

```

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 regressions 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 congruency.
47 . *      This concludes the test of part 1 of H1
48 . ***-----
    > -----
49 .
50 . * Part 2 Nottingham subscales
51 . *      1: hp2work

```

```

52 . * 2: hp2hmcare
53 . * 3: hp2probsoc
54 . * 4: hp2pbfhm
55 . * 5: hp2sexlife
56 . * 6: hp2inthob
57 . * 7: hp2vactn
58 .
59 .
60 . local dvwhole HP2work-HP2vacatn

61 . local dv2 HP2work HP2hmcare HP2probsoc HP2pbfhm HP2sexlife HP2inthob HP2vacat
    > n

62 .
63 .
64 .
65 . di "$User"
    Robert Alan Yaffee

66 .
67 . title "Testing part 2 of hypothesis 1 for wave three"

```

```

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****      Testing part 2 of hypothesis 1 for wave three      ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****
> *
*****
> *

```

```

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 20:32:48 *****
> *
*****
> *
*****
> *

```

```

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

```

87 .
88 . cap gen havmilsq = havmil^2

89 .
90 . cap rename Havmil havmil

91 . // controlling for potential confounders
92 . // socio-demographics age gender educ income occp marstat children inc
93 . // distance from accident side
94 . // perceived Chornobyl related health threat to oneself
95 .
96 . local w1bf bf1 bf4 bf9 bf10 bf11 bf4m bf15m bf20 bf22 bf30 bf40

97 . local w3bf bf1 bf4 bf6 bf7 bf14 bf15 bf40

98 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0

99 .
100 . *-----
    > ----
101 . * Hypothesis 1 Part 2 wave 3 tests male and female
102 . * endogeneous Nottingham pt 2 subscales: HP2work HP2hmcare HP2probsoc HP2pbfh
    > m ///
    > *
        HP2sxlife HP2inthob HP2vacatn
103 . * structure of models
104 . * 1. general models on all Pt 2 subscales with all potential confounders
105 . * 2. trimmed models on all Pt 2 subscales with from all potential confoun
    > ders
106 . * 3. from trimmed models examination of possible moderator variables
107 . * 4. from trimmed models examination of possible mediator variables
108 . * 5. Summary analysis and model evaluation of final models only
109 . * program is divided into 8 chunks one a general model and 1 for each
110 . * endogenous variable
111 . *-----
    > ----
112 . * Chunk 1 General models for all part 2 of Nottingham Health Profile

```

```

113 . est clear

114 . set linesize 80

115 . title "Zero order effects test for wave 3"

```

```

*****
> *
*****
> *
*****
> *
*****
Zero order effects test for wave 3
*****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:32:48    ****
> *
*****
> *
*****
> *

```

```

116 .
117 .
118 .
119 . foreach var in hp2work hp2hmcare hp2prbsoc HP2pbfhm HP2sxlife ///
    >   HP2inthob HP2vacatn {
      2.   forvalues k=2/2 {
      3.     set more off
      4.     logit `var' avgcumdosew3 if gender==`k', nolog
      5.     eststo `var'
      6.   }
      7.   }

```

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	5.91
	Prob > chi2	=	0.0150
Log likelihood = -203.60666	Pseudo R2	=	0.0143

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1515886	.0639414	2.37	0.018	.0262658	.2769114
_cons	-1.258846	.1466856	-8.58	0.000	-1.546344	-.9713471

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	0.04
	Prob > chi2	=	0.8368
Log likelihood = -233.70738	Pseudo R2	=	0.0001

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.0131553	.0643514	-0.20	0.838	-.1392816	.1129711
_cons	-.6282335	.1343551	-4.68	0.000	-.8915646	-.3649023

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	25.59
	Prob > chi2	=	0.0000
Log likelihood = -170.77453	Pseudo R2	=	0.0697

hp2prbsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.3818633	.1004161	3.80	0.000	.1850514	.5786752
_cons	-1.855996	.1805781	-10.28	0.000	-2.209923	-1.50207

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	1.39
	Prob > chi2	=	0.2389
Log likelihood = -139.20329	Pseudo R2	=	0.0050

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.0875242	.0693786	1.26	0.207	-.0484553	.2235037
_cons	-2.020197	.1850603	-10.92	0.000	-2.382909	-1.657486

Logistic regression	Number of obs	=	363
	LR chi2(1)	=	13.23
	Prob > chi2	=	0.0003
Log likelihood = -201.00372	Pseudo R2	=	0.0319

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.2420078	.0764553	3.17	0.002	.0921582	.3918573
_cons	-1.357074	.1533357	-8.85	0.000	-1.657606	-1.056541

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(1)      =       5.02
                                                    Prob > chi2     =       0.0250
Log likelihood = -169.60139                        Pseudo R2       =       0.0146

```

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1444902	.0628294	2.30	0.021	.0213469	.2676336
_cons	-1.695781	.1633385	-10.38	0.000	-2.015919	-1.375643

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(1)      =       4.68
                                                    Prob > chi2     =       0.0305
Log likelihood = -165.17453                        Pseudo R2       =       0.0140

```

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1408134	.0629055	2.24	0.025	.017521	.2641059
_cons	-1.748135	.1659602	-10.53	0.000	-2.073411	-1.422859

```

120 .
121 . title "Summary of zero-order tests for females in wave three"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *

```

```

*****                               1 Jul 2012    20:32:58    ****
> *
*****
> *
*****
> *

```

```

122 .
123 .
124 . estout    hp2work hp2hmcare hp2prbsoc HP2pbfhm, cells(b(star fmt(%9.3f)) se(p
> ar) t p)    ///
>              stats(r2_p bic N, fmt(%9.3f %9.0g) labels(Psuedo R^2))    ///
>              legend collabels(none) varlabels(_cons Constant)    ///
>              mlabels( work homecare socialprbs famprobs)    ///
>              title("Zero-order regression coefficients"    ///
>                    "of reconstructed dose on Nottingham Part 2")

```

Zero-order regression coefficients of reconstructed dose on Nottingham Part 2

	work	homecare	socialprbs	famprobs
main				
avgcumdosew3	0.152*	-0.013	0.382***	0.088
	(0.064)	(0.064)	(0.100)	(0.069)
	2.371	-0.204	3.803	1.262
	0.018	0.838	0.000	0.207
Constant	-1.259***	-0.628***	-1.856***	-2.020***
	(0.147)	(0.134)	(0.181)	(0.185)
	-8.582	-4.676	-10.278	-10.916
	0.000	0.000	0.000	0.000
Psuedo	0.014	0.000	0.070	0.005
R^2	419.0021	479.2036	353.3379	290.1954
N	363	363	363	363

* p<0.05, ** p<0.01, *** p<0.001

Zero-order regression coefficients of reconstructed dose on Nottingham Part 2

	sexlife	intshobbies	vacatnPlans
main			
avgcumdosew3	0.242**	0.144*	0.141*
	(0.076)	(0.063)	(0.063)
	3.165	2.300	2.238
	0.002	0.021	0.025
Constant	-1.357***	-1.696***	-1.748***
	(0.153)	(0.163)	(0.166)
	-8.850	-10.382	-10.533
	0.000	0.000	0.000
Pseudo	0.032	0.015	0.014
R^2	413.7963	350.9916	342.1379
N	363	363	363

```
126 .
127 . title "Trimmed model summary for females in wave three"
```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
Trimmed model summary for females in wave three
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:32:59
> *
*****

```

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

```
128 .
129 . forvalues j=3/3 {
      2. des age avgcumdosew`j'
      3. logistic HP2work age ///
>     avgcumdosew3 if gender==2, coef nolog
      4. eststo work
      5. }
```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009

Logistic regression	Number of obs	=	363
	LR chi2(2)	=	44.24
	Prob > chi2	=	0.0000
Log likelihood = -184.44118	Pseudo R2	=	0.1071

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0677348	.01171	5.78	0.000	.0447836	.0906861
avgcumdosew3	.102922	.0642392	1.60	0.109	-.0229846	.2288285
_cons	-4.750307	.6479129	-7.33	0.000	-6.020193	-3.480421

```
130 .
131 . title "Trimmed female homecare in wave three"
```

```

132 . * Dose work relationship for females in wave 3 washes out also
133 . set more off

134 . forvalues j=3/3 {
      2. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3. di _skip(4)
      4. di as input "For females hp2hmcare on wave 1 with dose ns"
      5. des age avgcumdosew`j' `w3bf'
      6. logistic HP2work age radhlw3 ///
      > avgcumdosew3 shhlw`j' if gender==2, coef nolog
      7. eststo homecare
      8.
135 . }

```



variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009
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(4)	=	54.20
	Prob > chi2	=	0.0000
Log likelihood = -179.46218	Pseudo R2	=	0.1312

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0604261	.0121821	4.96	0.000	.0365495	.0843027
radhlw3	.0091245	.0041171	2.22	0.027	.0010551	.0171938
avgcumdosew3	.0744838	.0646958	1.15	0.250	-.0523177	.2012853
shhlw3	.0068705	.0039339	1.75	0.081	-.0008399	.0145808
_cons	-5.221192	.6904908	-7.56	0.000	-6.574529	-3.867855

```

136 .
137 . title "Trimmed female dose-social problems in wave three model B: Dose is si
> gnificant"

```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****Trimmed female dose-social problems in wave three model B: Dose is signif
> icant*****
*****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:33:01    ****
> *
*****
> *
*****
> *

```

```

138 . set more off

```

```

139 . logit HP2probsoc age radhlw3 illw3  ///
> shrelaw3 avgcumdosew3 if gender==2

```

```

Iteration 0:  log likelihood = -183.5701
Iteration 1:  log likelihood = -125.28517
Iteration 2:  log likelihood = -117.19625
Iteration 3:  log likelihood = -116.97888
Iteration 4:  log likelihood = -116.97825
Iteration 5:  log likelihood = -116.97825

```

```

Logistic regression

```

```

Log likelihood = -116.97825

```

```

Number of obs    =      363
LR chi2(5)       =     133.18
Prob > chi2      =      0.0000
Pseudo R2       =      0.3628

```



```
145 . logit HP2pbfhm age bf4 bf40 if gender==2, iterate(50)
```

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

147 .

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
*****  
***** trimmed HP2sexlife main effects models *****  
> *  
***** wave 3 for H1 part 2 with dose ns *****  
> *  
*****  
> *  
*****  
> *  
*****  
*****  
*****  
*****  
*****
```

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

```
149 .      logit HP2sxlife age marrw31-marrw36 radhlw3 bf4 bf4m   ///
>          shfamw3 shrelaw3 avgcumdosew3   if gender==2
```

note: marrw36 omitted because of collinearity

```
Iteration 0:  log likelihood = -207.62116
Iteration 1:  log likelihood = -144.17685
Iteration 2:  log likelihood = -138.48259
Iteration 3:  log likelihood = -138.36775
Iteration 4:  log likelihood = -138.36738
Iteration 5:  log likelihood = -138.36738
```

Logistic regression

```
Number of obs   =      363
LR chi2(12)     =      138.51
Prob > chi2     =      0.0000
Pseudo R2      =      0.3336
```

Log likelihood = -138.36738

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0754579	.0170423	4.43	0.000	.0420555	.1088603
marrw31	-.9421212	.8010808	-1.18	0.240	-2.512211	.6279684
marrw32	-.440823	1.344699	-0.33	0.743	-3.076384	2.194738
marrw33	-.9501207	.4286832	-2.22	0.027	-1.790324	-.109917
marrw34	-.9642797	1.745537	-0.55	0.581	-4.38547	2.45691
marrw35	-.8586239	.6388872	-1.34	0.179	-2.11082	.393572
marrw36	0 (omitted)					
radhlw3	.0100484	.0049263	2.04	0.041	.000393	.0197038
bf4	-.5151847	.1744193	-2.95	0.003	-.8570402	-.1733292
bf4m	.3491023	.1586783	2.20	0.028	.0380985	.6601061
shfamw3	.0106246	.0054177	1.96	0.050	6.14e-06	.0212431
shrelaw3	-.0125055	.00593	-2.11	0.035	-.024128	-.0008829
avgcumdosew3	.1255823	.0854354	1.47	0.142	-.0418679	.2930326
_cons	-6.549884	1.704204	-3.84	0.000	-9.890063	-3.209705

```
150 . eststo sexlife
```

```
151 .
```

```
152 .
```

```
153 .
```

```
154 . set more off
```

```
155 .      logistic HP2inthob age    ///
>          radhlw3 avgcumdosew3 ///
>          bf4    ///
>          if gender==2, coef nolog difficult iterate(50)
```

Logistic regression	Number of obs	=	363
	LR chi2(4)	=	85.17
	Prob > chi2	=	0.0000
Log likelihood = -129.52718	Pseudo R2	=	0.2474

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0747817	.0159584	4.69	0.000	.0435038	.1060596
radhlw3	.0177314	.0055334	3.20	0.001	.0068862	.0285766
avgcumdosew3	.0423064	.0679809	0.62	0.534	-.0909337	.1755466
bf4	-.092667	.0312315	-2.97	0.003	-.1538797	-.0314543
_cons	-6.042759	1.092151	-5.53	0.000	-8.183336	-3.902181

```
156 . eststo intshobbies
```

```
157 .
```

```
158 . logistic hp2vacatn age radhlw3 avgcumdosew3    ///
>      deaw3 suchrw3    ///
>      if gender==2, coef nolog difficult iterate(50)
```

Logistic regression	Number of obs	=	363
	LR chi2(5)	=	69.60
	Prob > chi2	=	0.0000
Log likelihood = -132.71672	Pseudo R2	=	0.2077


```

163 .
164 .
165 .
166 . set more off

167 . estout work homecare probsoc familyprbs, cells(b(star fmt(%9.3f)) se(par) t
> p) ///
> stats(r2_p bic N, fmt(%9.3f %9.0g) labels(Psuedo R^2)) ///
> legend collabels(none) varlabels(_cons Constant) ///
> mlabels( work homecare socialprbs famprobs) ///
> title("Trimmed main effect models" ///
> "of reconstructed dose on Nottingham Part 2")

```

Trimmed main effect models of reconstructed dose on Nottingham Part 2

	work	homecare	socialprbs	famprobs
main				
age	0.068*** (0.012) 5.784 0.000	0.060*** (0.012) 4.960 0.000	0.122*** (0.019) 6.517 0.000	0.064*** (0.017) 3.684 0.000
avgcumdosew3	0.103 (0.064) 1.602 0.109	0.074 (0.065) 1.151 0.250	0.323** (0.110) 2.944 0.003	
radhlw3		0.009* (0.004) 2.216 0.027	0.022*** (0.006) 3.900 0.000	
shhlw3		0.007 (0.004) 1.746 0.081		
illw3			0.270* (0.136) 1.985 0.047	
shrelaw3			-0.016** (0.006) -2.787 0.005	
bf4				-0.203*** (0.039) -5.170 0.000
bf40				-0.194* (0.091) -2.125

				0.034
Constant	-4.750***	-5.221***	-9.764***	-3.086**
	(0.648)	(0.690)	(1.186)	(1.113)
	-7.332	-7.562	-8.235	-2.772
	0.000	0.000	0.000	0.006
Pseudo	0.107	0.131	0.363	0.241
R^2	386.5656	388.3964	269.3229	235.8194
N	363	363	363	363

* p<0.05, ** p<0.01, *** p<0.001

```
168 . estout sexlife intshobbies vacations, cells(b(star fmt(%9.3f)) se(par) t p)
>    ///
>          stats(r2_p bic N, fmt(%9.3f %9.0g) labels(Pseudo R^2))    ///
>          legend collabels(none) varlabels(_cons Constant)    ///
>          mlabels(sexlife intshobbies vacatnPlans)    ///
>          title("Trimmed main effect models"    ///
>          "of reconstructed dose on Nottingham Part 2")
```

Trimmed main effect models of reconstructed dose on Nottingham Part 2

	sexlife	intshobbies	vacatnPlans
main			
age	0.075***	0.075***	0.092***
	(0.017)	(0.016)	(0.016)
	4.428	4.686	5.805
	0.000	0.000	0.000
marrw31	-0.942		
	(0.801)		
	-1.176		
	0.240		
marrw32	-0.441		
	(1.345)		
	-0.328		
	0.743		
marrw33	-0.950*		
	(0.429)		
	-2.216		
	0.027		
marrw34	-0.964		
	(1.746)		
	-0.552		
	0.581		
marrw35	-0.859		
	(0.639)		
	-1.344		
	0.179		

o.marrw36	0.000		
	(.)		
	.		
	.		
radhlw3	0.010*	0.018**	0.012*
	(0.005)	(0.006)	(0.005)
	2.040	3.204	2.329
	0.041	0.001	0.020
bf4	-0.515**	-0.093**	
	(0.174)	(0.031)	
	-2.954	-2.967	
	0.003	0.003	
bf4m	0.349*		
	(0.159)		
	2.200		
	0.028		
shfamw3	0.011*		
	(0.005)		
	1.961		
	0.050		
shrelaw3	-0.013*		
	(0.006)		
	-2.109		
	0.035		
avgcumdosew3	0.126	0.042	0.099
	(0.085)	(0.068)	(0.069)
	1.470	0.622	1.423
	0.142	0.534	0.155
deaw3			0.343*
			(0.158)
			2.170
			0.030
suchrw3			-0.006
			(0.004)
			-1.668
			0.095
Constant	-6.550***	-6.043***	-7.502***
	(1.704)	(1.092)	(0.935)
	-3.843	-5.533	-8.024
	0.000	0.000	0.000
Pseudo	0.334	0.247	0.208
R^2	353.362	288.5264	300.7999
N	363	363	363

* p<0.05, ** p<0.01, *** p<0.001

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
*****  
Hypothesis 1 part2 wave 3 H1: General models  
> *  
*****  
> *  
*****  
> *  
*****  
1 Jul 2012 20:33:09  
> *  
*****  
> *
```

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```

179 .   foreach var in HP2work HP2hmcare HP2probsoc HP2pbfhm HP2sxlife HP2inthob /
>   //
>       HP2vacatn {
    5.           forvalues k=1/2 {
    6. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
    7.
180 . 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.
181 .       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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed

inc1w3	double %15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double %15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double %15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double %15.0g	LABJ	Income allows to comfortably afford luxury items NOW
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= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 for hp2vacatn

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

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: occ6w3 != 0 predicts failure perfectly

 occ6w3 dropped and 4 obs not used

note: bf17 != 0 predicts failure perfectly

 bf17 dropped and 5 obs not used

note: _Ieduc_6 omitted because of collinearity

note: occ8w3 omitted because of collinearity

note: marrw36 omitted because of collinearity

Logistic regression

Number of obs = **325**

LR chi2(**48**) = **107.62**

Prob > chi2 = **0.0000**

Pseudo R2 = **0.3178**

Log likelihood = **-115.51874**

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0398855	.0274181	1.45	0.146	-.0138531	.0936241
_Ieduc_2	1.063444	.984496	1.08	0.280	-.8661327	2.993021
_Ieduc_3	.0594211	.4628201	0.13	0.898	-.8476896	.9665319
_Ieduc_4	-.6292279	1.199379	-0.52	0.600	-2.979968	1.721512
_Ieduc_5	-.0324117	.5603466	-0.06	0.954	-1.130671	1.065848
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-16.21183	2056.545	-0.01	0.994	-4046.966	4014.542
occ2w3	-15.9512	2056.545	-0.01	0.994	-4046.705	4014.803
occ3w3	-16.80618	2056.545	-0.01	0.993	-4047.56	4013.948
occ4w3	-15.08231	2056.545	-0.01	0.994	-4045.836	4015.672
occ5w3	-15.97511	2056.545	-0.01	0.994	-4046.729	4014.779
occ6w3	0	(omitted)				
occ7w3	-15.17432	2056.545	-0.01	0.994	-4045.928	4015.58
occ8w3	0	(omitted)				
marrw31	1.816033	1.097265	1.66	0.098	-.3345671	3.966633
marrw32	.0757168	1.330041	0.06	0.955	-2.531115	2.682549
marrw33	-.7164591	1.109884	-0.65	0.519	-2.891791	1.458873
marrw35	.9690805	1.275825	0.76	0.448	-1.53149	3.469651
marrw36	0	(omitted)				
inc1w3	16.44823	2056.545	0.01	0.994	-4014.306	4047.202
inc2w3	16.79255	2056.545	0.01	0.993	-4013.961	4047.546
inc3w3	16.28275	2056.545	0.01	0.994	-4014.471	4047.037
inc4w3	16.19339	2056.545	0.01	0.994	-4014.561	4046.948
radhlw3	.0018951	.0075342	0.25	0.801	-.0128717	.0166619
havmil	-.0003047	.0050542	-0.06	0.952	-.0102109	.0096014
avgcumdosew3	.0388524	.0643134	0.60	0.546	-.0871996	.1649043
bf1	-.1090167	.0689067	-1.58	0.114	-.2440713	.026038
bf4	-.1845645	.1878566	-0.98	0.326	-.5527567	.1836277
bf2	.0001393	.0001535	0.91	0.364	-.0001616	.0004401
bf4m	-.0184667	.1657846	-0.11	0.911	-.3433984	.3064651
bf5m	.0009023	.0015537	0.58	0.561	-.0021429	.0039475
bf7m	.0008163	.0004923	1.66	0.097	-.0001485	.0017811
bf8	-.0001145	.0000456	-2.51	0.012	-.000204	-.0000251
bf15m	.0001838	.0002744	0.67	0.503	-.000354	.0007216
bf17	0	(omitted)				
bf20	.0923153	.0637829	1.45	0.148	-.0326969	.2173275
bf22	.0000533	.0001499	0.36	0.722	-.0002405	.0003471
bf29	.0000161	.0000149	1.08	0.282	-.0000132	.0000453
bf30	-.0004903	.0003941	-1.24	0.214	-.0012627	.0002822
bf40	.0752527	.2023106	0.37	0.710	-.3212688	.4717743
deaw3	-.1202184	.2295198	-0.52	0.600	-.570069	.3296321
dvcew3	-.0534217	1.08605	-0.05	0.961	-2.18204	2.075197
sepaw3	-.3670246	1.185339	-0.31	0.757	-2.690246	1.956196
accdw3	-.058659	.5773335	-0.10	0.919	-1.190212	1.072894

movew3	-.5628223	.5250647	-1.07	0.284	-1.59193	.4662856
illw3	.6145655	.2492311	2.47	0.014	.1260816	1.103049
shfamw3	-.0028773	.0074782	-0.38	0.700	-.0175343	.0117797
shhlw3	-.0003705	.0066844	-0.06	0.956	-.0134717	.0127307
shjobw3	.0119897	.0066255	1.81	0.070	-.0009961	.0249755
shrelaw3	-.0011615	.0067798	-0.17	0.864	-.0144496	.0121266
suprtw3	.0138766	.0081512	1.70	0.089	-.0020993	.0298526
suchrw3	-.0097666	.0065695	-1.49	0.137	-.0226425	.0031093
havmilsq	7.20e-07	7.22e-06	0.10	0.921	-.0000134	.0000149
_cons	-6.713085	3.586597	-1.87	0.061	-13.74269	.3165157

Note: 4 failures and 0 successes completely determined.

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	30	15	45
-	40	240	280
Total	70	255	325

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	42.86%
Specificity	$\Pr(- \sim D)$	94.12%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	85.71%

False + rate for true ~D	$\Pr(+ \sim D)$	5.88%
False - rate for true D	$\Pr(- D)$	57.14%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	14.29%

Correctly classified	83.08%
----------------------	--------

Logistic model for HP2work, goodness-of-fit test

number of observations =	325
number of covariate patterns =	325
Pearson $\chi^2(276)$ =	298.51
Prob > χ^2 =	0.1682

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

Log-Lik Intercept Only:	-169.326	Log-Lik Full Model:	-115.519
D(269):	231.037	LR(48):	107.615
		Prob > LR:	0.000
McFadden's R2:	0.318	McFadden's Adj R2:	-0.013
Maximum Likelihood R2:	0.282	Cragg & Uhler's R2:	0.436
McKelvey and Zavoina's R2:	0.713	Efron's R2:	0.332
Variance of y*:	11.462	Variance of error:	3.290
Count R2:	0.831	Adj Count R2:	0.214
AIC:	1.055	AIC*n:	343.037
BIC:	-1324.811	BIC':	170.008

Full main model for HP2work for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2work

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
 note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: occ8w3 != 0 predicts failure perfectly
 occ8w3 dropped and 1 obs not used

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

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

Logistic regression	Number of obs	=	345
	LR chi2(50)	=	106.32
	Prob > chi2	=	0.0000
Log likelihood = -147.91609	Pseudo R2	=	0.2644

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0539741	.0202532	2.66	0.008	.0142786	.0936696
_Ieduc_2	-12.55341	623.5872	-0.02	0.984	-1234.762	1209.655
_Ieduc_3	-13.54577	623.5871	-0.02	0.983	-1235.754	1208.663
_Ieduc_4	-12.04583	623.5872	-0.02	0.985	-1234.254	1210.163
_Ieduc_5	-13.6714	623.5873	-0.02	0.983	-1235.88	1208.537
_Ieduc_6	-13.3439	623.5871	-0.02	0.983	-1235.552	1208.864
_Ieduc_7	-14.44833	623.5903	-0.02	0.982	-1236.663	1207.766
_Ieduc_8	0	(omitted)				
occ1w3	.1126048	1.869311	0.06	0.952	-3.551177	3.776386
occ2w3	.1300177	1.92152	0.07	0.946	-3.636092	3.896127
occ3w3	.4109427	1.89228	0.22	0.828	-3.297858	4.119743
occ4w3	-.168581	2.072728	-0.08	0.935	-4.231054	3.893892
occ5w3	1.045375	2.389172	0.44	0.662	-3.637316	5.728065
occ6w3	0	(omitted)				

occ7w3	-.3503943	1.867461	-0.19	0.851	-4.01055	3.309761
occ8w3	0	(omitted)				
marrw31	-.807006	1.451843	-0.56	0.578	-3.652566	2.038554
marrw32	-.3908773	1.745393	-0.22	0.823	-3.811785	3.030031
marrw33	-.3675069	1.295392	-0.28	0.777	-2.906429	2.171415
marrw35	-.1977292	1.318807	-0.15	0.881	-2.782543	2.387085
marrw36	.7011152	1.329741	0.53	0.598	-1.90513	3.30736
inclw3	.9742727	1.913	0.51	0.611	-2.775139	4.723684
inc2w3	.8770803	1.873885	0.47	0.640	-2.795667	4.549827
inc3w3	.6085909	1.869674	0.33	0.745	-3.055903	4.273085
inc4w3	-.7888601	2.462315	-0.32	0.749	-5.614908	4.037188
radhlw3	.0045205	.0073058	0.62	0.536	-.0097986	.0188397
havmil	-.0009271	.0024979	-0.37	0.711	-.0058229	.0039686
avgcumdosew3	.115088	.0796177	1.45	0.148	-.0409598	.2711358
bf1	.0054828	.0325747	0.17	0.866	-.0583624	.069328
bf4	-.7222893	.236357	-3.06	0.002	-1.18554	-.2590382
bf2	-.0000397	.0001011	-0.39	0.694	-.0002378	.0001584
bf4m	.5355567	.2180534	2.46	0.014	.1081798	.9629336
bf5m	.0021761	.0013897	1.57	0.117	-.0005476	.0048998
bf7m	.0008931	.0005154	1.73	0.083	-.0001171	.0019033
bf8	-.000022	.0000319	-0.69	0.491	-.0000845	.0000406
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0052234	.0270949	-0.19	0.847	-.0583285	.0478817
bf22	-.0001469	.0001125	-1.31	0.192	-.0003673	.0000736
bf29	.0000122	.0000367	0.33	0.740	-.0000598	.0000841
bf30	.0000264	.0002891	0.09	0.927	-.0005402	.000593
bf40	.2842481	.1315066	2.16	0.031	.0264999	.5419962
deaw3	.0612074	.1656786	0.37	0.712	-.2635167	.3859315
dvcew3	-.3890334	.779063	-0.50	0.618	-1.915969	1.137902
sepaw3	1.192013	.8154298	1.46	0.144	-.4062002	2.790226
accdw3	.0577299	.4605728	0.13	0.900	-.8449761	.9604359
movew3	-1.554315	1.416782	-1.10	0.273	-4.331156	1.222526
illw3	-.2170464	.1492827	-1.45	0.146	-.5096352	.0755424
shfamw3	-.006443	.0065281	-0.99	0.324	-.0192379	.0063519
shhlw3	.0069987	.00596	1.17	0.240	-.0046826	.0186801
shjobw3	.002409	.0061202	0.39	0.694	-.0095863	.0144043
shrelaw3	-.0078238	.0063566	-1.23	0.218	-.0202824	.0046348
suprtw3	.0085376	.0067506	1.26	0.206	-.0046933	.0217685
suchrw3	-.007482	.0046136	-1.62	0.105	-.0165246	.0015606
havmilsq	-3.28e-09	1.73e-06	-0.00	0.998	-3.39e-06	3.38e-06
_cons	4.903623	623.5943	0.01	0.994	-1217.319	1227.126

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	45	24	69
-	48	228	276
Total	93	252	345

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	48.39%
Specificity	$\Pr(- \sim D)$	90.48%
Positive predictive value	$\Pr(D +)$	65.22%
Negative predictive value	$\Pr(\sim D -)$	82.61%
False + rate for true ~D	$\Pr(+ \sim D)$	9.52%
False - rate for true D	$\Pr(- D)$	51.61%
False + rate for classified +	$\Pr(\sim D +)$	34.78%
False - rate for classified -	$\Pr(D -)$	17.39%
Correctly classified		79.13%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      345
number of covariate patterns =    345
Pearson chi2(294) =      317.37
Prob > chi2 =      0.1668

```

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-201.075	Log-Lik Full Model:	-147.916
D(289):	295.832	LR(50):	106.318
		Prob > LR:	0.000
McFadden's R2:	0.264	McFadden's Adj R2:	-0.014
Maximum Likelihood R2:	0.265	Cragg & Uhler's R2:	0.385
McKelvey and Zavoina's R2:	0.488	Efron's R2:	0.291
Variance of y*:	6.432	Variance of error:	3.290
Count R2:	0.791	Adj Count R2:	0.226
AIC:	1.182	AIC*n:	407.832
BIC:	-1392.952	BIC':	185.860

Full main model for HP2hmcare for wave= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 for HP2work

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_8 != 0 predicts failure perfectly
 _Ieduc_8 dropped and 2 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

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

note: _Ieduc_7 omitted because of collinearity
 note: occ8w3 omitted because of collinearity
 note: marrw36 omitted because of collinearity

Logistic regression	Number of obs	=	315
	LR chi2(48)	=	139.93
	Prob > chi2	=	0.0000
Log likelihood = -96.893664	Pseudo R2	=	0.4193

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0323974	.0293162	1.11	0.269	-.0250612	.089856
_Ieduc_2	-4.152531	2.287775	-1.82	0.070	-8.636488	.3314257
_Ieduc_3	-1.864493	1.608696	-1.16	0.246	-5.017479	1.288493
_Ieduc_4	0	(omitted)				
_Ieduc_5	-1.404302	1.64491	-0.85	0.393	-4.628265	1.819662
_Ieduc_6	-2.017048	1.54335	-1.31	0.191	-5.041958	1.007861
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-11.82929	1296.263	-0.01	0.993	-2552.458	2528.799
occ2w3	-11.65702	1296.263	-0.01	0.993	-2552.286	2528.972
occ3w3	-12.78325	1296.263	-0.01	0.992	-2553.412	2527.846
occ4w3	-10.84152	1296.263	-0.01	0.993	-2551.47	2529.787
occ5w3	-10.72665	1296.263	-0.01	0.993	-2551.356	2529.903
occ6w3	0	(omitted)				
occ7w3	-11.31316	1296.263	-0.01	0.993	-2551.942	2529.316
occ8w3	0	(omitted)				
marrw31	.3643704	1.429352	0.25	0.799	-2.437107	3.165848
marrw32	-2.206121	1.844343	-1.20	0.232	-5.820966	1.408725
marrw33	-.7934545	1.390519	-0.57	0.568	-3.518821	1.931912
marrw35	-.2775718	1.556356	-0.18	0.858	-3.327973	2.772829
marrw36	0	(omitted)				
inc1w3	14.70395	1296.262	0.01	0.991	-2525.924	2555.332
inc2w3	14.77269	1296.262	0.01	0.991	-2525.855	2555.4
inc3w3	14.57764	1296.262	0.01	0.991	-2526.05	2555.205
inc4w3	15.74154	1296.263	0.01	0.990	-2524.887	2556.37

radhlw3	.0078686	.0080582	0.98	0.329	-.007925	.0236623
havmil	.0027954	.0078952	0.35	0.723	-.0126789	.0182698
avgcumdosew3	.0057068	.0769937	0.07	0.941	-.1451981	.1566117
bf1	-.0445389	.0484618	-0.92	0.358	-.1395224	.0504446
bf4	-.0327423	.2796012	-0.12	0.907	-.5807506	.515266
bf2	.0000822	.0001677	0.49	0.624	-.0002465	.0004108
bf4m	-.341802	.2609957	-1.31	0.190	-.8533441	.1697402
bf5m	.0012439	.0017995	0.69	0.489	-.0022831	.0047709
bf7m	.0005614	.0005422	1.04	0.300	-.0005013	.0016241
bf8	-.0000499	.0000448	-1.11	0.265	-.0001376	.0000379
bf15m	-.0000712	.0003918	-0.18	0.856	-.0008391	.0006966
bf17	0	(omitted)				
bf20	.019063	.0407736	0.47	0.640	-.0608518	.0989778
bf22	.0000146	.0001733	0.08	0.933	-.0003251	.0003543
bf29	.0000124	.0000229	0.54	0.589	-.0000325	.0000572
bf30	-.000416	.0004185	-0.99	0.320	-.0012364	.0004043
bf40	.1486565	.2411791	0.62	0.538	-.3240459	.6213588
deaw3	-.6566764	.3112091	-2.11	0.035	-1.266635	-.0467177
dvcew3	.7731044	1.122755	0.69	0.491	-1.427455	2.973664
sepaw3	.1659839	1.359372	0.12	0.903	-2.498337	2.830305
accdw3	.7493757	.6472786	1.16	0.247	-.519267	2.018018
movew3	.9688514	.5333557	1.82	0.069	-.0765066	2.014209
illw3	.2806377	.2813528	1.00	0.319	-.2708037	.832079
shfamw3	.0045809	.0088802	0.52	0.606	-.0128239	.0219857
shhlw3	-.0144819	.0077	-1.88	0.060	-.0295736	.0006098
shjobw3	-.0101653	.0077745	-1.31	0.191	-.0254031	.0050725
shrelaw3	-.0092584	.0083742	-1.11	0.269	-.0256716	.0071547
suprtw3	-.0009401	.0080071	-0.12	0.907	-.0166337	.0147535
suchrw3	-.004683	.0069496	-0.67	0.500	-.0183041	.008938
havmilsq	-7.50e-06	.0000145	-0.52	0.604	-.0000359	.0000209
_cons	3.229911	4.235709	0.76	0.446	-5.071927	11.53175

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	37	14	51
-	33	231	264
Total	70	245	315

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

Sensitivity	Pr(+ D)	52.86%
Specificity	Pr(- ~D)	94.29%
Positive predictive value	Pr(D +)	72.55%
Negative predictive value	Pr(~D -)	87.50%
False + rate for true ~D	Pr(+ ~D)	5.71%
False - rate for true D	Pr(- D)	47.14%
False + rate for classified +	Pr(~D +)	27.45%
False - rate for classified -	Pr(D -)	12.50%
Correctly classified		85.08%

Logistic model for HP2hmcare, goodness-of-fit test

```

number of observations =      315
number of covariate patterns =    315
    Pearson chi2(266) =    247.97
        Prob > chi2 =    0.7796
  
```

Measures of Fit for **logistic** of HP2hmcare

Log-Lik Intercept Only:	-166.857	Log-Lik Full Model:	-96.894
D(259):	193.787	LR(48):	139.928
		Prob > LR:	0.000
McFadden's R2:	0.419	McFadden's Adj R2:	0.084
Maximum Likelihood R2:	0.359	Cragg & Uhler's R2:	0.549
McKelvey and Zavoina's R2:	0.758	Efron's R2:	0.437
Variance of y*:	13.609	Variance of error:	3.290
Count R2:	0.851	Adj Count R2:	0.329
AIC:	0.971	AIC*n:	305.787
BIC:	-1296.129	BIC':	136.196

Full main model for HP2hmcare for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2hmcare

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

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: occ8w3 != 0 predicts failure perfectly
 occ8w3 dropped and 1 obs not used

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

note: _Ieduc_8 omitted because of collinearity
 convergence not achieved

Logistic regression	Number of obs	=	353
	LR chi2(50)	=	144.83
	Prob > chi2	=	0.0000
Log likelihood = -154.51255	Pseudo R2	=	0.3191

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0784128	.0199184	3.94	0.000	.0393735	.1174521
_Ieduc_2	-16.15888	2.72009	-5.94	0.000	-21.49016	-10.8276
_Ieduc_3	-16.70929	2.647032	-6.31	0.000	-21.89738	-11.5212
_Ieduc_4	-15.65932	2.672964	-5.86	0.000	-20.89823	-10.4204
_Ieduc_5	-16.93546	2.621945	-6.46	0.000	-22.07438	-11.79654
_Ieduc_6	-17.12993	2.678622	-6.40	0.000	-22.37993	-11.87993
_Ieduc_7	-16.6826	3.290952	-5.07	0.000	-23.13274	-10.23245
_Ieduc_8	0	(omitted)				
occ1w3	-17.5089	2870.035	-0.01	0.995	-5642.674	5607.656
occ2w3	-17.42465	2870.035	-0.01	0.995	-5642.59	5607.741
occ3w3	-17.38618	2870.035	-0.01	0.995	-5642.551	5607.779
occ4w3	-17.97919	2870.035	-0.01	0.995	-5643.145	5607.186
occ5w3	-16.19886	2870.036	-0.01	0.995	-5641.366	5608.968
occ6w3	0	(omitted)				
occ7w3	-17.37679	2870.035	-0.01	0.995	-5642.542	5607.789
occ8w3	0	(omitted)				
marrw31	.1254457	1.662878	0.08	0.940	-3.133735	3.384627
marrw32	.689276	1.963389	0.35	0.726	-3.158896	4.537448
marrw33	1.411752	1.537008	0.92	0.358	-1.600728	4.424232
marrw35	.6824445	1.564972	0.44	0.663	-2.384843	3.749732
marrw36	.9604788	1.548632	0.62	0.535	-2.074784	3.995742
inc1w3	18.76205	2870.035	0.01	0.995	-5606.403	5643.927
inc2w3	18.64464	2870.035	0.01	0.995	-5606.521	5643.81
inc3w3	18.13548	2870.035	0.01	0.995	-5607.03	5643.301
inc4w3	18.63139	2870.035	0.01	0.995	-5606.534	5643.797
radhlw3	-.0056373	.0071331	-0.79	0.429	-.0196178	.0083433
havmil	.0003358	.0026887	0.12	0.901	-.004934	.0056056
avgcumdosew3	-.1458757	.0962788	-1.52	0.130	-.3345787	.0428273
bf1	-.0155333	.0271811	-0.57	0.568	-.0688074	.0377407
bf4	-.4865728	.1784134	-2.73	0.006	-.8362567	-.136889
bf2	.0000926	.0001019	0.91	0.364	-.0001072	.0002923
bf4m	.3213367	.1603015	2.00	0.045	.0071516	.6355219
bf5m	-.000883	.0014167	-0.62	0.533	-.0036598	.0018937
bf7m	.0002998	.000443	0.68	0.499	-.0005684	.001168
bf8	6.84e-06	.0000322	0.21	0.832	-.0000563	.00007

bf15m	-.0163738	.5454291	-0.03	0.976	-1.085395	1.052648
bf17	.0008202	.0272715	0.03	0.976	-.0526309	.0542713
bf20	.00093	.0215397	0.04	0.966	-.041287	.043147
bf22	-.0000872	.0001081	-0.81	0.420	-.0002991	.0001247
bf29	0	(omitted)				
bf30	.0000251	.0002916	0.09	0.931	-.0005465	.0005967
bf40	.130008	.1227916	1.06	0.290	-.1106591	.3706751
deaw3	.0165154	.1614822	0.10	0.919	-.2999838	.3330147
dvcew3	.6982802	.7163029	0.97	0.330	-.7056476	2.102208
sepaw3	-.4992309	.8307882	-0.60	0.548	-2.127546	1.129084
accdw3	-.1706856	.4639657	-0.37	0.713	-1.080042	.7386705
movew3	-.4464406	1.157043	-0.39	0.700	-2.714203	1.821322
illw3	-.0890835	.1513588	-0.59	0.556	-.3857412	.2075743
shfamw3	-.0035627	.0062149	-0.57	0.566	-.0157436	.0086183
shhlw3	.0080044	.0056769	1.41	0.159	-.0031221	.0191309
shjobw3	-.0042351	.0058007	-0.73	0.465	-.0156042	.0071341
shrelaw3	-.010315	.0062344	-1.65	0.098	-.0225341	.0019041
suprtw3	-.0017061	.0061593	-0.28	0.782	-.0137782	.010366
suchrw3	-.0030007	.0044692	-0.67	0.502	-.0117602	.0057587
havmilsq	-1.55e-06	2.58e-06	-0.60	0.549	-6.61e-06	3.52e-06
_cons	10.07155	.	.	.	.	.

