sxlifefw2		5					

```
924 . matrix define H1pt2w2 = ( HP2wkMw2 \ HP2wkFw2 \ HP2hmcrMw2 \ HP2hmcrFw2 \ HP
> 2spMw2 \ HP2spFw2 \ HP2prbfamMw2 \ HP2prbfamFw2 \ HP2sxlifefw2 \ HP2sxlifefw
> 2 )
```

```
925 .
```

926 . matlist H1pt2w2

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 1	0						
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 2	0						
	HP2spMw2	1	2	3	1	0	
> 2	0						
	HP2spFw2	1	2	3	2	1	
> 5	5						
	HP2prbfamM	1	2	3	1	0	
> 5	0						
	HP2prbfamF	1	2	3	2	0	
> 2	2						
	HP2sxlifeMw2	1	2	3	1	0	
> 4	0						
	HP2sxlifeFw2	1	2	3	2	1	
> 6	0						
		c8					
	r1	4					
	r1	6					
	r1	2					
	r1	2					
	HP2spMw2	1					
	HP2spFw2	2					
	HP2prbfamM	1					
	HP2prbfamF	2					
	HP2sxlifeMw2	2					
	HP2sxlifeFw2	5					


```

930 .
931 .
932 .
933 .
934 . *===== Chunk 8      Dose => interests and Hobbies relationship
935 . * washes out for males
936 . * washes out for females in trimmed model
937 .
938 . title  "6. Moderators and Mediators of the Dose = > interests and hobbies Im
> pact"

```

```

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****6. Moderators and Mediators of the Dose = > interests and hobbies Impact*
> ****
*****                                     ****
> *
*****                                     ****
> *
*****                                     1 Jul 2012    15:05:35    ****
> *
*****
> *
*****
> *

```

```

939 .
940 . title4 " Hyp. 1. pt 2 wave 2 Main effects Dose=> Interests and Hobbies impac
> t identification"

```

```

Hyp. 1. pt 2 wave 2 Main effects Dose=> Interests and Hobbies impact identifi
> cation

```

```

941 .
942 . * Chunk 8 ---Female full Interest and hobbies model
943 . forvalues j=2/2 {
      2. set more off
      3.
944 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
945 .   foreach var in HP2inthob {
      5.       forvalues k=1/2 {
      6.   local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      7.
946 .   di as input "Full main model for `var' for wave= `j' "
      8.   di _skip(4)
      9.   di as input  "chunk 8 H1 test:Gender= `k'  model Wave = `j' for `e(depva
      > r)' "
     10.   di _skip(4)
     11.   title "Full Nottingham Part 2 subscale models for male and then females"
     12.   di as input "Model for gender==`k' and wave ==`j'"
     13.   di _skip(2)
     14.       xi: logistic `var' age i.educ occ1w`j'-occ8w`j' ///
      >           marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j'-inc4w`j' /
      > //
      >           radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
      >           deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
      >           illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
      > chrw`j' ///
      >           havmilsq radhlw2 if gender==2, coef nolog difficult iterat
      > e(50)
     15.               estat class
     16.               estat gof
     17.               fitstat
     18.   }
     19.   }
     20.   }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's


```
*****
> *
*****
> *
```

Model for gender==1 and wave == 2

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)

note: bf15m != 0 predicts failure perfectly

 bf15m dropped and 12 obs not used

note: sepaw2 != 0 predicts failure perfectly

 sepaw2 dropped and 7 obs not used

note: _Ieduc_8 omitted because of collinearity

note: marrw26 omitted because of collinearity

note: bf17 omitted because of collinearity

note: radhlw2 omitted because of collinearity

Logistic regression

Number of obs = 343

LR chi2(50) = 122.71

Prob > chi2 = 0.0000

Pseudo R2 = 0.3684

Log likelihood = -105.17277

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0823123	.0222811	3.69	0.000	.0386422	.1259824
_Ieduc_2	-11.49207	1090.325	-0.01	0.992	-2148.489	2125.505
_Ieduc_3	-10.49189	1090.324	-0.01	0.992	-2147.489	2126.505
_Ieduc_4	-9.521531	1090.325	-0.01	0.993	-2146.519	2127.476
_Ieduc_5	-10.03097	1090.325	-0.01	0.993	-2147.028	2126.966
_Ieduc_6	-10.65519	1090.325	-0.01	0.992	-2147.652	2126.342
_Ieduc_7	-10.56771	1090.33	-0.01	0.992	-2147.575	2126.44
_Ieduc_8	0	(omitted)				
occ1w2	-1.444251	1.786645	-0.81	0.419	-4.94601	2.057508
occ2w2	-1.72162	1.86422	-0.92	0.356	-5.375425	1.932185
occ3w2	-.6960307	1.813742	-0.38	0.701	-4.2509	2.858838
occ4w2	-1.340236	1.971898	-0.68	0.497	-5.205085	2.524613
occ5w2	-1.866674	2.177453	-0.86	0.391	-6.134403	2.401055
occ6w2	-.6630026	2.009767	-0.33	0.741	-4.602073	3.276067
occ7w2	-.3132082	1.768051	-0.18	0.859	-3.778525	3.152109
occ8w2	-.4424864	1.980995	-0.22	0.823	-4.325166	3.440193
marrw21	1.198754	1.252366	0.96	0.338	-1.255838	3.653346
marrw22	-.723147	1.45696	-0.50	0.620	-3.578736	2.132442
marrw23	-.1412732	.8614541	-0.16	0.870	-1.829692	1.547146
marrw25	.030411	1.273943	0.02	0.981	-2.466472	2.527294
marrw26	0	(omitted)				

inc1w2	.7639278	1.820866	0.42	0.675	-2.804904	4.33276
inc2w2	1.088119	1.754837	0.62	0.535	-2.351299	4.527537
inc3w2	.8549853	1.806256	0.47	0.636	-2.685212	4.395182
inc4w2	2.107171	2.102907	1.00	0.316	-2.014451	6.228794
radhlw2	.0162662	.0092193	1.76	0.078	-.0018033	.0343356
havmil	.0028568	.0035632	0.80	0.423	-.004127	.0098406
avgcumdosew2	.1191237	.1112746	1.07	0.284	-.0989705	.3372179
bf1	-.0579291	.0444461	-1.30	0.192	-.1450419	.0291837
bf4	-.5134212	.2911522	-1.76	0.078	-1.084069	.0572265
bf2	.0000225	.0001357	0.17	0.868	-.0002436	.0002885
bf4m	.3813738	.2769085	1.38	0.168	-.1613568	.9241045
bf5m	-.0013491	.0018728	-0.72	0.471	-.0050196	.0023214
bf7m	-.0007653	.0006452	-1.19	0.236	-.0020299	.0004993
bf8	.0000124	.0000428	0.29	0.772	-.0000716	.0000964
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0409398	.0388667	1.05	0.292	-.0352376	.1171172
bf22	.0000496	.0001446	0.34	0.732	-.0002338	.0003329
bf29	.0000147	.0000386	0.38	0.704	-.000061	.0000904
bf30	.0005975	.0003487	1.71	0.087	-.0000859	.0012809
bf40	-.092913	.1571517	-0.59	0.554	-.4009247	.2150987
deaw2	.1650922	.2350487	0.70	0.482	-.2955947	.6257792
dvcew2	-.44027	1.751166	-0.25	0.801	-3.872493	2.991953
sepaw2	0	(omitted)				
accdw2	.3072193	.6191348	0.50	0.620	-.9062626	1.520701
movew2	-.4208456	.8150343	-0.52	0.606	-2.018283	1.176592
illw2	.146668	.2184808	0.67	0.502	-.2815466	.5748825
shfamw2	.0028218	.0077742	0.36	0.717	-.0124154	.018059
shhlw2	.0082475	.0076919	1.07	0.284	-.0068283	.0233233
shjobw2	-.0093426	.0067931	-1.38	0.169	-.0226569	.0039716
shrelaw2	-.0142034	.0081278	-1.75	0.081	-.0301336	.0017268
suprtw2	-.0099735	.0060387	-1.65	0.099	-.021809	.0018621
suchrw2	-.0045113	.0068989	-0.65	0.513	-.0180329	.0090102
havmilsq	-2.60e-06	4.34e-06	-0.60	0.550	-.0000111	5.92e-06
radhlw2	0	(omitted)				
_cons	2.140849	1090.33	0.00	0.998	-2134.867	2139.148

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	32	12	44
-	33	266	299
Total	65	278	343

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	49.23%
Specificity	$\Pr(- \sim D)$	95.68%
Positive predictive value	$\Pr(D +)$	72.73%
Negative predictive value	$\Pr(\sim D -)$	88.96%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	4.32%
False - rate for true D	$\Pr(- D)$	50.77%
False + rate for classified +	$\Pr(\sim D +)$	27.27%
False - rate for classified -	$\Pr(D -)$	11.04%
Correctly classified		86.88%

Logistic model for HP2inthob, goodness-of-fit test

number of observations = **343**
 number of covariate patterns = **343**
 Pearson $\chi^2(292)$ = **307.38**
 Prob > χ^2 = **0.2568**

Measures of Fit for **logistic** of HP2inthob

Log-Lik Intercept Only:	-166.528	Log-Lik Full Model:	-105.173
D(286):	210.346	LR(50):	122.710
		Prob > LR:	0.000
McFadden's R2:	0.368	McFadden's Adj R2:	0.026
Maximum Likelihood R2:	0.301	Cragg & Uhler's R2:	0.484
McKelvey and Zavoina's R2:	0.627	Efron's R2:	0.388
Variance of y*:	8.828	Variance of error:	3.290
Count R2:	0.869	Adj Count R2:	0.308
AIC:	0.946	AIC*n:	324.346
BIC:	-1459.245	BIC':	169.177

Full main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= 2 model Wave = 2 for HP2inthob

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0823123	.0222811	3.69	0.000	.0386422	.1259824
_Ieduc_2	-11.49207	1090.325	-0.01	0.992	-2148.489	2125.505
_Ieduc_3	-10.49189	1090.324	-0.01	0.992	-2147.489	2126.505
_Ieduc_4	-9.521531	1090.325	-0.01	0.993	-2146.519	2127.476
_Ieduc_5	-10.03097	1090.325	-0.01	0.993	-2147.028	2126.966
_Ieduc_6	-10.65519	1090.325	-0.01	0.992	-2147.652	2126.342
_Ieduc_7	-10.56771	1090.33	-0.01	0.992	-2147.575	2126.44
_Ieduc_8	0	(omitted)				
occ1w2	-1.444251	1.786645	-0.81	0.419	-4.94601	2.057508
occ2w2	-1.72162	1.86422	-0.92	0.356	-5.375425	1.932185
occ3w2	-.6960307	1.813742	-0.38	0.701	-4.2509	2.858838
occ4w2	-1.340236	1.971898	-0.68	0.497	-5.205085	2.524613
occ5w2	-1.866674	2.177453	-0.86	0.391	-6.134403	2.401055
occ6w2	-.6630026	2.009767	-0.33	0.741	-4.602073	3.276067
occ7w2	-.3132082	1.768051	-0.18	0.859	-3.778525	3.152109
occ8w2	-.4424864	1.980995	-0.22	0.823	-4.325166	3.440193
marrw21	1.198754	1.252366	0.96	0.338	-1.255838	3.653346
marrw22	-.723147	1.45696	-0.50	0.620	-3.578736	2.132442
marrw23	-.1412732	.8614541	-0.16	0.870	-1.829692	1.547146
marrw25	.030411	1.273943	0.02	0.981	-2.466472	2.527294
marrw26	0	(omitted)				
inc1w2	.7639278	1.820866	0.42	0.675	-2.804904	4.33276
inc2w2	1.088119	1.754837	0.62	0.535	-2.351299	4.527537
inc3w2	.8549853	1.806256	0.47	0.636	-2.685212	4.395182
inc4w2	2.107171	2.102907	1.00	0.316	-2.014451	6.228794
radhlw2	.0162662	.0092193	1.76	0.078	-.0018033	.0343356
havmil	.0028568	.0035632	0.80	0.423	-.004127	.0098406
avgcumdosew2	.1191237	.1112746	1.07	0.284	-.0989705	.3372179
bf1	-.0579291	.0444461	-1.30	0.192	-.1450419	.0291837
bf4	-.5134212	.2911522	-1.76	0.078	-1.084069	.0572265
bf2	.0000225	.0001357	0.17	0.868	-.0002436	.0002885
bf4m	.3813738	.2769085	1.38	0.168	-.1613568	.9241045
bf5m	-.0013491	.0018728	-0.72	0.471	-.0050196	.0023214
bf7m	-.0007653	.0006452	-1.19	0.236	-.0020299	.0004993
bf8	.0000124	.0000428	0.29	0.772	-.0000716	.0000964
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0409398	.0388667	1.05	0.292	-.0352376	.1171172
bf22	.0000496	.0001446	0.34	0.732	-.0002338	.0003329
bf29	.0000147	.0000386	0.38	0.704	-.000061	.0000904
bf30	.0005975	.0003487	1.71	0.087	-.0000859	.0012809
bf40	-.092913	.1571517	-0.59	0.554	-.4009247	.2150987
deaw2	.1650922	.2350487	0.70	0.482	-.2955947	.6257792
dvcew2	-.44027	1.751166	-0.25	0.801	-3.872493	2.991953
sepaw2	0	(omitted)				
accdw2	.3072193	.6191348	0.50	0.620	-.9062626	1.520701

movew2	-.4208456	.8150343	-0.52	0.606	-2.018283	1.176592
illw2	.146668	.2184808	0.67	0.502	-.2815466	.5748825
shfamw2	.0028218	.0077742	0.36	0.717	-.0124154	.018059
shhlw2	.0082475	.0076919	1.07	0.284	-.0068283	.0233233
shjobw2	-.0093426	.0067931	-1.38	0.169	-.0226569	.0039716
shrelaw2	-.0142034	.0081278	-1.75	0.081	-.0301336	.0017268
suprtw2	-.0099735	.0060387	-1.65	0.099	-.021809	.0018621
suchrw2	-.0045113	.0068989	-0.65	0.513	-.0180329	.0090102
havmilsq	-2.60e-06	4.34e-06	-0.60	0.550	-.0000111	5.92e-06
radhlw2	0	(omitted)				
_cons	2.140849	1090.33	0.00	0.998	-2134.867	2139.148

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	32	12	44
-	33	266	299
Total	65	278	343

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	49.23%
Specificity	$\Pr(- \sim D)$	95.68%
Positive predictive value	$\Pr(D +)$	72.73%
Negative predictive value	$\Pr(\sim D -)$	88.96%
False + rate for true ~D	$\Pr(+ \sim D)$	4.32%
False - rate for true D	$\Pr(- D)$	50.77%
False + rate for classified +	$\Pr(\sim D +)$	27.27%
False - rate for classified -	$\Pr(D -)$	11.04%
Correctly classified		86.88%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	343
number of covariate patterns =	343
Pearson chi2(292) =	307.38
Prob > chi2 =	0.2568

Measures of Fit for **logistic** of **HP2inthob**

Log-Lik Intercept Only:	-166.528	Log-Lik Full Model:	-105.173
D(286):	210.346	LR(50):	122.710
		Prob > LR:	0.000
McFadden's R2:	0.368	McFadden's Adj R2:	0.026
Maximum Likelihood R2:	0.301	Cragg & Uhler's R2:	0.484
McKelvey and Zavoina's R2:	0.627	Efron's R2:	0.388
Variance of y*:	8.828	Variance of error:	3.290
Count R2:	0.869	Adj Count R2:	0.308
AIC:	0.946	AIC*n:	324.346
BIC:	-1459.245	BIC':	169.177