Note: 4 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	76	29	105
-	45	203	248
Total	121	232	353

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

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	62.81%
Specificity	$\Pr(- \sim D)$	87.50%
Positive predictive value	$\Pr(D +)$	72.38%
Negative predictive value	$\Pr(\sim D -)$	81.85%
False + rate for true ~D	$\Pr(+ \sim D)$	12.50%
False - rate for true D	$\Pr(- D)$	37.19%
False + rate for classified +	$\Pr(\sim D +)$	27.62%
False - rate for classified -	$\Pr(D -)$	18.15%
Correctly classified		79.04%

Logistic model for HP2hmcare, goodness-of-fit test

```
      number of observations =      353
number of covariate patterns =      353
      Pearson chi2(301) =      338.41
      Prob > chi2 =      0.0677
```

Measures of Fit for logistic of HP2hmcare

Log-Lik Intercept Only:	-226.929	Log-Lik Full Model:	-154.513
D(297):	309.025	LR(50):	144.834
		Prob > LR:	0.000
McFadden's R2:	0.319	McFadden's Adj R2:	0.072
Maximum Likelihood R2:	0.337	Cragg & Uhler's R2:	0.465
McKelvey and Zavoina's R2:	0.954	Efron's R2:	0.369
Variance of y*:	71.429	Variance of error:	3.290
Count R2:	0.790	Adj Count R2:	0.388
AIC:	1.193	AIC*n:	421.025
BIC:	-1433.316	BIC':	148.490

Full main model for HP2probsoc for wave= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 for HP2hmcare

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: occ5w3 != 0 predicts failure perfectly
 occ5w3 dropped and 15 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: marrw32 != 0 predicts failure perfectly
 marrw32 dropped and 20 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: occ8w3 omitted because of collinearity
note: marrw36 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	266
	LR chi2(44)	=	125.89
	Prob > chi2	=	0.0000
Log likelihood = -51.38371	Pseudo R2	=	0.5506

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1094616	.0479486	2.28	0.022	.015484	.2034392
_Ieduc_2	.7414425	1.297886	0.57	0.568	-1.802367	3.285252
_Ieduc_3	-1.614771	.8291042	-1.95	0.051	-3.239785	.0102435
_Ieduc_4	0	(omitted)				
_Ieduc_5	-1.309884	1.008415	-1.30	0.194	-3.286342	.6665737
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-14.19493	1124.783	-0.01	0.990	-2218.729	2190.339
occ2w3	-12.80013	1124.783	-0.01	0.991	-2217.335	2191.734
occ3w3	-14.84881	1124.785	-0.01	0.989	-2219.387	2189.689
occ4w3	-13.35572	1124.784	-0.01	0.991	-2217.891	2191.18
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-14.19043	1124.784	-0.01	0.990	-2218.726	2190.345
occ8w3	0	(omitted)				
marrw31	3.074981	1.891094	1.63	0.104	-.6314958	6.781458
marrw32	0	(omitted)				
marrw33	1.087086	1.851071	0.59	0.557	-2.540947	4.715119
marrw35	2.144183	1.926965	1.11	0.266	-1.632599	5.920964
marrw36	0	(omitted)				
inc1w3	12.66541	1124.784	0.01	0.991	-2191.87	2217.201
inc2w3	14.23621	1124.783	0.01	0.990	-2190.299	2218.771
inc3w3	11.68224	1124.783	0.01	0.992	-2192.853	2216.217
inc4w3	13.15717	1124.785	0.01	0.991	-2191.381	2217.695
radhlw3	.0116102	.013936	0.83	0.405	-.0157038	.0389242
havmil	.010259	.0190025	0.54	0.589	-.0269853	.0475032
avgcumdosew3	.013934	.0740721	0.19	0.851	-.1312447	.1591127
bf1	.0049612	.0648373	0.08	0.939	-.1221176	.1320399
bf4	.3309901	.3608169	0.92	0.359	-.376198	1.038178
bf2	.0003753	.0003121	1.20	0.229	-.0002364	.000987
bf4m	-.7073564	.3457629	-2.05	0.041	-1.385039	-.0296735
bf5m	.0055743	.0030295	1.84	0.066	-.0003633	.0115119
bf7m	.0005904	.001055	0.56	0.576	-.0014774	.0026582
bf8	-.0001253	.0000745	-1.68	0.093	-.0002713	.0000207
bf15m	0	(omitted)				

bf17	0	(omitted)				
bf20	-.0283325	.0488173	-0.58	0.562	-.1240127	.0673477
bf22	.000352	.0002932	1.20	0.230	-.0002227	.0009267
bf29	-.0000333	.0000588	-0.57	0.572	-.0001486	.000082
bf30	-.0013785	.0007131	-1.93	0.053	-.0027761	.0000191
bf40	-.3600239	.3692219	-0.98	0.330	-1.083686	.3636377
deaw3	-.5217994	.4891348	-1.07	0.286	-1.480486	.4368872
dvcew3	-.5047921	1.728469	-0.29	0.770	-3.892529	2.882945
sepaw3	1.877558	1.625412	1.16	0.248	-1.308191	5.063307
accdw3	-1.417017	1.419234	-1.00	0.318	-4.198664	1.364631
movew3	-1.057894	1.576256	-0.67	0.502	-4.1473	2.031511
illw3	.0330976	.3751226	0.09	0.930	-.7021292	.7683243
shfamw3	.012083	.0115403	1.05	0.295	-.0105354	.0347015
shhlw3	-.0165557	.0125582	-1.32	0.187	-.0411693	.0080578
shjobw3	.032774	.0134379	2.44	0.015	.0064363	.0591118
shrelaw3	-.0108059	.0117883	-0.92	0.359	-.0339106	.0122988
suprtw3	-.014138	.0155065	-0.91	0.362	-.0445303	.0162542
suchrw3	.0131393	.0111977	1.17	0.241	-.0088078	.0350865
havmilsq	-.000014	.0000386	-0.36	0.717	-.0000896	.0000616
_cons	.4495347	5.049973	0.09	0.929	-9.44823	10.3473

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	27	5	32
-	14	220	234
Total	41	225	266

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	65.85%
Specificity	$\Pr(- \sim D)$	97.78%
Positive predictive value	$\Pr(D +)$	84.38%
Negative predictive value	$\Pr(\sim D -)$	94.02%
False + rate for true ~D	$\Pr(+ \sim D)$	2.22%
False - rate for true D	$\Pr(- D)$	34.15%
False + rate for classified +	$\Pr(\sim D +)$	15.62%
False - rate for classified -	$\Pr(D -)$	5.98%
Correctly classified		92.86%

Logistic model for HP2probsoc, goodness-of-fit test

```
number of observations =      266
number of covariate patterns =    266
Pearson chi2(221) =    138.28
Prob > chi2 =    1.0000
```

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

Log-Lik Intercept Only:	-114.331	Log-Lik Full Model:	-51.384
D(210):	102.767	LR(44):	125.895
		Prob > LR:	0.000
McFadden's R2:	0.551	McFadden's Adj R2:	0.061
Maximum Likelihood R2:	0.377	Cragg & Uhler's R2:	0.654
McKelvey and Zavoina's R2:	0.833	Efron's R2:	0.549
Variance of y*:	19.713	Variance of error:	3.290
Count R2:	0.929	Adj Count R2:	0.537
AIC:	0.807	AIC*n:	214.767
BIC:	-1069.767	BIC':	119.779

Full main model for HP2probsoc for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2probsoc

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
note: occ4w3 != 0 predicts failure perfectly
 occ4w3 dropped and 8 obs not used

note: occ5w3 != 0 predicts failure perfectly
 occ5w3 dropped and 5 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: occ8w3 != 0 predicts failure perfectly
 occ8w3 dropped and 1 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 11 obs not used

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

Logistic regression	Number of obs	=	333
	LR chi2(48)	=	182.65
	Prob > chi2	=	0.0000
Log likelihood = -85.065495	Pseudo R2	=	0.5177

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1095324	.0321452	3.41	0.001	.0465289	.1725358
_Ieduc_2	-13.53237	1231.492	-0.01	0.991	-2427.212	2400.147
_Ieduc_3	-13.52493	1231.492	-0.01	0.991	-2427.204	2400.154
_Ieduc_4	-12.60239	1231.492	-0.01	0.992	-2426.282	2401.077
_Ieduc_5	-12.71374	1231.492	-0.01	0.992	-2426.393	2400.966
_Ieduc_6	-14.01871	1231.492	-0.01	0.991	-2427.698	2399.66
_Ieduc_7	-14.42024	1231.563	-0.01	0.991	-2428.239	2399.398
_Ieduc_8	0	(omitted)				
occ1w3	-1.43031	4.480321	-0.32	0.750	-10.21158	7.350959
occ2w3	-.9422793	4.54239	-0.21	0.836	-9.8452	7.960641
occ3w3	-.9893619	4.495549	-0.22	0.826	-9.800476	7.821752
occ4w3	0	(omitted)				
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-.3813499	4.479039	-0.09	0.932	-9.160105	8.397405
occ8w3	0	(omitted)				
marrw31	-1.356413	4.804963	-0.28	0.778	-10.77397	8.061141
marrw32	1.424321	4.907376	0.29	0.772	-8.193959	11.0426
marrw33	.9014745	4.669929	0.19	0.847	-8.251419	10.05437
marrw35	.1665893	4.645112	0.04	0.971	-8.937664	9.270842
marrw36	.3174753	4.648882	0.07	0.946	-8.794166	9.429116
inc1w3	.8600896	4.513897	0.19	0.849	-7.986987	9.707166
inc2w3	1.384829	4.490321	0.31	0.758	-7.416038	10.1857
inc3w3	.4792744	4.482989	0.11	0.915	-8.307222	9.26577
inc4w3	2.266942	4.835774	0.47	0.639	-7.211	11.74488
radhlw3	.0131788	.0108242	1.22	0.223	-.0080363	.0343939
havmil	.0001731	.0072695	0.02	0.981	-.0140748	.014421
avgcumdosew3	.4373021	.1594734	2.74	0.006	.12474	.7498642
bf1	.0565003	.0423978	1.33	0.183	-.0265978	.1395985
bf4	-.5202783	.2238014	-2.32	0.020	-.9589209	-.0816356
bf2	.0000421	.0001478	0.28	0.776	-.0002477	.0003318
bf4m	.2426577	.1977977	1.23	0.220	-.1450185	.630334
bf5m	-.0017451	.0026768	-0.65	0.514	-.0069915	.0035013
bf7m	.0007865	.0007919	0.99	0.321	-.0007656	.0023387
bf8	.0000207	.0000544	0.38	0.704	-.000086	.0001273
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0669294	.0330398	-2.03	0.043	-.1316862	-.0021726
bf22	-.0000944	.0001823	-0.52	0.605	-.0004517	.0002629
bf29	-.0000309	.000047	-0.66	0.511	-.0001229	.0000611
bf30	.0003246	.0004246	0.76	0.445	-.0005076	.0011567
bf40	.0606979	.1844629	0.33	0.742	-.3008427	.4222385
deaw3	.1696097	.2295421	0.74	0.460	-.2802844	.6195039
dvcew3	.3810548	1.285314	0.30	0.767	-2.138115	2.900224
sepaw3	-2.876602	1.529689	-1.88	0.060	-5.874737	.1215322
accdw3	.1226563	.714668	0.17	0.864	-1.278067	1.52338

movew3	1.918652	1.360681	1.41	0.159	-.7482334	4.585538
illw3	.2671943	.2045213	1.31	0.191	-.1336601	.6680487
shfamw3	-.0003116	.0095404	-0.03	0.974	-.0190104	.0183873
shhlw3	-.0026048	.0074647	-0.35	0.727	-.0172353	.0120256
shjobw3	.006075	.0086284	0.70	0.481	-.0108364	.0229864
shrelaw3	-.0267274	.010033	-2.66	0.008	-.0463918	-.007063
suprtw3	-.0065983	.0100162	-0.66	0.510	-.0262297	.0130331
suchrw3	.0015649	.0064519	0.24	0.808	-.0110806	.0142105
havmilsq	-3.19e-06	.0000124	-0.26	0.797	-.0000275	.0000211
_cons	6.986764	1231.505	0.01	0.995	-2406.718	2420.692

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	54	13	67
-	20	246	266
Total	74	259	333

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	72.97%
Specificity	$\Pr(- \sim D)$	94.98%
Positive predictive value	$\Pr(D +)$	80.60%
Negative predictive value	$\Pr(\sim D -)$	92.48%

False + rate for true ~D	$\Pr(+ \sim D)$	5.02%
False - rate for true D	$\Pr(- D)$	27.03%
False + rate for classified +	$\Pr(\sim D +)$	19.40%
False - rate for classified -	$\Pr(D -)$	7.52%

Correctly classified	90.09%
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Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	333
number of covariate patterns =	333
Pearson $\chi^2(284)$ =	335.12
Prob > χ^2 =	0.0199

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

Log-Lik Intercept Only:	-176.392	Log-Lik Full Model:	-85.065
D(277):	170.131	LR(48):	182.653
		Prob > LR:	0.000
McFadden's R2:	0.518	McFadden's Adj R2:	0.200
Maximum Likelihood R2:	0.422	Cragg & Uhler's R2:	0.646
McKelvey and Zavoina's R2:	0.810	Efron's R2:	0.561
Variance of y*:	17.273	Variance of error:	3.290
Count R2:	0.901	Adj Count R2:	0.554
AIC:	0.847	AIC*n:	282.131
BIC:	-1438.724	BIC':	96.138

Full main model for HP2pbfhm for wave= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 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 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: occ5w3 != 0 predicts failure perfectly
 occ5w3 dropped and 13 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 17 obs not used

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

note: movew3 != 0 predicts failure perfectly
 movew3 dropped and 22 obs not used

note: _Ieduc_6 omitted because of collinearity

note: occ8w3 omitted because of collinearity

note: marrw36 omitted because of collinearity

note: bf17 omitted because of collinearity

Logistic regression

Number of obs = 248

LR chi2(42) = 61.10

Prob > chi2 = 0.0286

Pseudo R2 = 0.4112

Log likelihood = -43.736999

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0762859	.0508028	1.50	0.133	-.0232857	.1758575
_Ieduc_2	0	(omitted)				
_Ieduc_3	-.1477637	.8109786	-0.18	0.855	-1.737253	1.441725
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.7596947	1.090598	-0.70	0.486	-2.897227	1.377837
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-10.90364	2018.344	-0.01	0.996	-3966.785	3944.977
occ2w3	-10.89538	2018.344	-0.01	0.996	-3966.777	3944.986
occ3w3	-9.963313	2018.344	-0.00	0.996	-3965.846	3945.919
occ4w3	-10.3499	2018.344	-0.01	0.996	-3966.232	3945.532
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-10.56369	2018.344	-0.01	0.996	-3966.445	3945.318
occ8w3	0	(omitted)				
marrw31	1.938945	1.834088	1.06	0.290	-1.655802	5.533692
marrw32	2.869349	2.03424	1.41	0.158	-1.117687	6.856385
marrw33	-2.070881	2.007923	-1.03	0.302	-6.006338	1.864576
marrw35	3.548252	2.186549	1.62	0.105	-.7373048	7.833809
marrw36	0	(omitted)				
inc1w3	12.37597	2018.344	0.01	0.995	-3943.505	3968.257
inc2w3	12.75723	2018.343	0.01	0.995	-3943.123	3968.637
inc3w3	11.01982	2018.344	0.01	0.996	-3944.861	3966.9
inc4w3	11.952	2018.345	0.01	0.995	-3943.931	3967.835
radhlw3	.032589	.0182947	1.78	0.075	-.0032679	.0684459
havmil	.0129536	.013774	0.94	0.347	-.0140429	.0399501
avgcumdosew3	-.3791136	.3273992	-1.16	0.247	-1.020804	.2625771
bf1	-.1029605	.0825755	-1.25	0.212	-.2648056	.0588846
bf4	-.1906164	.3464978	-0.55	0.582	-.8697396	.4885069
bf2	.0004772	.0003548	1.35	0.179	-.0002181	.0011725
bf4m	.0772469	.2972932	0.26	0.795	-.505437	.6599308
bf5m	-.0019382	.0047879	-0.40	0.686	-.0113224	.007446
bf7m	.0012129	.001013	1.20	0.231	-.0007725	.0031983
bf8	-3.27e-06	.0000957	-0.03	0.973	-.0001909	.0001843
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0430617	.0653802	0.66	0.510	-.0850811	.1712045
bf22	-4.46e-06	.0002995	-0.01	0.988	-.0005915	.0005826
bf29	0	(omitted)				
bf30	.000126	.0007197	0.18	0.861	-.0012845	.0015365

bf40	.071783	.4795976	0.15	0.881	-.8682111	1.011777
deaw3	.3272315	.4280065	0.76	0.445	-.5116458	1.166109
dvcew3	1.631036	1.568401	1.04	0.298	-1.442973	4.705045
sepaw3	.2595898	1.605075	0.16	0.872	-2.886299	3.405479
accdw3	-.9114258	2.076173	-0.44	0.661	-4.980649	3.157798
movew3	0	(omitted)				
illw3	-.5480408	.5150453	-1.06	0.287	-1.557511	.4614294
shfamw3	.0143257	.0164517	0.87	0.384	-.017919	.0465703
shhlw3	-.0109085	.0129224	-0.84	0.399	-.0362359	.014419
shjobw3	-.0129256	.0143995	-0.90	0.369	-.0411481	.0152969
shrelaw3	-.0047884	.012683	-0.38	0.706	-.0296466	.0200697
suprtw3	.025454	.0177967	1.43	0.153	-.0094269	.0603349
suchrw3	.0037567	.0120299	0.31	0.755	-.0198214	.0273349
havmilsq	-.0000259	.0000249	-1.04	0.299	-.0000746	.0000229
_cons	-12.84498	6.147159	-2.09	0.037	-24.89319	-.79677

Note: 5 failures and 0 successes completely determined.

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	9	4	13
-	13	222	235
Total	22	226	248

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	40.91%
Specificity	$\Pr(- \sim D)$	98.23%
Positive predictive value	$\Pr(D +)$	69.23%
Negative predictive value	$\Pr(\sim D -)$	94.47%

False + rate for true ~D	$\Pr(+ \sim D)$	1.77%
False - rate for true D	$\Pr(- D)$	59.09%
False + rate for classified +	$\Pr(\sim D +)$	30.77%
False - rate for classified -	$\Pr(D -)$	5.53%

Correctly classified	93.15%
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Logistic model for HP2pbfhm, goodness-of-fit test

```

        number of observations =      248
number of covariate patterns =      248
        Pearson chi2(205) =      151.48
            Prob > chi2 =      0.9980

```

Measures of Fit for **logistic** of **HP2pbfhm**

Log-Lik Intercept Only:	-74.286	Log-Lik Full Model:	-43.737
D(192):	87.474	LR(42):	61.099
		Prob > LR:	0.029
McFadden's R2:	0.411	McFadden's Adj R2:	-0.343
Maximum Likelihood R2:	0.218	Cragg & Uhler's R2:	0.485
McKelvey and Zavoina's R2:	0.816	Efron's R2:	0.329
Variance of y*:	17.878	Variance of error:	3.290
Count R2:	0.931	Adj Count R2:	0.227
AIC:	0.804	AIC*n:	199.474
BIC:	-971.104	BIC':	170.465

Full main model for HP2pbfhm for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2pbfhm

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

note: occ2w3 != 0 predicts failure perfectly
 occ2w3 dropped and 37 obs not used

note: occ4w3 != 0 predicts failure perfectly
 occ4w3 dropped and 8 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: occ8w3 != 0 predicts failure perfectly
 occ8w3 dropped and 1 obs not used

note: marrw32 != 0 predicts failure perfectly
 marrw32 dropped and 7 obs not used

note: inc4w3 != 0 predicts failure perfectly
 inc4w3 dropped and 8 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 11 obs not used

note: movew3 != 0 predicts failure perfectly
 movew3 dropped and 9 obs not used

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

Logistic regression

Number of obs = 277

LR chi2(45) = 88.17

Prob > chi2 = 0.0001

Log likelihood = -80.45257

Pseudo R2 = 0.3540

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0605232	.0301499	2.01	0.045	.0014305	.1196159
_Ieduc_2	14.33097	3050.48	0.00	0.996	-5964.5	5993.162
_Ieduc_3	14.57814	3050.48	0.00	0.996	-5964.253	5993.409
_Ieduc_4	14.71229	3050.48	0.00	0.996	-5964.118	5993.543
_Ieduc_5	14.46503	3050.48	0.00	0.996	-5964.366	5993.296
_Ieduc_6	14.13284	3050.48	0.00	0.996	-5964.698	5992.963
_Ieduc_7	16.45371	3050.482	0.01	0.996	-5962.381	5995.289
_Ieduc_8	0	(omitted)				
occ1w3	-.9142061	3.466224	-0.26	0.792	-7.70788	5.879468
occ2w3	0	(omitted)				
occ3w3	-.2867411	3.495557	-0.08	0.935	-7.137908	6.564426
occ4w3	0	(omitted)				
occ5w3	2.578209	4.53518	0.57	0.570	-6.310581	11.467
occ6w3	0	(omitted)				
occ7w3	-.5244179	3.46458	-0.15	0.880	-7.31487	6.266034
occ8w3	0	(omitted)				
marrw31	13.57521	900.684	0.02	0.988	-1751.733	1778.884
marrw32	0	(omitted)				
marrw33	15.5368	900.6835	0.02	0.986	-1749.77	1780.844
marrw35	15.43053	900.6834	0.02	0.986	-1749.877	1780.738
marrw36	15.00571	900.6833	0.02	0.987	-1750.301	1780.313
inc1w3	2.006505	3.516446	0.57	0.568	-4.885601	8.898612
inc2w3	2.111761	3.483985	0.61	0.544	-4.716724	8.940246
inc3w3	1.911831	3.463507	0.55	0.581	-4.876519	8.70018
inc4w3	0	(omitted)				
radhlw3	.0113673	.0123354	0.92	0.357	-.0128096	.0355442
havmil	-.0010166	.0142076	-0.07	0.943	-.0288629	.0268297
avgcumdosew3	-.0338506	.1440343	-0.24	0.814	-.3161526	.2484513
bf1	-.0040962	.0453653	-0.09	0.928	-.0930105	.0848181
bf4	-.3790747	.2483688	-1.53	0.127	-.8658686	.1077192
bf2	.0000525	.0001469	0.36	0.721	-.0002354	.0003404
bf4m	.1263528	.2275811	0.56	0.579	-.3196979	.5724036
bf5m	-.0049342	.0041169	-1.20	0.231	-.0130031	.0031348
bf7m	-.0004133	.0008454	-0.49	0.625	-.0020703	.0012437
bf8	.0001156	.0000755	1.53	0.125	-.0000323	.0002635
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0078983	.0366468	-0.22	0.829	-.0797248	.0639282
bf22	.000158	.0001863	0.85	0.396	-.0002071	.0005231
bf29	9.34e-06	.0000425	0.22	0.826	-.000074	.0000927
bf30	-.0000869	.0004483	-0.19	0.846	-.0009655	.0007917

bf40	-.2779981	.1983152	-1.40	0.161	-.6666887	.1106924
deaw3	-.0223131	.2253092	-0.10	0.921	-.4639109	.4192848
dvcew3	1.571998	1.037736	1.51	0.130	-.4619271	3.605923
sepaw3	-1.894764	1.527486	-1.24	0.215	-4.888582	1.099055
accdw3	-.2729555	.6926052	-0.39	0.694	-1.630437	1.084526
movew3	0	(omitted)				
illw3	-.1949663	.2468671	-0.79	0.430	-.6788169	.2888842
shfamw3	-.0082258	.0094908	-0.87	0.386	-.0268274	.0103758
shhlw3	.0062899	.0080613	0.78	0.435	-.00951	.0220898
shjobw3	-.0009012	.0093159	-0.10	0.923	-.0191601	.0173576
shrelaw3	-.0126452	.0092607	-1.37	0.172	-.0307958	.0055054
suprtw3	-.004099	.0105306	-0.39	0.697	-.0247385	.0165405
suchrw3	-.0078922	.0065901	-1.20	0.231	-.0208085	.0050241
havmilsq	-4.43e-06	.000039	-0.11	0.909	-.0000808	.000072
_cons	-32.88256	3180.671	-0.01	0.992	-6266.884	6201.119

Note: 5 failures and 0 successes completely determined.

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	22	9	31
-	24	222	246
Total	46	231	277

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	47.83%
Specificity	$\Pr(- \sim D)$	96.10%
Positive predictive value	$\Pr(D +)$	70.97%
Negative predictive value	$\Pr(\sim D -)$	90.24%

False + rate for true ~D	$\Pr(+ \sim D)$	3.90%
False - rate for true D	$\Pr(- D)$	52.17%
False + rate for classified +	$\Pr(\sim D +)$	29.03%
False - rate for classified -	$\Pr(D -)$	9.76%

Correctly classified	88.09%
----------------------	--------

Logistic model for HP2pbfhm, goodness-of-fit test

```

      number of observations =      277
number of covariate patterns =      277
      Pearson chi2(231) =     439.38
      Prob > chi2 =           0.0000

```

Measures of Fit for **logistic** of **HP2pbfhm**

Log-Lik Intercept Only:	-124.537	Log-Lik Full Model:	-80.453
D(221):	160.905	LR(45):	88.169
		Prob > LR:	0.000
McFadden's R2:	0.354	McFadden's Adj R2:	-0.096
Maximum Likelihood R2:	0.273	Cragg & Uhler's R2:	0.460
McKelvey and Zavoina's R2:	0.796	Efron's R2:	0.384
Variance of y*:	16.128	Variance of error:	3.290
Count R2:	0.881	Adj Count R2:	0.283
AIC:	0.985	AIC*n:	272.905
BIC:	-1082.003	BIC':	164.912

Full main model for HP2sxlife for wave= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 for HP2pbfhm

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
note: _Ieduc_7 != 0 predicts failure perfectly
 _Ieduc_7 dropped and 4 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 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: _Ieduc_8 omitted because of collinearity
note: occ8w3 omitted because of collinearity
note: marrw36 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	304
	LR chi2(47)	=	153.48
	Prob > chi2	=	0.0000
Log likelihood = -86.082561	Pseudo R2	=	0.4713

HP2sxlif	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1069256	.0319906	3.34	0.001	.0442252	.169626
_Ieduc_2	-.7455102	2.711615	-0.27	0.783	-6.060177	4.569157
_Ieduc_3	-1.187035	2.60622	-0.46	0.649	-6.295133	3.921063
_Ieduc_4	-2.546669	2.819292	-0.90	0.366	-8.072379	2.979041
_Ieduc_5	-.9083698	2.596245	-0.35	0.726	-5.996916	4.180177
_Ieduc_6	-.821989	2.54798	-0.32	0.747	-5.815938	4.17196
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-13.83588	1847.337	-0.01	0.994	-3634.551	3606.879
occ2w3	-14.1177	1847.337	-0.01	0.994	-3634.833	3606.597
occ3w3	-15.12911	1847.338	-0.01	0.993	-3635.845	3605.586
occ4w3	-14.04877	1847.338	-0.01	0.994	-3634.764	3606.666
occ5w3	-13.39243	1847.338	-0.01	0.994	-3634.108	3607.323
occ6w3	0	(omitted)				
occ7w3	-14.25779	1847.337	-0.01	0.994	-3634.973	3606.457
occ8w3	0	(omitted)				
marrw31	1.917986	1.336919	1.43	0.151	-.7023282	4.538299
marrw32	-.8798595	1.841469	-0.48	0.633	-4.489073	2.729354
marrw33	.8814069	1.275273	0.69	0.489	-1.618082	3.380896
marrw35	1.398611	1.615954	0.87	0.387	-1.768602	4.565823
marrw36	0	(omitted)				
inclw3	16.59262	1847.337	0.01	0.993	-3604.122	3637.307
inc2w3	16.41393	1847.337	0.01	0.993	-3604.3	3637.128
inc3w3	14.9931	1847.337	0.01	0.994	-3605.721	3635.708
inc4w3	13.76529	1847.339	0.01	0.994	-3606.952	3634.482
radhlw3	.0155883	.0090158	1.73	0.084	-.0020824	.0332591
havmil	.0032884	.0119659	0.27	0.783	-.0201643	.0267412
avgcumdosew3	.0366781	.0541231	0.68	0.498	-.0694012	.1427574
bf1	.0224773	.0438725	0.51	0.608	-.0635113	.108466
bf4	-.3119601	.2453847	-1.27	0.204	-.7929052	.168985
bf2	.0000786	.0001745	0.45	0.652	-.0002634	.0004207
bf4m	.0103662	.2174828	0.05	0.962	-.4158923	.4366247
bf5m	.0028825	.0019867	1.45	0.147	-.0010113	.0067763
bf7m	.0013372	.0006507	2.05	0.040	.0000618	.0026126
bf8	-.0000698	.0000479	-1.46	0.145	-.0001638	.0000241
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0288329	.0347084	-0.83	0.406	-.09686	.0391943
bf22	-.0000907	.0001888	-0.48	0.631	-.0004608	.0002793
bf29	0	(omitted)				
bf30	-5.44e-06	.0004196	-0.01	0.990	-.0008279	.0008171
bf40	.3549975	.2522025	1.41	0.159	-.1393104	.8493054
deaw3	-.1446966	.2515866	-0.58	0.565	-.6377974	.3484041
dvcew3	.2312151	1.685819	0.14	0.891	-3.07293	3.535361
sepaw3	1.563211	1.973158	0.79	0.428	-2.304108	5.430529
accdw3	-1.029126	.9986452	-1.03	0.303	-2.986435	.9281827

movew3	-.3161441	.7920977	-0.40	0.690	-1.868627	1.236339
illw3	.2509498	.2730406	0.92	0.358	-.2841998	.7860995
shfamw3	-.0049114	.0092237	-0.53	0.594	-.0229895	.0131668
shhlw3	-.0135671	.0078785	-1.72	0.085	-.0290087	.0018746
shjobw3	.0090088	.0079953	1.13	0.260	-.0066617	.0246793
shrelaw3	-.0052844	.0083104	-0.64	0.525	-.0215726	.0110037
suprtw3	.0083949	.0090554	0.93	0.354	-.0093533	.0261431
suchrw3	-.0115343	.0079215	-1.46	0.145	-.0270603	.0039916
havmilsq	-.0000122	.0000253	-0.48	0.630	-.0000618	.0000374
_cons	-6.912277	3.93482	-1.76	0.079	-14.62438	.7998281

Note: 4 failures and 0 successes completely determined.

Logistic model for HP2sxlif

Classified	True		Total
	D	~D	
+	44	14	58
-	25	221	246
Total	69	235	304

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

True D defined as HP2sxlif != 0

Sensitivity	$\Pr(+ D)$	63.77%
Specificity	$\Pr(- \sim D)$	94.04%
Positive predictive value	$\Pr(D +)$	75.86%
Negative predictive value	$\Pr(\sim D -)$	89.84%

False + rate for true ~D	$\Pr(+ \sim D)$	5.96%
False - rate for true D	$\Pr(- D)$	36.23%
False + rate for classified +	$\Pr(\sim D +)$	24.14%
False - rate for classified -	$\Pr(D -)$	10.16%

Correctly classified	87.17%
----------------------	--------

Logistic model for HP2sxlif, goodness-of-fit test

number of observations =	304
number of covariate patterns =	304
Pearson $\chi^2(256)$ =	202.32
Prob > χ^2 =	0.9943

Measures of Fit for logistic of HP2sxlif

Log-Lik Intercept Only:	-162.820	Log-Lik Full Model:	-86.083
D(248):	172.165	LR(47):	153.476
		Prob > LR:	0.000
McFadden's R2:	0.471	McFadden's Adj R2:	0.127
Maximum Likelihood R2:	0.396	Cragg & Uhler's R2:	0.603
McKelvey and Zavoina's R2:	0.800	Efron's R2:	0.484
Variance of y*:	16.474	Variance of error:	3.290
Count R2:	0.872	Adj Count R2:	0.435
AIC:	0.935	AIC*n:	284.165
BIC:	-1245.658	BIC':	115.224

Full main model for HP2sxlife for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2sxlife

i.educ _Ieduc_1-8 (naturally coded; _Ieduc_1 omitted)
 note: occ8w3 != 0 predicts failure perfectly
 occ8w3 dropped and 1 obs not used

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: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	345
	LR chi2(50)	=	168.03
	Prob > chi2	=	0.0000
Log likelihood = -114.00457	Pseudo R2	=	0.4243

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0813848	.0244496	3.33	0.001	.0334644	.1293053
_Ieduc_2	-12.79022	653.1326	-0.02	0.984	-1292.907	1267.326
_Ieduc_3	-11.94607	653.1326	-0.02	0.985	-1292.062	1268.17
_Ieduc_4	-11.36768	653.1328	-0.02	0.986	-1291.484	1268.749
_Ieduc_5	-12.54328	653.1327	-0.02	0.985	-1292.66	1267.573
_Ieduc_6	-11.93918	653.1326	-0.02	0.985	-1292.055	1268.177
_Ieduc_7	-12.87216	653.1524	-0.02	0.984	-1293.027	1267.283
_Ieduc_8	0	(omitted)				
occ1w3	-2.703036	2.21975	-1.22	0.223	-7.053665	1.647593
occ2w3	-2.165029	2.323461	-0.93	0.351	-6.718929	2.388871
occ3w3	-2.030908	2.234964	-0.91	0.364	-6.411358	2.349542
occ4w3	-1.625969	2.528132	-0.64	0.520	-6.581016	3.329078
occ5w3	.7269315	2.820396	0.26	0.797	-4.800943	6.254806
occ6w3	-.7633882	2.518786	-0.30	0.762	-5.700118	4.173342

occ7w3	-1.433838	2.203631	-0.65	0.515	-5.752876	2.8852
occ8w3	0	(omitted)				
marrw31	.3247443	1.774101	0.18	0.855	-3.152431	3.801919
marrw32	.8501767	2.207491	0.39	0.700	-3.476427	5.17678
marrw33	1.557872	1.575773	0.99	0.323	-1.530585	4.646329
marrw35	-.4253418	1.619183	-0.26	0.793	-3.598882	2.748198
marrw36	1.703593	1.601915	1.06	0.288	-1.436102	4.843288
inclw3	1.766812	2.253827	0.78	0.433	-2.650608	6.184231
inc2w3	2.269344	2.224897	1.02	0.308	-2.091374	6.630061
inc3w3	.9292343	2.201873	0.42	0.673	-3.386357	5.244826
inc4w3	1.449624	2.775037	0.52	0.601	-3.989349	6.888597
radhlw3	.0277216	.0091569	3.03	0.002	.0097745	.0456688
havmil	.0021336	.0032179	0.66	0.507	-.0041733	.0084405
avgcumdosew3	.1969924	.1165031	1.69	0.091	-.0313496	.4253343
bf1	.0285984	.0382244	0.75	0.454	-.04632	.1035168
bf4	-.4015139	.2038932	-1.97	0.049	-.8011373	-.0018905
bf2	-.0001649	.0001225	-1.35	0.178	-.0004051	.0000753
bf4m	.3523301	.1864609	1.89	0.059	-.0131266	.7177867
bf5m	-.0026053	.001955	-1.33	0.183	-.006437	.0012264
bf7m	-.0000741	.0006237	-0.12	0.905	-.0012966	.0011483
bf8	-5.22e-06	.0000423	-0.12	0.902	-.0000881	.0000777
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0120216	.031995	-0.38	0.707	-.0747307	.0506874
bf22	-.0001004	.0001357	-0.74	0.459	-.0003664	.0001655
bf29	0	(omitted)				
bf30	-.0002441	.0003438	-0.71	0.478	-.0009179	.0004298
bf40	.095062	.1371931	0.69	0.488	-.1738314	.3639555
deaw3	.0760781	.1918427	0.40	0.692	-.2999267	.4520829
dvcew3	1.127371	.952705	1.18	0.237	-.7398962	2.994639
sepaw3	.5833047	.936842	0.62	0.534	-1.252872	2.419481
accdw3	-.5118992	.5859911	-0.87	0.382	-1.660421	.6366223
movew3	-.6063637	1.823477	-0.33	0.739	-4.180313	2.967586
illw3	.1168429	.1761008	0.66	0.507	-.2283082	.4619941
shfamw3	.0084815	.007536	1.13	0.260	-.0062888	.0232518
shhlw3	.0066923	.0066985	1.00	0.318	-.0064365	.0198212
shjobw3	-.0046191	.0070704	-0.65	0.514	-.0184767	.0092386
shrelaw3	-.0123617	.0074084	-1.67	0.095	-.0268819	.0021585
suprtw3	-.0091554	.0078461	-1.17	0.243	-.0245335	.0062227
suchrw3	-.0034248	.0055225	-0.62	0.535	-.0142486	.0073991
havmilsq	-2.54e-06	2.55e-06	-1.00	0.319	-7.52e-06	2.45e-06
_cons	1.83356	653.1407	0.00	0.998	-1278.299	1281.966

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	60	12	72
-	30	243	273
Total	90	255	345

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	66.67%
Specificity	$\Pr(- \sim D)$	95.29%
Positive predictive value	$\Pr(D +)$	83.33%
Negative predictive value	$\Pr(\sim D -)$	89.01%
False + rate for true ~D	$\Pr(+ \sim D)$	4.71%
False - rate for true D	$\Pr(- D)$	33.33%
False + rate for classified +	$\Pr(\sim D +)$	16.67%
False - rate for classified -	$\Pr(D -)$	10.99%
Correctly classified		87.83%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      345
number of covariate patterns =    345
Pearson chi2(294) =      343.22
Prob > chi2 =      0.0254

```

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-198.018	Log-Lik Full Model:	-114.005
D(289):	228.009	LR(50):	168.026
		Prob > LR:	0.000
McFadden's R2:	0.424	McFadden's Adj R2:	0.141
Maximum Likelihood R2:	0.386	Cragg & Uhler's R2:	0.565
McKelvey and Zavoina's R2:	0.693	Efron's R2:	0.483
Variance of y*:	10.715	Variance of error:	3.290
Count R2:	0.878	Adj Count R2:	0.533
AIC:	0.986	AIC*n:	340.009
BIC:	-1460.775	BIC':	124.151

Full main model for HP2inthob for wave= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 for HP2sxlife

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: occ5w3 != 0 predicts failure perfectly
occ5w3 dropped and 15 obs not used

note: occ6w3 != 0 predicts failure perfectly
occ6w3 dropped and 4 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 18 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: occ8w3 omitted because of collinearity
note: marrw36 omitted because of collinearity
note: bf17 omitted because of collinearity
convergence not achieved

Logistic regression	Number of obs	=	276
	LR chi2(42)	=	117.91
	Prob > chi2	=	0.0000
Log likelihood = -51.649162	Pseudo R2	=	0.5330

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0817005	.0490304	1.67	0.096	-.0143972	.1777983
_Ieduc_2	-1.531634	1.790651	-0.86	0.392	-5.041245	1.977977
_Ieduc_3	-1.560462	.8580327	-1.82	0.069	-3.242176	.1212508
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.5489736	.8124194	-0.68	0.499	-2.141286	1.043339
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occlw3	-16.51737	2.253408	-7.33	0.000	-20.93397	-12.10077
occ2w3	-19.33038	2.062721	-9.37	0.000	-23.37324	-15.28752
occ3w3	-17.4588	2.676679	-6.52	0.000	-22.70499	-12.2126
occ4w3	-16.4147	2.207406	-7.44	0.000	-20.74113	-12.08826
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				

occ7w3	-16.18451	2.199404	-7.36	0.000	-20.49527	-11.87376
occ8w3	0	(omitted)				
marrw31	.8557338	1.989444	0.43	0.667	-3.043506	4.754973
marrw32	1.067638	2.133137	0.50	0.617	-3.113233	5.248509
marrw33	-.0597494	1.809944	-0.03	0.974	-3.607174	3.487675
marrw35	4.178796	2.178555	1.92	0.055	-.091092	8.448685
marrw36	0	(omitted)				
inclw3	14.99624	2.039372	7.35	0.000	10.99915	18.99334
inc2w3	15.54638	1.847372	8.42	0.000	11.92559	19.16716
inc3w3	16.08957	1.659414	9.70	0.000	12.83718	19.34196
inc4w3	20.06926	.	.	.	.	.
radhlw3	.0608448	.0162567	3.74	0.000	.0289822	.0927074
havmil	.004278	.0106932	0.40	0.689	-.0166802	.0252362
avgcumdosew3	-.3594081	.1656258	-2.17	0.030	-.6840288	-.0347874
bf1	-1.832947	.1402107	-13.07	0.000	-2.107755	-1.558139
bf4	-.1459909	.3386475	-0.43	0.666	-.8097278	.5177459
bf2	-.0007134	.0002919	-2.44	0.015	-.0012855	-.0001412
bf4m	-.0648788	.3169386	-0.20	0.838	-.6860671	.5563094
bf5m	-.0059221	.0033107	-1.79	0.074	-.0124109	.0005667
bf7m	-.00068	.0010134	-0.67	0.502	-.0026661	.0013062
bf8	.0000248	.0000707	0.35	0.726	-.0001137	.0001633
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	1.839453	.1331884	13.81	0.000	1.578408	2.100497
bf22	.000278	.0003035	0.92	0.360	-.0003168	.0008728
bf29	0	(omitted)				
bf30	.0006467	.000603	1.07	0.284	-.0005352	.0018286
bf40	.2996033	.3950361	0.76	0.448	-.4746533	1.07386
deaw3	-.6086988	.5212369	-1.17	0.243	-1.630304	.4129068
dvcew3	-.2319255	1.621511	-0.14	0.886	-3.410029	2.946178
sepaw3	-1.758194	2.087814	-0.84	0.400	-5.850234	2.333846
accdw3	.9189185	1.049895	0.88	0.381	-1.138839	2.976676
movew3	-1.391188	1.335043	-1.04	0.297	-4.007824	1.225448
illw3	-.3817302	.3999312	-0.95	0.340	-1.165581	.4021205
shfamw3	.0654585	.0176224	3.71	0.000	.0309192	.0999978
shhlw3	-.0105181	.0103515	-1.02	0.310	-.0308067	.0097705
shjobw3	-.0144707	.0115767	-1.25	0.211	-.0371606	.0082192
shrelaw3	-.0392022	.0137786	-2.85	0.004	-.0662077	-.0121967
suprtw3	.0070974	.0130297	0.54	0.586	-.0184403	.0326352
suchrw3	-.00232	.0110986	-0.21	0.834	-.0240728	.0194327
havmilsq	-7.67e-06	.0000192	-0.40	0.690	-.0000453	.00003
_cons	-80.28913	.	.	.	.	.

Note: 32 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	23	7	30
-	15	231	246
Total	38	238	276

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	60.53%
Specificity	$\Pr(- \sim D)$	97.06%
Positive predictive value	$\Pr(D +)$	76.67%
Negative predictive value	$\Pr(\sim D -)$	93.90%
False + rate for true ~D	$\Pr(+ \sim D)$	2.94%
False - rate for true D	$\Pr(- D)$	39.47%
False + rate for classified +	$\Pr(\sim D +)$	23.33%
False - rate for classified -	$\Pr(D -)$	6.10%
Correctly classified		92.03%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      276
number of covariate patterns =    276
Pearson chi2(231) =      123.26
Prob > chi2 =      1.0000

```

Measures of Fit for logistic of HP2inthob

Log-Lik Intercept Only:	-110.602	Log-Lik Full Model:	-51.649
D(220):	103.298	LR(42):	117.906
		Prob > LR:	0.000
McFadden's R2:	0.533	McFadden's Adj R2:	0.027
Maximum Likelihood R2:	0.348	Cragg & Uhler's R2:	0.631
McKelvey and Zavoina's R2:	0.982	Efron's R2:	0.500
Variance of y*:	180.636	Variance of error:	3.290
Count R2:	0.920	Adj Count R2:	0.421
AIC:	0.780	AIC*n:	215.298
BIC:	-1133.190	BIC':	118.151

Full main model for HP2inthob for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2inthob

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

note: occ4w3 != 0 predicts failure perfectly
occ4w3 dropped and 8 obs not used

note: occ5w3 != 0 predicts failure perfectly
occ5w3 dropped and 5 obs not used

note: occ8w3 != 0 predicts failure perfectly
occ8w3 dropped and 1 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 11 obs not used

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

Logistic regression	Number of obs	=	337
	LR chi2(49)	=	118.21
	Prob > chi2	=	0.0000
Log likelihood = -107.57156	Pseudo R2	=	0.3546

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0683881	.0247447	2.76	0.006	.0198893	.1168869
_Ieduc_2	-13.79024	962.4068	-0.01	0.989	-1900.073	1872.492
_Ieduc_3	-12.92792	962.4068	-0.01	0.989	-1899.211	1873.355
_Ieduc_4	-12.05387	962.4069	-0.01	0.990	-1898.337	1874.229
_Ieduc_5	-12.19345	962.407	-0.01	0.990	-1898.476	1874.09
_Ieduc_6	-13.09489	962.4068	-0.01	0.989	-1899.378	1873.188
_Ieduc_7	-13.1998	962.4102	-0.01	0.989	-1899.489	1873.089
_Ieduc_8	0	(omitted)				
occlw3	-1.2723	3.511631	-0.36	0.717	-8.154969	5.61037
occ2w3	-2.590551	3.713618	-0.70	0.485	-9.869108	4.688006
occ3w3	-.8635752	3.536644	-0.24	0.807	-7.79527	6.06812
occ4w3	0	(omitted)				
occ5w3	0	(omitted)				
occ6w3	-.2036246	3.739879	-0.05	0.957	-7.533652	7.126403
occ7w3	-.4066434	3.50728	-0.12	0.908	-7.280786	6.467499
occ8w3	0	(omitted)				
marrw31	-2.820802	1.835568	-1.54	0.124	-6.418449	.776846
marrw32	-2.10882	2.397053	-0.88	0.379	-6.806958	2.589318
marrw33	-2.047151	1.625637	-1.26	0.208	-5.233341	1.13904
marrw35	-2.933509	1.682447	-1.74	0.081	-6.231043	.3640262
marrw36	-2.100943	1.718745	-1.22	0.222	-5.469621	1.267736
inc1w3	1.771469	3.538577	0.50	0.617	-5.164014	8.706952
inc2w3	1.229926	3.52319	0.35	0.727	-5.675399	8.13525
inc3w3	1.602207	3.508288	0.46	0.648	-5.273911	8.478326
inc4w3	2.650063	3.832399	0.69	0.489	-4.861301	10.16143
radhlw3	.0254128	.010363	2.45	0.014	.0051018	.0457239

havmil	.0052121	.0043654	1.19	0.232	-.003344	.0137682
avgcumdosew3	.0592875	.0898505	0.66	0.509	-.1168163	.2353913
bf1	-.0386178	.0465636	-0.83	0.407	-.1298807	.0526452
bf4	-.3299735	.2318908	-1.42	0.155	-.7844712	.1245242
bf2	5.14e-06	.0001261	0.04	0.967	-.000242	.0002523
bf4m	.24058	.2177227	1.10	0.269	-.1861487	.6673088
bf5m	-.0019924	.0019912	-1.00	0.317	-.0058951	.0019104
bf7m	-.000918	.0006896	-1.33	0.183	-.0022697	.0004336
bf8	6.91e-06	.0000428	0.16	0.872	-.0000771	.0000909
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0290415	.0410365	0.71	0.479	-.0513885	.1094715
bf22	.000145	.000139	1.04	0.297	-.0001275	.0004175
bf29	.0000291	.0000389	0.75	0.455	-.0000472	.0001054
bf30	.0005863	.0003477	1.69	0.092	-.0000953	.0012679
bf40	-.1903404	.1540477	-1.24	0.217	-.4922683	.1115876
deaw3	-.0727208	.201017	-0.36	0.718	-.4667069	.3212652
dvcew3	-.3675995	.8921998	-0.41	0.680	-2.116279	1.38108
sepaw3	1.146748	.9391994	1.22	0.222	-.6940491	2.987545
accdw3	-.0400125	.5697822	-0.07	0.944	-1.156765	1.07674
movev3	.1242816	1.400684	0.09	0.929	-2.621008	2.869572
illw3	.0326786	.1772251	0.18	0.854	-.3146761	.3800333
shfamw3	-.0089451	.0081686	-1.10	0.273	-.0249552	.0070651
shhlw3	-.0019331	.0067351	-0.29	0.774	-.0151336	.0112673
shjobw3	.0022608	.0074164	0.30	0.760	-.012275	.0167966
shrelaw3	.0045217	.0078937	0.57	0.567	-.0109497	.0199931
suprtw3	-.0034378	.0085075	-0.40	0.686	-.0201123	.0132366
suchrw3	-.0106093	.0056039	-1.89	0.058	-.0215928	.0003741
havmilsq	-4.33e-06	6.65e-06	-0.65	0.515	-.0000174	8.70e-06
_cons	7.330327	962.4125	0.01	0.994	-1878.964	1893.624

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	33	12	45
-	33	259	292
Total	66	271	337

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	50.00%
Specificity	$\Pr(- \sim D)$	95.57%
Positive predictive value	$\Pr(D +)$	73.33%
Negative predictive value	$\Pr(\sim D -)$	88.70%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	4.43%
False - rate for true D	$\Pr(- D)$	50.00%
False + rate for classified +	$\Pr(\sim D +)$	26.67%
False - rate for classified -	$\Pr(D -)$	11.30%
Correctly classified		86.65%

Logistic model for HP2inthob, goodness-of-fit test

```

      number of observations =      337
number of covariate patterns =      337
      Pearson chi2(287) =      317.53
          Prob > chi2 =      0.1040
  
```

Measures of Fit for **logistic** of HP2inthob

Log-Lik Intercept Only:	-166.677	Log-Lik Full Model:	-107.572
D(281):	215.143	LR(49):	118.210
		Prob > LR:	0.000
McFadden's R2:	0.355	McFadden's Adj R2:	0.019
Maximum Likelihood R2:	0.296	Cragg & Uhler's R2:	0.471
McKelvey and Zavoina's R2:	0.678	Efron's R2:	0.373
Variance of y*:	10.209	Variance of error:	3.290
Count R2:	0.866	Adj Count R2:	0.318
AIC:	0.971	AIC*n:	327.143
BIC:	-1420.300	BIC':	166.974