```

947 .
948 . * Chunk 8 ---Female trimmed Interest and hobbies model
949 . forvalues j=2/2 {
      2. set more off
      3.
950 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
951 .   foreach var in HP2inthob {
      5.       forvalues k=2/2 {
      6.   local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      7.
952 .   di as input "trimmed main model for `var' for wave= `j' "
      8.   di _skip(4)
      9.   di as input  "chunk 8 H1 test:Gender= `k'  model Wave = `j' for `e(depva
      > r)' "
     10.   di _skip(4)
     11.   title "Full Nottingham Part 2 subscale models for male and then females"
     12.   di as input "Model for gender==`k' and wave == `j'"
     13.   di _skip(2)
     14.       logit `var' age    ///
      >               avgcumdosew`j' bf4 bf30    ///
      >               shrelaw`j' suprtw`j'    ///
      >               radhlw2 if gender==2,   difficult iterate(50)   nolog
     15.   }
     16.   }
     17.   }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

trimmed main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= 2 model Wave = 2 for HP2inthob

```

*****
> *
*****
> *
*****
> *
*****
> *
***** Full Nottingham Part 2 subscale models for male and then females *****
> *
*****
> *
*****
> *
***** 1 Jul 2012 15:05:39 *****
> *
*****
> *
*****
> *

```

Model for gender==2 and wave == 2

Logistic regression	Number of obs	=	363
	LR chi2(7)	=	101.28
	Prob > chi2	=	0.0000
Log likelihood = -121.47255	Pseudo R2	=	0.2942

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0729699	.016233	4.50	0.000	.0411537	.104786
avgcumdosew2	.0713471	.0870475	0.82	0.412	-.0992629	.2419571
bf4	-.12277	.0348875	-3.52	0.000	-.1911482	-.0543918
bf30	.0005237	.0002568	2.04	0.041	.0000204	.001027
shrelaw2	-.0121549	.0056037	-2.17	0.030	-.0231379	-.001172
suprtw2	-.0103307	.0040941	-2.52	0.012	-.018355	-.0023065
radhlw2	.0119091	.0056652	2.10	0.036	.0008055	.0230128
_cons	-4.716583	1.190104	-3.96	0.000	-7.049144	-2.384021

```

953 .
954 .
955 .
956 . // female interests and hobbies wash out
957 .
958 .
959 . *-----
960 .
961 .
962 .
963 .
964 .
965 .
966 .
967 .
968 . label var radhlw2 "Self-perceived Chernobyl health threat in wave 2"

969 .
970 . title4 "6. trimmed Moderators of male Dose => Interests and Hobbies Impact"

```

```

6. trimmed Moderators of male Dose => Interests and Hobbies Impact

```

```

971 .
972 . di as input "wave 2 Main effects Dose=> Interests and Hobbies impact identif
    > ication"
    wave 2 Main effects Dose=> Interests and Hobbies impact identification

973 . forvalues j=2/2 {
    2. set more off
    3.
974 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
    > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
    4.
975 . foreach var in HP2inthob {
    5. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
    > bf40
    6. di _skip(2)
    7. di as input "Full main model for `var' for wave= `j' "
    8. di _skip(4)
    9. di as input "chunk 8 H1 test:Gender= male model Wave = `j' for `e(dep
    > v ar)' "
    10. di _skip(4)
    11. title "Full Nottingham Part 2 subscale models " "males on wave=`j'"
    12. des bf5m shfamw2 radhlw2 bf4m
    13. xi: logistic `var' age radhlw2 avgcumdosew2 shfamw2 ///
    > bf5m if gender==1, coef nolog difficult iterate(50)
    14. estat class
    15. estat gof

```

```

16.                                fitstat
17. di _skip(2)
18. di as input "Note: bf4m is necessary for bf5 but if bf4m is in model bf5 i
> s not signif."
19. di as input " Therefore, bf5 is not deemed significant."
20. }
21. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic necessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic necessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996
inc4w2	double	%15.0g	LABJ	Income allows to comfortably afford luxury items in 1996
bf1	float	%9.0g		bf1 = max(0, kzchorn - 40)
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)
bf9	float	%9.0g		bf9= max(0, 30 - shhlw1)
bf11	float	%9.0g		bf11= max(0, 20 - sufamw1)
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
bf15m	float	%9.0g		bf15m= max(0, 1 - icdxcnt) * bf2
bf30	float	%9.0g		bf30 = max(0, neiwl - 85) * bf20
bf40	float	%9.0g		bf40 = max(0, icdxcnt - 1.01635E-007)

Full main model for HP2inthob for wave= 2

chunk 8 H1 test:Gender= male model Wave = 2 for HP2inthob

```

*****
> *
*****
> *
*****
> *
*****
Full Nottingham Part 2 subscale models
> *
*****
males on wave=2
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:05:40
> *
*****
> *
*****
> *

```

variable name	storage type	display format	value label	variable label
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996
radhlw2	double	%8.0g		Self-perceived Chornobyl health threat in wave 2
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)
Logistic regression				Number of obs = 339
				LR chi2(5) = 55.04
				Prob > chi2 = 0.0000
Log likelihood = -91.424671				Pseudo R2 = 0.2314

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0431333	.0167168	2.58	0.010	.010369	.0758976
radhlw2	.0348063	.0070847	4.91	0.000	.0209205	.048692
avgcumdosew2	-.1062023	.1574615	-0.67	0.500	-.4148212	.2024166
shfamw2	.0030601	.0048986	0.62	0.532	-.006541	.0126612
bf5m	-.0015801	.0010798	-1.46	0.143	-.0036965	.0005363
_cons	-6.400487	1.022095	-6.26	0.000	-8.403758	-4.397217

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	8	4	12
-	30	297	327
Total	38	301	339

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	21.05%
Specificity	$\Pr(- \sim D)$	98.67%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	90.83%
False + rate for true ~D	$\Pr(+ \sim D)$	1.33%
False - rate for true D	$\Pr(- D)$	78.95%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	9.17%
Correctly classified		89.97%

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	339
number of covariate patterns =	327
Pearson chi2(321) =	372.91
Prob > chi2 =	0.0242

Measures of Fit for **logistic** of **HP2inthob**

Log-Lik Intercept Only:	-118.946	Log-Lik Full Model:	-91.425
D(333):	182.849	LR(5):	55.042
		Prob > LR:	0.000
McFadden's R2:	0.231	McFadden's Adj R2:	0.181
Maximum Likelihood R2:	0.150	Cragg & Uhler's R2:	0.297
McKelvey and Zavoina's R2:	0.397	Efron's R2:	0.214
Variance of y*:	5.454	Variance of error:	3.290
Count R2:	0.900	Adj Count R2:	0.105
AIC:	0.575	AIC*n:	194.849
BIC:	-1757.209	BIC':	-25.912

Note: bf4m is necessary for bf5 but if bf4m is in model bf5 is not signif.
Therefore, bf5 is not deemed significant.

```

976 .
977 . cap gen bf5mXd3 = bf5m*avgcumdosew2

978 .
979 .
980 .
981 . title3 "wave 2 Main effects Dose=> Interests and Hobbies impact identificati
> on"

-----
title3 : wave 2 Main effects Dose=> Interests and Hobbies impact identificatio
> n
1 Jul 2012
15:05:41
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2399 variables and 703 obser
> vations

982 . forvalues j=2/2 {
2. set more off
3.
983 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
> bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
4.

```

```

984 . foreach var in HP2inthob {
      5. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      6. di as input "Full main model for `var' for wave= `j' "
      7. di _skip(4)
      8. di as input "chunk 8 H1 test:Gender= male  model Wave = `j' for `e(depvar)'"
> ar)' "
      9. di _skip(4)
     10. title "Full Nottingham Part 2 subscale models for males in wave=`j'"
     11.
985 .      xi: logistic `var' age  ///
>          radhlw`j' avgcumdosew`j'  ///
>          shfamw`j'  bf4m ///
>          bf5m bf5mXd3  if gender==1, coef nolog  difficult iterate(5
> 0)
     12.          estat class
     13.          estat gof
     14.          fitstat
     15. }
     16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed
inc1w2	double	%15.0g	LABJ	Income is not sufficient for basic neccessities in 1996
inc2w2	double	%15.0g	LABJ	Income is just sufficient for basic neccessities in 1996
inc3w2	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings in 1996

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.030943	.0178289	1.74	0.083	-.0040009	.065887
radhlw2	.0256859	.0076857	3.34	0.001	.0106222	.0407496
avgcumdosew2	-.0706233	.347896	-0.20	0.839	-.752487	.6112404
shfamw2	.0004942	.0051095	0.10	0.923	-.0095202	.0105087
bf4m	-.0869807	.0356099	-2.44	0.015	-.1567749	-.0171866
bf5m	-.0007397	.0014331	-0.52	0.606	-.0035486	.0020692
bf5mXd3	-.0000719	.0008404	-0.09	0.932	-.0017191	.0015753
_cons	-3.59705	1.521825	-2.36	0.018	-6.579772	-.6143281

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	10	5	15
-	28	296	324
Total	38	301	339

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	26.32%
Specificity	$\Pr(- \sim D)$	98.34%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	91.36%

False + rate for true ~D	$\Pr(+ \sim D)$	1.66%
False - rate for true D	$\Pr(- D)$	73.68%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	8.64%

Correctly classified	90.27%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      339
number of covariate patterns =    334
    Pearson chi2(326) =    295.89
        Prob > chi2 =    0.8832

```

Measures of Fit for **logistic** of **HP2inthob**

```

986 . scalar SigDoseInthbMw2 = "no"

987 . scalar MainEffInthbMw2 = "age radhlw2 shfamw2"

988 . scalar InthbMw2 = "none"

989 .

990 . *-----chunk 8   female moderator models

991 . title "trimmed Moderators of female Dose => Interests and Hobbies Impact"

```



```

992 .
993 .
994 . forvalues j=2/2 {
      2. set more off
      3.
995 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
996 . foreach var in HP2inthob {
      5. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      6. di as input "Full main model for `var' for wave= `j' "
      7. di _skip(4)
      8. di as input "chunk 8 H1 test:Gender= male model Wave = `j' for `e(depvar)'"
      > ar)' "
      9. di _skip(4)
      10. title "Full Nottingham Part 2 subscale models for females "
      11.
997 . xi: logistic `var' age ///
      > radhlw`j' avgcumdosew`j' ///
      > bf4 ///
      > if gender==2, coef nolog difficult iterate(50)
      12. estat class
      13. estat gof
      14. fitstat
      15. }
      16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed

Logistic regression

Number of obs = 363

LR chi2(4) = 85.23

Prob > chi2 = 0.0000

Log likelihood = -129.49784

Pseudo R2 = 0.2476

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0747628	.0160244	4.67	0.000	.0433556	.10617
radhlw2	.0174604	.0053569	3.26	0.001	.0069611	.0279597
avgcumdosew2	.0556287	.0871446	0.64	0.523	-.1151717	.226429
bf4	-.0957645	.0312145	-3.07	0.002	-.1569439	-.0345852
_cons	-5.962105	1.09169	-5.46	0.000	-8.101778	-3.822431

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	27	8	35
-	39	289	328
Total	66	297	363

Classified + if predicted Pr(D) >= .5

True D defined as HP2inthob != 0

Sensitivity	Pr(+ D)	40.91%
Specificity	Pr(- ~D)	97.31%
Positive predictive value	Pr(D +)	77.14%
Negative predictive value	Pr(~D -)	88.11%
False + rate for true ~D	Pr(+ ~D)	2.69%
False - rate for true D	Pr(- D)	59.09%
False + rate for classified +	Pr(~D +)	22.86%
False - rate for classified -	Pr(D -)	11.89%
Correctly classified		87.05%

Logistic model for HP2inthob, goodness-of-fit test

number of observations = 363
number of covariate patterns = 361
Pearson chi2(356) = 453.01
Prob > chi2 = 0.0004

Log-Lik Intercept Only:	-172.113	Log-Lik Full Model:	-129.498
D(358):	258.996	LR(4):	85.229
		Prob > LR:	0.000
McFadden's R2:	0.248	McFadden's Adj R2:	0.219
Maximum Likelihood R2:	0.209	Cragg & Uhler's R2:	0.342
McKelvey and Zavoina's R2:	0.407	Efron's R2:	0.292
Variance of y*:	5.547	Variance of error:	3.290
Count R2:	0.871	Adj Count R2:	0.288
AIC:	0.741	AIC*n:	268.996
BIC:	-1851.201	BIC':	-61.652

```

998 . scalar SigdoseInthbFw2 = "no"

999 . scalar MainEffInthbFw2 = "age radhlw2 bf4"

1000 .
1001 . *-----chunk 8 testing female moderators
1002 . title "trimmed Moderators of female Dose => Interests and Hobbies Impact"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
***** trimmed Moderators of female Dose => Interests and Hobbies Impact ***
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:05:44 ***
> *
*****
> *
*****
> *

```

```

1003 .
1004 .
1005 . forvalues j=2/2 {
      2. set more off
      3.
1006 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1007 . foreach var in HP2inthob {
      5. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      6. di as input "Full main model for `var' for wave= `j' "
      7. di _skip(4)
      8. di as input "chunk 8 H1 test:Gender= male model Wave = `j' for `e(depvar)'"
      > ar)' "
      9. di _skip(4)
      10. title "Full Nottingham Part 2 subscale models for females in wave=`j' "
      11.
1008 . xi: logistic `var' age ///
      > radhlw`j' avgcumdosew`j' ///
      > bf4 bf4Xd3 ageXd3 radhlw2Xd3 ///
      > if gender==2, coef nolog difficult iterate(50)
      12. estat class
      13. estat gof
      14. fitstat
      15. }
      16. }

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
educ1	byte	%8.0g		educ==1. did not graduate high school
educ2	byte	%8.0g		educ==2. graduated high school
educ3	byte	%8.0g		educ==3. technical degree
educ4	byte	%8.0g		educ==4. did not finish college/bachelor's
educ5	byte	%8.0g		educ==5. graduated college/bachelor's
educ6	byte	%8.0g		educ==6. finished specialist/master's degree
educ7	byte	%8.0g		educ==7. doctor of science/phd
marrw21	byte	%8.0g		marrw2==1. single
marrw22	byte	%8.0g		marrw2==2. cohabitating
marrw23	byte	%8.0g		marrw2==3. married
marrw24	byte	%8.0g		marrw2==4. separated
marrw25	byte	%8.0g		marrw2==5. divorced
marrw26	byte	%8.0g		marrw2==6. widowed

Logistic regression

Number of obs = 363

LR chi2(7) = 88.01

Prob > chi2 = 0.0000

Log likelihood = -128.11005

Pseudo R2 = 0.2557

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0684009	.0187006	3.66	0.000	.0317484	.1050534
radhlw2	.0215957	.0064007	3.37	0.001	.0090506	.0341409
avgcumdosew2	-.1117068	.8606863	-0.13	0.897	-1.798621	1.575207
bf4	-.0939457	.0393671	-2.39	0.017	-.1711039	-.0167876
bf4Xd3	-.0023725	.0194992	-0.12	0.903	-.0405902	.0358453
ageXd3	.0062659	.0102599	0.61	0.541	-.0138431	.0263749
radhlw2Xd3	-.0033605	.0032954	-1.02	0.308	-.0098193	.0030983
_cons	-5.94901	1.257396	-4.73	0.000	-8.41346	-3.484559

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	28	8	36
-	38	289	327
Total	66	297	363

Classified + if predicted $\Pr(D) \geq .5$

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	42.42%
Specificity	$\Pr(- \sim D)$	97.31%
Positive predictive value	$\Pr(D +)$	77.78%
Negative predictive value	$\Pr(\sim D -)$	88.38%

False + rate for true ~D	$\Pr(+ \sim D)$	2.69%
False - rate for true D	$\Pr(- D)$	57.58%
False + rate for classified +	$\Pr(\sim D +)$	22.22%
False - rate for classified -	$\Pr(D -)$	11.62%

Correctly classified	87.33%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

```

        number of observations =      363
    number of covariate patterns =      361
            Pearson chi2(353) =     461.18
                Prob > chi2 =      0.0001

```

Measures of Fit for **logistic** of **HP2inthob**

Log-Lik Intercept Only:	-172.113	Log-Lik Full Model:	-128.110
D(355):	256.220	LR(7):	88.005
		Prob > LR:	0.000
McFadden's R2:	0.256	McFadden's Adj R2:	0.209
Maximum Likelihood R2:	0.215	Cragg & Uhler's R2:	0.351
McKelvey and Zavoina's R2:	0.418	Efron's R2:	0.305
Variance of y*:	5.654	Variance of error:	3.290
Count R2:	0.873	Adj Count R2:	0.303
AIC:	0.750	AIC*n:	272.220
BIC:	-1836.293	BIC':	-46.744

```
1009 . scalar InthbModFw2 = "none"
```

```
1010 .
```

```
1011 . title4 "Chunk 8  interests and hobbies testing mediator effects "
```

```
Chunk 8  interests and hobbies testing mediator effects
```

```
1012 .
```

```
1013 . * age is a mediating effect for males for Dose=> sex life for men
```

```
1014 .
```

```
1015 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1330.6004
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	147.6853
Deviance	= 49917.64009	(1/df) Deviance	=	147.6853
Pearson	= 49917.64009	(1/df) Pearson	=	147.6853
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]
		<u>AIC</u>	=	7.838826
Log likelihood	= -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
1016 . glm HP2inthob age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 224.8585
Iteration 2: deviance = 219.8355
Iteration 3: deviance = 219.6997
Iteration 4: deviance = 219.6996
Iteration 5: deviance = 219.6996
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 219.6996277	(1/df) Deviance	=	.6499989
Pearson = 354.7105724	(1/df) Pearson	=	1.04944

```
Variance function: V(u) = u*(1-u) [Bernoulli]
Link function : g(u) = invnorm(u) [Probit]
```

```
BIC = -1750.484
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.031726	.0062563	5.07	0.000	.0194638	.0439882
_cons	-2.867608	.344284	-8.33	0.000	-3.542392	-2.192824

(Standard errors scaled using square root of deviance-based dispersion.)