Full main model for HP2vacatn for wave= 3

chunk 2 H1 test:Gender= 1 model Wave = 3 for HP2inthob

```

i.educ      _Ieduc_1-8      (naturally coded; _Ieduc_1 omitted)
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: occ5w3 != 0 predicts failure perfectly
occ5w3 dropped and 18 obs not used

note: occ6w3 != 0 predicts failure perfectly
occ6w3 dropped and 4 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 19 obs not used

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

note: _Ieduc_6 omitted because of collinearity

note: occ8w3 omitted because of collinearity

note: marrw36 omitted because of collinearity

note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	286
	LR chi2(45)	=	130.35
	Prob > chi2	=	0.0000
Log likelihood = -52.374274	Pseudo R2	=	0.5544

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1141267	.0450696	2.53	0.011	.025792	.2024615
_Ieduc_2	1.212945	1.630503	0.74	0.457	-1.982782	4.408672
_Ieduc_3	-1.181748	.8345653	-1.42	0.157	-2.817465	.4539703
_Ieduc_4	-.2703336	1.707405	-0.16	0.874	-3.616786	3.076119
_Ieduc_5	.0781642	.821705	0.10	0.924	-1.532348	1.688676
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occlw3	-13.38278	1622.421	-0.01	0.993	-3193.27	3166.504
occ2w3	-12.82938	1622.421	-0.01	0.994	-3192.717	3167.058
occ3w3	-12.16922	1622.422	-0.01	0.994	-3192.057	3167.719
occ4w3	-9.847245	1622.421	-0.01	0.995	-3189.735	3170.04
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-10.21639	1622.421	-0.01	0.995	-3190.104	3169.671
occ8w3	0	(omitted)				
marrw31	2.471663	1.877772	1.32	0.188	-1.208702	6.152028
marrw32	3.882172	2.040109	1.90	0.057	-.116367	7.880711
marrw33	.7861586	1.848468	0.43	0.671	-2.836772	4.409089
marrw35	5.481699	2.097529	2.61	0.009	1.370617	9.592781
marrw36	0	(omitted)				
inclw3	12.51469	1622.421	0.01	0.994	-3167.373	3192.402
inc2w3	14.55722	1622.421	0.01	0.993	-3165.329	3194.444
inc3w3	14.35316	1622.421	0.01	0.993	-3165.533	3194.24

inc4w3	15.92527	1622.422	0.01	0.992	-3163.963	3195.813
radhlw3	.0197321	.0147075	1.34	0.180	-.0090941	.0485583
havmil	.0234742	.0160068	1.47	0.143	-.0078985	.054847
avgcumdosew3	.1032883	.1755565	0.59	0.556	-.240796	.4473726
bf1	-.4769574	.3289335	-1.45	0.147	-1.121655	.1677405
bf4	-.1442369	.2873042	-0.50	0.616	-.7073429	.4188691
bf2	.0000186	.0002978	0.06	0.950	-.0005651	.0006023
bf4m	-.1956152	.2497206	-0.78	0.433	-.6850586	.2938281
bf5m	-.0071533	.0043294	-1.65	0.098	-.0156388	.0013321
bf7m	.0000185	.0010386	0.02	0.986	-.0020172	.0020542
bf8	-.0000173	.0000922	-0.19	0.851	-.0001981	.0001635
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.4362509	.3222411	1.35	0.176	-.1953299	1.067832
bf22	.0001349	.0003106	0.43	0.664	-.0004739	.0007437
bf29	0	(omitted)				
bf30	-.0009931	.0006553	-1.52	0.130	-.0022775	.0002912
bf40	.5185801	.3611964	1.44	0.151	-.1893518	1.226512
deaw3	.2097501	.3135963	0.67	0.504	-.4048875	.8243876
dvcew3	2.012022	1.543197	1.30	0.192	-1.012588	5.036632
sepaw3	-2.054184	1.443349	-1.42	0.155	-4.883097	.7747288
accdw3	.2022258	1.25899	0.16	0.872	-2.265349	2.669801
movew3	-4.177869	1.807922	-2.31	0.021	-7.721331	-.6344073
illw3	-.4549089	.4293751	-1.06	0.289	-1.296469	.3866508
shfamw3	.0141549	.0145895	0.97	0.332	-.0144399	.0427498
shhlw3	.004885	.011315	0.43	0.666	-.0172919	.0270619
shjobw3	-.0003857	.0112584	-0.03	0.973	-.0224516	.0216803
shrelaw3	-.008433	.0120996	-0.70	0.486	-.0321477	.0152817
suprtw3	.0050194	.0152005	0.33	0.741	-.0247729	.0348118
suchrw3	-.0175411	.0097951	-1.79	0.073	-.0367391	.0016569
havmilsq	-.000046	.0000341	-1.35	0.178	-.0001129	.0000209
_cons	-25.70032	13.82795	-1.86	0.063	-52.80261	1.40197

Note: 8 failures and 0 successes completely determined.

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	24	6	30
-	17	239	256
Total	41	245	286

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

Sensitivity	$\Pr(+ D)$	58.54%
Specificity	$\Pr(- \sim D)$	97.55%
Positive predictive value	$\Pr(D +)$	80.00%
Negative predictive value	$\Pr(\sim D -)$	93.36%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	2.45%
False - rate for true D	$\Pr(- D)$	41.46%
False + rate for classified +	$\Pr(\sim D +)$	20.00%
False - rate for classified -	$\Pr(D -)$	6.64%
Correctly classified		91.96%

Logistic model for HP2vacatn, goodness-of-fit test

```

number of observations =      286
number of covariate patterns =    286
    Pearson chi2(240) =    528.62
        Prob > chi2 =      0.0000
  
```

Measures of Fit for **logistic** of HP2vacatn

Log-Lik Intercept Only:	-117.549	Log-Lik Full Model:	-52.374
D(230):	104.749	LR(45):	130.349
		Prob > LR:	0.000
McFadden's R2:	0.554	McFadden's Adj R2:	0.078
Maximum Likelihood R2:	0.366	Cragg & Uhler's R2:	0.653
McKelvey and Zavoina's R2:	0.907	Efron's R2:	0.558
Variance of y*:	35.214	Variance of error:	3.290
Count R2:	0.920	Adj Count R2:	0.439
AIC:	0.758	AIC*n:	216.749
BIC:	-1196.130	BIC':	124.170

Full main model for HP2vacatn for wave= 3

chunk 2 H1 test:Gender= 2 model Wave = 3 for HP2vacatn

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

note: occ4w3 != 0 predicts failure perfectly
 occ4w3 dropped and 8 obs not used

note: occ5w3 != 0 predicts failure perfectly
 occ5w3 dropped and 5 obs not used

note: occ8w3 != 0 predicts failure perfectly
occ8w3 dropped and 1 obs not used

note: marrw32 != 0 predicts failure perfectly
marrw32 dropped and 8 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 11 obs not used

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

Logistic regression	Number of obs	=	329
	LR chi2(48)	=	107.68
	Prob > chi2	=	0.0000
Log likelihood = -106.83646	Pseudo R2	=	0.3351

HP2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0746889	.02598	2.87	0.004	.0237689	.1256088
_Ieduc_2	-16.28929	1372.198	-0.01	0.991	-2705.747	2673.169
_Ieduc_3	-16.27345	1372.198	-0.01	0.991	-2705.731	2673.185
_Ieduc_4	-13.92789	1372.198	-0.01	0.992	-2703.386	2675.53
_Ieduc_5	-15.70958	1372.198	-0.01	0.991	-2705.168	2673.749
_Ieduc_6	-15.75581	1372.198	-0.01	0.991	-2705.214	2673.702
_Ieduc_7	-16.71287	1372.201	-0.01	0.990	-2706.178	2672.752
_Ieduc_8	0	(omitted)				
occ1w3	-.9957645	2.610666	-0.38	0.703	-6.112575	4.121046
occ2w3	.3619615	2.64581	0.14	0.891	-4.82373	5.547653
occ3w3	-.2672451	2.620799	-0.10	0.919	-5.403917	4.869426
occ4w3	0	(omitted)				
occ5w3	0	(omitted)				
occ6w3	.7685654	2.898646	0.27	0.791	-4.912676	6.449807
occ7w3	-.2239682	2.598386	-0.09	0.931	-5.316711	4.868774
occ8w3	0	(omitted)				
marrw31	-3.154883	1.936003	-1.63	0.103	-6.949379	.6396133
marrw32	0	(omitted)				
marrw33	-1.629296	1.549774	-1.05	0.293	-4.666797	1.408206
marrw35	-.9785838	1.561258	-0.63	0.531	-4.038593	2.081425
marrw36	-.3736998	1.605068	-0.23	0.816	-3.519575	2.772176
inc1w3	1.236811	2.644541	0.47	0.640	-3.946394	6.420017
inc2w3	.3422181	2.612526	0.13	0.896	-4.778239	5.462675
inc3w3	.477638	2.599192	0.18	0.854	-4.616684	5.57196
inc4w3	.3174794	3.090064	0.10	0.918	-5.738935	6.373894
radhlw3	.0219342	.0098316	2.23	0.026	.0026647	.0412037
havmil	.0027203	.0039816	0.68	0.494	-.0050834	.010524
avgcumdosew3	.1848178	.1050999	1.76	0.079	-.0211742	.3908099
bf1	-.0115945	.040594	-0.29	0.775	-.0911573	.0679684

bf4	-.0350483	.2076999	-0.17	0.866	-.4421326	.372036
bf2	-.000079	.0001334	-0.59	0.554	-.0003406	.0001825
bf4m	-.0423071	.1886429	-0.22	0.823	-.4120403	.3274261
bf5m	.0008456	.0017602	0.48	0.631	-.0026043	.0042955
bf7m	-.0004985	.0006465	-0.77	0.441	-.0017657	.0007687
bf8	-.0000606	.0000411	-1.48	0.140	-.0001411	.0000199
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0059388	.0344891	0.17	0.863	-.0616586	.0735362
bf22	.000128	.0001403	0.91	0.362	-.000147	.0004031
bf29	.0000416	.0000406	1.02	0.305	-.000038	.0001212
bf30	-.0003884	.0003734	-1.04	0.298	-.0011201	.0003434
bf40	-.1764055	.1673262	-1.05	0.292	-.5043588	.1515477
deaw3	.3451488	.2008083	1.72	0.086	-.0484283	.7387259
dvcew3	-.5492396	.9270299	-0.59	0.554	-2.366185	1.267706
sepaw3	1.201095	.9159312	1.31	0.190	-.5940969	2.996287
accdw3	.4787823	.5402897	0.89	0.376	-.5801659	1.537731
movew3	-.0774101	1.282853	-0.06	0.952	-2.591756	2.436936
illw3	-.2768508	.1854421	-1.49	0.135	-.6403106	.0866091
shfamw3	-.0081517	.0081915	-1.00	0.320	-.0242067	.0079032
shhlw3	.00718	.0069706	1.03	0.303	-.0064821	.0208421
shjobw3	-.0010439	.0078157	-0.13	0.894	-.0163623	.0142745
shrelaw3	-.0076648	.0080911	-0.95	0.343	-.0235231	.0081936
suprtw3	.0076145	.0086776	0.88	0.380	-.0093932	.0246222
suchrw3	-.0085201	.0055112	-1.55	0.122	-.0193219	.0022816
havmilsq	-2.61e-06	5.42e-06	-0.48	0.630	-.0000132	8.01e-06
_cons	12.03817	1372.201	0.01	0.993	-2677.427	2701.503

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2vacatn

Classified	True		Total
	D	~D	
+	27	10	37
-	36	256	292
Total	63	266	329

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

Sensitivity	$\Pr(+ D)$	42.86%
Specificity	$\Pr(- \sim D)$	96.24%
Positive predictive value	$\Pr(D +)$	72.97%
Negative predictive value	$\Pr(\sim D -)$	87.67%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	3.76%
False - rate for true D	$\Pr(- D)$	57.14%
False + rate for classified +	$\Pr(\sim D +)$	27.03%
False - rate for classified -	$\Pr(D -)$	12.33%
Correctly classified		86.02%

Logistic model for HP2vacatn, goodness-of-fit test

```

      number of observations =      329
number of covariate patterns =      329
      Pearson chi2(280) =      296.45
          Prob > chi2 =      0.2388
  
```

Measures of Fit for logistic of HP2vacatn

Log-Lik Intercept Only:	-160.675	Log-Lik Full Model:	-106.836
D(273):	213.673	LR(48):	107.678
		Prob > LR:	0.000
McFadden's R2:	0.335	McFadden's Adj R2:	-0.013
Maximum Likelihood R2:	0.279	Cragg & Uhler's R2:	0.448
McKelvey and Zavoina's R2:	0.632	Efron's R2:	0.351
Variance of y*:	8.945	Variance of error:	3.290
Count R2:	0.860	Adj Count R2:	0.270
AIC:	0.990	AIC*n:	325.673
BIC:	-1368.651	BIC':	170.533

```

182 .
183 . title4 "trimming male moderator models of dose and HP2work relationship in w
    > ave 3 "

```

```
trimming male moderator models of dose and HP2work relationship in wave 3
```

```

184 . * male models
185 .     forvalues j=3/3 {
    2. di as input "Gender =1 HP2work model"
    3.     logit HP2work age bf8 illw`j' shjobw`j' havmilsq avgcumdosew`j' i
> f gender==1
    4.             estat class
    5.             estat gof
    6.             fitstat
    7. }
Gender =1 HP2work model

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -148.75217
Iteration 2:  log likelihood = -147.11486
Iteration 3:  log likelihood = -147.09824
Iteration 4:  log likelihood = -147.09823

```

Logistic regression	Number of obs	=	340
	LR chi2(6)	=	51.55
	Prob > chi2	=	0.0000
Log likelihood = -147.09823	Pseudo R2	=	0.1491

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0473544	.0138047	3.43	0.001	.0202977	.0744111
bf8	-.0000527	.0000245	-2.15	0.032	-.0001007	-4.62e-06
illw3	.7688236	.1582366	4.86	0.000	.4586855	1.078962
shjobw3	.0115141	.0039727	2.90	0.004	.0037277	.0193004
havmilsq	-1.04e-06	1.75e-06	-0.59	0.552	-4.46e-06	2.38e-06
avgcumdosew3	.0105615	.0472406	0.22	0.823	-.0820282	.1031513
_cons	-4.59543	.8195918	-5.61	0.000	-6.201801	-2.98906

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	17	6	23
-	53	264	317
Total	70	270	340

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	24.29%
Specificity	$\Pr(- \sim D)$	97.78%
Positive predictive value	$\Pr(D +)$	73.91%
Negative predictive value	$\Pr(\sim D -)$	83.28%
False + rate for true ~D	$\Pr(+ \sim D)$	2.22%
False - rate for true D	$\Pr(- D)$	75.71%
False + rate for classified +	$\Pr(\sim D +)$	26.09%
False - rate for classified -	$\Pr(D -)$	16.72%
Correctly classified		82.65%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    324
    Pearson chi2(317) =    321.28
        Prob > chi2 =      0.4224

```

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

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-147.098
D(333):	294.196	LR(6):	51.549
		Prob > LR:	0.000
McFadden's R2:	0.149	McFadden's Adj R2:	0.109
Maximum Likelihood R2:	0.141	Cragg & Uhler's R2:	0.220
McKelvey and Zavoina's R2:	0.240	Efron's R2:	0.164
Variance of y*:	4.329	Variance of error:	3.290
Count R2:	0.826	Adj Count R2:	0.157
AIC:	0.906	AIC*n:	308.196
BIC:	-1646.842	BIC':	-16.576

```

186 .
187 .
188 . forvalues j=3/3 {
      2. title4 "trimmed HP2work main effects models wave `j' for H1 part 2 with d
> ose ns"
      3.
189 . }

```

```
trimmed HP2work main effects models wave 3 for H1 part 2 with dose ns
```

```

190 .
191 .
192 . forvalues j=3/3 {
      2.                                sw, pr(.1):logistic HP2work age bf8 illw`j' shjobw`j' hav
> milsq ///
      3.                                avgcumdosew`j' if gender==1, coef nolog
      4.                                estat class
      5.                                estat gof
      6.                                fitstat
      7.                                begin with full model
p = 0.8231 >= 0.1000 removing avgcumdosew3
p = 0.5467 >= 0.1000 removing havmilsq

```

```

Logistic regression                                Number of obs   =          340
                                                    LR chi2(4)        =          51.04
                                                    Prob > chi2       =          0.0000
Log likelihood = -147.35095                        Pseudo R2        =          0.1476

```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0477661	.0137843	3.47	0.001	.0207495	.0747828
bf8	-.0000502	.0000239	-2.10	0.036	-.0000971	-3.37e-06
illw3	.7513091	.1545821	4.86	0.000	.4483337	1.054285
shjobw3	.011716	.0039653	2.95	0.003	.0039441	.0194878
_cons	-4.626957	.8195405	-5.65	0.000	-6.233227	-3.020687

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	16	7	23
-	54	263	317
Total	70	270	340

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	22.86%
Specificity	$\Pr(- \sim D)$	97.41%
Positive predictive value	$\Pr(D +)$	69.57%
Negative predictive value	$\Pr(\sim D -)$	82.97%
False + rate for true ~D	$\Pr(+ \sim D)$	2.59%
False - rate for true D	$\Pr(- D)$	77.14%
False + rate for classified +	$\Pr(\sim D +)$	30.43%
False - rate for classified -	$\Pr(D -)$	17.03%
Correctly classified		82.06%

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    272
    Pearson chi2(267) =    278.53
        Prob > chi2 =      0.3013

```

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-147.351
D(335):	294.702	LR(4):	51.044
		Prob > LR:	0.000
McFadden's R2:	0.148	McFadden's Adj R2:	0.119
Maximum Likelihood R2:	0.139	Cragg & Uhler's R2:	0.218
McKelvey and Zavoina's R2:	0.237	Efron's R2:	0.162
Variance of y*:	4.312	Variance of error:	3.290
Count R2:	0.821	Adj Count R2:	0.129
AIC:	0.896	AIC*n:	304.702
BIC:	-1657.995	BIC':	-27.728

```

193 .
194 . forvalues j=3/3 {
      2.          sw, pr(.1):logistic HP2work age bf8 illw`j' shjobw`j' hav
> milsq ///
>          avgcumdosew`j' if gender==2, coef nolog
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.9255 >= 0.1000 removing bf8
p = 0.8830 >= 0.1000 removing shjobw3
p = 0.5343 >= 0.1000 removing havmilsq
p = 0.6152 >= 0.1000 removing illw3
p = 0.1142 >= 0.1000 removing avgcumdosew3

```

```

Logistic regression                                Number of obs   =       362
                                                    LR chi2(1)         =       42.20
                                                    Prob > chi2        =       0.0000
Log likelihood =  -185.1665                      Pseudo R2          =       0.1023

```

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.070115	.0116471	6.02	0.000	.047287	.0929429
_cons	-4.733748	.6446886	-7.34	0.000	-5.997314	-3.470181

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	20	14	34
-	73	255	328
Total	93	269	362

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

Sensitivity	$\Pr(+ D)$	21.51%
Specificity	$\Pr(- \sim D)$	94.80%
Positive predictive value	$\Pr(D +)$	58.82%
Negative predictive value	$\Pr(\sim D -)$	77.74%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.20%
False - rate for true D	$\Pr(- D)$	78.49%
False + rate for classified +	$\Pr(\sim D +)$	41.18%
False - rate for classified -	$\Pr(D -)$	22.26%
Correctly classified		75.97%

Logistic model for HP2work, goodness-of-fit test

number of observations =	362
number of covariate patterns =	49
Pearson $\chi^2(47)$ =	58.24
Prob > χ^2 =	0.1261

Measures of Fit for logistic of HP2work

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-185.167
D(360):	370.333	LR(1):	42.199
		Prob > LR:	0.000
McFadden's R2:	0.102	McFadden's Adj R2:	0.093
Maximum Likelihood R2:	0.110	Cragg & Uhler's R2:	0.162
McKelvey and Zavoina's R2:	0.174	Efron's R2:	0.127
Variance of y*:	3.982	Variance of error:	3.290
Count R2:	0.760	Adj Count R2:	0.065
AIC:	1.034	AIC*n:	374.333
BIC:	-1750.659	BIC':	-36.308

```

195 .
196 .
197 . scalar SigDoseWkFw3 = "no"

198 .
199 .
200 . des bf8

```

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

```

201 . * male sign main effects in main effects model: 4- age, bf8, illw3 shjobw3
202 . * male main effects model avgcumdosew3 was not signif.
203 . * male hp2wk w3 mediators: age illw3 ageXillw3 bf8
204 . * female signif main effects in main effects model
205 . * female hp2wk w3 mediators: radhlw3 age ageXillw3 bf1 bf4 bf4m bf40
206 . * hypothnuym pt dv wave gender signif
207 .
208 .
209 .
210 .
211 . title4 " 1. Summary matrix construction Paid employment partition: first two
> rows"

```

```

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

```

```

212 .
213 .     matrix define HP2wkMw3 = J(1,8, 0)

214 .     matrix define HP2wkFw3 = J(1,8, 0)

215 . matrix colnames HP2wkMw3=  hypnum ptnum wave gender medsig numMA sig numModsi
> g numMed

```

```

216 . matrix colnames HP2wkFw3=  hypnum ptnum wave gender medsig numMAsig numModsi
    > g numMed

217 .      matrix rownames HP2wkMw3 = workM

218 .      matrix rownames HP2wkFw3 = workF

219 .          matrix define HP2wkMw3= (1, 2, 3, 1, 0 ,4,  0, 4 )

220 .          matrix define HP2wkFw3= (1, 2, 3, 2, 0, 1,  0, 6 )

221 .

222 .          matrix define H1pt2w3 = (HP2wkMw3 \ HP2wkFw3)

223 .      matrix colnames H1pt2w3 =  hypnum ptnum wave  medsig numMAsig numModsig
    > numMed

224 .      matrix rownames H1pt2w3 = HP2wkMw3 WHP2wkFw3

225 .      matlist H1pt2w3

```

	hypnum	ptnum	wave	medsig	numMAsig	numModsi
> g						
> —						
HP2wkMw3	1	2	3	1	0	
> 4						
WHP2wkFw3	1	2	3	2	0	
> 1						

	numMed	numMed
HP2wkMw3	0	4
WHP2wkFw3	0	6

```

226 .

227 . scalar SigDoseWKMw3 = "no"

```

```

228 . scalar MainEfffwkMw3 = "workM: age  bf8  illw3  shjobw3"

229 .
230 . scalar list `MainEfffwkMw3'
    VactnMedFw3 = age illw3 radhlw3
    VactnMedMw3 = age illw3
    VacatnModFw3 = none
    MainEffVactnFw3 = age radhlw3 deaw3
    SigDoseVactnFw3 = no
    vactnModMw3 = none
    MainEffVactnMw3 = age bf7m radhlw3
    SigDoseVactnMw3 = no
    sxLifeMedFw3 = age bf4 bf4m
    sxLifeMedMw3 = age illw3
    InthbModFw3 = none
    MainEffInthbFw3 = age radhlw3 bf4
    SigdoseInthbFw3 = no
    InthbMw3 = none
    MainEffInthbMw3 = age radhlw3 shfamw3
    SigDoseInthbMw3 = no
    sxlifeMedFw3 = age illw3 radhlw3 bf4 bf4m
    sxlifeMedMw3 = age illw3
    sxlifeModFw3 = none
    MainEffsxlifeFw3 = age radhlw3 bf4 bf4m shrelaw3 shfamw3
    SigDoseSxlifeFw3 = no
    sxlifeModMw3 = none
    SigDosesxlifeMw3 = no
    MainEffsxlifeMw3 = age bf4 illw3 radhlw3
    PrbfmhmMedFw3 = age bf4
    PrbfmhmMedMw3 = age
    PrbfmhmModFw3 = none
    MainEffPrbfmhmFw3 = age bf4 bf40
    SigDosePrbfmhmFw3 = no
    PrbfmhmModw3 = none
    SigDosePrbfmhmMw3 = no
    SigDosePrbfhmMw3 = no
    MainEffPrbfhmMw3 = bf1 bf4 dvcew3 bf7m
    ProbsocMedFw3 = age radhlw3
    ProbsocMedMw3 = age
    ProbsocModFw3 = none
    MainEffProbSocFw3 = age radhlw3 illw3 Shrelaw3 avgcumodsew3
    SigDoseProbsocFw3 = yes
    ProbSocModMw3 = none
    SigDoseProbsocMw3 = no
    MainEffPrbsocMw3 = age radhlw3 shjobw3
    hmcareMedFw3 = age illw3
    hmcareMedMw3 = age illw3
    hmcareModFw3 = none
    SigdoseHmcareFw3 = no

```

```

hmcareModMw3 = none
MainEffhmcareMw3 = none
SigDoseHmcareMw3 = no
    wkMedFw3 = radhlw3 age bf40 bf4m bf1
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no
    medsigFw2 = 1
    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

```

```

231 .
232 . * moderator construction
233 . * none ussed because basic dose work relationship washes out
234 .
235 .
236 .
237 . title4 "testing male hp2work moderators for hypothesis 1 pt 2 wave 3"

```

```

testing male hp2work moderators for hypothesis 1 pt 2 wave 3

```

```

238 . * Dose work relationship washes out for males in wave 3 also
239 . cap gen hp2hmcare=HP2hmcare

240 .
241 . forvalues j=3/3 {
      2. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3. di as input "For females HP2work on wave 3 with dose ns"
      4.          des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' bf8 /
      > //
      >          marrw`j'1-marrw`j'6 `w3bf'
      5.          sw, pr(.1): logistic HP2work marrw`j'3-marrw`j'6 age havmilsq //
      > /
      >          avgcumdosew3 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 3 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w3	double	%15.0g	LABJ	professional executive administration now
occ2w3	double	%15.0g	LABJ	technical sales admin support now
occ3w3	double	%15.0g	LABJ	service occup protective services now
occ4w3	double	%15.0g	LABJ	precision prod mechan craft construction now
occ5w3	double	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	double	%15.0g	LABJ	homemaking or caregiving now

occ8w3	double	%15.0g	LABJ	student now
inclw3	double	%15.0g	LABJ	Income is not sufficient for
				basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for
				basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics
				plus extra purchases/savings
				NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably
				afford luxury items NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending
				12/31/2009
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) *
				bf5m
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==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)
				begin with full model
p = 0.9521	>=	0.1000	removing bf8	
p = 0.9034	>=	0.1000	removing marrw33	
p = 0.8340	>=	0.1000	removing shjobw3	
p = 0.6525	>=	0.1000	removing marrw35	
p = 0.5244	>=	0.1000	removing havmilsq	

p = **0.5971** >= 0.1000 removing **illw3**
 p = **0.5333** >= 0.1000 removing **suprtw3**
 p = **0.5822** >= 0.1000 removing **marrw34**
 p = **0.4224** >= 0.1000 removing **marrw36**
 p = **0.1142** >= 0.1000 removing **avgcumdosew3**

Logistic regression	Number of obs	=	362
	LR chi2(1)	=	42.20
	Prob > chi2	=	0.0000
Log likelihood = -185.1665	Pseudo R2	=	0.1023

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.070115	.0116471	6.02	0.000	.047287	.0929429
_cons	-4.733748	.6446886	-7.34	0.000	-5.997314	-3.470181

Logistic model for HP2work, goodness-of-fit test

number of observations =	362
number of covariate patterns =	49
Pearson chi2(47) =	58.24
Prob > chi2 =	0.1261

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	20	14	34
-	73	255	328
Total	93	269	362

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

Sensitivity	Pr(+ D)	21.51%
Specificity	Pr(- ~D)	94.80%
Positive predictive value	Pr(D +)	58.82%
Negative predictive value	Pr(~D -)	77.74%
False + rate for true ~D	Pr(+ ~D)	5.20%
False - rate for true D	Pr(- D)	78.49%
False + rate for classified +	Pr(~D +)	41.18%
False - rate for classified -	Pr(D -)	22.26%

Correctly classified

75.97%

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

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-185.167
D(360):	370.333	LR(1):	42.199
		Prob > LR:	0.000
McFadden's R2:	0.102	McFadden's Adj R2:	0.093
Maximum Likelihood R2:	0.110	Cragg & Uhler's R2:	0.162
McKelvey and Zavoina's R2:	0.174	Efron's R2:	0.127
Variance of y*:	3.982	Variance of error:	3.290
Count R2:	0.760	Adj Count R2:	0.065
AIC:	1.034	AIC*n:	374.333
BIC:	-1750.659	BIC':	-36.308

```
242 .
243 . scalar MainEffwkFw3 = "age"

244 .
245 .
246 .
247 . forvalues j=3/3 {
      2. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3.
248 . di as input "For females HP2work on wave 3 with dose ns"
      4.      des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' bf8 /
      > //
      >      marrw`j'1-marrw`j'6 `w3bf'
      5.      sw, pr(.1): logistic HP2work marrw`j'3-marrw`j'6 age havmilsq //
      > /
      >      avgcumdosew3 bf8 illw`j' shjobw`j' suprtw`j' if gender==1, c
      > oef nolog
      6.      estat gof
      7.      estat class
      8.      fitstat
      9.      }
For females HP2work on wave 3 with dose ns
```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w3	double	%15.0g	LABJ	professional executive administration now
occ2w3	double	%15.0g	LABJ	technical sales admin support now
occ3w3	double	%15.0g	LABJ	service occup protective services now
occ4w3	double	%15.0g	LABJ	precision prod mechan craft construction now
occ5w3	double	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	double	%15.0g	LABJ	homemaking or caregiving now
occ8w3	double	%15.0g	LABJ	student now
inc1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009
bf8	float	%9.0g		bf8 = max(0, radtlw3 - 40) * bf5m
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==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: marrw34 dropped because of collinearity

begin with full model

p = **0.6924** >= 0.1000 removing **avgcumdosew3**

p = **0.5691** >= 0.1000 removing **marrw36**

p = **0.5489** >= 0.1000 removing **havmilsq**

p = **0.5439** >= 0.1000 removing **marrw35**

Logistic regression

Number of obs = **340**

LR chi2(6) = **54.97**

Prob > chi2 = **0.0000**

Log likelihood = **-145.3871**

Pseudo R2 = **0.1590**

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
marrw33	-.9533134	.4976353	-1.92	0.055	-1.928661	.0220339
bf8	-.0000528	.0000242	-2.18	0.029	-.0001002	-5.32e-06
shjobw3	.0109505	.0039896	2.74	0.006	.003131	.0187701
age	.0475117	.0137133	3.46	0.001	.0206342	.0743892
illw3	.7534933	.157365	4.79	0.000	.4450635	1.061923
suprtw3	.0095264	.0057237	1.66	0.096	-.0016919	.0207447
_cons	-4.534902	.8292162	-5.47	0.000	-6.160136	-2.909668

Logistic model for HP2work, goodness-of-fit test

```

number of observations = 340
number of covariate patterns = 320
Pearson chi2(313) = 320.59
Prob > chi2 = 0.3716

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	18	7	25
-	52	263	315
Total	70	270	340

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

True D defined as HP2work != 0

Sensitivity	$\Pr(+ D)$	25.71%
Specificity	$\Pr(- \sim D)$	97.41%
Positive predictive value	$\Pr(D +)$	72.00%
Negative predictive value	$\Pr(\sim D -)$	83.49%
False + rate for true ~D	$\Pr(+ \sim D)$	2.59%
False - rate for true D	$\Pr(- D)$	74.29%
False + rate for classified +	$\Pr(\sim D +)$	28.00%
False - rate for classified -	$\Pr(D -)$	16.51%
Correctly classified		82.65%

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

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-145.387
D(333):	290.774	LR(6):	54.972
		Prob > LR:	0.000
McFadden's R2:	0.159	McFadden's Adj R2:	0.119
Maximum Likelihood R2:	0.149	Cragg & Uhler's R2:	0.234
McKelvey and Zavoina's R2:	0.253	Efron's R2:	0.177
Variance of y*:	4.403	Variance of error:	3.290
Count R2:	0.826	Adj Count R2:	0.157
AIC:	0.896	AIC*n:	304.774
BIC:	-1650.265	BIC':	-19.998

```

249 .
250 .
251 .
252 . * capturing significant vars from last analysis
253 . local cn1: colnames(e(b))

254 . di "`cn1'"
      marrw33 bf8 shjobw3 age illw3 suprtw3 _cons

255 . local leng1 = length( "`cn1'")

256 . di `leng1'
      43

257 . local leng1b `leng1'-6

258 . di `leng1b'
      37

259 . local nuvlist = substr("`cn1'",1,`leng1b')

260 . di "`nuvlist'"
      marrw33 bf8 shjobw3 age illw3 suprtw3

261 . local rhsvars = "`nuvlist'"

262 . local nuvlist= "`nuvlist'"

263 . local nuvlist= substr("`cn1'",1,`leng1b')

264 . di "`nuvlist'"
      marrw33 bf8 shjobw3 age illw3 suprtw3

265 . sw, pr(.1):logit hp2hmcare `nuvlist' if gender==1
                        begin with full model
p = 0.9998 >= 0.1000 removing marrw33
p = 0.9539 >= 0.1000 removing shjobw3
p = 0.4193 >= 0.1000 removing suprtw3
p = 0.1605 >= 0.1000 removing bf8

Logistic regression                                Number of obs   =       340
                                                    LR chi2(2)      =       37.81
                                                    Prob > chi2     =       0.0000
Log likelihood = -153.96835                        Pseudo R2       =       0.1094

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.050053	.0120837	4.14	0.000	.0263694	.0737367
illw3	.450018	.1335457	3.37	0.001	.1882732	.7117629
_cons	-4.209924	.6577161	-6.40	0.000	-5.499024	-2.920824

```

266 . di "`rhsvars'"
      marrw3 bf8 shjobw3 age illw3 suprtw3

267 . matrix define c=e(b)

268 . local cn2: colnames(c)

269 . di "`cn2'"
      age illw3 _cons

270 . local leng2 = length("`cn2'")

271 . local leng2b = `leng2'-6

272 . local rhsvars = substr("`cn2'",1,`leng2b')

273 . logit hp2work `rhsvars' if gender==1

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -155.70854
Iteration 2:  log likelihood = -154.73483
Iteration 3:  log likelihood = -154.7292
Iteration 4:  log likelihood = -154.7292

```

Logistic regression	Number of obs	=	340
	LR chi2(2)	=	36.29
	Prob > chi2	=	0.0000
Log likelihood = -154.7292	Pseudo R2	=	0.1050

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.029911	.0118759	2.52	0.012	.0066346	.0531873
illw3	.6323839	.1414947	4.47	0.000	.3550594	.9097083
_cons	-3.26854	.6276516	-5.21	0.000	-4.498715	-2.038366

```

274 .
275 .
276 .
277 . di "`rhsvars'"
    age illw3

278 . local varlist2 =substr("`rhsvars'",1,9)

279 . di "`varlist2'"
    age illw3

280 .
281 . * constructing potential moderators
282 . foreach var in age illw3 {
    2. cap gen `var'Xd3 = `var'* avgcumdosew3
    3. }

283 .
284 . * main effects model
285 .
286 . logit hp2work `rhsvars' if gender==1, nolog

```

```

Logistic regression                                Number of obs   =          340
                                                    LR chi2(2)      =          36.29
                                                    Prob > chi2     =          0.0000
Log likelihood =  -154.7292                      Pseudo R2       =          0.1050

```

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.029911	.0118759	2.52	0.012	.0066346	.0531873
illw3	.6323839	.1414947	4.47	0.000	.3550594	.9097083
_cons	-3.26854	.6276516	-5.21	0.000	-4.498715	-2.038366

```

287 .
288 . *x no signif male moderators for paid employment

```

```

289 .
290 . logit hp2work `rhsvars' illw3Xd3 if gender==1

```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -155.25678
Iteration 2:  log likelihood = -154.38518
Iteration 3:  log likelihood = -154.38145
Iteration 4:  log likelihood = -154.38145

```

```

Logistic regression                                Number of obs   =          340
                                                    LR chi2(3)      =          36.98
                                                    Prob > chi2     =          0.0000
Log likelihood = -154.38145                        Pseudo R2      =          0.1070

```

hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0293019	.0119141	2.46	0.014	.0059507	.0526531
illw3	.5890952	.14968	3.94	0.000	.2957278	.8824626
illw3Xd3	.0284995	.0363345	0.78	0.433	-.0427148	.0997139
_cons	-3.238806	.6288194	-5.15	0.000	-4.471269	-2.006342

```

291 . fitstat

```

Measures of Fit for **logit** of **hp2work**

```

Log-Lik Intercept Only:      -172.873      Log-Lik Full Model:      -154.381
D(336):                      308.763      LR(3):                  36.983
                               Prob > LR:      0.000
McFadden's R2:              0.107      McFadden's Adj R2:      0.084
Maximum Likelihood R2:      0.103      Cragg & Uhler's R2:      0.161
McKelvey and Zavoina's R2:  0.160      Efron's R2:             0.127
Variance of y*:             3.919      Variance of error:      3.290
Count R2:                   0.818      Adj Count R2:           0.114
AIC:                        0.932      AIC*n:                  316.763
BIC:                        -1649.763    BIC':                   -19.496

```

```

292 .
293 . scalar wkModMw3 = "none"

294 . * Testing female moderator models xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
    > xxxxx
295 .
296 . title4 "testing general female moderator models for hp2work"

```

```

testing general female moderator models for hp2work

```

```

297 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0

298 . * Moderator testing for women also
299 . * Dose work relationship for females in wave 3 washes out also
300 .
301 . forvalues j=3/3 {
    2. di as input "For females HP2work on wave 3 with dose ns"
    3. des age occ1w`j'-occ8w`j' incl1w`j'-inc4w`j' avgcumdosew`j' `w3bf'
    4. sw, pr(.1): logistic HP2work age havmilsq ///
    > avgcumdosew3 illw`j' shjobw`j' suprtw`j' if gender==2, coef nolog
    5. estat gof
    6. estat class
    7. fitstat
    8. }
For females HP2work on wave 3 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w3	double	%15.0g	LABJ	professional executive administration now
occ2w3	double	%15.0g	LABJ	technical sales admin support now
occ3w3	double	%15.0g	LABJ	service occup protective services now
occ4w3	double	%15.0g	LABJ	precision prod mechan craft construction now
occ5w3	double	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	double	%15.0g	LABJ	homemaking or caregiving now
occ8w3	double	%15.0g	LABJ	student now
incl1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for

inc3w3	double	%15.0g	LABJ	basic neccessities NOW Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009
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 = **0.8907** >= 0.1000 removing **suprtw3**
p = **0.8830** >= 0.1000 removing **shjobw3**
p = **0.5343** >= 0.1000 removing **havmilsq**
p = **0.6152** >= 0.1000 removing **illw3**
p = **0.1142** >= 0.1000 removing **avgcumdosew3**

Logistic regression

Log likelihood = **-185.1665**

Number of obs	=	362
LR chi2(1)	=	42.20
Prob > chi2	=	0.0000
Pseudo R2	=	0.1023

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.070115	.0116471	6.02	0.000	.047287	.0929429
_cons	-4.733748	.6446886	-7.34	0.000	-5.997314	-3.470181

Logistic model for HP2work, goodness-of-fit test

```

number of observations =      362
number of covariate patterns =    49
    Pearson chi2(47) =    58.24
        Prob > chi2 =    0.1261

```

Logistic model for HP2work

Classified	True		Total
	D	~D	
+	20	14	34
-	73	255	328
Total	93	269	362

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

Sensitivity	Pr(+ D)	21.51%
Specificity	Pr(- ~D)	94.80%
Positive predictive value	Pr(D +)	58.82%
Negative predictive value	Pr(~D -)	77.74%

False + rate for true ~D	Pr(+ ~D)	5.20%
False - rate for true D	Pr(- D)	78.49%
False + rate for classified +	Pr(~D +)	41.18%
False - rate for classified -	Pr(D -)	22.26%

Correctly classified	75.97%
----------------------	---------------

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

Log-Lik Intercept Only:	-206.266	Log-Lik Full Model:	-185.167
D(360):	370.333	LR(1):	42.199
		Prob > LR:	0.000
McFadden's R2:	0.102	McFadden's Adj R2:	0.093
Maximum Likelihood R2:	0.110	Cragg & Uhler's R2:	0.162
McKelvey and Zavoina's R2:	0.174	Efron's R2:	0.127
Variance of y*:	3.982	Variance of error:	3.290
Count R2:	0.760	Adj Count R2:	0.065
AIC:	1.034	AIC*n:	374.333
BIC:	-1750.659	BIC':	-36.308

```

302 .
303 . replace ageXd3 = age*avgcumdosew3
    (0 real changes made)

304 .
305 . * capturing significant vars
306 . local cn3: colnames(e(b))

307 . di "`cn3'"
    age _cons

308 . local leng1 = length( "`cn3'")

309 . di `leng3'

310 . local leng1b `leng1'-6

311 . di `leng3b'

312 . local nuvlist3 = substr("`cn1'",1,`leng1b')

313 . di "`nuvlist3'"
    mar

```

```

314 . local rhsvars3 = "`nuvlist3'"
315 . local nuvlist3= "`nuvlist3'"
316 . local nuvlist3= substr("`cn1'",1,`lengthb')
317 . di "`nuvlist3'"
    mar
318 .
319 . * moderators for hp2work female and male are saved as scalars:
320 . scalar wkModFw3="none"
321 . scalar wkModMw3="none"
322 .
323 . *x trimmed female main effects model for paid employment
324 . forvalues j=3/3 {
    2. di as input "For females hp2probsoc on wave 1 with dose ns"
    3. des age occ1w`j'-occ8w`j' inc1w`j'-inc4w`j' avgcumdosew`j' `w3bf'
    4. logistic HP2work age ///
    > avgcumdosew3 illw`j' if gender==2, coef nolog
    5.
325 . }
For females hp2probsoc on wave 1 with dose ns

```

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w3	double	%15.0g	LABJ	professional executive administration now
occ2w3	double	%15.0g	LABJ	technical sales admin support now
occ3w3	double	%15.0g	LABJ	service occup protective services now
occ4w3	double	%15.0g	LABJ	precision prod mechan craft construction now
occ5w3	double	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	double	%15.0g	LABJ	homemaking or caregiving now
occ8w3	double	%15.0g	LABJ	student now
inc1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics

```

                                plus extra purchases/savings
                                NOW
inc4w3          double %15.0g      LABJ      Income allows to comfortably
                                afford luxury items NOW
avgcumdosew3    double %8.0g              Avg Mean dose of CS137 ending
                                12/31/2009
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(3)      =      44.36
Prob > chi2     =      0.0000
Pseudo R2      =      0.1074

```

Log likelihood = **-184.38047**

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0671516	.0118118	5.69	0.000	.044001	.0903022
avgcumdosew3	.098591	.0655698	1.50	0.133	-.0299235	.2271054
illw3	.0384557	.1099365	0.35	0.726	-.1770159	.2539274
_cons	-4.743303	.6477105	-7.32	0.000	-6.012792	-3.473814

```

326 .
327 . title4 " Mediator analysis for Dose=>paid employment wave three"
-----
Mediator analysis for Dose=>paid employment wave three
-----

328 . title4 "age may be a male mediator for dose- paid employment impact"
-----
age may be a male mediator for dose- paid employment impact
-----

329 .
330 . * we test for the possibility by testing a probit analysis
331 . glm radhlw3 avgcumdosew3 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-1695.1855**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1261.052
Deviance = 426235.7205	(1/df) Deviance	=	1261.052
Pearson = 426235.7205	(1/df) Pearson	=	1261.052

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

	<u>AIC</u>	=	9.983444
Log likelihood = -1695.185473	<u>BIC</u>	=	424265.5

radhlw3	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew3	.9606492	.7224692		1.33	0.184	-.4553645	2.376663
_cons	46.19995	2.117563		21.82	0.000	42.0496	50.3503

```
332 . glm hp2work radhlw3 if gender==1, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 327.9117
Iteration 2:  deviance = 327.3424
Iteration 3:  deviance = 327.342
Iteration 4:  deviance = 327.342
```

```
Generalized linear models          No. of obs      =       340
Optimization      : MQL Fisher scoring  Residual df    =       338
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 327.3419871         (1/df) Deviance = .9684674
Pearson           = 339.544695          (1/df) Pearson  = 1.00457
```

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

```
BIC = -1642.842
```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0094116	.0021904	4.30	0.000	.0051185	.0137048
_cons	-1.312207	.1427935	-9.19	0.000	-1.592077	-1.032337

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

```
333 .
334 .
335 . di as input "age is a possible male mediator for paid employment"
    age is a possible male mediator for paid employment
336 .
337 . glm age avgcumdosew3 if gender==1, family(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -1330.6336
```

```
Generalized linear models          No. of obs      =       340
Optimization      : ML              Residual df    =       338
Scale parameter = 147.7142
Deviance          = 49927.38549      (1/df) Deviance = 147.7142
Pearson           = 49927.38549      (1/df) Pearson  = 147.7142
```

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

```
Log likelihood = -1330.633586      AIC = 7.839021
                                   BIC = 47957.2
```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.5433648	.2472657	2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376	66.95	0.000	47.09975	49.94067

```
338 . glm hp2work age if gender==1, family(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 332.6127
Iteration 2:  deviance = 332.2035
Iteration 3:  deviance = 332.2034
Iteration 4:  deviance = 332.2034
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 332.2034085	(1/df) Deviance	=	.9828503
Pearson = 339.5831812	(1/df) Pearson	=	1.004684

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

BIC = **-1637.98**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0233394	.0063554	3.67	0.000	.0108831	.0357956
_cons	-2.001321	.3351159	-5.97	0.000	-2.658136	-1.344506

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

```
339 .
340 .
```

```

341 . di as input "Illness in wave 3 is a possible mediator for dose-paid employe
    > nt impact"
    Illness in wave 3 is a possible mediator for dose-paid employment impact

```

```

342 . glm illw3 avgcumdosew3 if gender==1, family(gaussian) link(identity)

```

```

Iteration 0:   log likelihood = -461.99206

```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.8919217
Deviance =	(1/df) Deviance	=	.8919217
Pearson =	(1/df) Pearson	=	.8919217

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

	<u>AIC</u>	=	2.729365
Log likelihood = -461.9920626	<u>BIC</u>	=	-1668.714

illw3	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew3	.038211	.0192139	1.99	0.047	.0005524	.0758696
_cons	.4504952	.0563162	8.00	0.000	.3401176	.5608729

```

343 . glm hp2work illw3 if gender==1, family(binomial) irls scale(dev) link(probit
    > )

```

```

Iteration 1:   deviance = 315.5535
Iteration 2:   deviance = 315.5149
Iteration 3:   deviance = 315.5148
Iteration 4:   deviance = 315.5148

```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
	Scale parameter	=	1
Deviance =	(1/df) Deviance	=	.9334758
Pearson =	(1/df) Pearson	=	.9946404

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

	BIC	=	-1654.669
--	-----	---	------------------

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.4173011	.0774431	5.39	0.000	.2655154	.5690869
_cons	-1.077182	.0906493	-11.88	0.000	-1.254852	-.899513

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

```

344 . * constructing an interaction
345 .
346 .
347 . di as input "Interaction of age & illness in wave 3 is moderator that mediat
    > es for males"
    Interaction of age & illness in wave 3 is moderator that mediates for males

348 .
349 . cap gen ageXillw3 = age*illw3

350 . glm illw3 avgcumdosew3 if gender==1, family(gaussian) link(identity)

```

Iteration 0: log likelihood = **-461.99206**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.8919217
Deviance = 301.469521	(1/df) Deviance	=	.8919217
Pearson = 301.469521	(1/df) Pearson	=	.8919217

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

	<u>AIC</u>	=	2.729365
Log likelihood = -461.9920626	<u>BIC</u>	=	-1668.714

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.038211	.0192139	1.99	0.047	.0005524	.0758696
_cons	.4504952	.0563162	8.00	0.000	.3401176	.5608729

```

351 . glm hp2work illw3 avgcumdosew3 ageXillw3 if gender==1, family(binomial) ///
>      irls scale(dev) link(probit)

```

```

Iteration 1:  deviance = 306.4966
Iteration 2:  deviance = 306.1716
Iteration 3:  deviance = 306.1695
Iteration 4:  deviance = 306.1695

```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	336
(IRLS EIM)	Scale parameter	=	1
Deviance = 306.1695162	(1/df) Deviance	=	.9112188
Pearson = 333.6560038	(1/df) Pearson	=	.9930238

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

BIC = -1652.356

hp2work	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
illw3	-.9049112	.4534263	-2.00	0.046	-1.79361	-.0162121
avgcumdosew3	-.004425	.0291879	-0.15	0.879	-.0616323	.0527822
ageXillw3	.0235805	.0080114	2.94	0.003	.0078785	.0392825
_cons	-1.048466	.0954586	-10.98	0.000	-1.235561	-.8613702

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

```

352 .
353 .
354 .
355 . des bf8