```
1017 .
```

```

1018 . * illness is a mediating effect for males = > sex life for men
1019 . des illw2

```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```

1020 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-303.59609**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	.0085423	.0128556	0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406	7.96	0.000	.2066336	.3416382

```

1021 . glm HP2inthob illw2 if gender==1, fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 237.2651
Iteration 2: deviance = 236.0196
Iteration 3: deviance = 236.0142
Iteration 4: deviance = 236.0142
Iteration 5: deviance = 236.0142

```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 236.0141663	(1/df) Deviance	=	.6982668
Pearson = 338.89241	(1/df) Pearson	=	1.00264

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1734.169

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.2044103	.113873	1.80	0.073	-.0187766	.4275973
_cons	-1.284117	.0852302	-15.07	0.000	-1.451165	-1.117069

(Standard errors scaled using square root of deviance-based dispersion.)

1022 .
 1023 . des radhlw2

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		Self-perceived Chernobyl health threat in wave 2

1024 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1693.4076

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]

Log likelihood = -1693.407647
 AIC = 9.972986
 BIC = 419831.3

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522

```
1025 . glm HP2inthob radhlw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 207.4869
Iteration 2:  deviance = 195.0786
Iteration 3:  deviance = 193.7239
Iteration 4:  deviance = 193.6942
Iteration 5:  deviance = 193.6942
Iteration 6:  deviance = 193.6942
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  MQL Fisher scoring                  Residual df     =       338
                   (IRLS EIM)                           Scale parameter =        1
Deviance          =   193.694234                        (1/df) Deviance =   .5730599
Pearson           =   330.3909814                       (1/df) Pearson  =   .9774881
```

```
Variance function: V(u) = u*(1-u)                      [Bernoulli]
Link function     :  g(u) = invnorm(u)                  [Probit]
```

```
BIC = -1776.489
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0187765	.0024049	7.81	0.000	.014063	.02349
_cons	-2.360804	.1846104	-12.79	0.000	-2.722634	-1.998974

(Standard errors scaled using square root of deviance-based dispersion.)

```
1026 .
1027 .
1028 . des shfamw2
```

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

```
1029 . glm shfamw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1704.8947
```

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1375.284
Deviance = 463470.769	(1/df) Deviance	=	1375.284
Pearson = 463470.769	(1/df) Pearson	=	1375.284

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	10.07017
Log likelihood = -1704.894657	<u>BIC</u>	=	461507.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.7484378	.8043765	-0.93	0.352	-2.324987	.8281112
_cons	34.76184	2.15791	16.11	0.000	30.53241	38.99127

```
1030 . glm HP2inthob shfamw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 236.0134
Iteration 2: deviance = 234.459
Iteration 3: deviance = 234.4495
Iteration 4: deviance = 234.4495
```

Generalized linear models	No. of obs	=	339
Optimization : ML Fisher scoring	Residual df	=	337
(IRLS EIM)	Scale parameter	=	1
Deviance = 234.4495475	(1/df) Deviance	=	.695696
Pearson = 340.0883436	(1/df) Pearson	=	1.009164

Variance function: V(u) = u*(1-u)	[Bernoulli]
Link function : g(u) = invnorm(u)	[Probit]

	BIC	=	-1728.912
--	------------	---	-----------

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	.0043459	.0019602	2.22	0.027	.0005039	.0081879
_cons	-1.379269	.1084635	-12.72	0.000	-1.591853	-1.166684

(Standard errors scaled using square root of deviance-based dispersion.)

1031 .
1032 . des bf5m

variable name	storage type	display format	value label	variable label
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m

1033 . glm bf5m avgcumdosew2 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-2273.2523**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	37801.15
Deviance = 12776789.76	(1/df) Deviance	=	37801.15
Pearson = 12776789.76	(1/df) Pearson	=	37801.15

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	13.38384
Log likelihood = -2273.252279	<u>BIC</u>	=	1.28e+07

bf5m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	9.243905	4.217043	2.19	0.028	.9786526	17.50916
_cons	104.6228	11.29756	9.26	0.000	82.47996	126.7656

```
1034 . glm HP2inthob bf5m if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 238.9021
Iteration 2:  deviance = 238.0124
Iteration 3:  deviance = 238.0098
Iteration 4:  deviance = 238.0098
Iteration 5:  deviance = 238.0098
```

```
Generalized linear models          No. of obs      =       340
Optimization      : ML Fisher scoring      Residual df    =       338
                    (IRLS EIM)              Scale parameter =         1
Deviance          = 238.0098185          (1/df) Deviance =  .7041711
Pearson           = 339.8073754          (1/df) Pearson  =  1.005347
```

```
Variance function: V(u) = u*(1-u)          [Bernoulli]
Link function     : g(u) = invnorm(u)      [Probit]
```

```
BIC = -1732.174
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf5m	.0001615	.000378	0.43	0.669	-.0005794	.0009024
_cons	-1.236147	.0878768	-14.07	0.000	-1.408382	-1.063912

(Standard errors scaled using square root of deviance-based dispersion.)

```
1035 .
```

```
1036 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1027.1225
```

```
Generalized linear models          No. of obs      =       340
Optimization      : ML                  Residual df    =       338
Scale parameter = 24.7771
Deviance          = 8374.659221          (1/df) Deviance = 24.7771
Pearson           = 8374.659221          (1/df) Pearson  = 24.7771
```

```
Variance function: V(u) = 1              [Gaussian]
Link function     : g(u) = u              [Identity]
```

```
Log likelihood    = -1027.122509          AIC           = 6.053662
BIC           = 6404.476
```

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2447701	.1784427
_cons	12.52896	.2892393	43.32	0.000	11.96206	13.09586

```
1037 . glm HP2inthob bf4 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 201.5914
Iteration 2: deviance = 191.8769
Iteration 3: deviance = 191.2682
Iteration 4: deviance = 191.2622
Iteration 5: deviance = 191.2622
Iteration 6: deviance = 191.2622
```

```
Generalized linear models                      No. of obs      =       340
Optimization      : ML Fisher scoring          Residual df      =       338
                  (IRLS EIM)                   Scale parameter =         1
Deviance          = 191.2622075                (1/df) Deviance = .5658645
Pearson           = 305.593706                  (1/df) Pearson  = .9041234
```

```
Variance function: V(u) = u*(1-u)             [Bernoulli]
Link function      : g(u) = invnorm(u)         [Probit]
```

```
BIC = -1778.921
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1182178	.013496	-8.76	0.000	-.1446695	-.091766
_cons	.0441185	.1517879	0.29	0.771	-.2533804	.3416174

(Standard errors scaled using square root of deviance-based dispersion.)

```

1038 .
1039 .
1040 . * age is a mediating effect for females for Dose=> sex life for women
1041 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1406.9403**

Generalized linear models		No. of obs	=	363
Optimization : ML		Residual df	=	361
		Scale parameter	=	136.9184
Deviance	=	49427.52828	(1/df) Deviance	= 136.9184
Pearson	=	49427.52828	(1/df) Pearson	= 136.9184
Variance function: V(u) = 1				[Gaussian]
Link function : g(u) = u				[Identity]
		<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271		<u>BIC</u>	=	47299.65

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

```

1042 . glm HP2inthob age if gender==2, fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 293.9671
Iteration 2: deviance = 289.27
Iteration 3: deviance = 289.1951
Iteration 4: deviance = 289.1951
Iteration 5: deviance = 289.1951

```

Generalized linear models		No. of obs	=	363
Optimization : ML Fisher scoring		Residual df	=	361
		Scale parameter	=	1
Deviance	=	289.1950995	(1/df) Deviance	= .8010945
Pearson	=	415.3464621	(1/df) Pearson	= 1.150544
Variance function: V(u) = u*(1-u)				[Bernoulli]
Link function : g(u) = invnorm(u)				[Probit]
		<u>BIC</u>	=	-1838.684

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0515323	.0068567	7.52	0.000	.0380933	.0649713
_cons	-3.649661	.3847198	-9.49	0.000	-4.403698	-2.895624

(Standard errors scaled using square root of deviance-based dispersion.)

```
1043 .
1044 . des bf4    // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSI_{soma})

```
1045 . * bf4 is a meditating effect for females for Dose=> sex life for women
1046 . glm bf4 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1109.0983**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.53281
Deviance = 9578.344971	(1/df) Deviance	=	26.53281
Pearson = 9578.344971	(1/df) Pearson	=	26.53281

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	6.121754
Log likelihood = -1109.098281	<u>BIC</u>	=	7450.466

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.595012	.1960703	-3.03	0.002	-.9793027	-.2107212
_cons	11.02048	.3223763	34.19	0.000	10.38863	11.65232

```
1047 . glm HP2inthob bf4 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 304.5744
Iteration 2:  deviance = 301.504
Iteration 3:  deviance = 301.4488
Iteration 4:  deviance = 301.4487
Iteration 5:  deviance = 301.4487
```

```
Generalized linear models                               No. of obs      =       363
Optimization      :  MQL Fisher scoring                 Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 301.4486672                        (1/df) Deviance =  .8350379
Pearson           = 341.1451194                        (1/df) Pearson  =  .9450003
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                  [Probit]
```

```
BIC = -1826.431
```

HP2inthob	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.0993749	.0142594	-6.97	0.000	-.1273229	-.071427
_cons	.0117358	.1447759	0.08	0.935	-.2720197	.2954914

(Standard errors scaled using square root of deviance-based dispersion.)

```
1048 .
1049 . des bf4m // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1050 . * bf4m is a possible mediating effect for female sex life
```

```
1051 . glm bf4m avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1140.8259
```

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
		Scale parameter	=	31.60104
Deviance	= 11407.97484	(1/df) Deviance	=	31.60104
Pearson	= 11407.97484	(1/df) Pearson	=	31.60104

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	6.296561
Log likelihood = -1140.825904	<u>BIC</u>	=	9280.095

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.599311	.2139789	-2.80	0.005	-1.018702	-.1799202
_cons	18.83424	.3518214	53.53	0.000	18.14469	19.5238

```
1052 . glm HP2sxlife bf4m if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 356.1451
Iteration 2: deviance = 355.6209
Iteration 3: deviance = 355.6178
Iteration 4: deviance = 355.6178
Iteration 5: deviance = 355.6178
```

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	361
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 355.6178202	(1/df) Deviance	=	.9850909
Pearson	= 340.0032816	(1/df) Pearson	=	.9418373

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1772.262
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4m	-.0990193	.0135516	-7.31	0.000	-.12558	-.0724586
_cons	1.063679	.244399	4.35	0.000	.584666	1.542693

(Standard errors scaled using square root of deviance-based dispersion.)

```
1053 .
1054 . des shfamw2
```

variable name	storage type	display format	value label	variable label
shfamw2	double	%8.0g		Percentage of strains and hassles related to family in 1996

```
1055 . glm shfamw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1704.8947**

Generalized linear models	No. of obs	=	339
Optimization : ML	Residual df	=	337
	Scale parameter	=	1375.284
Deviance = 463470.769	(1/df) Deviance	=	1375.284
Pearson = 463470.769	(1/df) Pearson	=	1375.284

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	10.07017
Log likelihood = -1704.894657	<u>BIC</u>	=	461507.4

shfamw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.7484378	.8043765	-0.93	0.352	-2.324987	.8281112
_cons	34.76184	2.15791	16.11	0.000	30.53241	38.99127

```
1056 . glm HP2sxlife shfamw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 338.2157
Iteration 2:  deviance = 338.0066
Iteration 3:  deviance = 338.0065
Iteration 4:  deviance = 338.0065
```

```
Generalized linear models          No. of obs      =       339
Optimization      :  MQL Fisher scoring  Residual df    =       337
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 338.0064771         (1/df) Deviance = 1.002987
Pearson           = 339.3157137         (1/df) Pearson  = 1.006872
```

```
Variance function: V(u) = u*(1-u)      [Bernoulli]
Link function     : g(u) = invnorm(u)   [Probit]
```

```
BIC                                     = -1625.356
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw2	.0027669	.0020626	1.34	0.180	-.0012757	.0068096
_cons	-.9380005	.1081399	-8.67	0.000	-1.149951	-.7260503

(Standard errors scaled using square root of deviance-based dispersion.)