```

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

```
356 . title4 "bf8 is a male mediator of paid employment"
```

```
bf8 is a male mediator of paid employment
```

```
357 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
> 0
```

```
358 . foreach var in `w3bf'{
      2. glm `var' avgcumdosew3 if gender==1, family(gaussian) link(identity)
      3. glm hp2work `var' illw3 avgcumdosew3 ageXillw3 if gender==1, family(binom
> ial) ///
>      irls scale(dev) link(probit)
      4. }
```

```
Iteration 0:    log likelihood = -1551.9192
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	542.9186
Deviance = 183506.4901	(1/df) Deviance	=	542.9186
Pearson = 183506.4901	(1/df) Pearson	=	542.9186

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

	<u>AIC</u>	=	9.140701
Log likelihood = -1551.91925	<u>BIC</u>	=	181536.3

bf1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.002304	.4740456	-0.00	0.996	-.9314164	.9268084
_cons	32.04104	1.389431	23.06	0.000	29.31781	34.76428

```
Iteration 1:    deviance = 301.0309
Iteration 2:    deviance = 300.1656
Iteration 3:    deviance = 300.1621
Iteration 4:    deviance = 300.1621
Iteration 5:    deviance = 300.1621
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	335
	Scale parameter	=	1
Deviance = 300.1621391	(1/df) Deviance	=	.8960064
Pearson = 331.1205639	(1/df) Pearson	=	.9884196

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

[Bernoulli]
 [Probit]

BIC = -1652.535

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf1	.0089452	.0034596	2.59	0.010	.0021644	.0157259
illw3	-.77203	.4386134	-1.76	0.078	-1.631697	.0876365
avgcumdosew3	-.00216	.0295424	-0.07	0.942	-.0600621	.0557421
ageXillw3	.020558	.0077394	2.66	0.008	.005389	.0357271
_cons	-1.346332	.1529226	-8.80	0.000	-1.646055	-1.04661

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

Iteration 0: log likelihood = -1027.1072

Generalized linear models

Optimization : ML

No. of obs = 340

Residual df = 338

Scale parameter = 24.77487

Deviance = 8373.906252

(1/df) Deviance = 24.77487

Pearson = 8373.906252

(1/df) Pearson = 24.77487

Variance function: $V(u) = 1$

[Gaussian]

Link function : $g(u) = u$

[Identity]

Log likelihood = -1027.107224

AIC = 6.053572

BIC = 6403.723

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.0357675	.1012648	-0.35	0.724	-.2342429	.1627078
_cons	12.54064	.2968079	42.25	0.000	11.95891	13.12238

Iteration 1: deviance = 282.7342

Iteration 2: deviance = 280.9952

Iteration 3: deviance = 280.9756

Iteration 4: deviance = 280.9756

Iteration 5: deviance = 280.9756

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4	-.0819747	.0150372	-5.45	0.000	-.1114471	-.0525023
illw3	-.5388859	.4267744	-1.26	0.207	-1.375348	.2975765
avgcumdosew3	.0024099	.0278188	0.09	0.931	-.052114	.0569338
ageXillw3	.0153271	.0074554	2.06	0.040	.0007149	.0299394
_cons	-.0701321	.2003312	-0.35	0.726	-.4627742	.3225099

```
Iteration 0:  log likelihood = -3110.5209
```

	OIM					
bf2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-40.64822	46.41724	-0.88	0.381	-131.6243	50.3279
_cons	1991.578	136.0493	14.64	0.000	1724.926	2258.229

Iteration 1: deviance = 299.7774
 Iteration 2: deviance = 299.1194
 Iteration 3: deviance = 299.1177
 Iteration 4: deviance = 299.1177
 Iteration 5: deviance = 299.1177

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	335
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 299.1177398	(1/df) Deviance	=	.8928888
Pearson	= 333.2413587	(1/df) Pearson	=	.9947503

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

BIC = -1653.579

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf2	.0000949	.0000336	2.82	0.005	.000029	.0001608
illw3	-.6262331	.449099	-1.39	0.163	-1.506451	.2539847
avgcumdosew3	.0027738	.0281975	0.10	0.922	-.0524922	.0580398
ageXillw3	.0180516	.0079115	2.28	0.023	.0025454	.0335579
_cons	-1.256084	.1228394	-10.23	0.000	-1.496845	-1.015323

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

Iteration 0: log likelihood = -1060.7697

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	30.20008
Deviance	= 10207.62832	(1/df) Deviance	=	30.20008
Pearson	= 10207.62832	(1/df) Pearson	=	30.20008

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

		<u>AIC</u>	=	6.251587
Log likelihood	= -1060.769747	<u>BIC</u>	=	8237.445

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.0292413	.1118039	-0.26	0.794	-.2483729	.1898903
_cons	20.35328	.327698	62.11	0.000	19.711	20.99556

Iteration 1: deviance = 284.2146
Iteration 2: deviance = 282.8347
Iteration 3: deviance = 282.8223
Iteration 4: deviance = 282.8223
Iteration 5: deviance = 282.8223

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	335
(IRLS EIM)	Scale parameter	=	1
Deviance = 282.8222621	(1/df) Deviance	=	.8442456
Pearson = 311.8592054	(1/df) Pearson	=	.930923

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

BIC = -1669.875

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4m	-.0702538	.0135383	-5.19	0.000	-.0967884	-.0437191
illw3	-.5205682	.4244129	-1.23	0.220	-1.352402	.3112658
avgcumdosew3	.0026156	.0277534	0.09	0.925	-.05178	.0570112
ageXillw3	.0151759	.0074121	2.05	0.041	.0006484	.0297034
_cons	.3364223	.2818414	1.19	0.233	-.2159766	.8888213

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

Iteration 0: log likelihood = -2273.014

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	37748.2
Deviance = 12758891.39	(1/df) Deviance	=	37748.2
Pearson = 12758891.39	(1/df) Pearson	=	37748.2

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

Log likelihood	= -2273.013968	<u>AIC</u>	= 13.38244
		<u>BIC</u>	= 1.28e+07

	OIM					
bf5m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	9.087842	3.952764	2.30	0.021	1.340566	16.83512
_cons	102.4403	11.58558	8.84	0.000	79.73302	125.1477

```
Iteration 1:    deviance =    304.1111
Iteration 2:    deviance =    303.3297
Iteration 3:    deviance =     303.318
Iteration 4:    deviance =     303.318
Iteration 5:    deviance =     303.318
```

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	335
(IRLS EIM)	Scale parameter	=	1
Deviance = 303.3180183	(1/df) Deviance	=	.9054269
Pearson = 334.3846422	(1/df) Pearson	=	.9981631

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

BIC = -1649.379

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf5m	-.0008032	.0004666	-1.72	0.085	-.0017178	.0001114
illw3	-.8955598	.4670831	-1.92	0.055	-1.811026	.0199063
avgcumdosew3	.0024508	.0286972	0.09	0.932	-.0537946	.0586962
ageXillw3	.0244622	.0082752	2.96	0.003	.0082431	.0406812
_cons	-1.001258	.0981618	-10.20	0.000	-1.193652	-.8088645

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

```
Iteration 0:  log likelihood = -2733.8489
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	567778.4
Deviance = 191909111.2	(1/df) Deviance	=	567778.4
Pearson = 191909111.2	(1/df) Pearson	=	567778.4

[Gaussian]
[Identity]

<u>AIC</u>	=	16.09323
<u>BIC</u>	=	1.92e+08

	OIM					
bf7m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	9.565438	15.33	0.62	0.533	-20.48082	39.61169
_cons	1022.573	44.93236	22.76	0.000	934.5073	1110.639

```
Iteration 1:    deviance =    306.253
Iteration 2:    deviance =    305.9082
Iteration 3:    deviance =    305.9062
Iteration 4:    deviance =    305.9062
Iteration 5:    deviance =    305.9062
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	335
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 305.9062256	(1/df) Deviance	=	.9131529
Pearson	= 334.7424736	(1/df) Pearson	=	.9992313

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1646.791

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf7m	-.000056	.0001041	-0.54	0.591	-.00026	.000148
illw3	-.8870307	.45488	-1.95	0.051	-1.778579	.0045177
avgcumdosew3	-.0034059	.0290164	-0.12	0.907	-.060277	.0534652
ageXillw3	.0233076	.0080353	2.90	0.004	.0075586	.0390565
_cons	-.9935662	.1388801	-7.15	0.000	-1.265766	-.7213662

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

```
Iteration 0:  log likelihood = -3529.6624
```

```

Generalized linear models
Optimization      : ML
Deviance          = 2.07081e+10
Pearson           = 2.07081e+10

No. of obs       = 340
Residual df      = 338
Scale parameter  = 6.13e+07
(1/df) Deviance  = 6.13e+07
(1/df) Pearson   = 6.13e+07

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

[ Gaussian ]
[ Identity ]

Log likelihood    = -3529.662384
AIC               = 20.77448
BIC               = 2.07e+10

```

bf8	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	355.615	159.2444	2.23	0.026	43.5018	667.7282
_cons	2733.121	466.7464	5.86	0.000	1818.315	3647.927

```

Iteration 1: deviance = 302.6209
Iteration 2: deviance = 301.3338
Iteration 3: deviance = 301.2925
Iteration 4: deviance = 301.2924
Iteration 5: deviance = 301.2924

```

```

Generalized linear models
Optimization      : MQL Fisher scoring
                   (IRLS EIM)
Deviance          = 301.2924095
Pearson           = 336.2938827

No. of obs       = 340
Residual df      = 335
Scale parameter   = 1
(1/df) Deviance  = .8993803
(1/df) Pearson   = 1.003862

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

[ Bernoulli ]
[ Probit ]

BIC               = -1651.404

```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf8	-.000027	.0000125	-2.15	0.031	-.0000516	-2.44e-06
illw3	-.9474576	.4820727	-1.97	0.049	-1.892303	-.0026126
avgcumdosew3	.0061317	.0278623	0.22	0.826	-.0484774	.0607408
ageXillw3	.0256323	.008669	2.96	0.003	.0086413	.0426233
_cons	-1.016811	.0955984	-10.64	0.000	-1.204181	-.8294416

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

Iteration 0: log likelihood = **-2696.8709**

Generalized linear models

Optimization : **ML**

Deviance = **154393458.8**

Pearson = **154393458.8**

No. of obs = **340**

Residual df = **338**

Scale parameter = **456785.4**

(1/df) Deviance = **456785.4**

(1/df) Pearson = **456785.4**

Variance function: **V(u) = 1**

[**Gaussian**]

Link function : **g(u) = u**

[**Identity**]

Log likelihood = **-2696.870867**

AIC = **15.87571**

BIC = **1.54e+08**

bf15m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-3.628301	13.7502	-0.26	0.792	-30.57819	23.32159
_cons	115.892	40.30193	2.88	0.004	36.90167	194.8823

Iteration 1: deviance = **306.0016**

Iteration 2: deviance = **305.6478**

Iteration 3: deviance = **305.6457**

Iteration 4: deviance = **305.6457**

Generalized linear models

Optimization : **MQL Fisher scoring**
(**IRLS EIM**)

Deviance = **305.6457012**

Pearson = **333.5001091**

No. of obs = **340**

Residual df = **335**

Scale parameter = **1**

(1/df) Deviance = **.9123752**

(1/df) Pearson = **.9955227**

Variance function: **V(u) = u*(1-u)**

[**Bernoulli**]

Link function : **g(u) = invnorm(u)**

[**Probit**]

BIC = **-1647.051**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf15m	.0000806	.000105	0.77	0.443	-.0001252	.0002864
illw3	-.8957517	.4543388	-1.97	0.049	-1.786239	-.0052639
avgcumdosew3	-.0042893	.0292684	-0.15	0.883	-.0616544	.0530759
ageXillw3	.0235238	.0080267	2.93	0.003	.0077918	.0392559
_cons	-1.061944	.0973897	-10.90	0.000	-1.252824	-.871064

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

Iteration 0: log likelihood = **-3469.0024**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	4.29e+07
Deviance = 1.44935e+10	(1/df) Deviance	=	4.29e+07
Pearson = 1.44935e+10	(1/df) Pearson	=	4.29e+07

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

	<u>AIC</u>	=	20.41766
Log likelihood = -3469.002409	<u>BIC</u>	=	1.45e+10

bf17	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-17.08696	133.2235	-0.13	0.898	-278.2002	244.0263
_cons	434.0573	390.4791	1.11	0.266	-331.2677	1199.382

Iteration 1: deviance = 306.2652
Iteration 2: deviance = 305.7886
Iteration 3: deviance = 305.7001
Iteration 4: deviance = 305.5515
Iteration 5: deviance = 305.1672
Iteration 6: deviance = 305.0101
Iteration 7: deviance = 304.9255
Iteration 8: deviance = 304.8717
Iteration 9: deviance = 304.8247
Iteration 10: deviance = 304.7365
Iteration 11: deviance = 304.6723
Iteration 12: deviance = 304.6508
Iteration 13: deviance = 304.6429
Iteration 14: deviance = 304.6398
Iteration 15: deviance = 304.6384

```
Iteration 16: deviance = 304.6377
Iteration 17: deviance = 304.6373
Iteration 18: deviance = 304.637
Iteration 19: deviance = 304.6369
Iteration 20: deviance = 304.6368
Iteration 21: deviance = 304.6367
Iteration 22: deviance = 304.6366
Iteration 23: deviance = 304.6366
Iteration 24: deviance = 304.6365
Iteration 25: deviance = 304.6365
Iteration 26: deviance = 304.6365
Iteration 27: deviance = 304.6364
Iteration 28: deviance = 304.6364
Iteration 29: deviance = 304.6364
Iteration 30: deviance = 304.6364
Iteration 31: deviance = 304.6364
Iteration 32: deviance = 304.6364
Iteration 33: deviance = 304.6364
Iteration 34: deviance = 304.6364
Iteration 35: deviance = 304.6363
Iteration 36: deviance = 304.6363
Iteration 37: deviance = 304.6363
Iteration 38: deviance = 304.6363
Iteration 39: deviance = 304.6363
Iteration 40: deviance = 304.6363
Iteration 41: deviance = 304.6363
Iteration 42: deviance = 304.6363
Iteration 43: deviance = 304.6363
Iteration 44: deviance = 304.6363
Iteration 45: deviance = 304.6363
Iteration 46: deviance = 304.6363
Iteration 47: deviance = 304.6363
Iteration 48: deviance = 304.6363
Iteration 49: deviance = 304.6363
Iteration 50: deviance = 304.6363
Iteration 51: deviance = 304.6363
Iteration 52: deviance = 304.6363
Iteration 53: deviance = 304.6363
Iteration 54: deviance = 304.6363
Iteration 55: deviance = 304.6363
Iteration 56: deviance = 304.6363
Iteration 57: deviance = 304.6363
Iteration 58: deviance = 304.6363
Iteration 59: deviance = 304.6363
Iteration 60: deviance = 304.6363
Iteration 61: deviance = 304.6363
Iteration 62: deviance = 304.6363
Iteration 63: deviance = 304.6363
Iteration 64: deviance = 304.6363
```

Iteration 65: deviance = 304.6363
 Iteration 66: deviance = 304.6363
 Iteration 67: deviance = 304.6363
 Iteration 68: deviance = 304.6363

Generalized linear models		No. of obs	=	340
Optimization	: MQL Fisher scoring	Residual df	=	335
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 304.636255	(1/df) Deviance	=	.909362
Pearson	= 328.9419784	(1/df) Pearson	=	.9819164

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

BIC = -1648.061

hp2work	EIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
bf17	-.0061172	.0135397	-0.45	0.651	-.0326545	.0204201	
illw3	-.8919627	.4536997	-1.97	0.049	-1.781198	-.0027277	
avgcumdosew3	-.0045617	.029111	-0.16	0.875	-.0616181	.0524948	
ageXillw3	.023281	.0080101	2.91	0.004	.0075815	.0389804	
_cons	-1.03774	.0956856	-10.85	0.000	-1.225281	-.8502001	

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

Iteration 0: log likelihood = -1596.6648

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	706.3908
Deviance	= 238760.0795	(1/df) Deviance	=	706.3908
Pearson	= 238760.0795	(1/df) Pearson	=	706.3908

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

		<u>AIC</u>	=	9.403911
Log likelihood	= -1596.664807	<u>BIC</u>	=	236789.9

bf20	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.1398753	.5407236	-0.26	0.796	-1.199674	.9199234
_cons	70.35574	1.584865	44.39	0.000	67.24947	73.46202

Iteration 1: deviance = 300.1457
Iteration 2: deviance = 299.0235
Iteration 3: deviance = 299.0152
Iteration 4: deviance = 299.0152
Iteration 5: deviance = 299.0152

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring	Residual df	=	335
(IRLS EIM)	Scale parameter	=	1
Deviance = 299.0152272	(1/df) Deviance	=	.8925828
Pearson = 330.25436	(1/df) Pearson	=	.9858339

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

BIC = -1653.682

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf20	.0088228	.003147	2.80	0.005	.0026548	.0149908
illw3	-.7807362	.4376076	-1.78	0.074	-1.638431	.076959
avgcumdosew3	-.0015929	.0300016	-0.05	0.958	-.060395	.0572092
ageXillw3	.0206881	.0077194	2.68	0.007	.0055584	.0358178
_cons	-1.683938	.2508128	-6.71	0.000	-2.175522	-1.192354

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

Iteration 0: log likelihood = -3143.6434

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	6325138
Deviance = 2137896613	(1/df) Deviance	=	6325138
Pearson = 2137896613	(1/df) Pearson	=	6325138

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

Log likelihood	= -3143.643356	<u>AIC</u>	= 18.50378
		<u>BIC</u>	= 2.14e+09

	OIM					
bf22	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	72.68941	51.16675	1.42	0.155	-27.59557	172.9744
_cons	2107.73	149.9701	14.05	0.000	1813.794	2401.666

```
Iteration 1: deviance = 305.3026
Iteration 2: deviance = 304.9396
Iteration 3: deviance = 304.9374
Iteration 4: deviance = 304.9374
Iteration 5: deviance = 304.9374
```

Generalized linear models		No. of obs	=	340
Optimization	: ML Fisher scoring	Residual df	=	335
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 304.9374153	(1/df) Deviance	=	.9102609
Pearson	= 331.1091682	(1/df) Pearson	=	.9883856

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

BIC = -1647.759

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf22	.0000371	.0000318	1.17	0.243	-.0000252	.0000993
illw3	-.918145	.4518314	-2.03	0.042	-1.803718	-.0325717
avgcumdosew3	-.006472	.0296204	-0.22	0.827	-.0645268	.0515829
ageXillw3	.0231361	.0079661	2.90	0.004	.0075229	.0387493
_cons	-1.114315	.1113817	-10.00	0.000	-1.332619	-.8960105

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

Iteration 0: log likelihood = -3683.6189

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1.52e+08
Deviance = 5.12210e+10	(1/df) Deviance	=	1.52e+08
Pearson = 5.12210e+10	(1/df) Pearson	=	1.52e+08

[Gaussian]
[Identity]

<u>AIC</u>	=	21.68011
<u>BIC</u>	=	5.12e+10

	OIM					
bf29	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	72.89759	250.4485	0.29	0.771	-417.9724	563.7676
_cons	1316.168	734.0664	1.79	0.073	-122.5761	2754.911

```
Iteration 1:    deviance = 306.2986
Iteration 2:    deviance = 305.9514
Iteration 3:    deviance = 305.9494
Iteration 4:    deviance = 305.9494
```

```
Generalized linear models
Optimization      : ML Fisher scoring
                   (IRLS EIM)
Deviance          = 305.9493576
Pearson           = 332.9706028
```

No. of obs	=	340
Residual df	=	335
Scale parameter	=	1
(1/df) Deviance	=	.9132817
(1/df) Pearson	=	.9939421

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

[Bernoulli]
[Probit]

BIC = -1646.747

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf29	2.79e-06	5.58e-06	0.50	0.617	-8.15e-06	.0000137
illw3	-.9120386	.4552478	-2.00	0.045	-1.804308	-.0197692
avgcumdosew3	-.0047071	.0293276	-0.16	0.872	-.0621882	.052774
ageXillw3	.0237101	.0080424	2.95	0.003	.0079473	.0394729
_cons	-1.052896	.0959692	-10.97	0.000	-1.240992	-.8647998

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

```
Iteration 0:  log likelihood = -2661.1782
```

```

Generalized linear models                      No. of obs      =       340
Optimization      : ML                      Residual df      =       338
                                                Scale parameter =    370279
Deviance          =   125154318.2          (1/df) Deviance =    370279
Pearson           =   125154318.2          (1/df) Pearson  =    370279

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

                                                AIC              =    15.66575
Log likelihood    =  -2661.17822           BIC              =    1.25e+08

```

bf30	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-8.740799	12.37991	-0.71	0.480	-33.00497	15.52337
_cons	499.3279	36.2856	13.76	0.000	428.2095	570.4464

```

Iteration 1:  deviance =  302.7978
Iteration 2:  deviance =  302.3054
Iteration 3:  deviance =  302.3037
Iteration 4:  deviance =  302.3037
Iteration 5:  deviance =  302.3037

```

```

Generalized linear models                      No. of obs      =       340
Optimization      : MQL Fisher scoring       Residual df      =       335
                  (IRLS EIM)                Scale parameter =         1
Deviance          =   302.3036646           (1/df) Deviance =     .902399
Pearson           =   330.9769023           (1/df) Pearson  =     .9879908

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

                                                BIC              =   -1650.393

```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf30	.0002605	.0001257	2.07	0.038	.0000141	.000507
illw3	-.704577	.4520917	-1.56	0.119	-1.590661	.1815065
avgcumdosew3	-.0017053	.0295427	-0.06	0.954	-.059608	.0561974
ageXillw3	.0200764	.0079446	2.53	0.012	.0045054	.0356475
_cons	-1.198337	.1213319	-9.88	0.000	-1.436144	-.960531

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

Iteration 0: log likelihood = **-658.90158**

Generalized linear models

Optimization : **ML**

Deviance = **960.025842**

Pearson = **960.025842**

Variance function: **V(u) = 1**

Link function : **g(u) = u**

No. of obs = **340**

Residual df = **338**

Scale parameter = **2.840313**

(1/df) Deviance = **2.840313**

(1/df) Pearson = **2.840313**

[**Gaussian**]

[**Identity**]

Log likelihood = **-658.9015808**

AIC = **3.887656**

BIC = **-1010.158**

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.0494693	.0342875	1.44	0.149	-.017733	.1166715
_cons	2.083835	.1004969	20.74	0.000	1.886864	2.280805

Iteration 1: deviance = **300.0331**

Iteration 2: deviance = **299.3058**

Iteration 3: deviance = **299.3023**

Iteration 4: deviance = **299.3023**

Iteration 5: deviance = **299.3023**

Generalized linear models

Optimization : **ML Fisher scoring**
(**IRLS EIM**)

Deviance = **299.302286**

Pearson = **332.1283637**

No. of obs = **340**

Residual df = **335**

Scale parameter = **1**

(1/df) Deviance = **.8934397**

(1/df) Pearson = **.991428**

Variance function: **V(u) = u*(1-u)**

Link function : **g(u) = invnorm(u)**

[**Bernoulli**]

[**Probit**]

BIC = **-1653.394**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.1459653	.0519808	2.81	0.005	.0440849	.2478458
illw3	-.8596898	.4456734	-1.93	0.054	-1.733194	.0138141
avgcumdosew3	-.004707	.0285947	-0.16	0.869	-.0607516	.0513375
ageXillw3	.0204911	.0078874	2.60	0.009	.005032	.0359502
_cons	-1.321598	.1388504	-9.52	0.000	-1.593739	-1.049456

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

```

359 .
360 . **** male mediators of dose paid employment: bf8, age, illw3 ageXillw3
361 . scalar wkMedMw3 = "bf8 age illw3 ageXillw3"

```

```

362 .
363 . title4 "Female mediator models for dose-paid employment"

```

Female mediator models for dose-paid employment

```

364 . glm radhlw3 avgcumdosew3 if gender==2, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-1798.7074**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1185.454
Deviance = 427948.9522	(1/df) Deviance	=	1185.454
Pearson = 427948.9522	(1/df) Pearson	=	1185.454
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.921253
Log likelihood = -1798.707367	<u>BIC</u>	=	425821.1

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	2.751602	1.03038	2.67	0.008	.7320943	4.77111
_cons	57.70689	2.190692	26.34	0.000	53.41321	62.00057

```
365 . glm hp2work radhlw3 if gender==2, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =    395.05
Iteration 2:  deviance =   394.6898
Iteration 3:  deviance =   394.6898
Iteration 4:  deviance =   394.6898
```

```
Generalized linear models                               No. of obs      =       363
Optimization      :  MQL Fisher scoring                 Residual df    =       361
                  (IRLS EIM)                           Scale parameter =         1
Deviance          =   394.6897802                      (1/df) Deviance =   1.093323
Pearson           =   364.9268795                      (1/df) Pearson  =   1.010878
```

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

```
BIC = -1733.19
```

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0091162	.0022772	4.00	0.000	.004653	.0135795
_cons	-1.244306	.1697735	-7.33	0.000	-1.577055	-.9115557

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

```
366 . glm age avgcumdosew3 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -1408.064
```

```
Generalized linear models                               No. of obs      =       363
Optimization      :  ML                                 Residual df    =       361
Scale parameter =   137.7687
Deviance          =   49734.51399                      (1/df) Deviance =   137.7687
Pearson           =   49734.51399                      (1/df) Pearson  =   137.7687
```

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

```
AIC = 7.768948
BIC = 47606.63
Log likelihood = -1408.06405
```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

```
367 . 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.)

```
368 . glm illw3 avgcumdosew3 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -562.81042
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.308042
Deviance = 472.2033151	(1/df) Deviance	=	1.308042
Pearson = 472.2033151	(1/df) Pearson	=	1.308042

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

Log likelihood	= -562.8104237	<u>AIC</u>	= 3.111903
		<u>BIC</u>	= -1655.676

	OIM					
illw3	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1284565	.0342268	3.75	0.000	.0613733	.1955398
_cons	.5563644	.0727696	7.65	0.000	.4137387	.6989902

```
369 . glm hp2work illw3 if gender==2, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:    deviance = 410.7265
Iteration 2:    deviance = 410.1776
Iteration 3:    deviance = 410.1774
Iteration 4:    deviance = 410.1774
```

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 410.1774283	(1/df) Deviance	=	1.136226
Pearson = 362.4869354	(1/df) Pearson	=	1.004119

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

BIC = -1717.702

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.1024787	.0628325	1.63	0.103	-.0206709	.2256282
_cons	-.7324278	.090138	-8.13	0.000	-.909095	-.5557606

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

```

370 .
371 . * interaction of ageXillw3 impacts paid employment as mediator and moderator
372 . glm illw3 avgcumdosew3 if gender==2, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-562.81042**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.308042
Deviance = 472.2033151	(1/df) Deviance	=	1.308042
Pearson = 472.2033151	(1/df) Pearson	=	1.308042
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	3.111903
Log likelihood = -562.8104237	<u>BIC</u>	=	-1655.676

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1284565	.0342268	3.75	0.000	.0613733	.1955398
_cons	.5563644	.0727696	7.65	0.000	.4137387	.6989902

```

373 . glm hp2work ageXillw3 illw3 avgcumdosew3 if gender==2, fam(binomial) irls sc
> ale(dev) link(probit)

```

Iteration 1: deviance = **392.5389**
 Iteration 2: deviance = **391.8976**
 Iteration 3: deviance = **391.8969**
 Iteration 4: deviance = **391.8969**
 Iteration 5: deviance = **391.8969**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 391.8968943	(1/df) Deviance	=	1.091635
Pearson = 370.0301694	(1/df) Pearson	=	1.030725
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	BIC	=	-1724.194

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ageXillw3	.0187409	.0060019	3.12	0.002	.0069775	.0305044
illw3	-.9562978	.343609	-2.78	0.005	-1.629759	-.2828366
avgcumdosew3	.0662197	.0429198	1.54	0.123	-.0179015	.150341
_cons	-.79789	.1001619	-7.97	0.000	-.9942036	-.6015764

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

```

374 .
375 .
376 .
377 .
378 .
379 .
380 . title4 "bf8 is a male mediator of paid employment"

```

bf8 is a male mediator of paid employment

```

381 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0
382 . foreach var in `w3bf'{
    2. glm `var' avgcumdosew3 if gender==2, family(gaussian) link(identity)
    3. glm hp2work `var' illw3 avgcumdosew3 if gender==2, family(binomial) irls
    > scale(dev) link(probit)
    4.
383 .
384 . }

```

Iteration 0: log likelihood = **-1647.6213**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	515.6618
Deviance = 186153.9233	(1/df) Deviance	=	515.6618
Pearson = 186153.9233	(1/df) Pearson	=	515.6618

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

	<u>AIC</u>	=	9.088823
Log likelihood = -1647.621315	<u>BIC</u>	=	184026

bf1	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.403532	.6795752	2.07	0.039	.0715889	2.735475
_cons	37.53913	1.444846	25.98	0.000	34.70728	40.37097

Iteration 1: deviance = **400.7858**
Iteration 2: deviance = **400.3649**
Iteration 3: deviance = **400.3647**
Iteration 4: deviance = **400.3647**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.3647141	(1/df) Deviance	=	1.115222
Pearson = 362.3414503	(1/df) Pearson	=	1.009308

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

BIC = **-1715.726**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf1	.0075263	.0035043	2.15	0.032	.0006579	.0143947
illw3	.0566488	.0651687	0.87	0.385	-.0710796	.1843771
avgcumdosew3	.0748818	.0422562	1.77	0.076	-.007939	.1577025
_cons	-1.099425	.1680193	-6.54	0.000	-1.428737	-.7701136

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

Iteration 0: log likelihood = **-1109.6569**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.6146
Deviance = 9607.869105	(1/df) Deviance	=	26.6146
Pearson = 9607.869105	(1/df) Pearson	=	26.6146

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

	<u>AIC</u>	=	6.124831
Log likelihood = -1109.656873	<u>BIC</u>	=	7479.99

bf4	OIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
avgcumdosew3	-.4386292	.1543885	-2.84	0.004	-.7412252	-.1360333
_cons	11.01475	.3282456	33.56	0.000	10.3714	11.6581

Iteration 1: deviance = **368.0458**
Iteration 2: deviance = **367.7561**
Iteration 3: deviance = **367.7558**
Iteration 4: deviance = **367.7558**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 367.7557582	(1/df) Deviance	=	1.024389
Pearson = 356.2171479	(1/df) Pearson	=	.9922483

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

BIC = **-1748.335**

hp2work	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
bf4	-.0912403	.015392	-5.93	0.000	-.1214082	-.0610725
illw3	-.0442384	.0678425	-0.65	0.514	-.1772072	.0887305
avgcumdosew3	.0676603	.041034	1.65	0.099	-.0127647	.1480854
_cons	.179333	.1922188	0.93	0.351	-.1974089	.5560748

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

Iteration 0: log likelihood = **-3335.9695**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	5652705
Deviance = 2040626644	(1/df) Deviance	=	5652705
Pearson = 2040626644	(1/df) Pearson	=	5652705

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

	<u>AIC</u>	=	18.39102
Log likelihood = -3335.969457	<u>BIC</u>	=	2.04e+09

bf2	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-14.66006	71.15136	-0.21	0.837	-154.1142	124.794
_cons	2486.833	151.275	16.44	0.000	2190.34	2783.327

Iteration 1: deviance = **400.7561**
Iteration 2: deviance = **400.3769**
Iteration 3: deviance = **400.3768**
Iteration 4: deviance = **400.3768**

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.3767744	(1/df) Deviance	=	1.115256
Pearson = 362.4243987	(1/df) Pearson	=	1.009539

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

BIC = **-1715.714**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf2	.0000693	.0000321	2.16	0.031	6.50e-06	.0001322
illw3	.0579184	.0652264	0.89	0.375	-.069923	.1857598
avgcumdosew3	.0863439	.041937	2.06	0.040	.0041489	.168539
_cons	-.9883744	.1289169	-7.67	0.000	-1.241047	-.7357019

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

Iteration 0: log likelihood = **-1141.3116**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	31.68572
Deviance = 11438.54371	(1/df) Deviance	=	31.68572
Pearson = 11438.54371	(1/df) Pearson	=	31.68572

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

Log likelihood = -1141.311602	<u>AIC</u>	=	6.299237
	<u>BIC</u>	=	9310.664

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.441173	.1684561	-2.62	0.009	-.771341	-.1110051
_cons	18.82772	.3581548	52.57	0.000	18.12575	19.52969

Iteration 1: deviance = 376.2521
Iteration 2: deviance = 376.1219
Iteration 3: deviance = 376.1216
Iteration 4: deviance = 376.1216
Iteration 5: deviance = 376.1216

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 376.1216056	(1/df) Deviance	=	1.047692
Pearson = 352.597962	(1/df) Pearson	=	.982167

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

BIC = -1739.969

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf4m	-.0718043	.0138855	-5.17	0.000	-.0990193	-.0445893
illw3	-.0199722	.06741	-0.30	0.767	-.1520934	.112149
avgcumdosew3	.070842	.0412807	1.72	0.086	-.0100667	.1517506
_cons	.5296971	.2777901	1.91	0.057	-.0147615	1.074156

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

Iteration 0: log likelihood = -2474.3315

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	49036.9
Deviance = 17702319.75	(1/df) Deviance	=	49036.9
Pearson = 17702319.75	(1/df) Pearson	=	49036.9

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

Log likelihood	= -2474.331507	<u>AIC</u>	= 13.6437
		<u>BIC</u>	= 1.77e+07

	OIM					
bf5m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	11.51759	6.626993	1.74	0.082	-1.471077	24.50626
_cons	146.1251	14.08966	10.37	0.000	118.5098	173.7403

```
Iteration 1:    deviance = 406.0898
Iteration 2:    deviance = 405.5971
Iteration 3:    deviance = 405.5969
Iteration 4:    deviance = 405.5969
Iteration 5:    deviance = 405.5969
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 405.5968814	(1/df) Deviance	=	1.129796
Pearson = 362.2771278	(1/df) Pearson	=	1.009128

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

BIC = -1710.494

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf5m	.0000253	.000346	0.07	0.942	-.0006528	.0007034
illw3	.0757307	.0648804	1.17	0.243	-.0514326	.202894
avgcumdosew3	.0816456	.0425803	1.92	0.055	-.0018103	.1651014
_cons	-.8200136	.1118444	-7.33	0.000	-1.039225	-.6008026

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

Iteration 0: log likelihood = **-2919.8803**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	570998.8
Deviance = 206130564.2	(1/df) Deviance	=	570998.8
Pearson = 206130564.2	(1/df) Pearson	=	570998.8

[Gaussian]
[Identity]

<u>AIC</u>	=	16.09851
<u>BIC</u>	=	2.06e+08

	OIM					
bf7m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-9.882168	22.61375	-0.44	0.662	-54.20431	34.43997
_cons	1192.342	48.07913	24.80	0.000	1098.109	1286.575

```
Iteration 1:    deviance = 405.7923
Iteration 2:    deviance = 405.3032
Iteration 3:    deviance = 405.303
Iteration 4:    deviance = 405.303
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 405.3030164	(1/df) Deviance	=	1.128978
Pearson = 362.1616249	(1/df) Pearson	=	1.008807

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1710.788

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf7m	-.0000542	.0001026	-0.53	0.598	-.0002553	.000147
illw3	.0715496	.0653324	1.10	0.273	-.0564996	.1995988
avgcumdosew3	.0819746	.0424018	1.93	0.053	-.0011314	.1650805
_cons	-.7500788	.1604213	-4.68	0.000	-1.064499	-.4356588

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

```
Iteration 0:  log likelihood = -3888.8378
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.19e+08
Deviance = 4.29211e+10	(1/df) Deviance	=	1.19e+08
Pearson = 4.29211e+10	(1/df) Pearson	=	1.19e+08

[Gaussian]
[Identity]

<u>AIC</u>	=	21.43712
<u>BIC</u>	=	4.29e+10

	OIM					
bf8	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	474.4107	326.3149	1.45	0.146	-165.1547	1113.976
_cons	5499.472	693.7785	7.93	0.000	4139.691	6859.253

```
Iteration 1:    deviance =    406.001
Iteration 2:    deviance =    405.5105
Iteration 3:    deviance =    405.5103
Iteration 4:    deviance =    405.5103
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 405.510287	(1/df) Deviance	=	1.129555
Pearson = 362.2128945	(1/df) Pearson	=	1.00895

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1710.58

	EIM					
hp2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf8	2.02e-06	6.97e-06	0.29	0.772	-.0000116	.0000157
illw3	.0763832	.0648403	1.18	0.239	-.0507015	.2034678
avgcumdosew3	.0810208	.0425231	1.91	0.057	-.0023229	.1643645
_cons	-.8280872	.1080894	-7.66	0.000	-1.039939	-.6162358

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

Iteration 0: log likelihood = **-2865.4294**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	423004.2
Deviance = 152704509.3	(1/df) Deviance	=	423004.2
Pearson = 152704509.3	(1/df) Pearson	=	423004.2

[Gaussian]
[Identity]

<u>AIC</u>	=	15.79851
<u>BIC</u>	=	1.53e+08

	OIM					
bf15m	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-16.31159	19.46379	-0.84	0.402	-54.45991	21.83674
_cons	119.7135	41.38199	2.89	0.004	38.60629	200.8207

Iteration 1:	deviance =	403.0022
Iteration 2:	deviance =	401.3838
Iteration 3:	deviance =	400.8551
Iteration 4:	deviance =	400.4877
Iteration 5:	deviance =	400.1075
Iteration 6:	deviance =	399.7784
Iteration 7:	deviance =	399.6168
Iteration 8:	deviance =	399.5208
Iteration 9:	deviance =	399.4454
Iteration 10:	deviance =	399.3984
Iteration 11:	deviance =	399.3819
Iteration 12:	deviance =	399.3763
Iteration 13:	deviance =	399.3744
Iteration 14:	deviance =	399.3737
Iteration 15:	deviance =	399.3734
Iteration 16:	deviance =	399.3733
Iteration 17:	deviance =	399.3732
Iteration 18:	deviance =	399.3732
Iteration 19:	deviance =	399.3732
Iteration 20:	deviance =	399.3732
Iteration 21:	deviance =	399.3732
Iteration 22:	deviance =	399.3732
Iteration 23:	deviance =	399.3732
Iteration 24:	deviance =	399.3732
Iteration 25:	deviance =	399.3732
Iteration 26:	deviance =	399.3732
Iteration 27:	deviance =	399.3732
Iteration 28:	deviance =	399.3732
Iteration 29:	deviance =	399.3732

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML Fisher scoring         Residual df     =       359
                  (IRLS EIM)                 Scale parameter =         1
Deviance          =   399.3731679             (1/df) Deviance =   1.11246
Pearson           =   350.463985             (1/df) Pearson  =   .9762228

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

                                          BIC              =  -1716.717

```

hp2work	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf15m	-.0185517	.1405693	-0.13	0.895	-.2940624	.2569591
illw3	.0637593	.064584	0.99	0.324	-.0628231	.1903417
avgcumdosew3	.0795244	.0419333	1.90	0.058	-.0026634	.1617122
_cons	-.779424	.1009676	-7.72	0.000	-.9773168	-.5815312

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

Iteration 0: log likelihood = **-3826.3372**

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                       Residual df     =       361
                                          Scale parameter =   8.43e+07
Deviance          =   3.04172e+10             (1/df) Deviance =   8.43e+07
Pearson           =   3.04172e+10             (1/df) Pearson  =   8.43e+07

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

                                          AIC              =   21.09277
Log likelihood    =  -3826.337161             BIC              =   3.04e+10

```

bf17	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew3	-210.5363	274.7014	-0.77	0.443	-748.9411	327.8686
_cons	1283.326	584.043	2.20	0.028	138.6227	2428.029

```

Iteration 1:  deviance = 404.4868
Iteration 2:  deviance = 403.3612
Iteration 3:  deviance = 403.0401
Iteration 4:  deviance = 402.7883
Iteration 5:  deviance = 402.5042
Iteration 6:  deviance = 402.3328
Iteration 7:  deviance = 402.2311
Iteration 8:  deviance = 402.1401
Iteration 9:  deviance = 402.0781
Iteration 10: deviance = 402.0571
Iteration 11: deviance = 402.05
Iteration 12: deviance = 402.0475
Iteration 13: deviance = 402.0467
Iteration 14: deviance = 402.0463
Iteration 15: deviance = 402.0462
Iteration 16: deviance = 402.0462
Iteration 17: deviance = 402.0462
Iteration 18: deviance = 402.0461
Iteration 19: deviance = 402.0461
Iteration 20: deviance = 402.0461
Iteration 21: deviance = 402.0461
Iteration 22: deviance = 402.0461
Iteration 23: deviance = 402.0461
Iteration 24: deviance = 402.0461
Iteration 25: deviance = 402.0461

```

Generalized linear models

Optimization : **MQL Fisher scoring**
(**IRLS EIM**)

Deviance = 402.0461284

Pearson = 355.4109876

No. of obs = 363

Residual df = 359

Scale parameter = 1

(1/df) Deviance = 1.119906

(1/df) Pearson = .9900028

Variance function: $V(u) = u*(1-u)$

[**Bernoulli**]

Link function : $g(u) = \text{invnorm}(u)$

[**Probit**]

BIC = -1714.044

hp2work	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf17	-.0009418	.0098647	-0.10	0.924	-.0202762	.0183926
illw3	.0690879	.0646796	1.07	0.285	-.0576818	.1958576
avgcumdosew3	.0802034	.0421293	1.90	0.057	-.0023685	.1627752
_cons	-.7949403	.1007866	-7.89	0.000	-.9924784	-.5974022

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

Iteration 0: log likelihood = **-1708.7675**

Generalized linear models

Optimization : **ML**

Deviance = **260725.2848**

Pearson = **260725.2848**

No. of obs = **363**

Residual df = **361**

Scale parameter = **722.2307**

(1/df) Deviance = **722.2307**

(1/df) Pearson = **722.2307**

Variance function: **V(u) = 1**

[**Gaussian**]

Link function : **g(u) = u**

[**Identity**]

Log likelihood = **-1708.767472**

AIC = **9.425716**

BIC = **258597.4**

bf20	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.430073	.8042536	1.78	0.075	-.1462347	3.006382
_cons	75.65323	1.709925	44.24	0.000	72.30184	79.00463

Iteration 1: deviance = **400.9177**

Iteration 2: deviance = **400.4591**

Iteration 3: deviance = **400.4589**

Iteration 4: deviance = **400.4589**

Generalized linear models

Optimization : **MQL Fisher scoring**
(**IRLS EIM**)

Deviance = **400.4588662**

Pearson = **362.8847271**

No. of obs = **363**

Residual df = **359**

Scale parameter = **1**

(1/df) Deviance = **1.115484**

(1/df) Pearson = **1.010821**

Variance function: **V(u) = u*(1-u)**

[**Bernoulli**]

Link function : **g(u) = invnorm(u)**

[**Probit**]

BIC = **-1715.632**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf20	.0064287	.0030571	2.10	0.035	.0004369	.0124206
illw3	.0564777	.0651612	0.87	0.386	-.0712358	.1841913
avgcumdosew3	.0763386	.0422654	1.81	0.071	-.0065001	.1591772
_cons	-1.303581	.2556066	-5.10	0.000	-1.804561	-.8026017

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

Iteration 0: log likelihood = **-3441.3735**

Generalized linear models

Optimization : **ML**

Deviance = **3647330298**

Pearson = **3647330298**

No. of obs = **363**

Residual df = **361**

Scale parameter = **1.01e+07**

(1/df) Deviance = **1.01e+07**

(1/df) Pearson = **1.01e+07**

Variance function: **V(u) = 1**

[**Gaussian**]

Link function : **g(u) = u**

[**Identity**]

Log likelihood = **-3441.373501**

AIC = **18.97175**

BIC = **3.65e+09**

bf22	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	198.9575	95.12376	2.09	0.036	12.51832	385.3966
_cons	3099.215	202.2427	15.32	0.000	2702.826	3495.603

Iteration 1: deviance = **404.7126**

Iteration 2: deviance = **404.2497**

Iteration 3: deviance = **404.2495**

Iteration 4: deviance = **404.2495**

Generalized linear models

Optimization : **MQL Fisher scoring**
(**IRLS EIM**)

Deviance = **404.2495058**

Pearson = **361.0837357**

No. of obs = **363**

Residual df = **359**

Scale parameter = **1**

(1/df) Deviance = **1.126043**

(1/df) Pearson = **1.005804**

Variance function: **V(u) = u*(1-u)**

[**Bernoulli**]

Link function : **g(u) = invnorm(u)**

[**Probit**]

BIC = **-1711.841**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf22	.0000268	.0000236	1.14	0.256	-.0000194	.000073
illw3	.0662768	.0652813	1.02	0.310	-.0616722	.1942257
avgcumdosew3	.0787126	.0424878	1.85	0.064	-.004562	.1619871
_cons	-.8976713	.1234173	-7.27	0.000	-1.139565	-.6557778

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

Iteration 0: log likelihood = **-3484.9822**

Generalized linear models

Optimization : **ML**

Deviance = **4637909003**

Pearson = **4637909003**

No. of obs = **363**

Residual df = **361**

Scale parameter = **1.28e+07**

(1/df) Deviance = **1.28e+07**

(1/df) Pearson = **1.28e+07**

Variance function: **V(u) = 1**

[**Gaussian**]

Link function : **g(u) = u**

[**Identity**]

Log likelihood = **-3484.982169**

AIC = **19.21202**

BIC = **4.64e+09**

bf29	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	40.03151	107.2661	0.37	0.709	-170.2062	250.2692
_cons	265.9396	228.0586	1.17	0.244	-181.0471	712.9263

Iteration 1: deviance = **405.4201**

Iteration 2: deviance = **404.937**

Iteration 3: deviance = **404.9369**

Iteration 4: deviance = **404.9369**

Generalized linear models

Optimization : **MQL Fisher scoring**
(**IRLS EIM**)

Deviance = **404.9368816**

Pearson = **362.1381099**

No. of obs = **363**

Residual df = **359**

Scale parameter = **1**

(1/df) Deviance = **1.127958**

(1/df) Pearson = **1.008741**

Variance function: **V(u) = u*(1-u)**

[**Bernoulli**]

Link function : **g(u) = invnorm(u)**

[**Probit**]

BIC = **-1711.154**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf29	.000015	.0000199	0.75	0.452	-.0000241	.000054
illw3	.0693319	.0654643	1.06	0.290	-.0589757	.1976395
avgcumdosew3	.0823559	.0423081	1.95	0.052	-.0005665	.1652783
_cons	-.8176021	.1003576	-8.15	0.000	-1.014299	-.6209049

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

Iteration 0: log likelihood = **-2855.9026**

Generalized linear models

Optimization : **ML**

Deviance = **144895947.3**

Pearson = **144895947.3**

Variance function: **V(u) = 1**

Link function : **g(u) = u**

No. of obs = **363**

Residual df = **361**

Scale parameter = **401373.8**

(1/df) Deviance = **401373.8**

(1/df) Pearson = **401373.8**

[**Gaussian**]

[**Identity**]