```
1057 .
1058 . des bf4
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
1059 . glm bf4 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1027.1225
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  ML          Residual df    =       338
Scale parameter = 24.7771
Deviance          = 8374.659221     (1/df) Deviance = 24.7771
Pearson           = 8374.659221     (1/df) Pearson  = 24.7771
```

```
Variance function: V(u) = 1          [Gaussian]
Link function     : g(u) = u         [Identity]
```

	OIM					
bf4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	-.0331637	.1079644	-0.31	0.759	-.2447701	.1784427
_cons	12.52896	.2892393	43.32	0.000	11.96206	13.09586

Variance function: $V(u) = u \cdot (1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1708.557

	EIM					
HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.1431725	.0149643	-9.57	0.000	-.172502	-.1138431
_cons	.7780696	.180124	4.32	0.000	.425033	1.131106



```
1061 .
1062 . des bf4m // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1063 . * bf4m is a possible mediating effect for female ints and hobbies
1064 . glm bf4m avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1140.8259**

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
Deviance	= 11407.97484	Scale parameter	=	31.60104
Pearson	= 11407.97484	(1/df) Deviance	=	31.60104
		(1/df) Pearson	=	31.60104
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	6.296561
Log likelihood = -1140.825904		<u>BIC</u>	=	9280.095

bf4m	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	-.599311	.2139789	-2.80	0.005	-1.018702	-.1799202	
_cons	18.83424	.3518214	53.53	0.000	18.14469	19.5238	

```
1065 . glm HP2inthob bf4m if gender==2, fam(bin) irls scale(dev) link(probit)
```

Iteration 1: deviance = **310.9241**
 Iteration 2: deviance = **308.9696**
 Iteration 3: deviance = **308.9479**
 Iteration 4: deviance = **308.9478**
 Iteration 5: deviance = **308.9478**

Generalized linear models		No. of obs	=	363
Optimization	: ML Fisher scoring	Residual df	=	361
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 308.9478254	(1/df) Deviance	=	.8558112
Pearson	= 336.1855337	(1/df) Pearson	=	.9312619

[Bernoulli]
[Probit]

BIC = -1818.932

	EIM					
HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4m	-.0801416	.0127284	-6.30	0.000	-.1050887	-.0551944
_cons	.4618823	.2255505	2.05	0.041	.0198113	.9039532

(Standard errors scaled using square root of deviance-based dispersion.)

1066 .

```
1067 . des age // age is a possilbe mediating effect for interest and hobbies
```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age

```
1068 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:    log likelihood = -1330.6004
```

No. of obs = 340

Residual df = 338

Scale parameter = 147.6853

(1/df) Deviance = 147.6853

[Gaussian]

[Identity]

Log likelihood	=	-1330.6004		<u>AIC</u>	=	7.838826
				<u>BIC</u>	=	47947.46

	OIM					
age	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```
1069 . glm HP2inthob age if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 224.8585
Iteration 2:  deviance = 219.8355
Iteration 3:  deviance = 219.6997
Iteration 4:  deviance = 219.6996
Iteration 5:  deviance = 219.6996
```

```
Generalized linear models                               No. of obs      =       340
Optimization      :  MQL Fisher scoring                 Residual df     =       338
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 219.6996277                        (1/df) Deviance =  .6499989
Pearson           = 354.7105724                        (1/df) Pearson  =  1.04944
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                  [Probit]
```

```
BIC = -1750.484
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.031726	.0062563	5.07	0.000	.0194638	.0439882
_cons	-2.867608	.344284	-8.33	0.000	-3.542392	-2.192824

(Standard errors scaled using square root of deviance-based dispersion.)

```
1070 .
```

```
1071 . des illw2
```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```
1072 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -303.59609
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	.3512988
Deviance	= 118.7390083	(1/df) Deviance	=	.3512988
Pearson	= 118.7390083	(1/df) Pearson	=	.3512988

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
avgcumdosew2	.0085423	.0128556	0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406	7.96	0.000	.2066336	.3416382

```
1073 . glm HP2inthob illw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 237.2651
Iteration 2: deviance = 236.0196
Iteration 3: deviance = 236.0142
Iteration 4: deviance = 236.0142
Iteration 5: deviance = 236.0142
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 236.0141663	(1/df) Deviance	=	.6982668
Pearson	= 338.89241	(1/df) Pearson	=	1.00264

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1734.169
--	-----	---	-----------

HP2inthob	EIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
illw2	.2044103	.113873	1.80	0.073	-.0187766	.4275973	
_cons	-1.284117	.0852302	-15.07	0.000	-1.451165	-1.117069	

(Standard errors scaled using square root of deviance-based dispersion.)

```

1074 .
1075 .
1076 . *xx summary of mediating effects: males only age and illw2 2
1077 . *xx          females: age
1078 .
1079 .
1080 .
1081 . * summary of sxlife moderator effects  none
1082 . scalar sxLifeMedMw2 = "age illw2"

1083 . scalar sxLifeMedFw2 = "age bf4 bf4m"

1084 .
1085 . * no sign main dose effect for males
1086 . * no male moderators
1087 . * 3 signif main effects in male main effect model
1088 .
1089 .
1090 . * no signif dose main effect for females
1091 . * 3 main female effects
1092 . * no significant female moderators
1093 . matrix define HP2inthbMw2 = J(1,8, 0)

1094 .          matrix define HP2inthbFw2 = J(1,8, 0)

1095 . matrix colnames HP2inthbMw2 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

```

```

1096 . matrix colnames HP2inthbFw2 = hypnum ptnum wave gender medsig numMA sig numM
      > odsig numMed

```

```

1097 .      matrix define HP2inthbMw2 = (1, 2, 3, 1, 0, 3, 0, 2 )

```

```

1098 .      matrix define HP2inthbFw2 = (1, 2, 3, 2, 0, 3, 0, 3 )

```

```

1099 .      matrix rowname HP2inthbMw2 = HP2inthbM

```

```

1100 .      matrix rowname HP2inthbFw2 = HP2inthobF

```

```

1101 .      matlist HP2inthbMw2

```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	HP2inthbM	1	2	3	1	0	
> 3	0						
		c8					
	HP2inthbM	2					

```

1102 .      matlist HP2inthbFw2

```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	HP2inthobF	1	2	3	2	0	
> 3	0						
		c8					
	HP2inthobF	3					

```

1103 .      matrix define H1pt2w2 = ( HP2wkMw2 \ HP2wkFw2 \ HP2hmcrMw2 \ HP2hmcr
> Fw2 \ HP2spMw2 ///
>      \ HP2spFw2 \ HP2prbfamMw2 \ HP2prbfamFw2 \ HP2inthbMw2 \ HP2inth
> bFw2 )

```

```

1104 .      matlist H1pt2w2

```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 1	0						
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 2	0						
	HP2spMw2	1	2	3	1	0	
> 2	0						
	HP2spFw2	1	2	3	2	1	
> 5	5						
	HP2prbfamM	1	2	3	1	0	
> 5	0						
	HP2prbfamF	1	2	3	2	0	
> 2	2						
	HP2inthbM	1	2	3	1	0	
> 3	0						
	HP2inthobF	1	2	3	2	0	
> 3	0						
		c8					
	r1	4					
	r1	6					
	r1	2					
	r1	2					
	HP2spMw2	1					
	HP2spFw2	2					
	HP2prbfamM	1					
	HP2prbfamF	2					
	HP2inthbM	2					
	HP2inthobF	3					

```
1105 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
1106 .      matrix rownames H1pt2w2 =  HP2wkMw2 HP2wkFw2 HP2hmcrMw2 HP2hmcrFw2 HP2s
> pMw2 HP2spFw2 HP2prbfamMw2 HP2prbfamFw2 HP2inthbMw2 HP2inthbFw2
```

```
1107 .      matlist H1pt2w2
```

		hypnum	ptnum	wave	gender	medsig	numMASi
> g numModsig							
>							
	HP2wkMw2	1	2	3	1	0	
> 4	0						
	HP2wkFw2	1	2	3	2	0	
> 1	0						
	HP2hmcrMw2	1	2	3	1	0	
> 4	0						
	HP2hmcrFw2	1	2	3	2	0	
> 2	0						
	HP2spMw2	1	2	3	1	0	
> 2	0						
	HP2spFw2	1	2	3	2	1	
> 5	5						
	HP2prbfamMw2	1	2	3	1	0	
> 5	0						
	HP2prbfamFw2	1	2	3	2	0	
> 2	2						
	HP2inthbMw2	1	2	3	1	0	
> 3	0						
	HP2inthbFw2	1	2	3	2	0	
> 3	0						
		numMed					
		HP2wkMw2	4				
		HP2wkFw2	6				
		HP2hmcrMw2	2				
		HP2hmcrFw2	2				
		HP2spMw2	1				
		HP2spFw2	2				
		HP2prbfamMw2	1				
		HP2prbfamFw2	2				
		HP2inthbMw2	2				
		HP2inthbFw2	3				


```

1115 . di as input "Female model wave 2 dose-hp2vacatn moderator model "
      9. di _skip(4)
      10. logit hp2vacatn age i.educ occ1w`j' -occ8w`j' ///
>   marrw`j'1- marrw`j'3 marrw`j'5-marrw`j'6 inclw`j' -inc4w`j' ///
>   radhlw`j' havmil avgcumdosew`j' `w`j'bf' ///
>   deaw`j' dvcew`j' sepaw`j' accdw`j' movew`j' ///
>   illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' suchrw`j' havmil
> sq ///
> radhlw`j' avgcumdosew`j' if gender==2, nolog
      11. di _skip(4)
      12. title3 "trimmed hp2hmcare main effects models for H1 no direct dose effe
> ct for male"
      13. pwcrr hp2vacatn age deaw2 shjobw2 bf7m shjobw2 havmilsq ///
> radhlw2 avgcumdosew2 if gender==2, sig obs sidak star(.05) listwise
      14. di _skip(1)
      15. di as input "For females trimmed vacation plans model on wave2 and d2 is
> not signif "
      16. di _skip(1)
      17. logistic hp2vacatn age deaw2 shjobw2 bf7m havmil ///
> radhlw2 avgcumdosew2 if ///
> gender==2, coef nolog
      18. }

```

```

*****
> *
*****
> *
*****
> *
*****
> *
***** wave 2 Dose = >hp2vacatn Female main effects models for H1 pt2 *****
> *
*****
> *
*****
> *
*****
1 Jul 2012 15:06:27 *****
> *
*****
> *
*****
> *

```

Female model wave 2 dose-hp2vactn moderator model

note: 1.educ != 0 predicts success perfectly
1.educ dropped and 1 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 12 obs not used

note: sepaw2 != 0 predicts failure perfectly
sepaw2 dropped and 7 obs not used

note: 7.educ omitted because of collinearity
note: marrw26 omitted because of collinearity
note: bf17 omitted because of collinearity
note: radhlw2 omitted because of collinearity
note: avgcumdosew2 omitted because of collinearity

Logistic regression	Number of obs	=	342
	LR chi2(49)	=	109.68
	Prob > chi2	=	0.0000
Log likelihood = -105.52458	Pseudo R2	=	0.3420

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0854768	.0223995	3.82	0.000	.0415747	.129379
educ						
1	0 (empty)					
2	-.1593387	2.114879	-0.08	0.940	-4.304426	3.985748
3	.0597641	2.056969	0.03	0.977	-3.971821	4.091349
4	1.938135	2.166629	0.89	0.371	-2.308379	6.184649
5	.5746086	2.110158	0.27	0.785	-3.561224	4.710442
6	.514209	2.047201	0.25	0.802	-3.498231	4.526649
7	0 (omitted)					
occ1w2	-1.136832	2.2792	-0.50	0.618	-5.603982	3.330319
occ2w2	-.2856505	2.305307	-0.12	0.901	-4.803969	4.232668
occ3w2	-.2169427	2.294811	-0.09	0.925	-4.714689	4.280804
occ4w2	-.683475	2.371054	-0.29	0.773	-5.330655	3.963705
occ5w2	-1.371472	2.630882	-0.52	0.602	-6.527906	3.784962
occ6w2	.0514752	2.451671	0.02	0.983	-4.753711	4.856661
occ7w2	-.1816542	2.247999	-0.08	0.936	-4.587651	4.224342
occ8w2	.8447307	2.549827	0.33	0.740	-4.152839	5.8423
marrw21	-.3962689	1.357581	-0.29	0.770	-3.057079	2.264541
marrw22	-.7029234	1.344493	-0.52	0.601	-3.338081	1.932234
marrw23	-.2946087	.8362371	-0.35	0.725	-1.933603	1.344386
marrw25	-.3847095	1.312384	-0.29	0.769	-2.956935	2.187516

marrw26	0	(omitted)				
inclw2	-.1652011	2.308319	-0.07	0.943	-4.689424	4.359021
inc2w2	.5715606	2.259621	0.25	0.800	-3.857216	5.000337
inc3w2	.4239638	2.273454	0.19	0.852	-4.031925	4.879853
inc4w2	-.1023039	2.63108	-0.04	0.969	-5.259126	5.054518
radhlw2	.0311845	.0092957	3.35	0.001	.0129652	.0494037
havmil	.0003107	.0031022	0.10	0.920	-.0057695	.006391
avgcumdosew2	.0845855	.1349954	0.63	0.531	-.1800007	.3491716
bf1	-.0293284	.0365427	-0.80	0.422	-.1009508	.042294
bf4	-.035894	.2239004	-0.16	0.873	-.4747308	.4029428
bf2	.0000573	.0001382	0.41	0.678	-.0002135	.0003281
bf4m	-.0145711	.2099542	-0.07	0.945	-.4260738	.3969316
bf5m	-.0005728	.0016599	-0.35	0.730	-.0038262	.0026805
bf7m	-.0009478	.0006252	-1.52	0.130	-.0021731	.0002775
bf8	-.0000327	.0000408	-0.80	0.422	-.0001126	.0000472
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0039952	.030974	0.13	0.897	-.0567128	.0647032
bf22	.0000865	.0001546	0.56	0.576	-.0002165	.0003895
bf29	.0000586	.0000394	1.49	0.137	-.0000187	.000136
bf30	-.0003297	.0003684	-0.89	0.371	-.0010518	.0003924
bf40	-.1986581	.1714089	-1.16	0.246	-.5346134	.1372973
deaw2	.2948255	.2283224	1.29	0.197	-.1526782	.7423292
dvcew2	1.55263	1.538911	1.01	0.313	-1.463579	4.56884
sepaw2	0	(omitted)				
accdw2	-.6724545	.7843213	-0.86	0.391	-2.209696	.8647871
movew2	-.2536562	.8260121	-0.31	0.759	-1.87261	1.365298
illw2	.1944001	.2307879	0.84	0.400	-.2579358	.646736
shfamw2	.010723	.0072538	1.48	0.139	-.0034942	.0249402
shhlw2	.0100536	.0078834	1.28	0.202	-.0053977	.0255048
shjobw2	-.0092745	.0068673	-1.35	0.177	-.0227342	.0041852
shrelaw2	-.0224849	.0085804	-2.62	0.009	-.0393023	-.0056675
suprtw2	-.0043936	.0060874	-0.72	0.470	-.0163246	.0075375
suchrw2	.0021145	.0069953	0.30	0.762	-.0115961	.015825
havmilsq	-6.40e-07	2.42e-06	-0.26	0.792	-5.39e-06	4.11e-06
radhlw2	0	(omitted)				
avgcumdosew2	0	(omitted)				
_cons	-5.212149	3.615206	-1.44	0.149	-12.29782	1.873525

```

title3 : trimmed hp2hmcare main effects models for H1 no direct dose effect fo
> r male
1 Jul 2012
15:06:28
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2399 variables and 703 obser

```

> vations

	hp2vac~n	age	deaw2	shjobw2	bf7m	shjobw2	havmilsq
hp2vacatn	1.0000						
	363						
age	0.3765*	1.0000					
	0.0000						
	363	363					
deaw2	0.1195	0.1404	1.0000				
	0.5641	0.2337					
	363	363	363				
shjobw2	-0.0747	-0.0331	-0.0711	1.0000			
	0.9977	1.0000	0.9991				
	363	363	363	363			
bf7m	-0.0670	-0.0780	0.0244	-0.1112	1.0000		
	0.9997	0.9953	1.0000	0.7134			
	363	363	363	363	363		
shjobw2	-0.0747	-0.0331	-0.0711	1.0000*	-0.1112	1.0000	
	0.9977	1.0000	0.9991	0.0000	0.7134		
	363	363	363	363	363	363	
havmilsq	-0.0378	-0.0465	-0.0150	0.0080	0.0150	0.0080	1.0000
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
	363	363	363	363	363	363	363
radhlw2	0.2650*	0.2605*	0.1095	-0.0109	0.2974*	-0.0109	-0.0284
	0.0000	0.0000	0.7430	1.0000	0.0000	1.0000	1.0000
	363	363	363	363	363	363	363
avgcumdosew2	0.1224	0.1748*	-0.0214	0.0826	-0.0270	0.0826	-0.0052
	0.5104	0.0292	1.0000	0.9883	1.0000	0.9883	1.0000
	363	363	363	363	363	363	363

	radhlw2 avgcum~2	
radhlw2	1.0000	
	363	
avgcumdosew2	0.1342	1.0000
	0.3162	
	363	363

For females trimmed vacation plans model on wave2 and d2 is not signif

Logistic regression	Number of obs	=	363
	LR chi2(7)	=	76.69
	Prob > chi2	=	0.0000
Log likelihood = -129.17206	Pseudo R2	=	0.2289

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.079348	.0155749	5.09	0.000	.0488217	.1098742
deaw2	.1646231	.1715933	0.96	0.337	-.1716935	.5009397
shjobw2	-.0056137	.0041432	-1.35	0.175	-.0137341	.0025068
bf7m	-.0006133	.00025	-2.45	0.014	-.0011032	-.0001234
havmil	-.0001958	.0011139	-0.18	0.860	-.0023791	.0019875
radhlw2	.0233367	.005861	3.98	0.000	.0118494	.034824
avgcumdosew2	.0651649	.0909818	0.72	0.474	-.1131561	.243486
_cons	-6.606305	1.018983	-6.48	0.000	-8.603475	-4.609135

```

1116 .
1117 . // vacation plans washes out for females also
1118 .
1119 .
1120 . scalar SigDoseVactnMw2 = "no"

```

```

1121 . scalar MainEffVactnMw2 = "age bf7m radhlw2 "
1122 .
1123 . local cn7:colnames(e(b))
1124 . di "`cn7'"
      age deaw2 shjobw2 bf7m havmil radhlw2 avgcumdosew2 _cons
1125 . local len7 = length("`cn7'")
1126 . di `len7'
      56
1127 . local len7b = `len7' - 6
1128 . di `len7b'
      50
1129 . local myvarlist = substr("`cn7'",1,`len7b')
1130 . di "`myvarlist'"
      age deaw2 shjobw2 bf7m havmil radhlw2 avgcumdosew2
1131 .
1132 . foreach var in `myvarlist' {
      2. cap gen `var'Xd3 = `var'*avgcumdosew2
      3. }
1133 .
1134 . title " Trimmed male main effects dose=> vacation plans  model"

```

```
> *
*****
> *
```

```
1135 . di as input "No sig main male dose main effects model"
      No sig main male dose main effects model
```

```
1136 . sw, pr(.1): logit hp2vacatn `myvarlist' if gender==1
      begin with full model
p = 0.7095 >= 0.1000 removing deaw2
p = 0.6626 >= 0.1000 removing avgcumdosew2
p = 0.4924 >= 0.1000 removing shjobw2
p = 0.4544 >= 0.1000 removing havmil
p = 0.1243 >= 0.1000 removing bf7m
```

```
Logistic regression                                Number of obs   =       340
                                                    LR chi2(2)      =       36.09
                                                    Prob > chi2     =       0.0000
Log likelihood = -107.10862                      Pseudo R2       =       0.1442
```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0587352	.0156958	3.74	0.000	.027972	.0894984
radhlw2	.0163217	.005398	3.02	0.002	.0057417	.0269016
_cons	-6.0454	.8953448	-6.75	0.000	-7.800244	-4.290557

```
1137 .
1138 .
1139 . local cn8:colnames(e(b))

1140 . di "`cn8'"
      age radhlw2 _cons
```

```

1141 . local len8 = length("`cn8'")

1142 . di `len7'
      56

1143 . local len8b = `len8' - 6

1144 . di `len8b'
      11

1145 . local myvarlist = substr("`cn8'",1,`len8b')

1146 . di "`myvarlist'"
      age radhlw2

1147 .
1148 .
1149 .
1150 . title4 "Trimmed male interaction dose=> vacation plans model"

-----
Trimmed male interaction dose=> vacation plans model
-----

1151 . logit hp2vacatn age radhlw2 ageXd3 bf7m avgcumdosew2 bf4m bf4mXd3 bf7mXd3 i
      > f gender==1

Iteration 0:   log likelihood = -125.15243
Iteration 1:   log likelihood = -103.75295
Iteration 2:   log likelihood = -95.975162
Iteration 3:   log likelihood = -95.713486
Iteration 4:   log likelihood = -95.674656
Iteration 5:   log likelihood = -95.673437
Iteration 6:   log likelihood = -95.673437

Logistic regression                                Number of obs   =           340
                                                    LR chi2(8)      =           58.96
                                                    Prob > chi2     =           0.0000
Log likelihood = -95.673437                    Pseudo R2      =           0.2355