Log likelihood = **-2855.902622**

AIC = **15.74602**

BIC = **1.45e+08**

bf30	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	45.42508	18.95962	2.40	0.017	8.264914	82.58525
_cons	474.094	40.31007	11.76	0.000	395.0877	553.1003

Iteration 1: deviance = **403.2568**

Iteration 2: deviance = **402.8398**

Iteration 3: deviance = **402.8396**

Iteration 4: deviance = **402.8396**

Iteration 5: deviance = **402.8396**

Generalized linear models

Optimization : **ML Fisher scoring**
(**IRLS EIM**)

Deviance = **402.8396329**

Pearson = **362.9011676**

No. of obs = **363**

Residual df = **359**

Scale parameter = **1**

(1/df) Deviance = **1.122116**

(1/df) Pearson = **1.010867**

Variance function: **V(u) = u*(1-u)**

Link function : **g(u) = invnorm(u)**

[**Bernoulli**]

[**Probit**]

BIC = **-1713.251**

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf30	.0001877	.0001196	1.57	0.116	-.0000466	.0004221
illw3	.0850723	.065274	1.30	0.192	-.0428624	.2130069
avgcumdosew3	.0727348	.0430132	1.69	0.091	-.0115696	.1570391
_cons	-.9155104	.1202543	-7.61	0.000	-1.151204	-.6798163

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

Iteration 0: log likelihood = **-818.14796**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	5.340664
Deviance = 1927.979854	(1/df) Deviance	=	5.340664
Pearson = 1927.979854	(1/df) Pearson	=	5.340664
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	4.518722
Log likelihood = -818.1479598	<u>BIC</u>	=	-199.8996

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.152897	.0691596	2.21	0.027	.0173466	.2884474
_cons	2.981537	.1470404	20.28	0.000	2.693343	3.269731

Iteration 1: deviance = **401.3653**
Iteration 2: deviance = **400.9889**
Iteration 3: deviance = **400.9888**
Iteration 4: deviance = **400.9888**

Generalized linear models	No. of obs	=	363
Optimization : MQL Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 400.9887605	(1/df) Deviance	=	1.11696
Pearson = 359.9660415	(1/df) Pearson	=	1.002691
Variance function: V(u) = u*(1-u)	[Bernoulli]		
Link function : g(u) = invnorm(u)	[Probit]		
	BIC	=	-1715.102

hp2work	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf40	.0689094	.0331691	2.08	0.038	.0038992	.1339195
illw3	.0376887	.0670381	0.56	0.574	-.0937035	.1690809
avgcumdosew3	.0782343	.0423534	1.85	0.065	-.0047769	.1612455
_cons	-1.010896	.13795	-7.33	0.000	-1.281273	-.7405191

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

```

385 . * Saving mediators as scalars for Dose=work relationship
386 . **** female mediators of dose-paid employment: radhlw3, age, bf40, bf4m, bf4
    > , bf1
387 . scalar wkMedFw3 = "radhlw3 age bf40 bf4m bf1"

388 . scalar list
    VactnMedFw3 = age illw3 radhlw3
    VactnMedMw3 = age illw3
    VacatnModFw3 = none
    MainEffVactnFw3 = age radhlw3 deaw3
    SigDoseVactnFw3 = no
    vactnModMw3 = none
    MainEffVactnMw3 = age bf7m radhlw3
    SigDoseVactnMw3 = no
    sxLifeMedFw3 = age bf4 bf4m
    sxLifeMedMw3 = age illw3
    InthbModFw3 = none
    MainEffInthbFw3 = age radhlw3 bf4
    SigdoseInthbFw3 = no
    InthbMw3 = none
    MainEffInthbMw3 = age radhlw3 shfamw3
    SigDoseInthbMw3 = no
    sxlifeMedFw3 = age illw3 radhlw3 bf4 bf4m
    sxlifeMedMw3 = age illw3
    sxlifeModFw3 = none
    MainEffsxlifeFw3 = age radhlw3 bf4 bf4m shrelaw3 shfamw3
    SigDoseSxlifeFw3 = no
    sxlifeModMw3 = none
    SigDosesxlifeMw3 = no
    MainEffsxlifeMw3 = age bf4 illw3 radhlw3
    PrbfmhmMedFw3 = age bf4
    PrbfmhmMedMw3 = age
    PrbfmhmModFw3 = none
    MainEffPrbfmhmFw3 = age bf4 bf40
    SigDosePrbfmhmFw3 = no
    PrbfmhmModw3 = none
    SigDosePrbfmhmMw3 = no
    SigDosePrbfhmMw3 = no

```

```

MainEffPrbfbhmMw3 = bf1 bf4 dvcew3 bf7m
ProbsocMedFw3 = age radhlw3
ProbsocMedMw3 = age
ProbsocModFw3 = none
MainEffProbSocFw3 = age radhlw3 illw3 Shrelaw3 avgcumodsew3
SigDoseProbsocFw3 = yes
ProbSocModMw3 = none
SigDoseProbsocMw3 = no
MainEffPrbsocMw3 = age radhlw3 shjobw3
hmcareMedFw3 = age illw3
hmcareMedMw3 = age illw3
hmcareModFw3 = none
SigdoseHmcareFw3 = no
hmcareModMw3 = none
MainEffhmcareMw3 = none
SigDoseHmcareMw3 = no
    wkMedFw3 = radhlw3 age bf40 bf4m bf1
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no
    medsigFw2 = 1
    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
prbsocnumMASig =      8

389 .
390 .
391 .
392 .
393 .
394 . *XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
> xxxx
395 . *----- Chunk 3      Dose=> hp2hmcare impact for males and females
396 . *XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
> xxxx
397 .
398 . title "2. Wave 3 part2 H1: dose home care relationship " ///
> " Wave 3 Dose - HP2home care Main effects identification"

*****
> *
*****
> *
*****
> *
*****
> *
*****      2. Wave 3 part2 H1: dose home care relationship      ****
> *
*****      Wave 3 Dose - HP2home care Main effects identification      ****
> *
*****
> *
*****
> *
*****
> *
*****      1 Jul 2012      20:36:21      ****
> *
*****
> *
*****
> *

```

```

399 .
400 . * review of general model for men and women
401 .
402 . forvalues j=3/3 {
      2. set more off
      3.
403 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
404 .   foreach var in HP2hmcare {
      5.
405 .       forvalues k=1/2 {
      6.   local w3bf 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.
406 .
407 .       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' radhlw3 ///
      >           illw`j' shfamw`j' shhlw`j' shjobw`j' shrelaw`j' suprtw`j' su
      > chrw`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

marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed
inclw3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
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)

```

*****
> *
*****
> *
*****
> *
*****
> *
***** chunk 3 H1 test pt 2 :Gender= 1 model Wave = 3 for hp2work *****
> *
*****
> *
*****
> *
*****
> *
***** 1 Jul 2012 20:36:21 *****
> *
*****
> *
*****
> *

```

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_8 != 0 predicts failure perfectly
 _Ieduc_8 dropped and 2 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

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

note: _Ieduc_7 omitted because of collinearity

note: occ8w3 omitted because of collinearity

note: marrw36 omitted because of collinearity

note: radhlw3 omitted because of collinearity

Logistic regression	Number of obs	=	315
	LR chi2(48)	=	139.93
	Prob > chi2	=	0.0000
Log likelihood = -96.893664	Pseudo R2	=	0.4193

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0323974	.0293162	1.11	0.269	-.0250612	.089856
_Ieduc_2	-4.152531	2.287775	-1.82	0.070	-8.636488	.3314257
_Ieduc_3	-1.864493	1.608696	-1.16	0.246	-5.017479	1.288493
_Ieduc_4	0	(omitted)				
_Ieduc_5	-1.404302	1.64491	-0.85	0.393	-4.628265	1.819662
_Ieduc_6	-2.017048	1.54335	-1.31	0.191	-5.041958	1.007861
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-11.82929	1296.263	-0.01	0.993	-2552.458	2528.799
occ2w3	-11.65702	1296.263	-0.01	0.993	-2552.286	2528.971
occ3w3	-12.78325	1296.263	-0.01	0.992	-2553.412	2527.846
occ4w3	-10.84152	1296.263	-0.01	0.993	-2551.47	2529.787
occ5w3	-10.72665	1296.263	-0.01	0.993	-2551.356	2529.903
occ6w3	0	(omitted)				
occ7w3	-11.31316	1296.263	-0.01	0.993	-2551.942	2529.316
occ8w3	0	(omitted)				
marrw31	.3643704	1.429352	0.25	0.799	-2.437107	3.165848
marrw32	-2.206121	1.844343	-1.20	0.232	-5.820966	1.408725
marrw33	-.7934545	1.390519	-0.57	0.568	-3.518821	1.931912
marrw35	-.2775718	1.556356	-0.18	0.858	-3.327973	2.772829
marrw36	0	(omitted)				
inclw3	14.70395	1296.262	0.01	0.991	-2525.924	2555.332

inc2w3	14.77269	1296.262	0.01	0.991	-2525.855	2555.4
inc3w3	14.57764	1296.262	0.01	0.991	-2526.05	2555.205
inc4w3	15.74154	1296.263	0.01	0.990	-2524.886	2556.37
radhlw3	.0078686	.0080582	0.98	0.329	-.007925	.0236623
havmil	.0027954	.0078952	0.35	0.723	-.0126789	.0182698
avgcumdosew3	.0057068	.0769937	0.07	0.941	-.1451981	.1566117
bf1	-.0445389	.0484618	-0.92	0.358	-.1395224	.0504446
bf4	-.0327423	.2796012	-0.12	0.907	-.5807506	.515266
bf2	.0000822	.0001677	0.49	0.624	-.0002465	.0004108
bf4m	-.341802	.2609957	-1.31	0.190	-.8533441	.1697402
bf5m	.0012439	.0017995	0.69	0.489	-.0022831	.0047709
bf7m	.0005614	.0005422	1.04	0.300	-.0005013	.0016241
bf8	-.0000499	.0000448	-1.11	0.265	-.0001376	.0000379
bf15m	-.0000712	.0003918	-0.18	0.856	-.0008391	.0006966
bf17	0	(omitted)				
bf20	.019063	.0407736	0.47	0.640	-.0608518	.0989778
bf22	.0000146	.0001733	0.08	0.933	-.0003251	.0003543
bf29	.0000124	.0000229	0.54	0.589	-.0000325	.0000572
bf30	-.000416	.0004185	-0.99	0.320	-.0012364	.0004043
bf40	.1486565	.2411791	0.62	0.538	-.3240459	.6213588
deaw3	-.6566764	.3112091	-2.11	0.035	-1.266635	-.0467177
dvcew3	.7731044	1.122755	0.69	0.491	-1.427455	2.973664
sepaw3	.1659839	1.359372	0.12	0.903	-2.498337	2.830305
accdw3	.7493757	.6472786	1.16	0.247	-.519267	2.018018
movew3	.9688514	.5333557	1.82	0.069	-.0765066	2.014209
radhlw3	0	(omitted)				
illw3	.2806377	.2813528	1.00	0.319	-.2708037	.832079
shfamw3	.0045809	.0088802	0.52	0.606	-.0128239	.0219857
shhlw3	-.0144819	.0077	-1.88	0.060	-.0295736	.0006098
shjobw3	-.0101653	.0077745	-1.31	0.191	-.0254031	.0050725
shrelaw3	-.0092584	.0083742	-1.11	0.269	-.0256716	.0071547
suprtw3	-.0009401	.0080071	-0.12	0.907	-.0166337	.0147535
suchrw3	-.004683	.0069496	-0.67	0.500	-.0183041	.008938
havmilsq	-7.50e-06	.0000145	-0.52	0.604	-.0000359	.0000209
_cons	3.229911	4.235709	0.76	0.446	-5.071927	11.53175

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	37	14	51
-	33	231	264
Total	70	245	315

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

Sensitivity	$\Pr(+ D)$	52.86%
Specificity	$\Pr(- \sim D)$	94.29%
Positive predictive value	$\Pr(D +)$	72.55%
Negative predictive value	$\Pr(\sim D -)$	87.50%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	5.71%
False - rate for true D	$\Pr(- D)$	47.14%
False + rate for classified +	$\Pr(\sim D +)$	27.45%
False - rate for classified -	$\Pr(D -)$	12.50%
Correctly classified		85.08%

Logistic model for HP2hmcare, goodness-of-fit test

number of observations =	315
number of covariate patterns =	315
Pearson $\chi^2(266)$ =	247.97
Prob > χ^2 =	0.7796

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

Log-Lik Intercept Only:	-166.857	Log-Lik Full Model:	-96.894
D(258):	193.787	LR(48):	139.928
		Prob > LR:	0.000
McFadden's R2:	0.419	McFadden's Adj R2:	0.078
Maximum Likelihood R2:	0.359	Cragg & Uhler's R2:	0.549
McKelvey and Zavoina's R2:	0.758	Efron's R2:	0.437
Variance of y*:	13.609	Variance of error:	3.290
Count R2:	0.851	Adj Count R2:	0.329
AIC:	0.977	AIC*n:	307.787
BIC:	-1290.376	BIC':	136.196

HP2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0784128	.0199184	3.94	0.000	.0393735	.1174521
_Ieduc_2	-16.15888	2.72009	-5.94	0.000	-21.49016	-10.8276
_Ieduc_3	-16.70929	2.647032	-6.31	0.000	-21.89738	-11.5212
_Ieduc_4	-15.65932	2.672964	-5.86	0.000	-20.89823	-10.4204
_Ieduc_5	-16.93546	2.621945	-6.46	0.000	-22.07438	-11.79654
_Ieduc_6	-17.12993	2.678622	-6.40	0.000	-22.37993	-11.87993
_Ieduc_7	-16.6826	3.290952	-5.07	0.000	-23.13274	-10.23245
_Ieduc_8	0	(omitted)				
occ1w3	-17.5089	2870.035	-0.01	0.995	-5642.674	5607.656
occ2w3	-17.42465	2870.035	-0.01	0.995	-5642.59	5607.741
occ3w3	-17.38618	2870.035	-0.01	0.995	-5642.551	5607.779
occ4w3	-17.97919	2870.035	-0.01	0.995	-5643.145	5607.186
occ5w3	-16.19886	2870.036	-0.01	0.995	-5641.366	5608.968
occ6w3	0	(omitted)				
occ7w3	-17.37679	2870.035	-0.01	0.995	-5642.542	5607.789
occ8w3	0	(omitted)				
marrw31	.1254457	1.662878	0.08	0.940	-3.133735	3.384627
marrw32	.689276	1.963389	0.35	0.726	-3.158896	4.537448
marrw33	1.411752	1.537008	0.92	0.358	-1.600728	4.424232
marrw35	.6824445	1.564972	0.44	0.663	-2.384843	3.749732
marrw36	.9604788	1.548632	0.62	0.535	-2.074784	3.995742
inclw3	18.76205	2870.035	0.01	0.995	-5606.403	5643.927
inc2w3	18.64464	2870.035	0.01	0.995	-5606.521	5643.81
inc3w3	18.13548	2870.035	0.01	0.995	-5607.03	5643.301
inc4w3	18.63139	2870.035	0.01	0.995	-5606.534	5643.797
radhlw3	-.0056373	.0071331	-0.79	0.429	-.0196178	.0083433
havmil	.0003358	.0026887	0.12	0.901	-.004934	.0056056
avgcumdosew3	-.1458757	.0962788	-1.52	0.130	-.3345787	.0428273
bf1	-.0155333	.0271811	-0.57	0.568	-.0688074	.0377407
bf4	-.4865728	.1784134	-2.73	0.006	-.8362567	-.136889
bf2	.0000926	.0001019	0.91	0.364	-.0001072	.0002923
bf4m	.3213367	.1603015	2.00	0.045	.0071516	.6355219
bf5m	-.000883	.0014167	-0.62	0.533	-.0036598	.0018937
bf7m	.0002998	.000443	0.68	0.499	-.0005684	.001168
bf8	6.84e-06	.0000322	0.21	0.832	-.0000563	.00007
bf15m	-.0163738	.5454291	-0.03	0.976	-1.085395	1.052648
bf17	.0008202	.0272715	0.03	0.976	-.0526309	.0542713
bf20	.00093	.0215397	0.04	0.966	-.041287	.043147
bf22	-.0000872	.0001081	-0.81	0.420	-.0002991	.0001247
bf29	0	(omitted)				
bf30	.0000251	.0002916	0.09	0.931	-.0005465	.0005967
bf40	.130008	.1227916	1.06	0.290	-.1106591	.3706751
deaw3	.0165154	.1614822	0.10	0.919	-.2999838	.3330147
dvcew3	.6982802	.7163029	0.97	0.330	-.7056476	2.102208
sepaw3	-.4992309	.8307882	-0.60	0.548	-2.127546	1.129084
accdw3	-.1706856	.4639657	-0.37	0.713	-1.080042	.7386705

movew3	-.4464406	1.157043	-0.39	0.700	-2.714203	1.821322
radhlw3	0	(omitted)				
illw3	-.0890835	.1513588	-0.59	0.556	-.3857412	.2075743
shfamw3	-.0035627	.0062149	-0.57	0.566	-.0157436	.0086183
shhlw3	.0080044	.0056769	1.41	0.159	-.0031221	.0191309
shjobw3	-.0042351	.0058007	-0.73	0.465	-.0156042	.0071341
shrelaw3	-.010315	.0062344	-1.65	0.098	-.0225341	.0019041
suprtw3	-.0017061	.0061593	-0.28	0.782	-.0137782	.010366
suchrw3	-.0030007	.0044692	-0.67	0.502	-.0117602	.0057587
havmilsq	-1.55e-06	2.58e-06	-0.60	0.549	-6.61e-06	3.52e-06
_cons	10.07155	.	.	.	.	.

Note: 4 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2hmcare

Classified	True		Total
	D	~D	
+	76	29	105
-	45	203	248
Total	121	232	353

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

True D defined as HP2hmcare != 0

Sensitivity	$\Pr(+ D)$	62.81%
Specificity	$\Pr(- \sim D)$	87.50%
Positive predictive value	$\Pr(D +)$	72.38%
Negative predictive value	$\Pr(\sim D -)$	81.85%
False + rate for true ~D	$\Pr(+ \sim D)$	12.50%
False - rate for true D	$\Pr(- D)$	37.19%
False + rate for classified +	$\Pr(\sim D +)$	27.62%
False - rate for classified -	$\Pr(D -)$	18.15%
Correctly classified		79.04%

Logistic model for HP2hmcare, goodness-of-fit test

number of observations =	353
number of covariate patterns =	353
Pearson chi2(301) =	338.41
Prob > chi2 =	0.0677

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

Log-Lik Intercept Only:	-226.929	Log-Lik Full Model:	-154.513
D(296):	309.025	LR(50):	144.834
		Prob > LR:	0.000
McFadden's R2:	0.319	McFadden's Adj R2:	0.068
Maximum Likelihood R2:	0.337	Cragg & Uhler's R2:	0.465
McKelvey and Zavoina's R2:	0.954	Efron's R2:	0.369
Variance of y*:	71.429	Variance of error:	3.290
Count R2:	0.790	Adj Count R2:	0.388
AIC:	1.198	AIC*n:	423.025
BIC:	-1427.449	BIC':	148.490

408 .

409 . title4 "Male Main effects model for dose=> homcare wave 3"

Male Main effects model for dose=> homcare wave 3

410 . logit hp2hmcare age radhlw3 avgcumdosew3 bf4 bf4m bf40 if gender==1

Iteration 0: log likelihood = **-172.87291**
 Iteration 1: log likelihood = **-133.30015**
 Iteration 2: log likelihood = **-130.66001**
 Iteration 3: log likelihood = **-130.56564**
 Iteration 4: log likelihood = **-130.56534**
 Iteration 5: log likelihood = **-130.56534**

Logistic regression	Number of obs	=	340
	LR chi2(6)	=	84.62
	Prob > chi2	=	0.0000
Log likelihood = -130.56534	Pseudo R2	=	0.2447

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0212427	.0145356	1.46	0.144	-.0072466	.0497319
radhlw3	-.0004747	.0052658	-0.09	0.928	-.0107954	.0098461
avgcumdosew3	.0109468	.049766	0.22	0.826	-.0865928	.1084864
bf4	-.0254029	.2104548	-0.12	0.904	-.4378867	.3870809
bf4m	-.172073	.19389	-0.89	0.375	-.5520905	.2079444
bf40	.1415116	.0924687	1.53	0.126	-.0397237	.3227469
_cons	.7537844	1.701465	0.44	0.658	-2.581025	4.088594

```

411 .
412 . 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

413 . 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

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

415 .
416 . scalar SigDoseHmcareMw3 = "no"

417 . scalar MainEffhmcareMw3= "none"

418 . scalar list
    VactnMedFw3 = age illw3 radhlw3
    VactnMedMw3 = age illw3
    VacatnModFw3 = none
    MainEffVactnFw3 = age radhlw3 deaw3
    SigDoseVactnFw3 = no
    vactnModMw3 = none
    MainEffVactnMw3 = age bf7m radhlw3
    SigDoseVactnMw3 = no
    sxLifeMedFw3 = age bf4 bf4m
    sxLifeMedMw3 = age illw3
    InthbModFw3 = none
    MainEffInthbFw3 = age radhlw3 bf4
    SigdoseInthbFw3 = no
    InthbMw3 = none
    MainEffInthbMw3 = age radhlw3 shfamw3
    SigDoseInthbMw3 = no
    sxlifeMedFw3 = age illw3 radhlw3 bf4 bf4m
    sxlifeMedMw3 = age illw3
    sxlifeModFw3 = none
    MainEffsxlifeFw3 = age radhlw3 bf4 bf4m shrelaw3 shfamw3
    SigDoseSxlifeFw3 = no
    sxlifeModMw3 = none
    SigDosesxlifeMw3 = no
    MainEffsxlifeMw3 = age bf4 illw3 radhlw3
    PrbfmhmMedFw3 = age bf4
    PrbfmhmMedMw3 = age
    PrbfmhmModFw3 = none
    MainEffPrbfmhmFw3 = age bf4 bf40
    SigDosePrbfmhmFw3 = no
    PrbfmhmModw3 = none
    SigDosePrbfmhmMw3 = no

```

```

SigDosePrbfhmMw3 = no
MainEffPrbfhmMw3 = bf1 bf4 dvcew3 bf7m
ProbsocMedFw3 = age radhlw3
ProbsocMedMw3 = age
ProbsocModFw3 = none
MainEffProbSocFw3 = age radhlw3 illw3 Shrelaw3 avgcumodsew3
SigDoseProbsocFw3 = yes
ProbSocModMw3 = none
SigDoseProbsocMw3 = no
MainEffPrbsocMw3 = age radhlw3 shjobw3
hmcareMedFw3 = age illw3
hmcareMedMw3 = age illw3
hmcareModFw3 = none
SigdoseHmcareFw3 = no
hmcareModMw3 = none
MainEffhmcareMw3 = none
SigDoseHmcareMw3 = no
    wkMedFw3 = radhlw3 age bf40 bf4m bf1
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no
    medsigFw2 = 1
    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

```

```

419 .
420 . title4 "male main effect plus interaction model"

```

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

```
421 . logit hp2hmcare age radhlw3 avgcumdosew3 ageXd3 illw3 if gender==1
```

```

Iteration 0:  log likelihood = -172.87291
Iteration 1:  log likelihood = -149.81879
Iteration 2:  log likelihood = -148.25194
Iteration 3:  log likelihood = -148.24243
Iteration 4:  log likelihood = -148.24243

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	49.26
	Prob > chi2	=	0.0000
Log likelihood = -148.24243	Pseudo R2	=	0.1425

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0437867	.0172121	2.54	0.011	.0100515	.0775219
radhlw3	.0144867	.0043947	3.30	0.001	.0058733	.0231002
avgcumdosew3	.3109469	.7827747	0.40	0.691	-1.223263	1.845157
ageXd3	-.0057849	.0134227	-0.43	0.666	-.0320929	.020523
illw3	.40549	.1399082	2.90	0.004	.1312749	.679705
_cons	-4.648689	.9666744	-4.81	0.000	-6.543336	-2.754042

```

422 . cap gen radhlw3Xillw3 = radhlw3*illw3

423 . cap drop radhlw3Xd1

424 . cap gen radhlw3Xd3 = radhlw3*avgcumdosew3

425 . cap drop illw3Xd1

426 . cap gen illw3Xd3 = illw3*avgcumdosew3

427 .
428 .
429 . * there are no significant moderators for male dose=hmcare relationship
430 . scalar hmcareModMw3 = "none"

431 .
432 . *----- Male moderator tests for Dose-Hmcare in wave 3: -----
    > -----
433 .
434 . title "Dose-home care impact relationship reveals no male moderators"

*****
> *
*****
> *
*****
> *
*****
> *
***** Dose-home care impact relationship reveals no male moderators *****
> *
*****
> *
*****
> *
*****
> *
***** 1 Jul 2012 20:36:27 *****
> *
*****
> *
*****
> *

```

```

435 . logit hp2hmcare radhlw3 avgcumdosew3 illw3 radhlw3Xillw3 radhlw3Xd3 illw3Xd3
>   ///
>   if gender==1

```

```

Iteration 0:   log likelihood = -172.87291
Iteration 1:   log likelihood = -153.71153
Iteration 2:   log likelihood = -152.25962
Iteration 3:   log likelihood = -152.22817
Iteration 4:   log likelihood = -152.22779
Iteration 5:   log likelihood = -152.22779

```

Logistic regression

```

Number of obs   =      340
LR chi2(6)      =      41.29
Prob > chi2     =      0.0000
Pseudo R2      =      0.1194

```

Log likelihood = **-152.22779**

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
hp2hmcare						
radhlw3	.0200281	.0064545	3.10	0.002	.0073775	.032678
avgcumdosew3	-.1252158	.2932467	-0.43	0.669	-.6999688	.449537
illw3	.677266	.2824634	2.40	0.016	.1236479	1.23088
radhlw3Xillw3	-.0042432	.0039636	-1.07	0.284	-.0120118	.003525
radhlw3Xd3	.0007389	.0042983	0.17	0.864	-.0076857	.009163
illw3Xd3	.0384326	.0812891	0.47	0.636	-.120891	.197756
_cons	-2.652783	.4389838	-6.04	0.000	-3.513175	-1.79239

436 . estat gof

Logistic model for hp2hmcare, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      306
      Pearson chi2(299) =     319.87
          Prob > chi2 =         0.1945

```

437 . estat class

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	8	5	13
-	62	265	327
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	11.43%
Specificity	$\Pr(- \sim D)$	98.15%
Positive predictive value	$\Pr(D +)$	61.54%
Negative predictive value	$\Pr(\sim D -)$	81.04%

False + rate for true ~D	$\Pr(+ \sim D)$	1.85%
False - rate for true D	$\Pr(- D)$	88.57%
False + rate for classified +	$\Pr(\sim D +)$	38.46%
False - rate for classified -	$\Pr(D -)$	18.96%

Correctly classified		80.29%
----------------------	--	--------

```
438 . fitstat
```

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

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-152.228
D(333):	304.456	LR(6):	41.290
		Prob > LR:	0.000
McFadden's R2:	0.119	McFadden's Adj R2:	0.079
Maximum Likelihood R2:	0.114	Cragg & Uhler's R2:	0.179
McKelvey and Zavoina's R2:	0.208	Efron's R2:	0.130
Variance of y*:	4.154	Variance of error:	3.290
Count R2:	0.803	Adj Count R2:	0.043
AIC:	0.937	AIC*n:	318.456
BIC:	-1636.583	BIC':	-6.317

439 .

440 .

```
441 . title "trimming female moderators for hp2hmcare"
```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
trimming female moderators for hp2hmcare
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:36:29
> *
*****
> *
*****
> *
*****

```

```

442 .
443 . * Dose work relationship for females in wave 3 washes out also
444 . set more off

445 . forvalues j=3/3 {
      2. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      3. di _skip(4)
      4. di as input "For females hp2hmcare on wave 1 with dose ns"
      5. des age avgcumdosew`j' `w3bf'
      6. logistic HP2work age radhlw3 ///
      > avgcumdosew3 shhlw`j' if gender==2, coef nolog
      7.
446 . }

```

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
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009
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(4) = 54.20

Prob > chi2 = 0.0000

Log likelihood = -179.46218

Pseudo R2 = 0.1312

HP2work	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0604261	.0121821	4.96	0.000	.0365495	.0843027
radhlw3	.0091245	.0041171	2.22	0.027	.0010551	.0171938
avgcumdosew3	.0744838	.0646958	1.15	0.250	-.0523177	.2012853
shhlw3	.0068705	.0039339	1.75	0.081	-.0008399	.0145808
_cons	-5.221192	.6904908	-7.56	0.000	-6.574529	-3.867855

```
447 .
448 .
449 .
450 .
451 .
452 .
453 .
454 .
455 . scalar SigdoseHmcareFw3="no"

456 .
457 . * capturing significant vars to test as moderators
458 . local cn4: colnames(e(b))

459 . di "`cn4'"
      age radhlw3 avgcumdosew3 shhlw3 _cons

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

461 . di `leng4'
37
```

```

462 . local leng4b `leng4'-6
463 . di `leng3b'

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

465 . di "`nuvlist4'"
      radhlw3 avgcumdosew3 shhlw3 _c

466 . local rhsvars4 = "`nuvlist4'"

467 . local nuvlist4= "`nuvlist4'"

468 . local nuvlist4= substr("`cn4'",1,`leng4b')

469 . di "`nuvlist4'"
      age radhlw3 avgcumdosew3 shhlw3

470 .
471 . cap gen shhlw3Xd3 = shhlw3*avgcumdosew3

472 .
473 . 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    20:36:30    ****
> *
*****
> *
*****
> *

```

```
474 . logit hp2hmcare age shhlw3 avgcumdosew3 ageXd3 shhlw3Xd3 if gender==2
```

```
Iteration 0:  log likelihood = -233.72859
Iteration 1:  log likelihood = -194.59265
Iteration 2:  log likelihood = -193.8132
Iteration 3:  log likelihood = -193.8113
Iteration 4:  log likelihood = -193.8113
```

```
Logistic regression                                Number of obs   =       363
                                                    LR chi2(5)      =       79.83
                                                    Prob > chi2     =       0.0000
Log likelihood = -193.8113                        Pseudo R2      =       0.1708
```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0869437	.0159483	5.45	0.000	.0556857	.1182017
shhlw3	.0025983	.0052389	0.50	0.620	-.0076698	.0128663
avgcumdosew3	-.5753628	.7013698	-0.82	0.412	-1.950022	.7992968
ageXd3	.0054767	.0110707	0.49	0.621	-.0162215	.0271749
shhlw3Xd3	.0024363	.0033657	0.72	0.469	-.0041603	.0090329
_cons	-5.058574	.9113937	-5.55	0.000	-6.844872	-3.272275

```
475 .
```

```
476 . set more off
```

```
477 . *----- Mediator relationships for home care are tested below: -----
> ----
```

```
478 . title "Mediator relationships of Dose - home care impact are tested"
```

```
*****
> *
*****
> *
*****
> *
*****
> *
***** Mediator relationships of Dose - home care impact are tested *****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:36:32    *****
> *
*****
```

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

```
479 . forvalues k=1/2 {
      2. forvalues j=3/3 {
      3. local w3bf 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' `w3bf'
      7. sw, pr(.1): logistic hp2hmcare age havmilsq ///
> avgcumdosew3 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 3

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w3	double	%15.0g	LABJ	professional executive administration now
occ2w3	double	%15.0g	LABJ	technical sales admin support now
occ3w3	double	%15.0g	LABJ	service occup protective services now
occ4w3	double	%15.0g	LABJ	precision prod mechan craft construction now
occ5w3	double	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	double	%15.0g	LABJ	homemaking or caregiving now
occ8w3	double	%15.0g	LABJ	student now
incl1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW

```

inc4w3          double %15.0g      LABJ      Income allows to comfortably
              afford luxury items NOW
avgcumdosew3    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 = 0.8890 >= 0.1000 removing shjobw3
p = 0.7169 >= 0.1000 removing avgcumdosew3
p = 0.6181 >= 0.1000 removing ageXd3
p = 0.3884 >= 0.1000 removing suprtw3
p = 0.3741 >= 0.1000 removing havmilsq

```

Logistic regression

```

Number of obs   =      340
LR chi2(2)      =      37.81
Prob > chi2     =      0.0000
Pseudo R2      =      0.1094

```

Log likelihood = -153.96835

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.050053	.0120837	4.14	0.000	.0263694	.0737367
illw3	.450018	.1335457	3.37	0.001	.1882732	.7117629
_cons	-4.209924	.6577161	-6.40	0.000	-5.499024	-2.920824

Logistic model for hp2hmcare, goodness-of-fit test

```
number of observations =      340
number of covariate patterns =    108
Pearson chi2(105) =    123.84
Prob > chi2 =      0.1012
```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	9	5	14
-	61	265	326
Total	70	270	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as hp2hmcare != 0

Sensitivity	$\Pr(+ D)$	12.86%
Specificity	$\Pr(- \sim D)$	98.15%
Positive predictive value	$\Pr(D +)$	64.29%
Negative predictive value	$\Pr(\sim D -)$	81.29%
False + rate for true ~D	$\Pr(+ \sim D)$	1.85%
False - rate for true D	$\Pr(- D)$	87.14%
False + rate for classified +	$\Pr(\sim D +)$	35.71%
False - rate for classified -	$\Pr(D -)$	18.71%
Correctly classified		80.59%

Measures of Fit for logistic of hp2hmcare

Log-Lik Intercept Only:	-172.873	Log-Lik Full Model:	-153.968
D(337):	307.937	LR(2):	37.809
		Prob > LR:	0.000
McFadden's R2:	0.109	McFadden's Adj R2:	0.092
Maximum Likelihood R2:	0.105	Cragg & Uhler's R2:	0.165
McKelvey and Zavoina's R2:	0.170	Efron's R2:	0.126
Variance of y*:	3.965	Variance of error:	3.290
Count R2:	0.806	Adj Count R2:	0.057
AIC:	0.923	AIC*n:	313.937
BIC:	-1656.418	BIC':	-26.151

Trimmed gender=2 hp2hmcare impact of dose in wave 3

variable name	storage type	display format	value label	variable label
age	double	%8.0g		* Respondent's age
occ1w3	double	%15.0g	LABJ	professional executive administration now
occ2w3	double	%15.0g	LABJ	technical sales admin support now
occ3w3	double	%15.0g	LABJ	service occup protective services now
occ4w3	double	%15.0g	LABJ	precision prod mechan craft construction now
occ5w3	double	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	double	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	double	%15.0g	LABJ	homemaking or caregiving now
occ8w3	double	%15.0g	LABJ	student now
inc1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009
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 = 0.8360 >= 0.1000 removing ageXd3
p = 0.7775 >= 0.1000 removing suprtw3
p = 0.3880 >= 0.1000 removing havmilsq
p = 0.3482 >= 0.1000 removing shjobw3
p = 0.2310 >= 0.1000 removing illw3
p = 0.1422 >= 0.1000 removing avgcumdosew3

```

```

Logistic regression                                Number of obs   =       362
                                                    LR chi2(1)      =       75.69
                                                    Prob > chi2     =       0.0000
Log likelihood = -195.46039                      Pseudo R2      =       0.1622

```

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0916735	.0119861	7.65	0.000	.0681811	.1151659
_cons	-5.391274	.6487	-8.31	0.000	-6.662703	-4.119845

Logistic model for hp2hmcare, goodness-of-fit test

```

number of observations =       362
number of covariate patterns =       49
Pearson chi2(47) =       40.39
Prob > chi2 =       0.7413

```

Logistic model for hp2hmcare

Classified	True		Total
	D	~D	
+	62	32	94
-	63	205	268
Total	125	237	362

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as `hp2hmcare != 0`

Sensitivity	$\Pr(+ D)$	49.60%
Specificity	$\Pr(- \sim D)$	86.50%
Positive predictive value	$\Pr(D +)$	65.96%
Negative predictive value	$\Pr(\sim D -)$	76.49%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	13.50%
False - rate for true D	$\Pr(- D)$	50.40%
False + rate for classified +	$\Pr(\sim D +)$	34.04%
False - rate for classified -	$\Pr(D -)$	23.51%
Correctly classified		73.76%

Measures of Fit for **logistic** of **hp2hmcare**

Log-Lik Intercept Only:	-233.306	Log-Lik Full Model:	-195.460
D(360):	390.921	LR(1):	75.691
		Prob > LR:	0.000
McFadden's R2:	0.162	McFadden's Adj R2:	0.154
Maximum Likelihood R2:	0.189	Cragg & Uhler's R2:	0.260
McKelvey and Zavoina's R2:	0.264	Efron's R2:	0.208
Variance of y*:	4.472	Variance of error:	3.290
Count R2:	0.738	Adj Count R2:	0.240
AIC:	1.091	AIC*n:	394.921
BIC:	-1730.071	BIC':	-69.799

```

480 .
481 . scalar hmcareModFw3 = "none"

482 .
483 .
484 .
485 . * age and illw3 are a female mediators of dose - home care impact
486 .

```

```

487 . * age is a male and female mediator with impact on home care
488 . glm age avgcumdosew3 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-1330.6336**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.7142
Deviance = 49927.38549	(1/df) Deviance	=	147.7142
Pearson = 49927.38549	(1/df) Pearson	=	147.7142
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.839021
Log likelihood = -1330.633586	<u>BIC</u>	=	47957.2

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.5433648	.2472657	2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376	66.95	0.000	47.09975	49.94067

```

489 . 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.)

490 .

491 . glm age avgcumdosew3 if gender==2, fam(gaussian) link(identity)

Iteration 0: log likelihood = **-1408.064**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	137.7687
Deviance = 49734.51399	(1/df) Deviance	=	137.7687
Pearson = 49734.51399	(1/df) Pearson	=	137.7687
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.768948
Log likelihood = -1408.06405	<u>BIC</u>	=	47606.63

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

492 . 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

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

[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.)

493 .
 494 .
 495 . * illw3 is a male mediator wrt dose home care impact
 496 . glm illw3 avgcumdosew3 if gender==1, fam(gaussian) link(identity)

Iteration 0: log likelihood = -461.99206

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.8919217
Deviance = 301.469521	(1/df) Deviance	=	.8919217
Pearson = 301.469521	(1/df) Pearson	=	.8919217

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

	<u>AIC</u>	=	2.729365
Log likelihood = -461.9920626	<u>BIC</u>	=	-1668.714

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.038211	.0192139	1.99	0.047	.0005524	.0758696
_cons	.4504952	.0563162	8.00	0.000	.3401176	.5608729

```
497 . glm hp2hmcare illw3 if gender==1, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =   325.666
Iteration 2:  deviance =   325.6236
Iteration 3:  deviance =   325.6236
Iteration 4:  deviance =   325.6236
```

```
Generalized linear models                               No. of obs      =       340
Optimization      : ML Fisher scoring                 Residual df    =       338
                  (IRLS EIM)                          Scale parameter =         1
Deviance          =   325.6235917                      (1/df) Deviance =   .9633834
Pearson           =   335.97027                         (1/df) Pearson  =   .9939949
```

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

```
BIC = -1644.56
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.3422616	.0758391	4.51	0.000	.1936197	.4909035
_cons	-1.024423	.0902165	-11.36	0.000	-1.201244	-.8476019

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

```
498 .
```

```
499 . glm illw3 avgcumdosew3 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0:  log likelihood = -562.81042
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML                                 Residual df    =       361
Scale parameter =   1.308042
Deviance          =   472.2033151                      (1/df) Deviance =   1.308042
Pearson           =   472.2033151                      (1/df) Pearson  =   1.308042
```

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

```
AIC = 3.111903
Log likelihood    = -562.8104237
BIC = -1655.676
```

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1284565	.0342268	3.75	0.000	.0613733	.1955398
_cons	.5563644	.0727696	7.65	0.000	.4137387	.6989902

```
500 . glm hp2hmcare illw3 if gender==2, fam(binomial) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 463.6739
Iteration 2:  deviance = 463.093
Iteration 3:  deviance = 463.0929
Iteration 4:  deviance = 463.0929
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 463.0929333	(1/df) Deviance	=	1.282806
Pearson = 362.4107813	(1/df) Pearson	=	1.003908

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

```
BIC = -1664.786
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.1203099	.0649774	1.85	0.064	-.0070435	.2476634
_cons	-.4898124	.0909036	-5.39	0.000	-.6679803	-.3116445

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

```
501 .
502 .
```

```

503 .
504 . scalar hmcareMedMw3 = "age illw3"

505 . scalar hmcareMedFw3 = "age illw3"

506 . scalar list
    VactnMedFw3 = age illw3 radhlw3
    VactnMedMw3 = age illw3
    VacatnModFw3 = none
    MainEffVactnFw3 = age radhlw3 deaw3
    SigDoseVactnFw3 = no
    vactnModMw3 = none
    MainEffVactnMw3 = age bf7m radhlw3
    SigDoseVactnMw3 = no
    sxLifeMedFw3 = age bf4 bf4m
    sxLifeMedMw3 = age illw3
    InthbModFw3 = none
    MainEffInthbFw3 = age radhlw3 bf4
    SigdoseInthbFw3 = no
    InthbMw3 = none
    MainEffInthbMw3 = age radhlw3 shfamw3
    SigDoseInthbMw3 = no
    sxlifeMedFw3 = age illw3 radhlw3 bf4 bf4m
    sxlifeMedMw3 = age illw3
    sxlifeModFw3 = none
    MainEffsxlifeFw3 = age radhlw3 bf4 bf4m shrelaw3 shfamw3
    SigDoseSxlifeFw3 = no
    sxlifeModMw3 = none
    SigDosesxlifeMw3 = no
    MainEffsxlifeMw3 = age bf4 illw3 radhlw3
    PrbfmhmMedFw3 = age bf4
    PrbfmhmMedMw3 = age
    PrbfmhmModFw3 = none
    MainEffPrbfmhmFw3 = age bf4 bf40
    SigDosePrbfmhmFw3 = no
    PrbfmhmModw3 = none
    SigDosePrbfmhmMw3 = no
    SigDosePrbfhmMw3 = no
    MainEffPrbfhmMw3 = bf1 bf4 dvcew3 bf7m
    ProbsocMedFw3 = age radhlw3
    ProbsocMedMw3 = age
    ProbsocModFw3 = none
    MainEffProbSocFw3 = age radhlw3 illw3 Shrelaw3 avgcumodsew3
    SigDoseProbsocFw3 = yes
    ProbSocModMw3 = none
    SigDoseProbsocMw3 = no
    MainEffPrbsocMw3 = age radhlw3 shjobw3
    hmcareMedFw3 = age illw3
    hmcareMedMw3 = age illw3

```

```

hmcareModFw3 = none
SigdoseHmcareFw3 = no
hmcareModMw3 = none
MainEffhmcareMw3 = none
SigDoseHmcareMw3 = no
    wkMedFw3 = radhlw3 age bf40 bf4m bf1
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no
    medsigFw2 = 1
    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
prbsocnumMASig = 8

```

```

507 .
508 . * conclusion "age & illw3 are main effects as possible male & female mediato
    > rs"
509 . * conclusion title "their interaction is not a mediator"
510 .
511 .
512 .
513 .
514 . * Other non-signif test results for mediators of the dose-homecare impact
515 .
516 . glm illw3Xd3 illw3 avgcumdosew3 if gender==1, fam(gaussian) link(identity)

```

Iteration 0: log likelihood = **-910.27475**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	12.49768
Deviance = 4211.718004	(1/df) Deviance	=	12.49768
Pearson = 4211.718004	(1/df) Pearson	=	12.49768

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

	<u>AIC</u>	=	5.372204
Log likelihood = -910.2747528	<u>BIC</u>	=	2247.363

illw3Xd3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	1.785312	.2036071	8.77	0.000	1.386249	2.184374
avgcumdosew3	1.08337	.0723425	14.98	0.000	.9415811	1.225159
_cons	-1.330357	.2298973	-5.79	0.000	-1.780947	-.8797666

```

517 . glm hp2hmcare illw3Xd3 illw3 avgcumdosew3 if gender==1, fam(binomial) ///
    > irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 324.9852
Iteration 2: deviance = 324.7765
Iteration 3: deviance = 324.755
Iteration 4: deviance = 324.7539
Iteration 5: deviance = 324.7539
Iteration 6: deviance = 324.7539

```

```

Generalized linear models                      No. of obs      =       340
Optimization      : MQL Fisher scoring      Residual df     =       336
                  (IRLS EIM)                Scale parameter =         1
Deviance          =   324.7538899          (1/df) Deviance =   .9665294
Pearson           =   334.7330022          (1/df) Pearson  =   .9962292

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

                                          BIC              =  -1633.772

```

hp2hmcare	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw3Xd3	.0296527	.0383533	0.77	0.439	-.0455184	.1048239
illw3	.3037802	.0878109	3.46	0.001	.131674	.4758864
avgcumdosew3	-.0397572	.0621297	-0.64	0.522	-.1615292	.0820148
_cons	-.9819848	.10943	-8.97	0.000	-1.196464	-.767506

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

```
518 . glm illw3Xd3 illw3 avgcumdosew3 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0:   log likelihood = -985.70781
```

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                      Residual df     =       360
                                          Scale parameter =   13.48151
Deviance          =   4853.341842          (1/df) Deviance =   13.48151
Pearson           =   4853.341842          (1/df) Pearson  =   13.48151

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

                                          AIC              =   5.447426
Log likelihood    =  -985.7078088          BIC              =   2731.357

```

illw3Xd3	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
illw3	1.708471	.1689681	10.11	0.000	1.377299	2.039642
avgcumdosew3	2.232994	.1120046	19.94	0.000	2.013469	2.452519
_cons	-2.648599	.251824	-10.52	0.000	-3.142165	-2.155033

```

519 . glm hp2hmcare illw3Xd3 illw3 avgcumdosew3 if gender==2, fam(binomial) ///
>      irls scale(dev) link(probit)

```

```

Iteration 1:  deviance =    460.104
Iteration 2:  deviance =   459.2782
Iteration 3:  deviance =   459.2401
Iteration 4:  deviance =   459.2395
Iteration 5:  deviance =   459.2395
Iteration 6:  deviance =   459.2395

```

```

Generalized linear models                                No. of obs      =       363
Optimization      : ML Fisher scoring                  Residual df     =       359
                   (IRLS EIM)                           Scale parameter =        1
Deviance          =   459.2395051                       (1/df) Deviance =   1.279219
Pearson           =   360.8121049                       (1/df) Pearson  =   1.005048

```

```

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

```

```

BIC                                                    = -1656.851

```

hp2hmcare	EIM					[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z		
illw3Xd3	-.0506129	.0397971	-1.27	0.203	-.1286138	.0273881
illw3	.1996924	.0831248	2.40	0.016	.0367707	.3626141
avgcumdosew3	.0648611	.0733042	0.88	0.376	-.0788126	.2085348
_cons	-.5685167	.1207782	-4.71	0.000	-.8052376	-.3317958

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

```

520 .
521 .
522 . glm havmilsq avgcumdosew3 if gender==1, fam(gaussian) link(identity)

```

```

Iteration 0:  log likelihood =    -4357.43

```

```

Generalized linear models                                No. of obs      =       340
Optimization      : ML                                  Residual df     =       338
Scale parameter =   7.98e+09
Deviance          =   2.69659e+12                       (1/df) Deviance =   7.98e+09
Pearson           =   2.69659e+12                       (1/df) Pearson  =   7.98e+09

```

```

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

```

Log likelihood	= -4357.430049	<u>AIC</u>	= 25.64371
		<u>BIC</u>	= 2.70e+12

	OIM					
havmilsq	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-1575.31	1817.197	-0.87	0.386	-5136.952	1986.331
_cons	18893.16	5326.219	3.55	0.000	8453.963	29332.36

```
523 . glm hp2hmcare havmilsg 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
Optimization      : ML Fisher scoring
                   (IRLS EIM)
Deviance          = 345.1644251
Pearson           = 339.1838387
```

No. of obs	=	340
Residual df	=	338
Scale parameter	=	1
(1/df) Deviance	=	1.021197
(1/df) Pearson	=	1.003502

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

[Bernoulli]
[Probit]

BIC = -1625.019

	EIM					
hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
havmilsq	-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.)

```
524 . glm havmilsq avgcumdosew3 if gender==2, fam(gaussian) link(identity)
```

```
Iteration 0: log likelihood = -5315.4087
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	3.08e+11
Deviance = 1.11219e+14	(1/df) Deviance	=	3.08e+11
Pearson = 1.11219e+14	(1/df) Pearson	=	3.08e+11

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

	<u>AIC</u>	=	29.29702
Log likelihood = -5315.408686	<u>BIC</u>	=	1.11e+14

havamilsq	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	8378.635	16610.83	0.50	0.614	-24177.99	40935.26
_cons	50752.51	35316.31	1.44	0.151	-18466.18	119971.2

```
525 . 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.)