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0351266	.0232179	1.51	0.130	-.0103796	.0806328
radhlw2	.0006782	.0066781	0.10	0.919	-.0124106	.0137669
ageXd3	.0103149	.0213141	0.48	0.628	-.0314599	.0520897
bf7m	.0001809	.0004722	0.38	0.702	-.0007446	.0011065
avgcumdosew2	-.5848691	1.717213	-0.34	0.733	-3.950545	2.780807
bf4m	-.1548807	.0718689	-2.16	0.031	-.2957412	-.0140202
bf4mXd3	-.0235592	.0602635	-0.39	0.696	-.1416735	.094555
bf7mXd3	.000194	.0003621	0.54	0.592	-.0005158	.0009038
_cons	-1.171738	1.695722	-0.69	0.490	-4.495293	2.151816

```

1152 .
1153 . scalar vactnModMw2 ="none"

1154 .
1155 . di as input "Trimmed Female model wave 2 main effects dose-hp2vacatn model
> "
Trimmed Female model wave 2 main effects dose-hp2vacatn model

1156 . forvalues j=2/2 {
2. local w2bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
3.
1157 . xi: logistic hp2vacatn age radhlw`j' avgcumdosew`j' ///
> deaw`j' suchrw`j' ///
> if gender==2, coef nolog difficult iterate(50)
4.
1158 . }

```

```

Logistic regression                                Number of obs   =          363
                                                    LR chi2(5)      =          70.03
                                                    Prob > chi2     =          0.0000
Log likelihood = -132.50308                        Pseudo R2       =          0.2090

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0851818	.0154813	5.50	0.000	.054839	.1155246
radhlw2	.0170145	.0053804	3.16	0.002	.0064692	.0275599
avgcumdosew2	.0786711	.0879844	0.89	0.371	-.0937752	.2511173
deaw2	.201149	.1681372	1.20	0.232	-.1283938	.5306918
suchrw2	-.0020193	.0038609	-0.52	0.601	-.0095866	.005548
_cons	-7.431055	.9998597	-7.43	0.000	-9.390744	-5.471366

```

1159 .
1160 . scalar SigDoseVactnMw2 = "no"

1161 .
1162 . * summary of male moderating effects: no sign main dose effect in main effe
    > cts model
1163 . *          no signif male moderators
1164 . *          3 significant main effects in main effects model
1165 .
1166 . * summary of female moderation main effects: no signif main dose effect
1167 . *          3 signif main effects
1168 .
1169 . local cn9:colnames(e(b))

1170 . di "`cn9'"
    age radhlw2 avgcumdosew2 deaw2 suchrw2 _cons

1171 . local len9 = length("`cn9'")

1172 . di `len9'
    44

1173 . local len9b = `len9' - 6

1174 . di `len9b'
    38

1175 . local myvarlist = substr("`cn9'",1,`len9b')

1176 . di "`myvarlist'"
    age radhlw2 avgcumdosew2 deaw2 suchrw2

1177 .
1178 .
1179 . foreach var in `myvarlist' {
    2.   cap gen `var'Xd3 = `var'*avgcumdosew2
    3.   }

```

```

1180 .
1181 .
1182 . * female dose vacatn w2 models
1183 .
1184 . title4 "trimmed hp2vacatn wave3 main effects models for H1"

```

```
trimmed hp2vacatn wave3 main effects models for H1
```

```

1185 . di as input "For females hp2vacatn on wave3"
      For females hp2vacatn on wave3

```

```

1186 . sw, pr(.1):logit hp2vacatn `myvarlist' if gender==2
              begin with full model
p = 0.6010 >= 0.1000 removing suchrw2
p = 0.4044 >= 0.1000 removing avgcumdosew2
p = 0.2500 >= 0.1000 removing deaw2

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(2)         =       67.78
                                                    Prob > chi2        =       0.0000
Log likelihood =   -133.624                      Pseudo R2         =       0.2023

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.087459	.0153711	5.69	0.000	.0573321	.1175858
radhlw2	.0183043	.0051588	3.55	0.000	.0081933	.0284153
_cons	-7.552753	.9504531	-7.95	0.000	-9.415607	-5.689899

```
1187 . estat class
```

```
Logistic model for hp2vacatn
```

Classified	True		Total
	D	~D	
+	18	3	21
-	45	297	342
Total	63	300	363

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as hp2vacatn != 0

Sensitivity	$\Pr(+ D)$	28.57%
Specificity	$\Pr(- \sim D)$	99.00%
Positive predictive value	$\Pr(D +)$	85.71%
Negative predictive value	$\Pr(\sim D -)$	86.84%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.00%
False - rate for true D	$\Pr(- D)$	71.43%
False + rate for classified +	$\Pr(\sim D +)$	14.29%
False - rate for classified -	$\Pr(D -)$	13.16%
Correctly classified		86.78%

1188 . estat gof

Logistic model for hp2vacatn, goodness-of-fit test

number of observations =	363
number of covariate patterns =	219
Pearson chi2(216) =	284.26
Prob > chi2 =	0.0013

1189 . fitstat

Measures of Fit for **logit** of **hp2vacatn**

Log-Lik Intercept Only:	-167.516	Log-Lik Full Model:	-133.624
D(360):	267.248	LR(2):	67.784
		Prob > LR:	0.000
McFadden's R2:	0.202	McFadden's Adj R2:	0.184
Maximum Likelihood R2:	0.170	Cragg & Uhler's R2:	0.283
McKelvey and Zavoina's R2:	0.354	Efron's R2:	0.237
Variance of y*:	5.091	Variance of error:	3.290
Count R2:	0.868	Adj Count R2:	0.238
AIC:	0.753	AIC*n:	273.248
BIC:	-1854.737	BIC':	-55.995

```

1190 .
1191 . scalar SigDoseVactnFw2 = "no"

1192 . scalar MainEffVactnFw2 = "age radhlw2 deaw2"

1193 .
1194 . di as result " Full moderator model for females for dose=> Vacation plans"
    Full moderator model for females for dose=> Vacation plans

1195 . logit hp2vacatn age radhlw2 deaw2 suchrw2 avgcumdosew2 ageXd3 radhlw2Xd3 dea
    > w2Xd3 ///
    >      suchrw2Xd3 havmilsq if gender==2

```

```

Iteration 0:  log likelihood =  -167.516
Iteration 1:  log likelihood = -135.52597
Iteration 2:  log likelihood = -131.52279
Iteration 3:  log likelihood =  -131.2764
Iteration 4:  log likelihood = -131.27069
Iteration 5:  log likelihood = -131.27061
Iteration 6:  log likelihood = -131.27061

```

Logistic regression

```

Number of obs   =      363
LR chi2(10)     =      72.49
Prob > chi2     =      0.0000
Pseudo R2      =      0.2164

```

Log likelihood = -131.27061

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0708879	.0190976	3.71	0.000	.0334572	.1083185
radhlw2	.0165656	.0064315	2.58	0.010	.0039601	.0291712
deaw2	.3060548	.241868	1.27	0.206	-.1679977	.7801073
suchrw2	-.0009912	.0046331	-0.21	0.831	-.0100718	.0080894
avgcumdosew2	-.9450174	1.222942	-0.77	0.440	-3.34194	1.451905
ageXd3	.0137792	.0133034	1.04	0.300	-.012295	.0398534
radhlw2Xd3	.001068	.0036864	0.29	0.772	-.0061572	.0082931
deaw2Xd3	-.1266981	.2241693	-0.57	0.572	-.5660619	.3126657
suchrw2Xd3	-.0004938	.0024641	-0.20	0.841	-.0053234	.0043359
havmilsq	-5.05e-07	1.35e-06	-0.37	0.708	-3.15e-06	2.14e-06
_cons	-6.701508	1.270732	-5.27	0.000	-9.192096	-4.210919

```

1196 .
1197 . di as result "trimmed female moderator model for dose=> vacation plans"
      trimmed female moderator model for dose=> vacation plans
1198 . logit hp2vacatn age avgcumdosew2 suchrw2 deaw2 deaw2Xd3 if gender==2

```

```

Iteration 0:  log likelihood =  -167.516
Iteration 1:  log likelihood = -140.72298
Iteration 2:  log likelihood = -137.85316
Iteration 3:  log likelihood = -137.83165
Iteration 4:  log likelihood = -137.83165

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(5)      =       59.37
                                                    Prob > chi2     =       0.0000
Log likelihood = -137.83165                      Pseudo R2      =       0.1772

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0896607	.0149698	5.99	0.000	.0603204	.1190011
avgcumdosew2	.1488443	.1025315	1.45	0.147	-.0521136	.3498023
suchrw2	-.0054654	.0036554	-1.50	0.135	-.0126297	.001699
deaw2	.2935759	.2210405	1.33	0.184	-.1396555	.7268074
deaw2Xd3	-.0992117	.1869089	-0.53	0.596	-.4655464	.267123
_cons	-6.416219	.881865	-7.28	0.000	-8.144642	-4.687795

```

1199 .
1200 . scalar VacatnModFw2 = "none"

1201 . *xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
    > xxxx
1202 . cap gen hp2vactn = HP2vacatn

1203 . title4 "Chunk 9 HP2vacatn plans mediator models for males"

```

Chunk 9 HP2vacatn plans mediator models for males

```

1204 .
1205 . * age is a mediator for males
1206 . glm age avgcumdosew2 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6004**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.6853
Deviance = 49917.64009	(1/df) Deviance	=	147.6853
Pearson = 49917.64009	(1/df) Pearson	=	147.6853
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.838826
Log likelihood = -1330.6004	<u>BIC</u>	=	47947.46

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.5832314	.2635871	2.21	0.027	.0666101	1.099853
_cons	48.62133	.7061562	68.85	0.000	47.23729	50.00537

```

1207 . glm hp2vactn age if gender==1, fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 230.5483
Iteration 2: deviance = 224.6254
Iteration 3: deviance = 224.4149
Iteration 4: deviance = 224.4147
Iteration 5: deviance = 224.4147

```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 224.4146771	(1/df) Deviance	=	.6639487
Pearson = 345.2370578	(1/df) Pearson	=	1.021411
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	BIC	=	-1745.769

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0377399	.0063833	5.91	0.000	.0252289	.0502509
_cons	-3.150096	.3549593	-8.87	0.000	-3.845803	-2.454388

(Standard errors scaled using square root of deviance-based dispersion.)

```
1208 .
1209 . * illness is a mediating effect for males = > vacatn for men
1210 . des illw2
```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```
1211 . glm illw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-303.59609**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.3512988
Deviance = 118.7390083	(1/df) Deviance	=	.3512988
Pearson = 118.7390083	(1/df) Pearson	=	.3512988

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	1.797624
Log likelihood = -303.5960853	<u>BIC</u>	=	-1851.445

illw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.0085423	.0128556	0.66	0.506	-.0166543	.0337389
_cons	.2741359	.0344406	7.96	0.000	.2066336	.3416382

```
1212 . glm hp2vactn illw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 246.5506
Iteration 2:  deviance = 245.3093
Iteration 3:  deviance = 245.3029
Iteration 4:  deviance = 245.3029
Iteration 5:  deviance = 245.3029
```

```
Generalized linear models                      No. of obs      =       340
Optimization      :  ML Fisher scoring      Residual df     =       338
                   (IRLS EIM)                Scale parameter =         1
Deviance          = 245.3029322              (1/df) Deviance =  .7257483
Pearson           = 335.4909761              (1/df) Pearson  =  .9925769
```

```
Variance function: V(u) = u*(1-u)          [Bernoulli]
Link function      : g(u) = invnorm(u)      [Probit]
```

```
BIC = -1724.881
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.3031606	.1114242	2.72	0.007	.0847731	.5215481
_cons	-1.277579	.0863769	-14.79	0.000	-1.446875	-1.108284

(Standard errors scaled using square root of deviance-based dispersion.)

```
1213 .
```

```
1214 . des radhlw2
```

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		Self-perceived Chornobyl health threat in wave 2

```
1215 . glm radhlw2 avgcumdosew2 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:    log likelihood = -1693.4076
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1247.933
Deviance = 421801.4584	(1/df) Deviance	=	1247.933
Pearson = 421801.4584	(1/df) Pearson	=	1247.933

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	9.972986
Log likelihood = -1693.407647	<u>BIC</u>	=	419831.3

radhlw2	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew2	1.220373	.766216	1.59	0.111	-.2813831	2.722128	
_cons	45.63198	2.052711	22.23	0.000	41.60874	49.65522	

```
1216 . glm hp2vactn radhlw2 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 234.5448
Iteration 2:    deviance = 229.6041
Iteration 3:    deviance = 229.4465
Iteration 4:    deviance = 229.4462
Iteration 5:    deviance = 229.4462
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 229.4462113	(1/df) Deviance	=	.6788349
Pearson = 340.4683102	(1/df) Pearson	=	1.007303

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1740.737
--	-----	---	-----------

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0116586	.0021811	5.35	0.000	.0073837	.0159334
_cons	-1.817407	.1519393	-11.96	0.000	-2.115203	-1.519612

(Standard errors scaled using square root of deviance-based dispersion.)

```
1217 .
1218 . title4 "HP2vacatn plans mediator models for females"
```

HP2vacatn plans mediator models for females

```
1219 .
1220 . * age is a mediator for females
1221 . glm age avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1406.9403**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	136.9184
Deviance = 49427.52828	(1/df) Deviance	=	136.9184
Pearson = 49427.52828	(1/df) Pearson	=	136.9184

Variance function: V(u) = 1	[Gaussian]
Link function : g(u) = u	[Identity]

	<u>AIC</u>	=	7.762756
Log likelihood = -1406.940271	<u>BIC</u>	=	47299.65

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	1.502324	.4454009	3.37	0.001	.6293547	2.375294
_cons	48.86944	.7323225	66.73	0.000	47.43412	50.30477

```
1222 . glm hp2vactn age if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 288.2228
Iteration 2:  deviance = 282.9212
Iteration 3:  deviance = 282.8
Iteration 4:  deviance = 282.8
Iteration 5:  deviance = 282.8
```

```
Generalized linear models                      No. of obs      =       363
Optimization      :  MQL Fisher scoring        Residual df     =       361
                   (IRLS EIM)                  Scale parameter =        1
Deviance          = 282.7999835                (1/df) Deviance =  .7833795
Pearson           = 396.9154874                (1/df) Pearson  = 1.099489
```

```
Variance function: V(u) = u*(1-u)             [Bernoulli]
Link function      : g(u) = invnorm(u)         [Probit]
```

```
BIC = -1845.079
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0510238	.0068535	7.44	0.000	.0375912	.0644564
_cons	-3.660305	.3855366	-9.49	0.000	-4.415943	-2.904667

(Standard errors scaled using square root of deviance-based dispersion.)

```
1223 .
1224 . * illness is a mediating effect for females = > vacatn
1225 . des illw2
```

variable name	storage type	display format	value label	variable label
illw2	double	%8.0g		Total number of illnesses experienced in time period 1987-1996

```
1226 . glm illw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -463.51524
```

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
		Scale parameter	=	.756881
Deviance	= 273.2340487	(1/df) Deviance	=	.756881
Pearson	= 273.2340487	(1/df) Pearson	=	.756881

Variance function: $V(u) = 1$	[Gaussian]
Link function : $g(u) = u$	[Identity]

	<u>AIC</u>	=	2.564822
Log likelihood = -463.5152411	<u>BIC</u>	=	-1854.645

illw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	.1249912	.0331157	3.77	0.000	.0600856	.1898968
_cons	.301285	.0544484	5.53	0.000	.194568	.4080019

```
1227 . glm hp2vactn illw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 329.874
Iteration 2: deviance = 329.8007
Iteration 3: deviance = 329.8005
Iteration 4: deviance = 329.8005
```

Generalized linear models		No. of obs	=	363
Optimization	: MQL Fisher scoring (IRLS EIM)	Residual df	=	361
		Scale parameter	=	1
Deviance	= 329.8005369	(1/df) Deviance	=	.9135749
Pearson	= 363.0908863	(1/df) Pearson	=	1.005792

Variance function: $V(u) = u*(1-u)$	[Bernoulli]
Link function : $g(u) = \text{invnorm}(u)$	[Probit]

	BIC	=	-1798.079
--	-----	---	-----------

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw2	.1861547	.0776301	2.40	0.016	.0340026	.3383068
_cons	-1.027515	.0837109	-12.27	0.000	-1.191586	-.8634451

(Standard errors scaled using square root of deviance-based dispersion.)

```
1228 .
1229 . * radhlw2 is a mediating effect for females => vactn
1230 . des radhlw2
```

variable name	storage type	display format	value label	variable label
radhlw2	double	%8.0g		Self-perceived Chernobyl health threat in wave 2

```
1231 . glm radhlw2 avgcumdosew2 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1791.2233**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1137.567
Deviance = 410661.5604	(1/df) Deviance	=	1137.567
Pearson = 410661.5604	(1/df) Pearson	=	1137.567

Variance function: **V(u) = 1** [Gaussian]
Link function : **g(u) = u** [Identity]

	<u>AIC</u>	=	9.880018
Log likelihood = -1791.223306	<u>BIC</u>	=	408533.7

radhlw2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew2	3.302288	1.283833	2.57	0.010	.7860214	5.818555
_cons	56.95167	2.110863	26.98	0.000	52.81445	61.08888

```
1232 . glm hp2vactn radhlw2 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 310.7426
Iteration 2:  deviance = 307.9144
Iteration 3:  deviance = 307.878
Iteration 4:  deviance = 307.878
Iteration 5:  deviance = 307.878
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  ML Fisher scoring                Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 307.8780006                        (1/df) Deviance =  .8528476
Pearson           = 369.926962                          (1/df) Pearson  =  1.024728
```

```
Variance function: V(u) = u*(1-u)                    [Bernoulli]
Link function     : g(u) = invnorm(u)                  [Probit]
```

```
BIC = -1820.001
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw2	.0127779	.0023866	5.35	0.000	.0081002	.0174555
_cons	-1.793767	.1848064	-9.71	0.000	-2.15598	-1.431553

(Standard errors scaled using square root of deviance-based dispersion.)

```
1233 .
1234 . * summary of male moderating effects: no sign main dose effect in main effe
> cts model
1235 . *          no signif male moderators
1236 . *          3 significant main effects in main effects model
1237 .
1238 . scalar VactnMedMw2 = "age illw2"

1239 . scalar VactnMedFw2 = "age illw2 radhlw2"
```

```

1240 .
1241 . *xx summary of moderator effects for females:
1242 .     * no signif main dose effect
1243 .     * 3 signif main effects in main effect model
1244 .     * 1 moderator: deaw2Xd3
1245 . title4 "7. SUMMARY MATRIX of dose - vacation plans impact"

```

```

7. SUMMARY MATRIX of dose - vacation plans impact

```

```

1246 . set more off

1247 .     matrix define HP2vactnMw2 = J(1,8, 0)

1248 .           matrix define HP2vactnFw2 = J(1,8, 0)

1249 . matrix colnames HP2vactnMw2=  hypnum ptnum wave gender medsig numMA sig numMo
> dsig numMed

1250 . matrix colnames HP2vactnFw2=  hypnum ptnum wave gender medsig numMA sig numMo
> dsig numMed

1251 .     matrix define HP2vactnMw2= (1, 2, 3, 1, 0, 3, 0, 2 )

1252 .           matrix define HP2vactnFw2= (1, 2, 3, 2, 0, 3, 1, 3 )

1253 .           matrix rowname HP2vactnMw2 = HP2vactnM

1254 .           matrix rowname HP2vactnFw2 = HP2vactnF

1255 .           matlist HP2vactnMw2

```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	HP2vactnM	1	2	3	1	0	
> 3	0						
		c8					
	HP2vactnM	2					

```
1256 .      matlist HP2vactnFw2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>	HP2vactnF	1	2	3	2	0	
> 3	1						
		c8					
	HP2vactnF	3					

```
1257 . matrix define H1pt2w2=(HP2wkMw2 \ HP2wkFw2 \ HP2hmcrMw2 \ HP2hmcrFw2 \ HP2sp
> Mw2 \ HP2spFw2 \ HP2prbfamMw2 \ HP2prbfamFw2 \ HP2inthbMw2 \ HP2inthbFw2 \ H
> P2vactnMw2 \ HP2vactnFw2 )
```

```
1258 .
```

```
1259 .      matlist H1pt2w2
```

		c1	c2	c3	c4	c5	c
> 6	c7						
>							
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 1	0						
	r1	1	2	3	1	0	
> 4	0						
	r1	1	2	3	2	0	
> 2	0						
	HP2spMw2	1	2	3	1	0	
> 2	0						
	HP2spFw2	1	2	3	2	1	
> 5	5						
	HP2prbfamM	1	2	3	1	0	
> 5	0						
	HP2prbfamF	1	2	3	2	0	
> 2	2						
	HP2inthbM	1	2	3	1	0	
> 3	0						
	HP2inthobF	1	2	3	2	0	
> 3	0						
	HP2vactnM	1	2	3	1	0	
> 3	0						
	HP2vactnF	1	2	3	2	0	
> 3	1						

	c8
r1	4
r1	6
r1	2
r1	2
HP2spMw2	1
HP2spFw2	2
HP2prbfamM	1
HP2prbfamF	2
HP2inthbM	2
HP2inthobF	3
HP2vactnM	2
HP2vactnF	3

```
1260 .      matrix colnames H1pt2w2 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
1261 . matrix rownames H1pt2w2 =HP2wkMw2 HP2wkFw2 HP2hmcrMw2 HP2hmcrFw2 HP2socprbMw
> 2 HP2socprbFw2 HP2prbfamMw2 HP2prbfamFw2 HP2inthbMw2 HP2inthbFw2 HP2vacatnMw
> 2 HP2vacatnFw2
```

```
1262 .      matlist H1pt2w2
```

	hypnum	ptnum	wave	gender	medsig	numMASi
> g numModsig						
> HP2wkMw2	1	2	3	1	0	
> 4	0					
HP2wkFw2	1	2	3	2	0	
> 1	0					
HP2hmcrMw2	1	2	3	1	0	
> 4	0					
HP2hmcrFw2	1	2	3	2	0	
> 2	0					
HP2socprbMw2	1	2	3	1	0	
> 2	0					
HP2socprbFw2	1	2	3	2	1	
> 5	5					
HP2prbfamMw2	1	2	3	1	0	
> 5	0					
HP2prbfamFw2	1	2	3	2	0	
> 2	2					
HP2inthbMw2	1	2	3	1	0	
> 3	0					
HP2inthbFw2	1	2	3	2	0	
> 3	0					
HP2vacatnMw2	1	2	3	1	0	

```

> 3      0
HP2vacatnFw2 |      1      2      3      2      0
> 3      1

```

	numMed
HP2wkMw2	4
HP2wkFw2	6
HP2hmcrMw2	2
HP2hmcrFw2	2
HP2socprbMw2	1
HP2socprbFw2	2
HP2prbfamMw2	1
HP2prbfamFw2	2
HP2inthbMw2	2
HP2inthbFw2	3
HP2vacatnMw2	2
HP2vacatnFw2	3

```

1263 .
1264 .
1265 . sjlog close, replace

```