526 .

527 . glm radhlw3 avgcumdosew3 if gender==1, fam(gaussian) link(identity)

Iteration 0: log likelihood = **-1695.1855**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1261.052
Deviance = 426235.7205	(1/df) Deviance	=	1261.052
Pearson = 426235.7205	(1/df) Pearson	=	1261.052
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	9.983444
Log likelihood = -1695.185473	<u>BIC</u>	=	424265.5

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.9606492	.7224692	1.33	0.184	-.4553645	2.376663
_cons	46.19995	2.117563	21.82	0.000	42.0496	50.3503

528 . glm hp2hmcare radhlw3 if gender==1, fam(binomial) irls scale(dev) link(probi
> t)

Iteration 1: deviance = **319.2576**
Iteration 2: deviance = **318.3456**
Iteration 3: deviance = **318.3441**
Iteration 4: deviance = **318.3441**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 318.3440747	(1/df) Deviance	=	.9418464
Pearson = 342.3257119	(1/df) Pearson	=	1.012798

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

[Bernoulli]
 [Probit]

BIC = -1651.84

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0115758	.0022053	5.25	0.000	.0072534	.0158982
_cons	-1.437377	.1466803	-9.80	0.000	-1.724866	-1.149889

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

529 . glm radhlw3 avgcumdosew3 if gender==2, fam(gaussian) link(identity)

Iteration 0: log likelihood = -1798.7074

Generalized linear models
 Optimization : ML

No. of obs = 363
 Residual df = 361
 Scale parameter = 1185.454
 (1/df) Deviance = 1185.454
 (1/df) Pearson = 1185.454

Deviance = 427948.9522
 Pearson = 427948.9522

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

[Gaussian]
 [Identity]

Log likelihood = -1798.707367

AIC = 9.921253
 BIC = 425821.1

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	2.751602	1.03038	2.67	0.008	.7320943	4.77111
_cons	57.70689	2.190692	26.34	0.000	53.41321	62.00057

```
530 . glm hp2hmcare radhlw3 if gender==2, fam(binomial) irls scale(dev) link(probi
> t)
```

```
Iteration 1:  deviance = 466.2486
Iteration 2:  deviance = 465.6482
Iteration 3:  deviance = 465.6481
Iteration 4:  deviance = 465.6481
```

```
Generalized linear models                               No. of obs      =       363
Optimization      :  MQL Fisher scoring                 Residual df    =       361
                   (IRLS EIM)                          Scale parameter =        1
Deviance          = 465.6481297                        (1/df) Deviance =  1.289884
Pearson           = 362.9350038                        (1/df) Pearson  =  1.00536
```

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

```
BIC = -1662.231
```

hp2hmcare	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0026441	.0022316	1.18	0.236	-.0017297	.0070179
_cons	-.5636837	.1583099	-3.56	0.000	-.8739654	-.2534021

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

```
531 .
532 . title4 "*----- summary matrix construction for dose home care"
```

```
*----- summary matrix construction for dose home care
```

```
533 .
534 . matrix define HP2hmcrMw3 = J(1,8, 0)
```

```

535 .      matrix define HP2hmcFw3 = J(1,8, 0)

536 . matrix colnames HP2hmcMw3=  hypnum ptnum wave gender medsig numMA sig numMod
    > sig ///
    >      numMed

537 . matrix colnames HP2hmcFw3=  hypnum ptnum wave gender medsig numMA sig numMod
    > sig ///
    >      numMed

538 .      matrix rownames HP2hmcMw3 = hmcareM

539 .      matrix rownames HP2hmcFw3 = hmcareF

540 .      matrix define HP2hmcFw3= (1, 2, 3, 2, 0 ,2, 0 , 2 )

541 .      matrix define HP2hmcMw3= (1, 2, 3, 1, 0 , 4, 0 , 2 )

542 .      matrix define H1pt2w3 = (HP2wkMw3 \ HP2wkFw3 \ HP2hmcMw3 \HP2hmcFw
    > 3)

543 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMA sig numM
    > odsig numMed

544 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMA sig numM
    > odsig numMed

545 .      matrix rownames H1pt2w3 = HP2wkMw3 WHP2wkFw3 HP2hmcMw3 HP2hmcFw3

546 .      matlist H1pt2w3

```

	hypnum	ptnum	wave	gender	medsig	numMA sig	numMod
HP2wkMw3	1	2	3	1	0		
WHP2wkFw3	1	2	3	2	0		
HP2hmcMw3	1	2	3	1	0		
HP2hmcFw3	1	2	3	2	0		

	numModsig	numMed
HP2wkMw3	0	4
WHP2wkFw3	0	6
HP2hmcrMw3	0	2
HP2hmcrFw3	0	2

```

547 .
548 . * see scalar list for names of variables
549 . scalar list
VactnMedFw3 = age illw3 radhlw3
VactnMedMw3 = age illw3
VacatnModFw3 = none
MainEffVactnFw3 = age radhlw3 deaw3
SigDoseVactnFw3 = no
vactnModMw3 = none
MainEffVactnMw3 = age bf7m radhlw3
SigDoseVactnMw3 = no
sxLifeMedFw3 = age bf4 bf4m
sxLifeMedMw3 = age illw3
InthbModFw3 = none
MainEffInthbFw3 = age radhlw3 bf4
SigDoseInthbFw3 = no
    InthbMw3 = none
MainEffInthbMw3 = age radhlw3 shfamw3
SigDoseInthbMw3 = no
sxlifeMedFw3 = age illw3 radhlw3 bf4 bf4m
sxlifeMedMw3 = age illw3
sxlifeModFw3 = none
MainEffsxlifeFw3 = age radhlw3 bf4 bf4m shrelaw3 shfamw3
SigDoseSxlifeFw3 = no
sxlifeModMw3 = none
SigDosesxlifeMw3 = no
MainEffsxlifeMw3 = age bf4 illw3 radhlw3
PrbfmhmMedFw3 = age bf4
PrbfmhmMedMw3 = age
PrbfmhmModFw3 = none
MainEffPrbfmhmFw3 = age bf4 bf40
SigDosePrbfmhmFw3 = no
PrbfmhmModw3 = none
SigDosePrbfmhmMw3 = no
SigDosePrbfhmMw3 = no
MainEffPrbfhmMw3 = bf1 bf4 dvcew3 bf7m
ProbsocMedFw3 = age radhlw3
ProbsocMedMw3 = age
ProbsocModFw3 = none
MainEffProbSocFw3 = age radhlw3 illw3 Shrelaw3 avgcumodsew3
SigDoseProbsocFw3 = yes
ProbSocModMw3 = none

```

```

SigDoseProbsocMw3 = no
MainEffPrbsocMw3 = age radhlw3 shjobw3
hmcareMedFw3 = age illw3
hmcareMedMw3 = age illw3
hmcareModFw3 = none
SigdoseHmcareFw3 = no
hmcareModMw3 = none
MainEffhmcareMw3 = none
SigDoseHmcareMw3 = no
    wkMedFw3 = radhlw3 age bf40 bf4m bf1
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no
    medsigFw2 = 1
    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

```

```

550 .
551 . * X * missing the number of main effects in the trimmed models
552 .
553 . ////////////////////////////////////////
> *----- Chunk 4   Dose prob soc impact relationship HP2probsoc
554 . *-----
> ----
555 . *       General model for all part 2 of Nottingham Health Profile
556 .
557 . title " 3. Wave 3 part2    H1: Test of hypothesis 1 Part 2 "


*****
> *
*****
> *
*****                               ****
> *
*****                               ****
> *
*****      3. Wave 3 part2    H1: Test of hypothesis 1 Part 2          ****
> *
*****                               ****
> *
*****                               ****
> *
*****                               ****
> *
*****                                1 Jul 2012     20:37:19     ****
> *
*****
> *
*****
> *

```

```

558 . title " Wave 3 Dose - HP2probsoc Main effects identification"
```

```

559 . forvalues j=3/3 {
      2. set more off
      3.
560 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      >   bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
561 .   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.

```

```

562 .      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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed
inclw3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
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: marrw32 != 0 predicts failure perfectly
 marrw32 dropped and 20 obs not used

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

note: _Ieduc_6 omitted because of collinearity
 note: occ8w3 omitted because of collinearity
 note: marrw36 omitted because of collinearity
 note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	266
	LR chi2(44)	=	125.89
	Prob > chi2	=	0.0000
Log likelihood = -51.38371	Pseudo R2	=	0.5506

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1094616	.0479486	2.28	0.022	.015484	.2034392
_Ieduc_2	.7414425	1.297886	0.57	0.568	-1.802367	3.285252
_Ieduc_3	-1.614771	.8291042	-1.95	0.051	-3.239785	.0102435
_Ieduc_4	0	(omitted)				
_Ieduc_5	-1.309884	1.008415	-1.30	0.194	-3.286342	.6665737
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-14.19493	1124.783	-0.01	0.990	-2218.729	2190.339
occ2w3	-12.80013	1124.783	-0.01	0.991	-2217.335	2191.734
occ3w3	-14.84881	1124.785	-0.01	0.989	-2219.387	2189.689
occ4w3	-13.35572	1124.784	-0.01	0.991	-2217.891	2191.18
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-14.19043	1124.784	-0.01	0.990	-2218.726	2190.345
occ8w3	0	(omitted)				
marrw31	3.074981	1.891094	1.63	0.104	-.6314958	6.781458
marrw32	0	(omitted)				
marrw33	1.087086	1.851071	0.59	0.557	-2.540947	4.715119
marrw35	2.144183	1.926965	1.11	0.266	-1.632599	5.920964
marrw36	0	(omitted)				
inc1w3	12.66541	1124.784	0.01	0.991	-2191.87	2217.201
inc2w3	14.23621	1124.783	0.01	0.990	-2190.299	2218.771
inc3w3	11.68224	1124.783	0.01	0.992	-2192.853	2216.217
inc4w3	13.15717	1124.785	0.01	0.991	-2191.381	2217.695
radhlw3	.0116102	.013936	0.83	0.405	-.0157038	.0389242
havmil	.010259	.0190025	0.54	0.589	-.0269853	.0475032
avgcumdosew3	.013934	.0740721	0.19	0.851	-.1312447	.1591127
bf1	.0049612	.0648373	0.08	0.939	-.1221176	.1320399
bf4	.3309901	.3608169	0.92	0.359	-.376198	1.038178

bf2	.0003753	.0003121	1.20	0.229	-.0002364	.000987
bf4m	-.7073564	.3457629	-2.05	0.041	-1.385039	-.0296735
bf5m	.0055743	.0030295	1.84	0.066	-.0003633	.0115119
bf7m	.0005904	.001055	0.56	0.576	-.0014774	.0026582
bf8	-.0001253	.0000745	-1.68	0.093	-.0002713	.0000207
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0283325	.0488173	-0.58	0.562	-.1240127	.0673477
bf22	.000352	.0002932	1.20	0.230	-.0002227	.0009267
bf29	-.0000333	.0000588	-0.57	0.572	-.0001486	.000082
bf30	-.0013785	.0007131	-1.93	0.053	-.0027761	.0000191
bf40	-.3600239	.3692219	-0.98	0.330	-1.083686	.3636377
deaw3	-.5217994	.4891348	-1.07	0.286	-1.480486	.4368872
dvcew3	-.5047921	1.728469	-0.29	0.770	-3.892529	2.882945
sepaw3	1.877558	1.625412	1.16	0.248	-1.308191	5.063307
accdw3	-1.417017	1.419234	-1.00	0.318	-4.198664	1.364631
movew3	-1.057894	1.576256	-0.67	0.502	-4.1473	2.031511
illw3	.0330976	.3751226	0.09	0.930	-.7021292	.7683243
shfamw3	.012083	.0115403	1.05	0.295	-.0105354	.0347015
shhlw3	-.0165557	.0125582	-1.32	0.187	-.0411693	.0080578
shjobw3	.032774	.0134379	2.44	0.015	.0064363	.0591118
shrelaw3	-.0108059	.0117883	-0.92	0.359	-.0339106	.0122988
suprtw3	-.014138	.0155065	-0.91	0.362	-.0445303	.0162542
suchrw3	.0131393	.0111977	1.17	0.241	-.0088078	.0350865
havmilsq	-.000014	.0000386	-0.36	0.717	-.0000896	.0000616
_cons	.4495347	5.049973	0.09	0.929	-9.44823	10.3473

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	27	5	32
-	14	220	234
Total	41	225	266

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

Sensitivity	Pr(+ D)	65.85%
Specificity	Pr(- ~D)	97.78%
Positive predictive value	Pr(D +)	84.38%
Negative predictive value	Pr(~D -)	94.02%
False + rate for true ~D	Pr(+ ~D)	2.22%
False - rate for true D	Pr(- D)	34.15%
False + rate for classified +	Pr(~D +)	15.62%
False - rate for classified -	Pr(D -)	5.98%
Correctly classified		92.86%

Logistic model for HP2probsoc, goodness-of-fit test

```

number of observations =      266
number of covariate patterns =    266
    Pearson chi2(221) =    138.28
        Prob > chi2 =      1.0000
  
```

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

Log-Lik Intercept Only:	-114.331	Log-Lik Full Model:	-51.384
D(210):	102.767	LR(44):	125.895
		Prob > LR:	0.000
McFadden's R2:	0.551	McFadden's Adj R2:	0.061
Maximum Likelihood R2:	0.377	Cragg & Uhler's R2:	0.654
McKelvey and Zavoina's R2:	0.833	Efron's R2:	0.549
Variance of y*:	19.713	Variance of error:	3.290
Count R2:	0.929	Adj Count R2:	0.537
AIC:	0.807	AIC*n:	214.767
BIC:	-1069.767	BIC':	119.779

Full main model for HP2probsoc for wave= 3

chunk 4 H1 test:Gender= 2 model Wave = 3 for HP2probsoc

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1095324	.0321452	3.41	0.001	.0465289	.1725358
_Ieduc_2	-13.53237	1231.492	-0.01	0.991	-2427.212	2400.147
_Ieduc_3	-13.52493	1231.492	-0.01	0.991	-2427.204	2400.154
_Ieduc_4	-12.60239	1231.492	-0.01	0.992	-2426.282	2401.077
_Ieduc_5	-12.71374	1231.492	-0.01	0.992	-2426.393	2400.966
_Ieduc_6	-14.01871	1231.492	-0.01	0.991	-2427.698	2399.66
_Ieduc_7	-14.42024	1231.563	-0.01	0.991	-2428.239	2399.398
_Ieduc_8	0	(omitted)				
occ1w3	-1.43031	4.480321	-0.32	0.750	-10.21158	7.350959
occ2w3	-.9422793	4.54239	-0.21	0.836	-9.8452	7.960641
occ3w3	-.9893619	4.495549	-0.22	0.826	-9.800476	7.821752
occ4w3	0	(omitted)				
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-.3813499	4.479039	-0.09	0.932	-9.160105	8.397405
occ8w3	0	(omitted)				
marrw31	-1.356413	4.804963	-0.28	0.778	-10.77397	8.061141
marrw32	1.424321	4.907376	0.29	0.772	-8.193959	11.0426
marrw33	.9014745	4.669929	0.19	0.847	-8.251419	10.05437
marrw35	.1665893	4.645112	0.04	0.971	-8.937664	9.270842
marrw36	.3174753	4.648882	0.07	0.946	-8.794166	9.429116
inc1w3	.8600896	4.513897	0.19	0.849	-7.986987	9.707166
inc2w3	1.384829	4.490321	0.31	0.758	-7.416038	10.1857
inc3w3	.4792744	4.482989	0.11	0.915	-8.307222	9.26577
inc4w3	2.266942	4.835774	0.47	0.639	-7.211	11.74488
radhlw3	.0131788	.0108242	1.22	0.223	-.0080363	.0343939
havmil	.0001731	.0072695	0.02	0.981	-.0140748	.014421
avgcumdosew3	.4373021	.1594734	2.74	0.006	.12474	.7498642
bf1	.0565003	.0423978	1.33	0.183	-.0265978	.1395985
bf4	-.5202783	.2238014	-2.32	0.020	-.9589209	-.0816356
bf2	.0000421	.0001478	0.28	0.776	-.0002477	.0003318
bf4m	.2426577	.1977977	1.23	0.220	-.1450185	.630334
bf5m	-.0017451	.0026768	-0.65	0.514	-.0069915	.0035013
bf7m	.0007865	.0007919	0.99	0.321	-.0007656	.0023387
bf8	.0000207	.0000544	0.38	0.704	-.000086	.0001273
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0669294	.0330398	-2.03	0.043	-.1316862	-.0021726
bf22	-.0000944	.0001823	-0.52	0.605	-.0004517	.0002629
bf29	-.0000309	.000047	-0.66	0.511	-.0001229	.0000611
bf30	.0003246	.0004246	0.76	0.445	-.0005076	.0011567
bf40	.0606979	.1844629	0.33	0.742	-.3008427	.4222385
deaw3	.1696097	.2295421	0.74	0.460	-.2802844	.6195039
dvcew3	.3810548	1.285314	0.30	0.767	-2.138115	2.900224
sepaw3	-2.876602	1.529689	-1.88	0.060	-5.874737	.1215322
accdw3	.1226563	.714668	0.17	0.864	-1.278067	1.52338

movew3	1.918652	1.360681	1.41	0.159	-.7482334	4.585538
illw3	.2671943	.2045213	1.31	0.191	-.1336601	.6680487
shfamw3	-.0003116	.0095404	-0.03	0.974	-.0190104	.0183873
shhlw3	-.0026048	.0074647	-0.35	0.727	-.0172353	.0120256
shjobw3	.006075	.0086284	0.70	0.481	-.0108364	.0229864
shrelaw3	-.0267274	.010033	-2.66	0.008	-.0463918	-.007063
suprtw3	-.0065983	.0100162	-0.66	0.510	-.0262297	.0130331
suchrw3	.0015649	.0064519	0.24	0.808	-.0110806	.0142105
havmilsq	-3.19e-06	.0000124	-0.26	0.797	-.0000275	.0000211
_cons	6.986764	1231.505	0.01	0.995	-2406.718	2420.692

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	54	13	67
-	20	246	266
Total	74	259	333

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	72.97%
Specificity	$\Pr(- \sim D)$	94.98%
Positive predictive value	$\Pr(D +)$	80.60%
Negative predictive value	$\Pr(\sim D -)$	92.48%

False + rate for true ~D	$\Pr(+ \sim D)$	5.02%
False - rate for true D	$\Pr(- D)$	27.03%
False + rate for classified +	$\Pr(\sim D +)$	19.40%
False - rate for classified -	$\Pr(D -)$	7.52%

Correctly classified	90.09%
----------------------	--------

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	333
number of covariate patterns =	333
Pearson chi2(284) =	335.12
Prob > chi2 =	0.0199

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

Log-Lik Intercept Only:	-176.392	Log-Lik Full Model:	-85.065
D(277):	170.131	LR(48):	182.653
		Prob > LR:	0.000
McFadden's R2:	0.518	McFadden's Adj R2:	0.200
Maximum Likelihood R2:	0.422	Cragg & Uhler's R2:	0.646
McKelvey and Zavoina's R2:	0.810	Efron's R2:	0.561
Variance of y*:	17.273	Variance of error:	3.290
Count R2:	0.901	Adj Count R2:	0.554
AIC:	0.847	AIC*n:	282.131
BIC:	-1438.724	BIC':	96.138

```

563 . ***** Possible signifi dose effect*****
564 . > ****
565 . *-----Chunk 4 dose3 social problem impact---for women in wave three
566 . *****
567 . > ***
568 . title4 "Chunk 4 trimmed models of dose and HP2work relationship in wave 3"

```

Chunk 4 trimmed models of dose and HP2work relationship in wave 3

```

567 . * male models
568 . set more off

569 .         forvalues j=3/3 {
570 .             2. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
571 .             > bf40
572 .             3. title3 "trimmed HP2probsoc main effects models wave 3 for H1 part 2 with
573 .             > dose ns"
574 .             4. title "Wave 3 dose HP2probsoc relationship but avgcumdosew`j': Dose not s
575 .             > ignif"
576 .             5. xi:logit HP2probsoc age i.educ radhlw3 accdw`j' bf8 shjobw`j' suchrw3 ha
577 .             > vmilsq ///
578 .             > avgcumdosew`j' if gender==1
579 .             6.                 estat class
580 .             7.                 estat gof
581 .             8.                 fitstat
582 .             9. }

```

```

title3 : trimmed HP2probsoc main effects models wave 3 for H1 part 2 with dose
> ns
1 Jul 2012
20:37:22
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwideljul2012.dta currently has 2402 variables and 703 obser
> vations

```


HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0535719	.0238163	2.25	0.024	.0068928	.100251
_Ieduc_2	.3605111	.9297636	0.39	0.698	-1.461792	2.182814
_Ieduc_3	-.6699915	.4771602	-1.40	0.160	-1.605208	.2652253
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.5495985	.5675642	-0.97	0.333	-1.662004	.5628069
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
radhlw3	.0305161	.0070656	4.32	0.000	.0166678	.0443643
accdw3	-1.646048	.8717553	-1.89	0.059	-3.354657	.0625614
bf8	-.0000366	.0000261	-1.40	0.161	-.0000877	.0000146
shjobw3	.0159184	.0057194	2.78	0.005	.0047085	.0271283
suchrw3	.0135001	.0055103	2.45	0.014	.0027001	.0243001
havmilsq	-1.21e-06	4.50e-06	-0.27	0.788	-.00001	7.61e-06
avgcumdosew3	.0300057	.0490462	0.61	0.541	-.0661232	.1261345
_cons	-7.526129	1.376102	-5.47	0.000	-10.22324	-4.829018

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	13	6	19
-	28	273	301
Total	41	279	320

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	31.71%
Specificity	$\Pr(- \sim D)$	97.85%
Positive predictive value	$\Pr(D +)$	68.42%
Negative predictive value	$\Pr(\sim D -)$	90.70%
False + rate for true ~D	$\Pr(+ \sim D)$	2.15%
False - rate for true D	$\Pr(- D)$	68.29%
False + rate for classified +	$\Pr(\sim D +)$	31.58%
False - rate for classified -	$\Pr(D -)$	9.30%
Correctly classified		89.38%

Logistic model for HP2probsoc, goodness-of-fit test

```
number of observations =      320
number of covariate patterns =    319
Pearson chi2(307) =    262.97
Prob > chi2 =    0.9673
```

Measures of Fit for logit of HP2probsoc

Log-Lik Intercept Only:	-122.498	Log-Lik Full Model:	-86.595
D(304):	173.191	LR(11):	71.806
		Prob > LR:	0.000
McFadden's R2:	0.293	McFadden's Adj R2:	0.162
Maximum Likelihood R2:	0.201	Cragg & Uhler's R2:	0.376
McKelvey and Zavoina's R2:	0.500	Efron's R2:	0.271
Variance of y*:	6.583	Variance of error:	3.290
Count R2:	0.894	Adj Count R2:	0.171
AIC:	0.641	AIC*n:	205.191
BIC:	-1580.379	BIC':	-8.354

```
570 .
571 .
572 . forvalues j=3/3 {
      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 3
> *
*****
for H1 part 2 with dose ns
> *
*****
> *
*****
1 Jul 2012    20:37:24    *****
> *
```

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

```
title2: Wave `j` dose HP2work relationship but avgcumdosew3: Dose not signif
Date and time: 1 Jul 2012 20:37:24
Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/H1tests/hlpt2
Stata data file: chwide1jul2012.dta h
> as 2402 variables and 703 observations
```

```
Wave `j` dose HP2work relationship but avgcumdosew3: Dose not signif
```

```
573 .
574 . foreach var in suchrw3 radhlw3 shjobw3 {
      2. cap gen `var'Xd3= `var'*avgcumdosew3
      3. }

575 .
576 . forvalues j=3/3 {
      2. title "Main effects Dose ProbSoc model for males"
      3. logit HP2probsoc age avgcumdosew3 radhlw3 shjobw`j' if gender==1
      4. estat class
      5. estat gof
      6. fitstat
      7. }
```

```
*****
> *
*****
> *
*****
> *
*****
Main effects Dose ProbSoc model for males
*****
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:37:24
> *
*****
```

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

```
Iteration 0: log likelihood = -125.15243
Iteration 1: log likelihood = -102.23967
Iteration 2: log likelihood = -97.397123
Iteration 3: log likelihood = -97.305516
Iteration 4: log likelihood = -97.305496
Iteration 5: log likelihood = -97.305496
```

```
Logistic regression                                Number of obs   =          340
                                                    LR chi2(4)      =          55.69
                                                    Prob > chi2     =          0.0000
Log likelihood = -97.305496                      Pseudo R2      =          0.2225
```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0793863	.0196172	4.05	0.000	.0409372	.1178353
avgcumdosew3	.0349899	.0473999	0.74	0.460	-.0579122	.1278919
radhlw3	.0232266	.0060628	3.83	0.000	.0113437	.0351094
shjobw3	.0140642	.0050535	2.78	0.005	.0041595	.0239689
_cons	-8.338983	1.267447	-6.58	0.000	-10.82313	-5.854832

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	5	3	8
-	36	296	332
Total	41	299	340

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

Sensitivity	$\Pr(+ D)$	12.20%
Specificity	$\Pr(- \sim D)$	99.00%
Positive predictive value	$\Pr(D +)$	62.50%
Negative predictive value	$\Pr(\sim D -)$	89.16%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.00%
False - rate for true D	$\Pr(- D)$	87.80%
False + rate for classified +	$\Pr(\sim D +)$	37.50%
False - rate for classified -	$\Pr(D -)$	10.84%
Correctly classified		88.53%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	340
number of covariate patterns =	328
Pearson $\chi^2(323)$ =	293.19
Prob > χ^2 =	0.8819

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-97.305
D(335):	194.611	LR(4):	55.694
		Prob > LR:	0.000
McFadden's R2:	0.223	McFadden's Adj R2:	0.183
Maximum Likelihood R2:	0.151	Cragg & Uhler's R2:	0.290
McKelvey and Zavoina's R2:	0.409	Efron's R2:	0.189
Variance of y*:	5.568	Variance of error:	3.290
Count R2:	0.885	Adj Count R2:	0.049
AIC:	0.602	AIC*n:	204.611
BIC:	-1758.086	BIC':	-32.378

```

577 .
578 . scalar MainEffPrbsocMw3 = "age radhlw3 shjobw3"

579 .
580 .
581 . forvalues j=3/3 {
      2.  logit HP2probsoc age  radhlw3 shjobw`j'  ///
>      avgcumdosew`j'  ///
>      shjobw3Xd3 if gender==1
      3.
      4.          estat class
      5.          estat gof
      6.          fitstat
      6. }

```

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood = -99.524419
Iteration 2:  log likelihood = -94.068605
Iteration 3:  log likelihood = -93.949644
Iteration 4:  log likelihood = -93.948748
Iteration 5:  log likelihood = -93.948746

```

Logistic regression	Number of obs	=	340
	LR chi2(5)	=	62.41
	Prob > chi2	=	0.0000
Log likelihood = -93.948746	Pseudo R2	=	0.2493

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0751262	.0195236	3.85	0.000	.0368608	.1133917
radhlw3	.0251104	.0062707	4.00	0.000	.0128201	.0374008
shjobw3	-.0001631	.0088177	-0.02	0.985	-.0174456	.0171193
avgcumdosew3	-.2525242	.2724481	-0.93	0.354	-.7865126	.2814642
shjobw3Xd3	.0124767	.0071063	1.76	0.079	-.0014514	.0264049
_cons	-7.860581	1.288837	-6.10	0.000	-10.38665	-5.334508

Note: 0 failures and 1 success completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	6	3	9
-	35	296	331
Total	41	299	340

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

Sensitivity	$\Pr(+ D)$	14.63%
Specificity	$\Pr(- \sim D)$	99.00%
Positive predictive value	$\Pr(D +)$	66.67%
Negative predictive value	$\Pr(\sim D -)$	89.43%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.00%
False - rate for true D	$\Pr(- D)$	85.37%
False + rate for classified +	$\Pr(\sim D +)$	33.33%
False - rate for classified -	$\Pr(D -)$	10.57%
Correctly classified		88.82%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	340
number of covariate patterns =	328
Pearson $\chi^2(322)$ =	318.24
Prob > χ^2 =	0.5488

Measures of Fit for **logit** of HP2probsoc

Log-Lik Intercept Only:	-125.152	Log-Lik Full Model:	-93.949
D(334):	187.897	LR(5):	62.407
		Prob > LR:	0.000
McFadden's R2:	0.249	McFadden's Adj R2:	0.201
Maximum Likelihood R2:	0.168	Cragg & Uhler's R2:	0.322
McKelvey and Zavoina's R2:	0.615	Efron's R2:	0.228
Variance of y*:	8.541	Variance of error:	3.290
Count R2:	0.888	Adj Count R2:	0.073
AIC:	0.588	AIC*n:	199.897
BIC:	-1758.970	BIC':	-33.263

```

582 . scalar SigDoseProbsocMw3 = "no"

583 . * xx no signific radhlw3 by dose effect
584 . * xx for males no signif dose social problem effect
585 . * xx for males no significant moderator in dose social problem effect
586 . scalar ProbSocModMw3 = "none"

587 .
588 .
589 . ***** Female social problems model possible significant dose relation
> ship
590 .
591 . * female models
592 .
593 . forvalues j=3/3 {
      2. set more off
      3. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      4. title3 "trimmed HP2probsoc main effects models wave 3 for H1 part 2 with
> dose ns"
      5. title "Wave 3 dose HP2probsoc relationship but avgcumdosew`j': Dose not s
> ignif"
      6. logit HP2probsoc age radhlw3 accdw`j' sepaw`j' illw`j' shjobw`j' ////
> shrelaw`j' suchrw3 havmilsq avgcumdosew`j' if gender==2
      7.                                estat class
      8.                                estat gof
      9.                                fitstat
     10. }

```

```

title3 : trimmed HP2probsoc main effects models wave 3 for H1 part 2 with dose
> ns
  1 Jul 2012
20:37:26
computer  Macintosh (Intel 64-bit)
folder   /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file  chwide1jul2012.dta  currently has  2402  variables and  703  obser
> vations

```

```

*****
> *
*****
> *
*****
> *
*****Wave 3 dose HP2probsoc relationship but avgcumdosew3: Dose not signif****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:37:26    ****
> *
*****
> *
*****
> *

```

```

Iteration 0:  log likelihood = -183.34177
Iteration 1:  log likelihood = -123.45484
Iteration 2:  log likelihood = -113.79263
Iteration 3:  log likelihood =   -112.73
Iteration 4:  log likelihood = -112.14405
Iteration 5:  log likelihood =  -112.0764
Iteration 6:  log likelihood = -112.07463
Iteration 7:  log likelihood = -112.07462

```

```

Logistic regression                                Number of obs   =       362
                                                    LR chi2(10)      =      142.53
                                                    Prob > chi2       =       0.0000
Log likelihood = -112.07462                      Pseudo R2        =       0.3887

```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1199451	.020794	5.77	0.000	.0791897	.1607005
radhlw3	.0211303	.0055776	3.79	0.000	.0101983	.0320622
accdw3	-.0504717	.5021919	-0.10	0.920	-1.03475	.9338064
sepaw3	-1.843435	1.040782	-1.77	0.077	-3.883329	.1964598
illw3	.3907454	.1531736	2.55	0.011	.0905306	.6909602
shjobw3	-.0025249	.005367	-0.47	0.638	-.0130441	.0079943
shrelaw3	-.0165931	.0059102	-2.81	0.005	-.028177	-.0050093
suchrw3	.0025861	.0039833	0.65	0.516	-.0052211	.0103933
havmilsq	-7.39e-06	6.74e-06	-1.10	0.273	-.0000206	5.82e-06

avgcumdosew3	.360538	.119122	3.03	0.002	.1270632	.5940128
_cons	-9.607496	1.314552	-7.31	0.000	-12.18397	-7.031022

Note: 3 failures and 0 successes completely determined.

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	39	12	51
-	35	276	311
Total	74	288	362

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	52.70%
Specificity	$\Pr(- \sim D)$	95.83%
Positive predictive value	$\Pr(D +)$	76.47%
Negative predictive value	$\Pr(\sim D -)$	88.75%

False + rate for true ~D	$\Pr(+ \sim D)$	4.17%
False - rate for true D	$\Pr(- D)$	47.30%
False + rate for classified +	$\Pr(\sim D +)$	23.53%
False - rate for classified -	$\Pr(D -)$	11.25%

Correctly classified	87.02%
----------------------	---------------

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	362
number of covariate patterns =	362
Pearson chi2(351) =	411.55
Prob > chi2 =	0.0142

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-183.342	Log-Lik Full Model:	-112.075
D(351):	224.149	LR(10):	142.534
		Prob > LR:	0.000
McFadden's R2:	0.389	McFadden's Adj R2:	0.329
Maximum Likelihood R2:	0.325	Cragg & Uhler's R2:	0.511
McKelvey and Zavoina's R2:	0.867	Efron's R2:	0.431
Variance of y*:	24.799	Variance of error:	3.290
Count R2:	0.870	Adj Count R2:	0.365
AIC:	0.680	AIC*n:	246.149
BIC:	-1843.818	BIC':	-83.618

```

594 .
595 . scalar SigDoseProbsocFw3 = "yes"

596 . scalar MainEffProbSocFw3 = "age radhlw3 illw3 Shrelaw3 avgcumodsew3"

597 .
598 . * trimmed female model with basis functions
599 . forvalues j=3/3 {
      2. set more off
      3. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      4. title "trimmed HP2probsoc main effects models wave 3 for H1 part 2 " "Dos
      > e is signif Females"
      5. title "Wave 3 dose HP2probsoc relationship but avgcumdosew`j': Dose signi
      > f"
      6. title "Possible agorithmic artifact needs checking"
      7. logit HP2probsoc age radhlw3 illw`j' `w3bf' ///
      > shrelaw`j' avgcumdosew`j' if gender==2
      8.          estat class
      9.          estat gof
      10.         fitstat
      11. }

```

```

*****
> *
*****
> *
*****
> *
***** trimmed HP2probsoc main effects models wave 3 for H1 part 2 *****
> *
***** Dose is signif Females *****
> *
*****
> *

```

```
*****
> *
*****                               1 Jul 2012      20:37:28   ****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
***** Wave 3 dose HP2probsoc relationship but avgcumdosew3: Dose signif *****
> *
*****
> *
*****
> *
*****                               1 Jul 2012      20:37:28   ****
> *
*****
> *
*****
> *
*****
> *
*****
> *
***** Possible algorithmic artifact needs checking *****
> *
*****
> *
```

```

> *
*****
1 Jul 2012    20:37:28    ****
> *
*****
> *
*****
> *

```

```

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

```

```

note: bf17 omitted because of collinearity

```

```

Iteration 0:  log likelihood = -180.7823
Iteration 1:  log likelihood = -112.88537
Iteration 2:  log likelihood = -100.94644
Iteration 3:  log likelihood = -100.42263
Iteration 4:  log likelihood = -100.42122
Iteration 5:  log likelihood = -100.42122

```

```

Logistic regression                                Number of obs   =          351
                                                    LR chi2(17)    =          160.72
                                                    Prob > chi2    =           0.0000
Log likelihood = -100.42122                      Pseudo R2      =           0.4445

```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1073124	.0208977	5.14	0.000	.0663537	.1482711
radhlw3	.0186595	.0090599	2.06	0.039	.0009026	.0364165
illw3	.2164694	.1656953	1.31	0.191	-.1082875	.5412263
bf1	.0336012	.0334153	1.01	0.315	-.0318916	.0990939
bf4	-.3133546	.1907491	-1.64	0.100	-.687216	.0605068
bf2	-4.52e-07	.0001044	-0.00	0.997	-.0002052	.0002043
bf4m	.1185749	.1733569	0.68	0.494	-.2211983	.4583481
bf5m	-.0032317	.0024163	-1.34	0.181	-.0079675	.0015042
bf7m	.0003788	.000645	0.59	0.557	-.0008853	.0016429
bf8	.0000426	.0000472	0.90	0.367	-.0000499	.000135
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0379984	.0263966	-1.44	0.150	-.0897347	.0137379
bf22	-.0000771	.0001567	-0.49	0.623	-.0003841	.00023
bf29	-3.07e-06	.0000388	-0.08	0.937	-.0000791	.0000729
bf30	.0001674	.0003328	0.50	0.615	-.0004848	.0008196
bf40	.0213847	.1643559	0.13	0.896	-.300747	.3435164
shrelaw3	-.0189004	.0066211	-2.85	0.004	-.0318775	-.0059234
avgcumdosew3	.393852	.138802	2.84	0.005	.121805	.665899
_cons	-6.458746	2.119349	-3.05	0.002	-10.61259	-2.304899

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	49	11	60
-	25	266	291
Total	74	277	351

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

Sensitivity	$\Pr(+ D)$	66.22%
Specificity	$\Pr(- \sim D)$	96.03%
Positive predictive value	$\Pr(D +)$	81.67%
Negative predictive value	$\Pr(\sim D -)$	91.41%
False + rate for true ~D	$\Pr(+ \sim D)$	3.97%
False - rate for true D	$\Pr(- D)$	33.78%
False + rate for classified +	$\Pr(\sim D +)$	18.33%
False - rate for classified -	$\Pr(D -)$	8.59%
Correctly classified		89.74%

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	351
number of covariate patterns =	351
Pearson chi2(333) =	457.28
Prob > chi2 =	0.0000

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-180.782	Log-Lik Full Model:	-100.421
D(331):	200.842	LR(17):	160.722
		Prob > LR:	0.000
McFadden's R2:	0.445	McFadden's Adj R2:	0.334
Maximum Likelihood R2:	0.367	Cragg & Uhler's R2:	0.571
McKelvey and Zavoina's R2:	0.662	Efron's R2:	0.488
Variance of y*:	9.746	Variance of error:	3.290
Count R2:	0.897	Adj Count R2:	0.514
AIC:	0.686	AIC*n:	240.842
BIC:	-1739.078	BIC':	-61.089

```
600 .  
601 . foreach var in bf4 shrelaw3 {  
      2. cap    gen `var'Xd3 = `var'*avgcumdosew3  
      3. }  
  
602 .  
603 . * testing the female moderator model with basis functions  
604 .  
605 . set more off  
  
606 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4  
      > 0  
  
607 . title "trimmed HP2socprob main effects   wv 3 for Hyp1 pt 2" "dose is signif  
      > for females"  
  
*****  
> *  
*****  
> *  
*****                                     *****  
> *  
*****                                     *****  
> *  
*****          trimmed HP2socprob main effects   wv 3 for Hyp1 pt 2          *****  
> *  
*****                  dose is signif for females                  *****  
> *  
*****                                     *****  
> *  
*****                                     *****  
> *  
*****                                     *****  
1 Jul 2012       20:37:29     *****  
> *  
*****  
> *  
*****
```

```
608 . title "Wave 3 dose HP2socprob relationship but avgcumdosew`j'" " Dose is sig
> nif for females"
```

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
Wave 3 dose HP2socprob relationship but avgcumdosew
> *
*****
Dose is signif for females
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:37:29
> *
*****
> *
*****
> *
*****

```

```
609 . title "But this signif may be false positive due to backward stepwise algori
    > thm"
```

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
*****  
*****  
> *  
*****But this signif may be false positive due to backward stepwise algorithm*  
> *****  
*****  
> *  
*****  
> *  
*****  
*****  
*****  
*****  
*****
```

1 Jul 2012 20:37:29 ****

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

```
610 .
611 .
612 . logit HP2probsoc age radhlw3 illw3 bf4 ///
> shrelaw3 avgcumdosew3 bf4Xd3 shrelaw3Xd3 ///
> if gender==2
```

```
Iteration 0: log likelihood = -183.5701
Iteration 1: log likelihood = -115.57598
Iteration 2: log likelihood = -104.01427
Iteration 3: log likelihood = -103.59509
Iteration 4: log likelihood = -103.59367
Iteration 5: log likelihood = -103.59367
```

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(8)      =        159.95
                                                    Prob > chi2     =         0.0000
Log likelihood = -103.59367                        Pseudo R2       =         0.4357
```

HP2probsoc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1028004	.0196031	5.24	0.000	.064379	.1412218
radhlw3	.0177202	.0060309	2.94	0.003	.0058999	.0295405
illw3	.1431181	.1461189	0.98	0.327	-.1432697	.4295058
bf4	-.1143471	.0744815	-1.54	0.125	-.2603281	.031634
shrelaw3	-.0144139	.0099309	-1.45	0.147	-.0338781	.0050504
avgcumdosew3	1.092776	.6493144	1.68	0.092	-.1798569	2.365409
bf4Xd3	-.0638129	.0641358	-0.99	0.320	-.1895167	.0618909
shrelaw3Xd3	-.0059117	.0071313	-0.83	0.407	-.0198889	.0080654
_cons	-7.465103	1.452311	-5.14	0.000	-10.31158	-4.618627

613 . estat class

Logistic model for HP2probsoc

Classified	True		Total
	D	~D	
+	46	10	56
-	28	279	307
Total	74	289	363

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

True D defined as HP2probsoc != 0

Sensitivity	$\Pr(+ D)$	62.16%
Specificity	$\Pr(- \sim D)$	96.54%
Positive predictive value	$\Pr(D +)$	82.14%
Negative predictive value	$\Pr(\sim D -)$	90.88%
False + rate for true ~D	$\Pr(+ \sim D)$	3.46%
False - rate for true D	$\Pr(- D)$	37.84%
False + rate for classified +	$\Pr(\sim D +)$	17.86%
False - rate for classified -	$\Pr(D -)$	9.12%
Correctly classified		89.53%

614 . estat gof

Logistic model for HP2probsoc, goodness-of-fit test

number of observations =	363
number of covariate patterns =	361
Pearson $\chi^2(352)$ =	427.83
Prob > χ^2 =	0.0035

615 . fitstat

Measures of Fit for **logit** of **HP2probsoc**

Log-Lik Intercept Only:	-183.570	Log-Lik Full Model:	-103.594
D(354):	207.187	LR(8):	159.953
		Prob > LR:	0.000
McFadden's R2:	0.436	McFadden's Adj R2:	0.387
Maximum Likelihood R2:	0.356	Cragg & Uhler's R2:	0.560
McKelvey and Zavoina's R2:	0.677	Efron's R2:	0.482
Variance of y*:	10.184	Variance of error:	3.290
Count R2:	0.895	Adj Count R2:	0.486
AIC:	0.620	AIC*n:	225.187
BIC:	-1879.431	BIC':	-112.798

616 .

617 . scalar ProbsocModFw3 = "none"

618 .

619 . title4 " testing for male and female dose probsoc mediators"

testing for male and female dose probsoc mediators

620 . * Male mediator dose social problem response models

621 .

622 .

623 .

624 . // age is a male mediator

625 . glm age avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1330.6336

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.7142
Deviance = 49927.38549	(1/df) Deviance	=	147.7142
Pearson = 49927.38549	(1/df) Pearson	=	147.7142
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.839021
Log likelihood = -1330.633586	<u>BIC</u>	=	47957.2

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.5433648	.2472657	2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376	66.95	0.000	47.09975	49.94067

626 . 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.)

627 .

```
628 . glm radhlw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1695.1855
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1261.052
Deviance = 426235.7205	(1/df) Deviance	=	1261.052
Pearson = 426235.7205	(1/df) Pearson	=	1261.052

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

	AIC	=	9.983444
Log likelihood = -1695.185473	BIC	=	424265.5

radhlw3	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew3	.9606492	.7224692	1.33	0.184	-.4553645	2.376663	
_cons	46.19995	2.117563	21.82	0.000	42.0496	50.3503	

```
629 . glm HP2probsoc radhlw3 if gender==1,fam(bin) irls link(probit) scale(dev)
```

```
Iteration 1: deviance = 224.6665
Iteration 2: deviance = 216.1679
Iteration 3: deviance = 215.5978
Iteration 4: deviance = 215.5929
Iteration 5: deviance = 215.5929
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 215.5929138	(1/df) Deviance	=	.6378489
Pearson = 333.7963451	(1/df) Pearson	=	.9875632

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

BIC	=	-1754.591
-----	---	-----------

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0156818	.0022898	6.85	0.000	.0111939	.0201697
_cons	-2.095692	.1691863	-12.39	0.000	-2.427291	-1.764093

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

630 .

631 . glm shjobw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1720.6013**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1464.409
Deviance = 494970.193	(1/df) Deviance	=	1464.409
Pearson = 494970.193	(1/df) Pearson	=	1464.409
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		

	<u>AIC</u>	=	10.13295
Log likelihood = -1720.601326	<u>BIC</u>	=	493000

shjobw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.2000973	.7785454	-0.26	0.797	-1.726018	1.325824
_cons	41.22913	2.281923	18.07	0.000	36.75664	45.70162

632 . glm HP2probsoc shjobw3 if gender==1,fam(bin) irls link(probit) scale(dev)

Iteration 1: deviance = **249.6649**
Iteration 2: deviance = **248.8792**
Iteration 3: deviance = **248.8773**
Iteration 4: deviance = **248.8773**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 248.8773343	(1/df) Deviance	=	.7363235
Pearson = 340.8400768	(1/df) Pearson	=	1.008403

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1721.306

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw3	.0026922	.0019572	1.38	0.169	-.0011439	.0065284
_cons	-1.288564	.1154816	-11.16	0.000	-1.514904	-1.062225

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

633 .
 634 . // shjobw3Xd3 is almost significant but not quite
 635 . glm radhlw3 shjobw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = -1694.063

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	337
	Scale parameter	=	1256.471
Deviance = 423430.6999	(1/df) Deviance	=	1256.471
Pearson = 423430.6999	(1/df) Pearson	=	1256.471

Variance function: $V(u) = 1$ [Gaussian]
 Link function : $g(u) = u$ [Identity]
 Log likelihood = -1694.063021
 AIC = 9.982724
 BIC = 421466.3

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw3	.0752798	.0503833	1.49	0.135	-.0234697	.1740293
avgcumdosew3	.9757125	.7212261	1.35	0.176	-.4378647	2.38929
_cons	43.09623	2.963577	14.54	0.000	37.28772	48.90473

```

636 . glm HP2probsoc shjobw3 avgcumdosew3 shjobw3Xd3 if gender==1,fam(bin) ///
> irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 244.6055
Iteration 2: deviance = 243.0617
Iteration 3: deviance = 241.3069
Iteration 4: deviance = 240.868
Iteration 5: deviance = 240.8657
Iteration 6: deviance = 240.8656
Iteration 7: deviance = 240.8656
Iteration 8: deviance = 240.8656

```

```

Generalized linear models                                No. of obs      =       340
Optimization      : ML Fisher scoring                  Residual df     =       336
                   (IRLS EIM)                          Scale parameter =         1
Deviance          = 240.8656032                        (1/df) Deviance =  .7168619
Pearson           = 340.9255101                        (1/df) Pearson  = 1.014659

```

```

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

```

```

BIC = -1717.66

```

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
shjobw3	-.0045194	.0035953	-1.26	0.209	-.0115661	.0025273
avgcumdosew3	-.0918458	.0746098	-1.23	0.218	-.2380783	.0543867
shjobw3Xd3	.0066355	.002922	2.27	0.023	.0009086	.0123624
_cons	-1.180909	.1352851	-8.73	0.000	-1.446063	-.9157549

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

```

637 .
638 . scalar ProbsocMedMw3 = "age"

```

```

639 .
640 . * female mediator tests: age radhlw3 bf4
641 .
642 . // age is a female mediator
643 . glm age avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1408.064**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	137.7687
Deviance = 49734.51399	(1/df) Deviance	=	137.7687
Pearson = 49734.51399	(1/df) Pearson	=	137.7687

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

	<u>AIC</u>	=	7.768948
Log likelihood = -1408.06405	<u>BIC</u>	=	47606.63

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

```

644 . 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.)

```

645 .
646 . // radhlw3 is a female mediator
647 . glm radhlw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1798.7074**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1185.454
Deviance = 427948.9522	(1/df) Deviance	=	1185.454
Pearson = 427948.9522	(1/df) Pearson	=	1185.454

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

	<u>AIC</u>	=	9.921253
Log likelihood = -1798.707367	<u>BIC</u>	=	425821.1

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	2.751602	1.03038	2.67	0.008	.7320943	4.77111
_cons	57.70689	2.190692	26.34	0.000	53.41321	62.00057

```

648 . glm HP2probsoc radhlw3 if gender==2,fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 332.0999
Iteration 2: deviance = 329.376
Iteration 3: deviance = 329.3467
Iteration 4: deviance = 329.3467
Iteration 5: deviance = 329.3467

```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 329.3467003	(1/df) Deviance	=	.9123177
Pearson = 374.561784	(1/df) Pearson	=	1.037567

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

[Bernoulli]
 [Probit]

BIC = -1798.533

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0145154	.0024198	6.00	0.000	.0097727	.0192582
_cons	-1.818717	.1912579	-9.51	0.000	-2.193576	-1.443859

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

```
649 .
650 .
651 . // bf4 is a mediator
652 . glm bf4 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = -1109.6569

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.6146
Deviance = 9607.869105	(1/df) Deviance	=	26.6146
Pearson = 9607.869105	(1/df) Pearson	=	26.6146

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

	<u>AIC</u>	=	6.124831
Log likelihood = -1109.656873	<u>BIC</u>	=	7479.99

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.4386292	.1543885	-2.84	0.004	-.7412252	-.1360333
_cons	11.01475	.3282456	33.56	0.000	10.3714	11.6581

```
653 . glm HP2probsoc bf4 if gender==2,fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 295.3213
Iteration 2:  deviance = 289.8751
Iteration 3:  deviance = 289.6607
Iteration 4:  deviance = 289.6591
Iteration 5:  deviance = 289.6591
Iteration 6:  deviance = 289.6591
```

```
Generalized linear models                      No. of obs      =       363
Optimization      :  MQL Fisher scoring        Residual df    =       361
                  (IRLS EIM)                  Scale parameter =        1
Deviance          = 289.6591069                (1/df) Deviance =  .8023798
Pearson           = 306.7680355                (1/df) Pearson  =  .849773
```

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

```
BIC = -1838.22
```

HP2probsoc	EIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
bf4	-.1364145	.0148745	-9.17	0.000	-.165568	-.107261
_cons	.3956217	.1443369	2.74	0.006	.1127267	.6785167

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

```
654 .
```

```
655 . glm shjobw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1782.2022
```

```
Generalized linear models                      No. of obs      =       362
Optimization      :  ML                      Residual df    =       360
Scale parameter = 1112.187
Deviance          = 400387.4607                (1/df) Deviance = 1112.187
Pearson           = 400387.4607                (1/df) Pearson  = 1112.187
```

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

```
AIC = 9.857471
BIC = 398266.5
Log likelihood = -1782.202176
```

shjobw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-1.527977	.9981622	-1.53	0.126	-3.484339	.4283847
_cons	32.25021	2.12484	15.18	0.000	28.0856	36.41482

```
656 . glm HP2probsoc shjobw3 avgcumdosew3 if gender==2,fam(bin) ///
>      irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 329.6578
Iteration 2:  deviance = 328.2396
Iteration 3:  deviance = 328.227
Iteration 4:  deviance = 328.2269
Iteration 5:  deviance = 328.2269
```

Generalized linear models	No. of obs	=	362
Optimization : ML Fisher scoring	Residual df	=	359
(IRLS EIM)	Scale parameter	=	1
Deviance = 328.2269272	(1/df) Deviance	=	.9142811
Pearson = 364.4863603	(1/df) Pearson	=	1.015282

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

BIC = -1786.873

HP2probsoc	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw3	-.0088534	.0025178	-3.52	0.000	-.0137883	-.0039185
avgcumdosew3	.2194295	.054413	4.03	0.000	.112782	.3260771
_cons	-.8734121	.1155844	-7.56	0.000	-1.099953	-.6468708

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

```

657 .
658 . scalar ProbsocMedFw3 = "age radhlw3 bf4"

659 .
660 . title4 "summary matrix for dose Hp2probsoc impact in wave 3"

```

```

summary matrix for dose Hp2probsoc impact in wave 3

```

```

661 . * male hp2spM w3 mediators: age
662 . * dose is not significant main effect for males
663 . * female hp2spF w3 mediators: age radhlw3 bf4
664 . * dose is not sig main effect for males
665 .
666 . scalar SigDoseProbsocMw3 = "no"

667 .
668 . matrix define HP2spMw3 = J(1,8, 0)

669 . matrix define HP2spFw3 = J(1,8, 0)

670 . matrix colnames HP2spMw3= hypnum ptnum wave gender medsig numMASig numModsi
    > g numMed

671 . matrix colnames HP2spFw3= hypnum ptnum wave gender medsig numMASig numModsi
    > g numMed

672 . matrix define HP2spFw3= (1, 2, 3, 2, 1, 5, 5, 3 )

673 . matrix define HP2spMw3= (1, 2, 3, 1, 0, 2, 0, 1 )

674 . matrix rowname HP2spMw3 = HP2spMw3

675 . matrix rowname HP2spFw3 = HP2spFw3

676 . matlist HP2spMw3

```

		c1	c2	c3	c4	c5	c
> 6							
> —							
HP2spMw3		1	2	3	1	0	
> 2							

	c7	c8
HP2spMw3	0	1

```
677 .      matlist HP2spFw3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2spFw3	1	2	3	2	1	
> 5						
	c7	c8				
HP2spFw3	5	3				

```
678 .      matrix define H1pt2w3 = ( HP2wkMw3 \ HP2wkFw3 \ HP2hmcrMw3 \ HP2hmcr
> Fw3 \ HP2spMw3 \ HP2spFw3 )
```

```
679 .
```

```
680 .      matlist H1pt2w3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
r1	1	2	3	1	0	
> 4						
r1	1	2	3	2	0	
> 1						
r1	1	2	3	1	0	
> 4						
r1	1	2	3	2	0	
> 2						
HP2spMw3	1	2	3	1	0	
> 2						
HP2spFw3	1	2	3	2	1	
> 5						
	c7	c8				
r1	0	4				
r1	0	6				
r1	0	2				
r1	0	2				
HP2spMw3	0	1				
HP2spFw3	5	3				

```
681 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed
```

```
682 .      matrix rownames H1pt2w3 =  HP2wkMw3 HP2wkFw3 HP2hmcrMw3 HP2hmcrFw3 HP2s
> ocprbMw3 HP2socprbFw3
```

```
683 .      matlist H1pt2w3
```

	hypnum	ptnum	wave	gender	medsig	numMA sig
> g						
> —						
HP2wkMw3	1	2	3	1	0	
> 4						
HP2wkFw3	1	2	3	2	0	
> 1						
HP2hmcrMw3	1	2	3	1	0	
> 4						
HP2hmcrFw3	1	2	3	2	0	
> 2						
HP2socprbMw3	1	2	3	1	0	
> 2						
HP2socprbFw3	1	2	3	2	1	
> 5						
	numModsig	numMed				
HP2wkMw3	0	4				
HP2wkFw3	0	6				
HP2hmcrMw3	0	2				
HP2hmcrFw3	0	2				
HP2socprbMw3	0	1				
HP2socprbFw3	5	3				

```
684 .
685 .
686 . *xx significant dose effect for females
```

```

687 . scalar ProbsocModFw3 = "none"

688 . *xx no female moderators for Dose Social problem impact relationship
689 . scalar list
    ProbsocMedFw3 = age radhlw3 bf4
    VactnMedFw3 = age illw3 radhlw3
    VactnMedMw3 = age illw3
    VacatnModFw3 = none
    MainEffVactnFw3 = age radhlw3 deaw3
    SigDoseVactnFw3 = no
    vactnModMw3 = none
    MainEffVactnMw3 = age bf7m radhlw3
    SigDoseVactnMw3 = no
    sxLifeMedFw3 = age bf4 bf4m
    sxLifeMedMw3 = age illw3
    InthbModFw3 = none
    MainEffInthbFw3 = age radhlw3 bf4
    SigdoseInthbFw3 = no
    InthbMw3 = none
    MainEffInthbMw3 = age radhlw3 shfamw3
    SigDoseInthbMw3 = no
    sxlifeMedFw3 = age illw3 radhlw3 bf4 bf4m
    sxlifeMedMw3 = age illw3
    sxlifeModFw3 = none
    MainEffsxlifeFw3 = age radhlw3 bf4 bf4m shrelaw3 shfamw3
    SigDoseSxlifeFw3 = no
    sxlifeModMw3 = none
    SigDosesxlifeMw3 = no
    MainEffsxlifeMw3 = age bf4 illw3 radhlw3
    PrbfmhmMedFw3 = age bf4
    PrbfmhmMedMw3 = age
    PrbfmhmModFw3 = none
    MainEffPrbfmhmFw3 = age bf4 bf40
    SigDosePrbfmhmFw3 = no
    PrbfmhmModw3 = none
    SigDosePrbfmhmMw3 = no
    SigDosePrbfhmMw3 = no
    MainEffPrbfhmMw3 = bf1 bf4 dvcew3 bf7m
    ProbsocMedMw3 = age
    ProbsocModFw3 = none
    MainEffProbSocFw3 = age radhlw3 illw3 Shrelaw3 avgcumodsew3
    SigDoseProbsocFw3 = yes
    ProbSocModMw3 = none
    SigDoseProbsocMw3 = no
    MainEffPrbsocMw3 = age radhlw3 shjobw3
    hmcareMedFw3 = age illw3
    hmcareMedMw3 = age illw3
    hmcareModFw3 = none
    SigdoseHmcareFw3 = no

```

```

hmcareModMw3 = none
MainEffhmcareMw3 = none
SigDoseHmcareMw3 = no
    wkMedFw3 = radhlw3 age bf40 bf4m bf1
    wkMedMw3 = bf8 age illw3 ageXillw3
    wkModFw3 = none
    wkModMw3 = none
MainEffwkFw3 = age
MainEffwkMw3 = workM: age bf8 illw3 shjobw3
SigDoseWKMw3 = no
SigDoseWkFw3 = no
    medsigFw2 = 1
    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

```

```

690 .
691 . *----- Chunk 5    Dose => Problems with the Family at home Impact
692 .
693 .
694 .
695 . title "4. Wave 3 part2 hypothesis 1 Pt2 Probs with Fam at home"

*****
> *
*****
> *
*****
> *
*****
> *
*****      4. Wave 3 part2 hypothesis 1 Pt2 Probs with Fam at home      *****
> *
*****
> *
*****
> *
*****
> *
*****      1 Jul 2012      20:37:53      *****
> *
*****
> *
*****
> *

696 . forvalues j=3/3 {
      2. set more off
      3.
697 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
>   bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.

```

```

698 .   foreach var in HP2pbfhm {
      5.       forvalues k=1/2 {
      6. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      7.
699 . 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.
700 .   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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed
inclw3	double	%15.0g	LABJ	Income is not sufficient for

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: occ5w3 != 0 predicts failure perfectly
occ5w3 dropped and 13 obs not used

note: occ6w3 != 0 predicts failure perfectly
occ6w3 dropped and 4 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 17 obs not used

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

note: movew3 != 0 predicts failure perfectly
movew3 dropped and 22 obs not used

note: _Ieduc_6 omitted because of collinearity
note: occ8w3 omitted because of collinearity
note: marrw36 omitted because of collinearity
note: bf17 omitted because of collinearity

Logistic regression	Number of obs	=	248
	LR chi2(42)	=	61.10
	Prob > chi2	=	0.0286
Log likelihood = -43.736999	Pseudo R2	=	0.4112

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0762859	.0508028	1.50	0.133	-.0232857	.1758575
_Ieduc_2	0	(omitted)				
_Ieduc_3	-.1477637	.8109786	-0.18	0.855	-1.737253	1.441725
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.7596947	1.090598	-0.70	0.486	-2.897227	1.377837
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occlw3	-10.90364	2018.344	-0.01	0.996	-3966.785	3944.977
occ2w3	-10.89538	2018.344	-0.01	0.996	-3966.777	3944.986
occ3w3	-9.963313	2018.344	-0.00	0.996	-3965.846	3945.919
occ4w3	-10.3499	2018.344	-0.01	0.996	-3966.232	3945.532

occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-10.56369	2018.344	-0.01	0.996	-3966.445	3945.318
occ8w3	0	(omitted)				
marrw31	1.938945	1.834088	1.06	0.290	-1.655802	5.533692
marrw32	2.869349	2.03424	1.41	0.158	-1.117687	6.856385
marrw33	-2.070881	2.007923	-1.03	0.302	-6.006338	1.864576
marrw35	3.548252	2.186549	1.62	0.105	-.7373048	7.833809
marrw36	0	(omitted)				
inclw3	12.37597	2018.344	0.01	0.995	-3943.505	3968.257
inc2w3	12.75723	2018.343	0.01	0.995	-3943.123	3968.637
inc3w3	11.01982	2018.344	0.01	0.996	-3944.861	3966.9
inc4w3	11.952	2018.345	0.01	0.995	-3943.931	3967.835
radhlw3	.032589	.0182947	1.78	0.075	-.0032679	.0684459
havmil	.0129536	.013774	0.94	0.347	-.0140429	.0399501
avgcumdosew3	-.3791136	.3273992	-1.16	0.247	-1.020804	.2625771
bf1	-.1029605	.0825755	-1.25	0.212	-.2648056	.0588846
bf4	-.1906164	.3464978	-0.55	0.582	-.8697396	.4885069
bf2	.0004772	.0003548	1.35	0.179	-.0002181	.0011725
bf4m	.0772469	.2972932	0.26	0.795	-.505437	.6599308
bf5m	-.0019382	.0047879	-0.40	0.686	-.0113224	.007446
bf7m	.0012129	.001013	1.20	0.231	-.0007725	.0031983
bf8	-3.27e-06	.0000957	-0.03	0.973	-.0001909	.0001843
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0430617	.0653802	0.66	0.510	-.0850811	.1712045
bf22	-4.46e-06	.0002995	-0.01	0.988	-.0005915	.0005826
bf29	0	(omitted)				
bf30	.000126	.0007197	0.18	0.861	-.0012845	.0015365
bf40	.071783	.4795976	0.15	0.881	-.8682111	1.011777
deaw3	.3272315	.4280065	0.76	0.445	-.5116458	1.166109
dvcew3	1.631036	1.568401	1.04	0.298	-1.442973	4.705045
sepaw3	.2595898	1.605075	0.16	0.872	-2.886299	3.405479
accdw3	-.9114258	2.076173	-0.44	0.661	-4.980649	3.157798
movew3	0	(omitted)				
illw3	-.5480408	.5150453	-1.06	0.287	-1.557511	.4614294
shfamw3	.0143257	.0164517	0.87	0.384	-.017919	.0465703
shhlw3	-.0109085	.0129224	-0.84	0.399	-.0362359	.014419
shjobw3	-.0129256	.0143995	-0.90	0.369	-.0411481	.0152969
shrelaw3	-.0047884	.012683	-0.38	0.706	-.0296466	.0200697
suprtw3	.025454	.0177967	1.43	0.153	-.0094269	.0603349
suchrw3	.0037567	.0120299	0.31	0.755	-.0198214	.0273349
havmilsq	-.0000259	.0000249	-1.04	0.299	-.0000746	.0000229
_cons	-12.84498	6.147159	-2.09	0.037	-24.89319	-.79677

Note: 5 failures and 0 successes completely determined.

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	9	4	13
-	13	222	235
Total	22	226	248

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	40.91%
Specificity	$\Pr(- \sim D)$	98.23%
Positive predictive value	$\Pr(D +)$	69.23%
Negative predictive value	$\Pr(\sim D -)$	94.47%
False + rate for true ~D	$\Pr(+ \sim D)$	1.77%
False - rate for true D	$\Pr(- D)$	59.09%
False + rate for classified +	$\Pr(\sim D +)$	30.77%
False - rate for classified -	$\Pr(D -)$	5.53%
Correctly classified		93.15%

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      248
number of covariate patterns = 248
Pearson chi2(205) =      151.48
Prob > chi2 =      0.9980

```

Measures of Fit for logistic of HP2pbfhm

Log-Lik Intercept Only:	-74.286	Log-Lik Full Model:	-43.737
D(192):	87.474	LR(42):	61.099
		Prob > LR:	0.029
McFadden's R2:	0.411	McFadden's Adj R2:	-0.343
Maximum Likelihood R2:	0.218	Cragg & Uhler's R2:	0.485
McKelvey and Zavoina's R2:	0.816	Efron's R2:	0.329
Variance of y*:	17.878	Variance of error:	3.290
Count R2:	0.931	Adj Count R2:	0.227
AIC:	0.804	AIC*n:	199.474
BIC:	-971.104	BIC':	170.465

Full main model for HP2pbfhm for wave= 3

chunk 5 H1 test:Gender= 2 model Wave = 3 for HP2pbfhm

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

Logistic regression

Number of obs = 277
LR chi2(45) = 88.17
Prob > chi2 = 0.0001
Pseudo R2 = 0.3540

Log likelihood = -80.45257

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0605232	.0301499	2.01	0.045	.0014305	.1196159
_Ieduc_2	14.33097	3050.48	0.00	0.996	-5964.5	5993.162
_Ieduc_3	14.57814	3050.48	0.00	0.996	-5964.253	5993.409
_Ieduc_4	14.71229	3050.48	0.00	0.996	-5964.118	5993.543
_Ieduc_5	14.46503	3050.48	0.00	0.996	-5964.366	5993.296
_Ieduc_6	14.13284	3050.48	0.00	0.996	-5964.698	5992.963
_Ieduc_7	16.45371	3050.482	0.01	0.996	-5962.381	5995.289
_Ieduc_8	0	(omitted)				
occ1w3	-.9142061	3.466224	-0.26	0.792	-7.70788	5.879468
occ2w3	0	(omitted)				
occ3w3	-.2867411	3.495557	-0.08	0.935	-7.137908	6.564426
occ4w3	0	(omitted)				
occ5w3	2.578209	4.53518	0.57	0.570	-6.310581	11.467
occ6w3	0	(omitted)				
occ7w3	-.5244179	3.46458	-0.15	0.880	-7.31487	6.266034
occ8w3	0	(omitted)				
marrw31	13.57521	900.684	0.02	0.988	-1751.733	1778.884
marrw32	0	(omitted)				
marrw33	15.5368	900.6835	0.02	0.986	-1749.77	1780.844
marrw35	15.43053	900.6834	0.02	0.986	-1749.877	1780.738
marrw36	15.00571	900.6833	0.02	0.987	-1750.301	1780.313
inc1w3	2.006505	3.516446	0.57	0.568	-4.885601	8.898612
inc2w3	2.111761	3.483985	0.61	0.544	-4.716724	8.940246
inc3w3	1.911831	3.463507	0.55	0.581	-4.876519	8.70018
inc4w3	0	(omitted)				
radhlw3	.0113673	.0123354	0.92	0.357	-.0128096	.0355442
havmil	-.0010166	.0142076	-0.07	0.943	-.0288629	.0268297
avgcumdosew3	-.0338506	.1440343	-0.24	0.814	-.3161526	.2484513
bf1	-.0040962	.0453653	-0.09	0.928	-.0930105	.0848181
bf4	-.3790747	.2483688	-1.53	0.127	-.8658686	.1077192
bf2	.0000525	.0001469	0.36	0.721	-.0002354	.0003404
bf4m	.1263528	.2275811	0.56	0.579	-.3196979	.5724036
bf5m	-.0049342	.0041169	-1.20	0.231	-.0130031	.0031348
bf7m	-.0004133	.0008454	-0.49	0.625	-.0020703	.0012437
bf8	.0001156	.0000755	1.53	0.125	-.0000323	.0002635
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0078983	.0366468	-0.22	0.829	-.0797248	.0639282

bf22	.000158	.0001863	0.85	0.396	-.0002071	.0005231
bf29	9.34e-06	.0000425	0.22	0.826	-.000074	.0000927
bf30	-.0000869	.0004483	-0.19	0.846	-.0009655	.0007917
bf40	-.2779981	.1983152	-1.40	0.161	-.6666887	.1106924
deaw3	-.0223131	.2253092	-0.10	0.921	-.4639109	.4192848
dvcew3	1.571998	1.037736	1.51	0.130	-.4619271	3.605923
sepaw3	-1.894764	1.527486	-1.24	0.215	-4.888582	1.099055
accdw3	-.2729555	.6926052	-0.39	0.694	-1.630437	1.084526
movev3	0	(omitted)				
illw3	-.1949663	.2468671	-0.79	0.430	-.6788169	.2888842
shfamw3	-.0082258	.0094908	-0.87	0.386	-.0268274	.0103758
shhlw3	.0062899	.0080613	0.78	0.435	-.00951	.0220898
shjobw3	-.0009012	.0093159	-0.10	0.923	-.0191601	.0173576
shrelaw3	-.0126452	.0092607	-1.37	0.172	-.0307958	.0055054
suprtw3	-.004099	.0105306	-0.39	0.697	-.0247385	.0165405
suchrw3	-.0078922	.0065901	-1.20	0.231	-.0208085	.0050241
havmilsq	-4.43e-06	.000039	-0.11	0.909	-.0000808	.000072
_cons	-32.88256	3180.671	-0.01	0.992	-6266.884	6201.119

Note: 5 failures and 0 successes completely determined.

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	22	9	31
-	24	222	246
Total	46	231	277

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

True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	47.83%
Specificity	$\Pr(- \sim D)$	96.10%
Positive predictive value	$\Pr(D +)$	70.97%
Negative predictive value	$\Pr(\sim D -)$	90.24%
False + rate for true ~D	$\Pr(+ \sim D)$	3.90%
False - rate for true D	$\Pr(- D)$	52.17%
False + rate for classified +	$\Pr(\sim D +)$	29.03%
False - rate for classified -	$\Pr(D -)$	9.76%
Correctly classified		88.09%

Logistic model for HP2pbfhm, goodness-of-fit test

```
number of observations =      277
number of covariate patterns =    277
Pearson chi2(231) =    439.38
Prob > chi2 =    0.0000
```

Measures of Fit for **logistic** of **HP2pbfhm**

Log-Lik Intercept Only:	-124.537	Log-Lik Full Model:	-80.453
D(221):	160.905	LR(45):	88.169
		Prob > LR:	0.000
McFadden's R2:	0.354	McFadden's Adj R2:	-0.096
Maximum Likelihood R2:	0.273	Cragg & Uhler's R2:	0.460
McKelvey and Zavoina's R2:	0.796	Efron's R2:	0.384
Variance of y*:	16.128	Variance of error:	3.290
Count R2:	0.881	Adj Count R2:	0.283
AIC:	0.985	AIC*n:	272.905
BIC:	-1082.003	BIC':	164.912

```
701 .
702 .
703 . title "Partly Trimmed male wave 3  Dose => Problems with Family at home mode
> ls"
```

```
*****
> *
*****
> *
*****
> *
*****
> *
*****Partly Trimmed male wave 3  Dose => Problems with Family at home models**
> ***
*****
> *
*****
> *
*****
1 Jul 2012    20:37:56    ****
> *
*****
> *
*****
```

```
704 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0
```

```
705 . logit HP2pbfhm age sepaw3 dvcew3 radhlw3 avgcumdosew3 suprtw3 ///
    > havmilsq illw3 `w3bf' if gender==1, iterate(50)
```

```
note: bf15m != 0 predicts failure perfectly
      bf15m dropped and 21 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 = -79.475349
Iteration 1:  log likelihood = -67.02422
Iteration 2:  log likelihood = -60.135828
Iteration 3:  log likelihood = -59.852788
Iteration 4:  log likelihood = -59.850816
Iteration 5:  log likelihood = -59.850815
```

Logistic regression	Number of obs	=	311
	LR chi2(19)	=	39.25
	Prob > chi2	=	0.0041
Log likelihood = -59.850815	Pseudo R2	=	0.2469

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.043687	.0250852	1.74	0.082	-.0054791	.092853
sepaw3	1.382077	1.196445	1.16	0.248	-.9629124	3.727067
dvcew3	1.720325	1.049833	1.64	0.101	-.3373098	3.77796
radhlw3	.0111639	.0118036	0.95	0.344	-.0119707	.0342986
avgcumdosew3	-.0948486	.2407308	-0.39	0.694	-.5666722	.376975
suprtw3	-.0049975	.0064124	-0.78	0.436	-.0175656	.0075705
havmilsq	-1.41e-06	6.40e-06	-0.22	0.826	-.000014	.0000111
illw3	-.190415	.3387342	-0.56	0.574	-.8543217	.4734918
bf1	-.0587243	.0691016	-0.85	0.395	-.194161	.0767123
bf4	-.2551053	.2251582	-1.13	0.257	-.6964073	.1861967
bf2	.0004205	.0002504	1.68	0.093	-.0000704	.0009113
bf4m	.0336013	.2032952	0.17	0.869	-.3648499	.4320525
bf5m	.0012898	.0029269	0.44	0.659	-.0044468	.0070264
bf7m	.0016168	.0007794	2.07	0.038	.0000891	.0031445
bf8	-.0000436	.0000621	-0.70	0.483	-.0001653	.0000781
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0203096	.0573578	0.35	0.723	-.0921097	.1327289
bf22	-.0000858	.0002375	-0.36	0.718	-.0005514	.0003797
bf29	0	(omitted)				

bf30	-.000487	.0004957	-0.98	0.326	-.0014586	.0004845
bf40	-.0932224	.3574103	-0.26	0.794	-.7937336	.6072889
_cons	-4.855589	3.519856	-1.38	0.168	-11.75438	2.043202

```
706 .
707 . estat class
```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	1	3	4
-	21	286	307
Total	22	289	311

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	4.55%
Specificity	$\Pr(- \sim D)$	98.96%
Positive predictive value	$\Pr(D +)$	25.00%
Negative predictive value	$\Pr(\sim D -)$	93.16%
False + rate for true ~D	$\Pr(+ \sim D)$	1.04%
False - rate for true D	$\Pr(- D)$	95.45%
False + rate for classified +	$\Pr(\sim D +)$	75.00%
False - rate for classified -	$\Pr(D -)$	6.84%
Correctly classified		92.28%

```
708 . estat gof
```

Logistic model for HP2pbfhm, goodness-of-fit test

```

number of observations =      311
number of covariate patterns =    310
    Pearson chi2(290) =    253.04
        Prob > chi2 =      0.9426
```

```
710 .
711 . title "fully Trimmed male main effects wv 3" " Dose => Problems with Family
    > at home models"
```

Log-Lik Intercept Only:	-79.475	Log-Lik Full Model:	-59.851
D(288):	119.702	LR(19):	39.249
		Prob > LR:	0.004
McFadden's R2:	0.247	McFadden's Adj R2:	-0.042
Maximum Likelihood R2:	0.119	Cragg & Uhler's R2:	0.296
McKelvey and Zavoina's R2:	0.486	Efron's R2:	0.165
Variance of y*:	6.405	Variance of error:	3.290
Count R2:	0.923	Adj Count R2:	-0.091
AIC:	0.533	AIC*n:	165.702
BIC:	-1533.359	BIC':	69.807

```
*****
> *
*****
> *
*****
> *
*****
> *
fully Trimmed male main effects wv 3
> *
Dose => Problems with Family at home models
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:37:58   ****
> *
*****
> *
```

```
712 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0
```

```
713 . sw, pr(.1):logit HP2pbfhm age sepaw3 dvcew3 radhlw3 avgcumdosew3 suprtw3 ///
    > havmilsq illw3 `w3bf' if gender==1, iterate(50)
note: bf15m dropped because of estimability
note: bf17 dropped because of estimability
note: bf29 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: 29 obs. dropped because of estimability
      begin with full model
p = 0.8687 >= 0.1000 removing bf4m
p = 0.8320 >= 0.1000 removing havmilsq
p = 0.7873 >= 0.1000 removing bf40
p = 0.7202 >= 0.1000 removing bf20
p = 0.6874 >= 0.1000 removing avgcumdosew3
p = 0.6350 >= 0.1000 removing bf5m
p = 0.5258 >= 0.1000 removing bf8
p = 0.4782 >= 0.1000 removing illw3
p = 0.4550 >= 0.1000 removing radhlw3
p = 0.4439 >= 0.1000 removing bf30
p = 0.3545 >= 0.1000 removing suprtw3
p = 0.2500 >= 0.1000 removing bf22
p = 0.3169 >= 0.1000 removing sepaw3
p = 0.1709 >= 0.1000 removing age
```

Logistic regression

```
Number of obs   =      311
LR chi2(5)      =      31.19
Prob > chi2     =      0.0000
Pseudo R2      =      0.1962
```

Log likelihood = -63.878677

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf1	-.0373492	.0219622	-1.70	0.089	-.0803943	.0056959
bf4	-.2457605	.0676591	-3.63	0.000	-.37837	-.1131511
dvcew3	2.001697	.80438	2.49	0.013	.4251407	3.578253
bf2	.0003872	.000212	1.83	0.068	-.0000283	.0008027
bf7m	.0014478	.0004687	3.09	0.002	.0005292	.0023664
_cons	-1.533868	.7653632	-2.00	0.045	-3.033953	-.0337839

```

714 .
715 . estat class

```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	22	289	311
Total	22	289	311

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	$\Pr(\sim D -)$	92.93%
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 -	$\Pr(D -)$	7.07%
Correctly classified		92.93%

```

716 . estat gof

```

Logistic model for HP2pbfhm, goodness-of-fit test

```

      number of observations =      311
number of covariate patterns =      263
      Pearson chi2(257) =    376.88
          Prob > chi2 =      0.0000

```

```
717 . fitstat
```

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-79.475	Log-Lik Full Model:	-63.879
D(305):	127.757	LR(5):	31.193
		Prob > LR:	0.000
McFadden's R2:	0.196	McFadden's Adj R2:	0.121
Maximum Likelihood R2:	0.095	Cragg & Uhler's R2:	0.238
McKelvey and Zavoina's R2:	0.411	Efron's R2:	0.128
Variance of y*:	5.587	Variance of error:	3.290
Count R2:	0.929	Adj Count R2:	0.000
AIC:	0.449	AIC*n:	139.757
BIC:	-1622.879	BIC':	-2.494

```
718 .
```

```
719 . scalar MainEffPrbfhmMw3 = "bf1 bf4 dvcew3 bf7m"
```

```
720 . scalar SigDosePrbfhmMw3 = "no"
```

```
721 . // construction of moderators for male model
```

```
722 .
```

```
723 . foreach var in bf1 bf4 dvcew3 bf2 bf7m {
      2.  cap gen `var'Xd3 = `var'*avgcumdosew3
      3.  }
```

```
724 .
```

```
725 .
```

```
726 .
```

```
727 .
```

```
728 . *****
> **
```

```
729 . *-----chunk 6 continued -testing moderators and none found for males
```

```
730 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
> 0
```

```
731 .
```

```

732 .
733 . 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 20:38:20 ****
> *
*****
> *
*****

734 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
    > 0

735 . sw, pr(.1):logit HP2pbfhm age sepaw3 dvcew3 radhlw3 avgcumdosew3 suprtw3 ///
    > havmilssq illw3 `w3bf' bf1Xd3 bf4Xd3 bf2Xd3 bf7mXd3 dvcew3Xd3 if ///
    > gender==1, iterate(50)
note: bf15m dropped because of estimability
note: bf17 dropped because of estimability
note: bf29 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: 29 obs. dropped because of estimability
begin with full model
p = 0.9832 >= 0.1000 removing bf2Xd3
p = 0.8995 >= 0.1000 removing bf4m
p = 0.8784 >= 0.1000 removing havmilssq
p = 0.8427 >= 0.1000 removing bf7mXd3
p = 0.8108 >= 0.1000 removing bf1Xd3

```

```

p = 0.7829 >= 0.1000 removing dvcew3Xd3
p = 0.7779 >= 0.1000 removing bf40
p = 0.6983 >= 0.1000 removing bf20
p = 0.6391 >= 0.1000 removing bf4Xd3
p = 0.6874 >= 0.1000 removing avgcumdosew3
p = 0.6350 >= 0.1000 removing bf5m
p = 0.5258 >= 0.1000 removing bf8
p = 0.4782 >= 0.1000 removing illw3
p = 0.4550 >= 0.1000 removing radhlw3
p = 0.4439 >= 0.1000 removing bf30
p = 0.3545 >= 0.1000 removing suprtw3
p = 0.2500 >= 0.1000 removing bf22
p = 0.3169 >= 0.1000 removing sepaw3
p = 0.1709 >= 0.1000 removing age

```

Logistic regression

Number of obs = 311

LR chi2(5) = 31.19

Prob > chi2 = 0.0000

Pseudo R2 = 0.1962

Log likelihood = -63.878677

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
bf1	-.0373492	.0219622	-1.70	0.089	-.0803943	.0056959
bf4	-.2457605	.0676591	-3.63	0.000	-.37837	-.1131511
dvcew3	2.001697	.80438	2.49	0.013	.4251407	3.578253
bf2	.0003872	.000212	1.83	0.068	-.0000283	.0008027
bf7m	.0014478	.0004687	3.09	0.002	.0005292	.0023664
_cons	-1.533868	.7653632	-2.00	0.045	-3.033953	-.0337839

736 .

737 . estat class

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	0	0	0
-	22	289	311
Total	22	289	311

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	$\Pr(\sim D -)$	92.93%
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 -	$\Pr(D -)$	7.07%
Correctly classified		92.93%

738 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	311
number of covariate patterns =	263
Pearson chi2(257) =	376.88
Prob > chi2 =	0.0000

739 . fitstat

Measures of Fit for **logit** of **HP2pbfhm**

Log-Lik Intercept Only:	-79.475	Log-Lik Full Model:	-63.879
D(305):	127.757	LR(5):	31.193
		Prob > LR:	0.000
McFadden's R2:	0.196	McFadden's Adj R2:	0.121
Maximum Likelihood R2:	0.095	Cragg & Uhler's R2:	0.238
McKelvey and Zavoina's R2:	0.411	Efron's R2:	0.128
Variance of y*:	5.587	Variance of error:	3.290
Count R2:	0.929	Adj Count R2:	0.000
AIC:	0.449	AIC*n:	139.757
BIC:	-1622.879	BIC':	-2.494

```

740 .
741 . scalar SigDosePrbfmhmMw3 = "no"

742 . scalar PrbfmhmModw3 = "none"

743 .
744 . * 3 main effects signif    no main effect for dose    for males
745 .
746 .
747 . *****
> ****
748 . title4 "Chunk 6    continued -testing meditors for females"

```

```

Chunk 6    continued -testing meditors for females

```

```

749 . title4 Simultaneous trimming to .1 female wave 3"    "Dose => Problems with Fa
> mily at home models"

```

```

Simultaneous trimming to

```

```

750 . local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf4
> 0

751 . logit HP2pbfhm age    dvcew3 avgcumdosew3 bf4 ///
>    if gender==2, iterate(50)

Iteration 0:    log likelihood = -139.89675
Iteration 1:    log likelihood = -113.53198
Iteration 2:    log likelihood = -107.97258
Iteration 3:    log likelihood = -107.87574
Iteration 4:    log likelihood = -107.87549
Iteration 5:    log likelihood = -107.87549

Logistic regression                                Number of obs    =          363
                                                    LR chi2(4)       =          64.04
                                                    Prob > chi2      =          0.0000
Log likelihood = -107.87549                    Pseudo R2       =          0.2289

```

HP2pbfhm	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0645234	.0172238	3.75	0.000	.0307654	.0982813
dvcew3	.8311533	.6285086	1.32	0.186	-.4007009	2.063007
avgcumdosew3	-.0017344	.0768006	-0.02	0.982	-.1522607	.148792
bf4	-.175564	.0365808	-4.80	0.000	-.2472611	-.1038669
_cons	-4.048039	1.095505	-3.70	0.000	-6.195189	-1.900889

```

752 .
753 . estat class

```

Logistic model for HP2pbfhm

Classified	True		Total
	D	~D	
+	8	5	13
-	39	311	350
Total	47	316	363

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2pbfhm != 0

Sensitivity	$\Pr(+ D)$	17.02%
Specificity	$\Pr(- \sim D)$	98.42%
Positive predictive value	$\Pr(D +)$	61.54%
Negative predictive value	$\Pr(\sim D -)$	88.86%
False + rate for true ~D	$\Pr(+ \sim D)$	1.58%
False - rate for true D	$\Pr(- D)$	82.98%
False + rate for classified +	$\Pr(\sim D +)$	38.46%
False - rate for classified -	$\Pr(D -)$	11.14%
Correctly classified		87.88%

754 . estat gof

Logistic model for HP2pbfhm, goodness-of-fit test

number of observations =	363
number of covariate patterns =	357
Pearson chi2(352) =	307.66
Prob > chi2 =	0.9574

755 . fitstat

Measures of Fit for logit of HP2pbfhm

Log-Lik Intercept Only:	-139.897	Log-Lik Full Model:	-107.875
D(358):	215.751	LR(4):	64.043
		Prob > LR:	0.000
McFadden's R2:	0.229	McFadden's Adj R2:	0.193
Maximum Likelihood R2:	0.162	Cragg & Uhler's R2:	0.301
McKelvey and Zavoina's R2:	0.381	Efron's R2:	0.194
Variance of y*:	5.316	Variance of error:	3.290
Count R2:	0.879	Adj Count R2:	0.064
AIC:	0.622	AIC*n:	225.751
BIC:	-1894.445	BIC':	-40.465

756 .

757 .

758 . title "Dose effect not significant when simultaneously trimmed for females"

```
*****
> *
*****
> *
*****
> *
*****Dose effect not significant when simultaneously trimmed for females *****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:38:50 *****
> *
*****
```

```
> *
```

```
759 .
```

```
760 . *-----Chunk 6 continued -testing meditors for females
```

```
761 . title "More partly female Trimmed wave 3" "Dose => Problems with Family at  
> home models"
```

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
*****  
*****  
More partly female Trimmed wave 3  
*****  
> *  
*****  
Dose => Problems with Family at home models  
*****  
> *  
*****  
*****  
*****  
> *  
*****  
1 Jul 2012 20:38:50 *****  
> *  
*****  
> *  
*****  
> *
```

```
762 . local w3bf bf1 bf4 bf2 bf8 bf15m bf17 bf20 bf22 bf29 bf30 bf40
```

```
763 . 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

```
764 .
```

```
765 . 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 ~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%**

766 . 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

767 . 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

768 .

769 . scalar SigDosePrbfmhmFw3 = "no"

770 . scalar MainEffPrbfmhmFw3 = "age bf4 bf40"

771 . * 3 significant main effects for females

772 . * no significant main effect for dose

773 .

774 . * constructing moderators

```

775 .
776 . foreach var in bf4 bf40 {
      2. cap gen `var'Xd3 = `var'*avgcumdosew3
      3. }

777 .
778 .
779 . *- testing female moderator effects:  no moderator effects for females
780 .
781 . 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

```
782 . 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

```

783 . 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%

784 . 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

```

785 .
786 . scalar PrbfmhmModFw3="none"

787 .
788 . *****
> ****
789 . *-----Chunk 6 continued testing mediating effects for Problems with fami
> ly
790 . *   at home
791 .
792 . * age is a mediating effect for males for Dose=> problems with family at hom
> e
793 . 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)

```

794 . glm age avgcumdosew3 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6336**

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
Deviance	= 49927.38549	Scale parameter	=	147.7142
Pearson	= 49927.38549	(1/df) Deviance	=	147.7142
		(1/df) Pearson	=	147.7142
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
Log likelihood = -1330.633586		<u>AIC</u>	=	7.839021
		<u>BIC</u>	=	47957.2

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew3	.5433648	.2472657	2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376	66.95	0.000	47.09975	49.94067

```
795 . 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      : ML 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) = 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.)

```
796 . glm bf4 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1027.1072
```

```
Generalized linear models                               No. of obs      =       340
Optimization      : ML                                 Residual df     =       338
Scale parameter = 24.77487
Deviance          = 8373.906252                        (1/df) Deviance = 24.77487
Pearson           = 8373.906252                        (1/df) Pearson  = 24.77487
```

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

```
Log likelihood    = -1027.107224                        AIC              = 6.053572
                                                           BIC              = 6403.723
```

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.0357675	.1012648	-0.35	0.724	-.2342429	.1627078
_cons	12.54064	.2968079	42.25	0.000	11.95891	13.12238

```
797 . 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.)

```

798 .
799 . * age is a mediating effect for females for Dose=> Problems with family at h
    > ome
800 . glm age avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

```
Iteration 0:    log likelihood =  -1408.064
```

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                      Residual df       =       361
                                                Scale parameter =   137.7687
Deviance          =   49734.51399          (1/df) Deviance =   137.7687
Pearson           =   49734.51399          (1/df) Pearson  =   137.7687

```

```

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

```

```

Log likelihood    =  -1408.06405             AIC                =   7.768948
                                                BIC                =  47606.63

```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

```
801 . 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.)

```

802 .
803 . * bf4 is a mediating effect for females for Dose=> Problems with family at ho
    > me
804 . glm bf4 avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1109.6569**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.6146
Deviance = 9607.869105	(1/df) Deviance	=	26.6146
Pearson = 9607.869105	(1/df) Pearson	=	26.6146

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

	<u>AIC</u>	=	6.124831
Log likelihood = -1109.656873	<u>BIC</u>	=	7479.99

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.4386292	.1543885	-2.84	0.004	-.7412252	-.1360333
_cons	11.01475	.3282456	33.56	0.000	10.3714	11.6581

```

805 . 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					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
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.)

```

806 .
807 .
808 . glm bf40  avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-818.14796**

```

Generalized linear models                      No. of obs      =       363
Optimization      : ML                       Residual df      =       361
                                          Scale parameter =   5.340664
Deviance          =   1927.979854             (1/df) Deviance =   5.340664
Pearson           =   1927.979854             (1/df) Pearson  =   5.340664

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

                                          AIC              =   4.518722
Log likelihood    = -818.1479598             BIC              = -199.8996

```

bf40	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.152897	.0691596	2.21	0.027	.0173466	.2884474
_cons	2.981537	.1470404	20.28	0.000	2.693343	3.269731

```
809 . 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.)

```
810 .
811 . scalar PrbfmhmMedMw3 = "age"

812 . scalar PrbfmhmMedFw3 = "age bf4"

813 .
814 . title4 " Summary of dose=problems with family at home mediating effects "
```

Summary of dose=problems with family at home mediating effects

```

815 . * males mediators age 1
816 . * females mediators age and BSIsoma rescaled (bf4) 2
817 .
818 .     matrix define HP2prbfamMw3 = J(1,8, 0)

819 .         matrix define HP2prbfamFw3 = J(1,8, 0)

820 . matrix colnames HP2prbfamMw3 =  hypnum ptnum wave gender medsig numMA sig num
    > Modsig numMed

821 .         matrix colnames HP2prbfamFw3=  hypnum ptnum wave gender medsig numMA
    > sig numModsig numMed

822 .     matrix define HP2prbfamMw3= (1, 2, 3, 1, 0, 5, 0, 1 )

823 .         matrix define HP2prbfamFw3= (1, 2, 3, 2, 0, 2, 2, 2)

824 .         matrix rowname HP2prbfamMw3 = HP2prbfamM

825 .         matrix rowname HP2prbfamFw3 = HP2prbfamF

826 .         matlist HP2prbfamMw3

```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2prbfamM	1	2	3	1	0	
> 5						
	c7	c8				
HP2prbfamM	0	1				

```

827 .         matlist HP2prbfamFw3

```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2prbfamF	1	2	3	2	0	
> 2						
	c7	c8				
HP2prbfamF	2	2				

```

828 .      matrix define H1pt2w3 = ( HP2wkMw3 \ HP2wkFw3 \ HP2hmcrMw3 \ HP2hmcr
> Fw3 \HP2spMw3 \HP2spFw3 \ HP2prbfamMw3 \ HP2prbfamFw3 )

```

```
829 .
```

```
830 .      matlist H1pt2w3
```

		c1	c2	c3	c4	c5	c
> 6							
> —							
	r1	1	2	3	1	0	
> 4							
	r1	1	2	3	2	0	
> 1							
	r1	1	2	3	1	0	
> 4							
	r1	1	2	3	2	0	
> 2							
	HP2spMw3	1	2	3	1	0	
> 2							
	HP2spFw3	1	2	3	2	1	
> 5							
	HP2prbfamM	1	2	3	1	0	
> 5							
	HP2prbfamF	1	2	3	2	0	
> 2							
		c7	c8				
	r1	0	4				
	r1	0	6				
	r1	0	2				
	r1	0	2				
	HP2spMw3	0	1				
	HP2spFw3	5	3				
	HP2prbfamM	0	1				
	HP2prbfamF	2	2				

```
831 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed
```

```
832 .      matrix rownames H1pt2w3 =  HP2wkMw3 HP2wkFw3 HP2hmcrMw3 HP2hmcrFw3 HP2p
> rbfhmMw3 HP2prbfhmFw3
```

```
833 .      matlist H1pt2w3
```

	hypnum	ptnum	wave	gender	medsig	numMA sig
> g						
> —						
HP2wkMw3	1	2	3	1	0	
> 4						
HP2wkFw3	1	2	3	2	0	
> 1						
HP2hmcrMw3	1	2	3	1	0	
> 4						
HP2hmcrFw3	1	2	3	2	0	
> 2						
HP2prbfhmMw3	1	2	3	1	0	
> 2						
HP2prbfhmFw3	1	2	3	2	1	
> 5						
HP2prbfhmFw3	1	2	3	1	0	
> 5						
HP2prbfhmFw3	1	2	3	2	0	
> 2						
	numModsig	numMed				
HP2wkMw3	0	4				
HP2wkFw3	0	6				
HP2hmcrMw3	0	2				
HP2hmcrFw3	0	2				
HP2prbfhmMw3	0	1				
HP2prbfhmFw3	5	3				
HP2prbfhmFw3	0	1				
HP2prbfhmFw3	2	2				

```

834 .
835 .
836 . *-----
> ----
837 . *****
> ****
838 . *-----Chunk 7   Dose==> problems with sex life impact
839 . * Chunk 7   General model for all part 2 of Nottingham Health Profile
840 .
841 . title "5.   Wave 3 part2 H1: Test of hypothesis 1 with Male and Female Respon
> dents" ///
>       " Wave 3 Main effects Dose=> sexlife impact identification"

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****5.   Wave 3 part2 H1: Test of hypothesis 1 with Male and Female Respondent
> s*****
*****       Wave 3 Main effects Dose=> sexlife impact identification       ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     1 Jul 2012    20:39:11    ****
> *
*****
> *
*****
> *

```

```

842 . forvalues j=3/3 {
      2. set more off
      3.
843 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      >   bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
844 .   foreach var in HP2sxlife {
      5.       forvalues k=1/2 {
      6. local w3bf 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.
845 . di _skip(4)
      10.
846 .
847 .   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 radhlw3 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

marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed
inclw3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
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 Nottingham Part 2 subscale models for male & females
> *
*****
Full main model for HP2sxlife for wave= 3
> *
*****
chunk 7 H1 test:Gender= 1 model Wave = 3 for HP2pbfhm
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:39:11
> *
*****
> *
*****

```

> *

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

note: _Ieduc_7 != 0 predicts failure perfectly

 _Ieduc_7 dropped and 4 obs not used

note: occ6w3 != 0 predicts failure perfectly

 occ6w3 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: _Ieduc_8 omitted because of collinearity

note: occ8w3 omitted because of collinearity

note: marrw36 omitted because of collinearity

note: bf17 omitted because of collinearity

note: radhlw3 omitted because of collinearity

Logistic regression

Number of obs = 304

LR chi2(47) = 153.48

Prob > chi2 = 0.0000

Pseudo R2 = 0.4713

Log likelihood = -86.082561

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1069256	.0319906	3.34	0.001	.0442252	.169626
_Ieduc_2	-.7455102	2.711615	-0.27	0.783	-6.060177	4.569157
_Ieduc_3	-1.187035	2.60622	-0.46	0.649	-6.295133	3.921063
_Ieduc_4	-2.546669	2.819292	-0.90	0.366	-8.072379	2.979041
_Ieduc_5	-.9083698	2.596245	-0.35	0.726	-5.996916	4.180177
_Ieduc_6	-.821989	2.54798	-0.32	0.747	-5.815938	4.17196
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-13.83588	1847.337	-0.01	0.994	-3634.551	3606.879
occ2w3	-14.1177	1847.337	-0.01	0.994	-3634.833	3606.597
occ3w3	-15.12911	1847.338	-0.01	0.993	-3635.845	3605.586
occ4w3	-14.04877	1847.338	-0.01	0.994	-3634.764	3606.666
occ5w3	-13.39243	1847.338	-0.01	0.994	-3634.108	3607.323
occ6w3	0	(omitted)				
occ7w3	-14.25779	1847.337	-0.01	0.994	-3634.973	3606.457
occ8w3	0	(omitted)				
marrw31	1.917986	1.336919	1.43	0.151	-.7023282	4.538299

marrw32	-.8798595	1.841469	-0.48	0.633	-4.489073	2.729354
marrw33	.8814069	1.275273	0.69	0.489	-1.618082	3.380896
marrw35	1.398611	1.615954	0.87	0.387	-1.768602	4.565823
marrw36	0	(omitted)				
inclw3	16.59262	1847.337	0.01	0.993	-3604.122	3637.307
inc2w3	16.41393	1847.337	0.01	0.993	-3604.3	3637.128
inc3w3	14.9931	1847.337	0.01	0.994	-3605.721	3635.708
inc4w3	13.76529	1847.339	0.01	0.994	-3606.952	3634.482
radhlw3	.0155883	.0090158	1.73	0.084	-.0020824	.0332591
havmil	.0032884	.0119659	0.27	0.783	-.0201643	.0267412
avgcumdosew3	.0366781	.0541231	0.68	0.498	-.0694012	.1427574
bf1	.0224773	.0438725	0.51	0.608	-.0635113	.108466
bf4	-.3119601	.2453847	-1.27	0.204	-.7929052	.168985
bf2	.0000786	.0001745	0.45	0.652	-.0002634	.0004207
bf4m	.0103662	.2174828	0.05	0.962	-.4158923	.4366247
bf5m	.0028825	.0019867	1.45	0.147	-.0010113	.0067763
bf7m	.0013372	.0006507	2.05	0.040	.0000618	.0026126
bf8	-.0000698	.0000479	-1.46	0.145	-.0001638	.0000241
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0288329	.0347084	-0.83	0.406	-.09686	.0391943
bf22	-.0000907	.0001888	-0.48	0.631	-.0004608	.0002793
bf29	0	(omitted)				
bf30	-5.44e-06	.0004196	-0.01	0.990	-.0008279	.0008171
bf40	.3549975	.2522025	1.41	0.159	-.1393104	.8493054
deaw3	-.1446966	.2515866	-0.58	0.565	-.6377974	.3484041
dvcew3	.2312151	1.685819	0.14	0.891	-3.07293	3.535361
sepaw3	1.563211	1.973158	0.79	0.428	-2.304108	5.430529
accdw3	-1.029126	.9986452	-1.03	0.303	-2.986435	.9281827
movew3	-.3161441	.7920977	-0.40	0.690	-1.868627	1.236339
illw3	.2509498	.2730406	0.92	0.358	-.2841998	.7860995
shfamw3	-.0049114	.0092237	-0.53	0.594	-.0229895	.0131668
shhlw3	-.0135671	.0078785	-1.72	0.085	-.0290087	.0018746
shjobw3	.0090088	.0079953	1.13	0.260	-.0066617	.0246793
shrelaw3	-.0052844	.0083104	-0.64	0.525	-.0215726	.0110037
suprtw3	.0083949	.0090554	0.93	0.354	-.0093533	.0261431
suchrw3	-.0115343	.0079215	-1.46	0.145	-.0270603	.0039916
havmilsq	-.0000122	.0000253	-0.48	0.630	-.0000618	.0000374
radhlw3	0	(omitted)				
_cons	-6.912277	3.93482	-1.76	0.079	-14.62438	.7998281

Note: 4 failures and 0 successes completely determined.

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	44	14	58
-	25	221	246
Total	69	235	304

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	63.77%
Specificity	$\Pr(- \sim D)$	94.04%
Positive predictive value	$\Pr(D +)$	75.86%
Negative predictive value	$\Pr(\sim D -)$	89.84%
False + rate for true ~D	$\Pr(+ \sim D)$	5.96%
False - rate for true D	$\Pr(- D)$	36.23%
False + rate for classified +	$\Pr(\sim D +)$	24.14%
False - rate for classified -	$\Pr(D -)$	10.16%
Correctly classified		87.17%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      304
number of covariate patterns =    304
Pearson chi2(256) =      202.32
Prob > chi2 =      0.9943

```

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-162.820	Log-Lik Full Model:	-86.083
D(247):	172.165	LR(47):	153.476
		Prob > LR:	0.000
McFadden's R2:	0.471	McFadden's Adj R2:	0.121
Maximum Likelihood R2:	0.396	Cragg & Uhler's R2:	0.603
McKelvey and Zavoina's R2:	0.800	Efron's R2:	0.484
Variance of y*:	16.474	Variance of error:	3.290
Count R2:	0.872	Adj Count R2:	0.435
AIC:	0.941	AIC*n:	286.165
BIC:	-1239.941	BIC':	115.224

```

*****
> *
*****
> *
*****
> *
*****
> *
*****
Full Nottingham Part 2 subscale models for male & females
> *
*****
Full main model for HP2sxlife for wave= 3
> *
*****
chunk 7 H1 test:Gender= 2 model Wave = 3 for HP2sxlife
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:39:12
> *
*****
> *
*****
> *

```

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

note: occ8w3 != 0 predicts failure perfectly
 occ8w3 dropped and 1 obs not used

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: bf17 omitted because of collinearity
 note: radhlw3 omitted because of collinearity

Logistic regression	Number of obs	=	345
	LR chi2(50)	=	168.03
	Prob > chi2	=	0.0000
Log likelihood = -114.00457	Pseudo R2	=	0.4243

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0813848	.0244496	3.33	0.001	.0334644	.1293053
_Ieduc_2	-12.79022	653.1326	-0.02	0.984	-1292.907	1267.326
_Ieduc_3	-11.94607	653.1326	-0.02	0.985	-1292.062	1268.17
_Ieduc_4	-11.36768	653.1328	-0.02	0.986	-1291.484	1268.749
_Ieduc_5	-12.54328	653.1327	-0.02	0.985	-1292.66	1267.573
_Ieduc_6	-11.93918	653.1326	-0.02	0.985	-1292.055	1268.177
_Ieduc_7	-12.87216	653.1524	-0.02	0.984	-1293.027	1267.283
_Ieduc_8	0	(omitted)				
occ1w3	-2.703036	2.21975	-1.22	0.223	-7.053665	1.647593
occ2w3	-2.165029	2.323461	-0.93	0.351	-6.718929	2.388871
occ3w3	-2.030908	2.234964	-0.91	0.364	-6.411358	2.349542
occ4w3	-1.625969	2.528132	-0.64	0.520	-6.581016	3.329078
occ5w3	.7269315	2.820396	0.26	0.797	-4.800943	6.254806
occ6w3	-.7633882	2.518786	-0.30	0.762	-5.700118	4.173342
occ7w3	-1.433838	2.203631	-0.65	0.515	-5.752876	2.8852
occ8w3	0	(omitted)				
marrw31	.3247443	1.774101	0.18	0.855	-3.152431	3.801919
marrw32	.8501767	2.207491	0.39	0.700	-3.476427	5.17678
marrw33	1.557872	1.575773	0.99	0.323	-1.530585	4.646329
marrw35	-.4253418	1.619183	-0.26	0.793	-3.598882	2.748198
marrw36	1.703593	1.601915	1.06	0.288	-1.436102	4.843288
inclw3	1.766812	2.253827	0.78	0.433	-2.650608	6.184231
inc2w3	2.269344	2.224897	1.02	0.308	-2.091374	6.630061
inc3w3	.9292343	2.201873	0.42	0.673	-3.386357	5.244826
inc4w3	1.449624	2.775037	0.52	0.601	-3.989349	6.888597
radhlw3	.0277216	.0091569	3.03	0.002	.0097745	.0456688
havmil	.0021336	.0032179	0.66	0.507	-.0041733	.0084405
avgcumdosew3	.1969924	.1165031	1.69	0.091	-.0313496	.4253343
bf1	.0285984	.0382244	0.75	0.454	-.04632	.1035168
bf4	-.4015139	.2038932	-1.97	0.049	-.8011373	-.0018905
bf2	-.0001649	.0001225	-1.35	0.178	-.0004051	.0000753
bf4m	.3523301	.1864609	1.89	0.059	-.0131266	.7177867
bf5m	-.0026053	.001955	-1.33	0.183	-.006437	.0012264
bf7m	-.0000741	.0006237	-0.12	0.905	-.0012966	.0011483
bf8	-5.22e-06	.0000423	-0.12	0.902	-.0000881	.0000777
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	-.0120216	.031995	-0.38	0.707	-.0747307	.0506874
bf22	-.0001004	.0001357	-0.74	0.459	-.0003664	.0001655
bf29	0	(omitted)				
bf30	-.0002441	.0003438	-0.71	0.478	-.0009179	.0004298
bf40	.095062	.1371931	0.69	0.488	-.1738314	.3639555
deaw3	.0760781	.1918427	0.40	0.692	-.2999267	.4520829
dvcew3	1.127371	.952705	1.18	0.237	-.7398962	2.994639
sepaw3	.5833047	.936842	0.62	0.534	-1.252872	2.419481
accdw3	-.5118992	.5859911	-0.87	0.382	-1.660421	.6366223

movew3	-.6063637	1.823477	-0.33	0.739	-4.180313	2.967586
illlw3	.1168429	.1761008	0.66	0.507	-.2283082	.4619941
shfamw3	.0084815	.007536	1.13	0.260	-.0062888	.0232518
shhlw3	.0066923	.0066985	1.00	0.318	-.0064365	.0198212
shjobw3	-.0046191	.0070704	-0.65	0.514	-.0184767	.0092386
shrelaw3	-.0123617	.0074084	-1.67	0.095	-.0268819	.0021585
suprtw3	-.0091554	.0078461	-1.17	0.243	-.0245335	.0062227
suchrw3	-.0034248	.0055225	-0.62	0.535	-.0142486	.0073991
havmilsq	-2.54e-06	2.55e-06	-1.00	0.319	-7.52e-06	2.45e-06
radhlw3	0	(omitted)				
_cons	1.83356	653.1407	0.00	0.998	-1278.299	1281.966

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	60	12	72
-	30	243	273
Total	90	255	345

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	66.67%
Specificity	$\Pr(- \sim D)$	95.29%
Positive predictive value	$\Pr(D +)$	83.33%
Negative predictive value	$\Pr(\sim D -)$	89.01%
False + rate for true ~D	$\Pr(+ \sim D)$	4.71%
False - rate for true D	$\Pr(- D)$	33.33%
False + rate for classified +	$\Pr(\sim D +)$	16.67%
False - rate for classified -	$\Pr(D -)$	10.99%
Correctly classified		87.83%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	345
number of covariate patterns =	345
Pearson chi2(294) =	343.22
Prob > chi2 =	0.0254

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

Log-Lik Intercept Only:	-198.018	Log-Lik Full Model:	-114.005
D(288):	228.009	LR(50):	168.026
		Prob > LR:	0.000
McFadden's R2:	0.424	McFadden's Adj R2:	0.136
Maximum Likelihood R2:	0.386	Cragg & Uhler's R2:	0.565
McKelvey and Zavoina's R2:	0.693	Efron's R2:	0.483
Variance of y*:	10.715	Variance of error:	3.290
Count R2:	0.878	Adj Count R2:	0.533
AIC:	0.991	AIC*n:	342.009
BIC:	-1454.932	BIC':	124.151

```

848 . *-----Chunk 7 dose3 moderator => sex life impact-----
849 . title "Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave
> 3"

```

```

*****
> *
*****
> *
*****
> *
*****Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave 3**
> ***
*****
> *
*****
> *
*****
1 Jul 2012    20:39:14    ****
> *
*****
> *
*****
> *

```

```

850 . * male models
851 .       forvalues j=3/3 {
      2. di as input  "trimmed HP2sexlife main effects models wave 1 for H1 part 2
> with dose ns"
      3. di as input  "Wave 3 male dose avgcumdosew`j' main effect not signif"
      4.       logit HP2sxlife age marrw31-marrw36 bf4 bf5m dvcew`j' illw`j' shh
> lw`j' ///
>       havmilsq shrelaw`j' ///
>       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 3 male dose avgcumdosew3 main effect not signif

note: marrw34 omitted because of collinearity
note: marrw36 omitted because of collinearity
Iteration 0: log likelihood = **-171.51396**
Iteration 1: log likelihood = **-116.02941**
Iteration 2: log likelihood = **-108.27742**
Iteration 3: log likelihood = **-107.96025**
Iteration 4: log likelihood = **-107.95802**
Iteration 5: log likelihood = **-107.95802**

Logistic regression	Number of obs	=	340
	LR chi2(14)	=	127.11
	Prob > chi2	=	0.0000
Log likelihood = -107.95802	Pseudo R2	=	0.3706

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0742276	.0176614	4.20	0.000	.0396119	.1088433
marrw31	1.295459	1.079283	1.20	0.230	-.8198963	3.410814
marrw32	-.2171872	1.393226	-0.16	0.876	-2.94786	2.513485
marrw33	.8215567	.8316513	0.99	0.323	-.80845	2.451563
marrw34	0	(omitted)				
marrw35	.6845196	1.274778	0.54	0.591	-1.813999	3.183038
marrw36	0	(omitted)				
bf4	-.1751874	.0433174	-4.04	0.000	-.2600878	-.0902869
bf5m	-.0005252	.001056	-0.50	0.619	-.002595	.0015447
dvcew3	.7519715	.9602947	0.78	0.434	-1.130172	2.634115
illw3	.4656174	.1837911	2.53	0.011	.1053935	.8258412
shhlw3	-.0078344	.0055669	-1.41	0.159	-.0187453	.0030765
havmilsq	-4.85e-06	5.73e-06	-0.85	0.398	-.0000161	6.39e-06
shrelaw3	-.0015114	.0058428	-0.26	0.796	-.0129631	.0099403
avgcumdosew3	.0567392	.0450409	1.26	0.208	-.0315395	.1450178
radhlw3	.0138841	.0063766	2.18	0.029	.0013861	.0263821

_cons	-4.875148	1.618703	-3.01	0.003	-8.047748	-1.702548
--------------	------------------	-----------------	--------------	--------------	------------------	------------------

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	37	17	54
-	32	254	286
Total	69	271	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	53.62%
Specificity	$\Pr(- \sim D)$	93.73%
Positive predictive value	$\Pr(D +)$	68.52%
Negative predictive value	$\Pr(\sim D -)$	88.81%
False + rate for true ~D	$\Pr(+ \sim D)$	6.27%
False - rate for true D	$\Pr(- D)$	46.38%
False + rate for classified +	$\Pr(\sim D +)$	31.48%
False - rate for classified -	$\Pr(D -)$	11.19%
Correctly classified		85.59%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations =	340
number of covariate patterns =	338
Pearson chi2(323) =	289.05
Prob > chi2 =	0.9130

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-107.958
D(323):	215.916	LR(14):	127.112
		Prob > LR:	0.000
McFadden's R2:	0.371	McFadden's Adj R2:	0.271
Maximum Likelihood R2:	0.312	Cragg & Uhler's R2:	0.491
McKelvey and Zavoina's R2:	0.534	Efron's R2:	0.390
Variance of y*:	7.057	Variance of error:	3.290
Count R2:	0.856	Adj Count R2:	0.290
AIC:	0.735	AIC*n:	249.916
BIC:	-1666.833	BIC':	-45.507

```
852 . title "Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave
> 3"
```

```
*****
> *
*****
> *
*****
> *
*****
> *
*****Chunk 7 trimmed male model of dose and HP2sxlife relationship in wave 3**
> ***
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
*****
> *
```

```

853 . * male models
854 .       forvalues j=3/3 {
      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 3 male dose avgcumdosew`j' main effect not signif"
      5.       logit HP2sexlife age  bf4  illw`j' shhlw`j' ///
>       havmilsq  ///
>       avgcumdosew`j' radhlw`j' if gender==1
      6.               estat class
      7.               estat gof
      8.               fitstat
      9. }

```

trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose ns
Wave 3 male dose avgcumdosew3 main effect not signif

```

Iteration 0:  log likelihood = -171.51396
Iteration 1:  log likelihood = -116.88501
Iteration 2:  log likelihood = -109.88634
Iteration 3:  log likelihood = -109.5831
Iteration 4:  log likelihood = -109.58073
Iteration 5:  log likelihood = -109.58073

```

Logistic regression	Number of obs	=	340
	LR chi2(7)	=	123.87
	Prob > chi2	=	0.0000
Log likelihood = -109.58073	Pseudo R2	=	0.3611

HP2sexlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0642517	.0157234	4.09	0.000	.0334344	.095069
bf4	-.1765469	.0392111	-4.50	0.000	-.2533993	-.0996945
illw3	.4690318	.1644894	2.85	0.004	.1466384	.7914252
shhlw3	-.0087591	.0051634	-1.70	0.090	-.0188791	.001361
havmilsq	-6.11e-06	5.71e-06	-1.07	0.285	-.0000173	5.09e-06
avgcumdosew3	.0558129	.0448722	1.24	0.214	-.032135	.1437607
radhlw3	.0122374	.0056656	2.16	0.031	.001133	.0233417
_cons	-3.483368	1.099461	-3.17	0.002	-5.638272	-1.328464

Logistic model for HP2sexlife

Classified	True		Total
	D	~D	
+	37	17	54
-	32	254	286
Total	69	271	340

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	53.62%
Specificity	$\Pr(- \sim D)$	93.73%
Positive predictive value	$\Pr(D +)$	68.52%
Negative predictive value	$\Pr(\sim D -)$	88.81%
False + rate for true ~D	$\Pr(+ \sim D)$	6.27%
False - rate for true D	$\Pr(- D)$	46.38%
False + rate for classified +	$\Pr(\sim D +)$	31.48%
False - rate for classified -	$\Pr(D -)$	11.19%
Correctly classified		85.59%

Logistic model for HP2sxlife, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    333
    Pearson chi2(325) =    283.30
        Prob > chi2 =    0.9540

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-109.581
D(332):	219.161	LR(7):	123.866
		Prob > LR:	0.000
McFadden's R2:	0.361	McFadden's Adj R2:	0.314
Maximum Likelihood R2:	0.305	Cragg & Uhler's R2:	0.481
McKelvey and Zavoina's R2:	0.515	Efron's R2:	0.378
Variance of y*:	6.788	Variance of error:	3.290
Count R2:	0.856	Adj Count R2:	0.290
AIC:	0.692	AIC*n:	235.161
BIC:	-1716.048	BIC':	-83.064

```

855 .
856 . scalar MainEffsxlifeMw3 = "age bf4 illw3 radhlw3"

857 . scalar SigDosesxlifeMw3 = "no"

858 .
859 .
860 . forvalues j=3/3 {
      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 3 for H1 part 2 with dose ns**
> ***
*****
> *
*****
> *
*****
> *
*****1 Jul 2012 20:39:17 ****
> *
*****
> *
*****
> *

```

```

title2: Wave `j dose HPsxlife relationship but avgcumdosew3: Dose not signif
Date and time: 1 Jul 2012 20:39:17
Working directory: /Users/robertyaffee
> /Documents/data/research/chwk/phase3/Htests/H1tests/h1pt2
Stata data file: chwide1jul2012.dta h
> as 2402 variables and 703 observations

Wave `j dose HPsxlife relationship but avgcumdosew3: Dose not signif

```

```

861 .
862 .
863 . cap gen radhlw3Xd3 = radhlw3*avgcumdosew3

864 .
865 . set more off

866 . des bf4

```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```

867 . forvalues j=3/3 {
      2.          sw, pr(.1):logistic HP2sxlife age bf4 illw`j' ///
>          avgcumdosew`j' radhlw`j' ageXd3 radhlw3Xd3 illw3Xd3 if gende
> r==1, coef nolog
      3.          estat class
      4.          estat gof
      5.          fitstat
      6. }

          begin with full model
p = 0.9949 >= 0.1000 removing illw3Xd3
p = 0.2976 >= 0.1000 removing radhlw3Xd3
p = 0.1716 >= 0.1000 removing avgcumdosew3
p = 0.1751 >= 0.1000 removing ageXd3

```

Logistic regression	Number of obs	=	340
	LR chi2(4)	=	117.89
	Prob > chi2	=	0.0000
Log likelihood = -112.56939	Pseudo R2	=	0.3437

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0655592	.0156078	4.20	0.000	.0349684	.09615
bf4	-.1526795	.0362827	-4.21	0.000	-.2237922	-.0815668
illw3	.3916574	.1538103	2.55	0.011	.0901948	.69312
radhlw3	.0122253	.0056017	2.18	0.029	.0012461	.0232046
_cons	-4.135046	1.063355	-3.89	0.000	-6.219184	-2.050907

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	37	15	52
-	32	256	288
Total	69	271	340

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	53.62%
Specificity	$\Pr(- \sim D)$	94.46%
Positive predictive value	$\Pr(D +)$	71.15%
Negative predictive value	$\Pr(\sim D -)$	88.89%
False + rate for true ~D	$\Pr(+ \sim D)$	5.54%
False - rate for true D	$\Pr(- D)$	46.38%
False + rate for classified +	$\Pr(\sim D +)$	28.85%
False - rate for classified -	$\Pr(D -)$	11.11%
Correctly classified		86.18%

Logistic model for HP2sxlife, goodness-of-fit test

```

      number of observations =      340
number of covariate patterns =      309
      Pearson chi2(304) =      278.23
           Prob > chi2 =      0.8529

```

Measures of Fit for logistic of HP2sxlife

Log-Lik Intercept Only:	-171.514	Log-Lik Full Model:	-112.569
D(335):	225.139	LR(4):	117.889
		Prob > LR:	0.000
McFadden's R2:	0.344	McFadden's Adj R2:	0.315
Maximum Likelihood R2:	0.293	Cragg & Uhler's R2:	0.461
McKelvey and Zavoina's R2:	0.477	Efron's R2:	0.359
Variance of y*:	6.295	Variance of error:	3.290
Count R2:	0.862	Adj Count R2:	0.319
AIC:	0.692	AIC*n:	235.139
BIC:	-1727.558	BIC':	-94.573

```

868 .
869 . scalar sxlifeModMw3 = "none"

870 . *xx male moderators: no main significant dose effect
871 . *xx no male moderators for sexlife impact
872 .
873 .
874 . * female models
875 . *-----Chunk 7 dose3 moderator => sex life impact-----
> -
876 . di as input "chunk 7  female wave=3"
    chunk 7  female wave=3

877 . title "Chunk 7 trimmed female model:" "dose and HP2sxlife relationship in wa
> ve 3"

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****          Chunk 7 trimmed female model:          ****
> *
*****          dose and HP2sxlife relationship in wave 3          ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****          1 Jul 2012    20:39:25          ****
> *
*****
> *
*****
> *

```

```

878 . * female models
879 .         forvalues j=3/3 {
      2.
880 . set more off
      3. des bf4 bf4m shfamw3 shrelaw3 avgcumdosew3
      4. title "trimmed HP2sexlife main effects models" "wave 3 for H1 part 2 with
> dose ns"
      5. title "Wave 3 dose HP2sexlife relationship" "avgcumdosew`j' Dose not sign
> if"
      6.         logit HP2sxlife age marrw31-marrw36   radhlw`j' bf4 bf4m   ///
>         shfamw`j' shrelaw`j' avgcumdosew`j'   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)
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009

```
*****
> *
*****
> *
*****
> *
*****
> *
***** trimmed HP2sexlife main effects models *****
> *
***** wave 3 for H1 part 2 with dose ns *****
> *
*****
> *
*****
> *
***** 1 Jul 2012 20:39:25 *****
> *
*****
```

```

> *
*****
> *

*****
> *
*****
> *
*****
> *
*****
Wave 3 dose HP2sexlife relationship
> *
*****
avgcumdosew3 Dose not signif
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:39:25
> *
*****
> *
*****
> *

```

note: marrrw36 omitted because of collinearity

```

Iteration 0: log likelihood = -207.62116
Iteration 1: log likelihood = -144.17685
Iteration 2: log likelihood = -138.48259
Iteration 3: log likelihood = -138.36775
Iteration 4: log likelihood = -138.36738
Iteration 5: log likelihood = -138.36738

```

Logistic regression

Log likelihood = -138.36738

```

Number of obs   =      363
LR chi2(12)     =     138.51
Prob > chi2     =      0.0000
Pseudo R2      =      0.3336

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0754579	.0170423	4.43	0.000	.0420555	.1088603
marrw31	-.9421212	.8010808	-1.18	0.240	-2.512211	.6279684
marrw32	-.440823	1.344699	-0.33	0.743	-3.076384	2.194738
marrw33	-.9501207	.4286832	-2.22	0.027	-1.790324	-.109917
marrw34	-.9642797	1.745537	-0.55	0.581	-4.38547	2.45691
marrw35	-.8586239	.6388872	-1.34	0.179	-2.11082	.393572
marrw36	0	(omitted)				
radhlw3	.0100484	.0049263	2.04	0.041	.000393	.0197038
bf4	-.5151847	.1744193	-2.95	0.003	-.8570402	-.1733292
bf4m	.3491023	.1586783	2.20	0.028	.0380985	.6601061
shfamw3	.0106246	.0054177	1.96	0.050	6.14e-06	.0212431
shrelaw3	-.0125055	.00593	-2.11	0.035	-.024128	-.0008829
avgcumdosew3	.1255823	.0854354	1.47	0.142	-.0418679	.2930326
_cons	-6.549884	1.704204	-3.84	0.000	-9.890063	-3.209705

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	57	16	73
-	37	253	290
Total	94	269	363

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	60.64%
Specificity	$\Pr(- \sim D)$	94.05%
Positive predictive value	$\Pr(D +)$	78.08%
Negative predictive value	$\Pr(\sim D -)$	87.24%

False + rate for true ~D	$\Pr(+ \sim D)$	5.95%
False - rate for true D	$\Pr(- D)$	39.36%
False + rate for classified +	$\Pr(\sim D +)$	21.92%
False - rate for classified -	$\Pr(D -)$	12.76%

Correctly classified	85.40%
----------------------	--------

Logistic model for HP2sxlife, goodness-of-fit test

Measures of Fit for **logit** of **HP2sxlife**

```

> *
*****
1 Jul 2012    20:39:26    ****
> *
*****
> *
*****
> *

```

```

888 . * female models
889 .     forvalues j=3/3 {
      2.
890 . set more off
      3. des bf4 bf4m shfamw3 shrelaw3 avgcumdosew3
      4. title "trimmed HP2sexlife main effects models" "wave 3 for H1 part 2 with
> dose ns"
      5. title "Wave 3 dose HP2sexlife relationship" "avgcumdosew`j' Dose not sign
> if"
      6.     logit HP2sxlife age marrw31-marrw36 radhlw`j' bf4 bf4m    ///
>         shfamw`j' shrelaw`j' avgcumdosew`j' ageXd3 marrw31Xd3 marrw32Xd3
>     ///
>         marrw33Xd3 marrw34Xd3 marrw35Xd3 bf4Xd3 bf4mXd3 shrelaw3Xd3 ///
>         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)
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009

note: marrw36 omitted because of collinearity

Iteration 0: log likelihood = -207.62116
 Iteration 1: log likelihood = -141.7263
 Iteration 2: log likelihood = -135.5357
 Iteration 3: log likelihood = -135.21704
 Iteration 4: log likelihood = -135.16073
 Iteration 5: log likelihood = -135.14259
 Iteration 6: log likelihood = -135.139
 Iteration 7: log likelihood = -135.13799
 Iteration 8: log likelihood = -135.13774
 Iteration 9: log likelihood = -135.13769
 Iteration 10: log likelihood = -135.13768

Logistic regression

Number of obs = 363
 LR chi2(21) = 144.97
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.3491

Log likelihood = -135.13768

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.092952	.0233865	3.97	0.000	.0471154	.1387886
marrw31	-1.341334	1.898438	-0.71	0.480	-5.062204	2.379537
marrw32	2.268161	4.581638	0.50	0.621	-6.711685	11.24801
marrw33	-.8067892	.6165677	-1.31	0.191	-2.01524	.4016614
marrw34	-32.82787	1800.902	-0.02	0.985	-3562.53	3496.875
marrw35	-.858144	1.080921	-0.79	0.427	-2.976711	1.260423
marrw36	0	(omitted)				
radhlw3	.0109474	.0050586	2.16	0.030	.0010328	.0208621
bf4	-.3690314	.3776717	-0.98	0.329	-1.109254	.3711915
bf4m	.245895	.3444988	0.71	0.475	-.4293101	.9211002
shfamw3	.0116586	.005533	2.11	0.035	.0008141	.0225031
shrelaw3	-.0021905	.0093988	-0.23	0.816	-.0206118	.0162308
avgcumdosew3	1.180905	2.36415	0.50	0.617	-3.452744	5.814553
ageXd3	-.0203615	.0150978	-1.35	0.177	-.0499527	.0092297
marrw31Xd3	.399261	1.599068	0.25	0.803	-2.734855	3.533377
marrw32Xd3	-3.261172	5.78271	-0.56	0.573	-14.59508	8.072732
marrw33Xd3	-.061554	.4565407	-0.13	0.893	-.9563573	.8332492
marrw34Xd3	17.30052	1074.65	0.02	0.987	-2088.975	2123.576
marrw35Xd3	.0357107	.7782966	0.05	0.963	-1.489723	1.561144
bf4Xd3	-.1255356	.3211828	-0.39	0.696	-.7550423	.5039711
bf4mXd3	.0907915	.2884138	0.31	0.753	-.4744893	.6560722
shrelaw3Xd3	-.0097172	.0069227	-1.40	0.160	-.0232854	.0038511
_cons	-7.579904	3.069205	-2.47	0.014	-13.59544	-1.564373

Note: 4 failures and 0 successes completely determined.

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	55	15	70
-	39	254	293
Total	94	269	363

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	58.51%
Specificity	$\Pr(- \sim D)$	94.42%
Positive predictive value	$\Pr(D +)$	78.57%
Negative predictive value	$\Pr(\sim D -)$	86.69%
False + rate for true ~D	$\Pr(+ \sim D)$	5.58%
False - rate for true D	$\Pr(- D)$	41.49%
False + rate for classified +	$\Pr(\sim D +)$	21.43%
False - rate for classified -	$\Pr(D -)$	13.31%
Correctly classified		85.12%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations = **363**
number of covariate patterns = **362**
Pearson $\chi^2(340)$ = **452.30**
Prob > χ^2 = **0.0000**

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-135.138
D(340):	270.275	LR(21):	144.967
		Prob > LR:	0.000
McFadden's R2:	0.349	McFadden's Adj R2:	0.238
Maximum Likelihood R2:	0.329	Cragg & Uhler's R2:	0.483
McKelvey and Zavoina's R2:	0.779	Efron's R2:	0.416
Variance of y*:	14.905	Variance of error:	3.290
Count R2:	0.851	Adj Count R2:	0.426
AIC:	0.871	AIC*n:	316.275
BIC:	-1733.822	BIC':	-21.185

```

891 . scalar sxlifeModFw3="none"

892 .
893 .
894 .
895 .
896 . *----- testing female moderators
897 . 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    20:39:28    ****
> *
*****
> *
*****
> *

898 . * male models
899 .     forvalues j=3/3 {
        2. set more off
        3. des bf4 bf4m shfamw3 shrelaw3 avgcumdosew3
        4. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
        5. title "Wave 3 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
        6.     logit HP2sxlife age marrw31-marrw36 radhlw`j' bf4 bf4m    ///
>         shfamw`j' shrelaw`j' avgcumdosew`j' marrw31Xd3 marrw32Xd3 ///
>         marrw33Xd3 marrw34Xd3 marrw35Xd3 marrw36Xd3 radhlw`j'Xd3 ///
>         bf4Xd3 shfamw3Xd3 shrelaw3Xd3 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)
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009

```
title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
1 Jul 2012
20:39:28
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /h1pt2
Data file chwide1jul2012.dta currently has 2402 variables and 703 obser
> vations
```

```
*****
> *
*****
> *
*****
> *
*****
> *
*****Wave 3 dose HP2sexlife relationship but avgcumdosew3: Dose not signif****
> *
*****
> *
*****
> *
*****
> *
*****1 Jul 201220:39:28*****
> *
*****
> *
*****
```

note: marrw36 omitted because of collinearity
note: marrw36Xd3 omitted because of collinearity

Iteration 0: log likelihood = -207.62116
Iteration 1: log likelihood = -141.24621
Iteration 2: log likelihood = -135.45322
Iteration 3: log likelihood = -135.06483
Iteration 4: log likelihood = -134.9957
Iteration 5: log likelihood = -134.97466
Iteration 6: log likelihood = -134.9706
Iteration 7: log likelihood = -134.96946
Iteration 8: log likelihood = -134.96923
Iteration 9: log likelihood = -134.96917
Iteration 10: log likelihood = -134.96916
Iteration 11: log likelihood = -134.96915

Logistic regression

Number of obs = 363
LR chi2(21) = 145.30
Prob > chi2 = 0.0000
Pseudo R2 = 0.3499

Log likelihood = -134.96915

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0704827	.0174387	4.04	0.000	.0363034	.104662
marrw31	-1.526734	1.875648	-0.81	0.416	-5.202936	2.149468
marrw32	1.103621	4.081036	0.27	0.787	-6.895063	9.102305
marrw33	-.8740582	.7389686	-1.18	0.237	-2.32241	.5742937
marrw34	-36.63611	3874.821	-0.01	0.992	-7631.146	7557.874
marrw35	-1.152859	1.129412	-1.02	0.307	-3.366467	1.060749
marrw36	0	(omitted)				
radhlw3	.0014141	.0096951	0.15	0.884	-.0175881	.0204162
bf4	-.4636015	.1826527	-2.54	0.011	-.8215941	-.1056089
bf4m	.3302633	.1629809	2.03	0.043	.0108266	.6497
shfamw3	.0067642	.0105079	0.64	0.520	-.0138309	.0273592
shrelaw3	.0028404	.0117929	0.24	0.810	-.0202733	.0259542
avgcumdosew3	-.2391157	1.08948	-0.22	0.826	-2.374458	1.896226
marrw31Xd3	.5553424	1.593846	0.35	0.728	-2.568538	3.679223
marrw32Xd3	-1.935909	5.073174	-0.38	0.703	-11.87915	8.007329
marrw33Xd3	-.0368709	.6566922	-0.06	0.955	-1.323964	1.250222
marrw34Xd3	19.23126	2306.55	0.01	0.993	-4501.524	4539.987
marrw35Xd3	.3214642	.8715872	0.37	0.712	-1.386815	2.029744
marrw36Xd3	0	(omitted)				
radhlw3Xd3	.0091172	.0095954	0.95	0.342	-.0096893	.0279238
bf4Xd3	-.0273194	.0643627	-0.42	0.671	-.1534679	.0988292
shfamw3Xd3	.0037913	.0100871	0.38	0.707	-.015979	.0235616
shrelaw3Xd3	-.0141156	.0103071	-1.37	0.171	-.0343171	.0060859
_cons	-5.898959	2.139999	-2.76	0.006	-10.09328	-1.704637

Note: 6 failures and 0 successes completely determined.

Logistic model for HP2sxlif

Classified	True		Total
	D	~D	
+	56	17	73
-	38	252	290
Total	94	269	363

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

True D defined as HP2sxlif $\neq 0$

Sensitivity	$\Pr(+ D)$	59.57%
Specificity	$\Pr(- \sim D)$	93.68%
Positive predictive value	$\Pr(D +)$	76.71%
Negative predictive value	$\Pr(\sim D -)$	86.90%

False + rate for true ~D	$\Pr(+ \sim D)$	6.32%
False - rate for true D	$\Pr(- D)$	40.43%
False + rate for classified +	$\Pr(\sim D +)$	23.29%
False - rate for classified -	$\Pr(D -)$	13.10%

Correctly classified	84.85%
----------------------	---------------

Logistic model for HP2sxlif, goodness-of-fit test

number of observations =	363
number of covariate patterns =	362
Pearson $\chi^2(340)$ =	451.96
Prob > χ^2 =	0.0000

Measures of Fit for **logit** of HP2sxlif

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-134.969
D(339):	269.938	LR(21):	145.304
		Prob > LR:	0.000
McFadden's R ² :	0.350	McFadden's Adj R ² :	0.234
Maximum Likelihood R ² :	0.330	Cragg & Uhler's R ² :	0.484
McKelvey and Zavoina's R ² :	0.810	Efron's R ² :	0.421
Variance of y*:	17.337	Variance of error:	3.290
Count R ² :	0.848	Adj Count R ² :	0.415
AIC:	0.876	AIC*n:	317.938
BIC:	-1728.264	BIC':	-21.522


```

903 .
904 . * female models
905 .       forvalues j=3/3 {
      2. des bf4 bf4m shfamw3 shrelaw3 avgcumdosew3
      3. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
      4. title "Wave 3 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
      5.       logit HP2sxlife age  radhlw`j' bf4 bf4m   ///
>       shrelaw3 shfamw`j'  avgcumdosew`j'  ///
>       shrelaw3Xd3 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)
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009

```

title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
  1 Jul 2012
20:39:29
computer  Macintosh (Intel 64-bit)
folder   /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file  chwide1jul2012.dta  currently has  2402  variables and  703  obser
> vations

```

```

*****
> *
*****
> *
*****
> *
*****Wave 3 dose HP2sexlife relationship but avgcumdosew3: Dose not signif****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:39:29    ****
> *
*****
> *
*****
> *

```

```

Iteration 0:  log likelihood = -207.62116
Iteration 1:  log likelihood = -144.9565
Iteration 2:  log likelihood = -139.33502
Iteration 3:  log likelihood = -139.24024
Iteration 4:  log likelihood = -139.24007
Iteration 5:  log likelihood = -139.24007

```

```

Logistic regression              Number of obs   =       363
                                LR chi2(8)       =       136.76
                                Prob > chi2       =       0.0000
Log likelihood = -139.24007      Pseudo R2      =       0.3294

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0850443	.0159459	5.33	0.000	.0537908	.1162978
radhlw3	.0101855	.0048586	2.10	0.036	.0006629	.0197081
bf4	-.5127452	.1800997	-2.85	0.004	-.8657342	-.1597562
bf4m	.3584755	.1654365	2.17	0.030	.034226	.682725
shrelaw3	-.0011763	.0085087	-0.14	0.890	-.017853	.0155004
shfamw3	.0102584	.0053613	1.91	0.056	-.0002495	.0207662
avgcumdosew3	.4196812	.2507095	1.67	0.094	-.0717004	.9110629
shrelaw3Xd3	-.0090959	.0060346	-1.51	0.132	-.0209235	.0027318
_cons	-8.337805	1.647879	-5.06	0.000	-11.56759	-5.108021

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	53	21	74
-	41	248	289
Total	94	269	363

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	56.38%
Specificity	$\Pr(- \sim D)$	92.19%
Positive predictive value	$\Pr(D +)$	71.62%
Negative predictive value	$\Pr(\sim D -)$	85.81%
False + rate for true ~D	$\Pr(+ \sim D)$	7.81%
False - rate for true D	$\Pr(- D)$	43.62%
False + rate for classified +	$\Pr(\sim D +)$	28.38%
False - rate for classified -	$\Pr(D -)$	14.19%
Correctly classified		82.92%

Logistic model for HP2sxlife, goodness-of-fit test

number of observations = **363**
 number of covariate patterns = **362**
 Pearson chi2(**353**) = **444.64**
 Prob > chi2 = **0.0007**

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-139.240
D(354):	278.480	LR(8):	136.762
		Prob > LR:	0.000
McFadden's R2:	0.329	McFadden's Adj R2:	0.286
Maximum Likelihood R2:	0.314	Cragg & Uhler's R2:	0.461
McKelvey and Zavoina's R2:	0.509	Efron's R2:	0.394
Variance of y*:	6.704	Variance of error:	3.290
Count R2:	0.829	Adj Count R2:	0.340
AIC:	0.817	AIC*n:	296.480
BIC:	-1808.138	BIC':	-89.607

```

906 . * female models
907 .         forvalues j=3/3 {
          2. des bf4 bf4m shfamw3 shrelaw3 avgcumdosew3
          3. title3 "trimmed HP2sexlife main effects models wave 1 for H1 part 2 with
> dose ns"
          4. title "Wave 3 dose HP2sexlife relationship but avgcumdosew`j': Dose not s
> ignif"
          5.         logit HP2sxlife age  radhlw`j' bf4 bf4m    ///
>         shrelaw3 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)
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW
avgcumdosew3	double	%8.0g		Avg Mean dose of CS137 ending 12/31/2009

```

title3 : trimmed HP2sexlife main effects models wave 1 for H1 part 2 with dose
> ns
1 Jul 2012
20:39:31
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2402 variables and 703 obser
> vations

```

```

*****
> *
*****
> *
*****
> *
*****Wave 3 dose HP2sexlife relationship but avgcumdosew3: Dose not signif****
> *
*****
> *
*****
> *
*****
1 Jul 2012    20:39:31    ****
> *
*****
> *
*****
> *

```

```

Iteration 0:  log likelihood = -207.62116
Iteration 1:  log likelihood = -148.10457
Iteration 2:  log likelihood = -142.10924
Iteration 3:  log likelihood = -142.00423
Iteration 4:  log likelihood = -142.00406
Iteration 5:  log likelihood = -142.00406

```

```

Logistic regression              Number of obs   =       363
                                LR chi2(6)       =      131.23
                                Prob > chi2       =       0.0000
Log likelihood = -142.00406      Pseudo R2      =       0.3160

```

HP2sxlife	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0888985	.0158716	5.60	0.000	.0577907	.1200062
radhlw3	.0104339	.0048228	2.16	0.031	.0009812	.0198865
bf4	-.5221133	.1784046	-2.93	0.003	-.8717799	-.1724467
bf4m	.3612435	.1636356	2.21	0.027	.0405235	.6819635
shrelaw3	-.0123377	.0056981	-2.17	0.030	-.0235058	-.0011696
shfamw3	.0113877	.005213	2.18	0.029	.0011705	.0216049
_cons	-8.106812	1.61823	-5.01	0.000	-11.27848	-4.93514

Logistic model for HP2sxlife

Classified	True		Total
	D	~D	
+	58	21	79
-	36	248	284
Total	94	269	363

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

True D defined as HP2sxlife != 0

Sensitivity	$\Pr(+ D)$	61.70%
Specificity	$\Pr(- \sim D)$	92.19%
Positive predictive value	$\Pr(D +)$	73.42%
Negative predictive value	$\Pr(\sim D -)$	87.32%

False + rate for true ~D	$\Pr(+ \sim D)$	7.81%
False - rate for true D	$\Pr(- D)$	38.30%
False + rate for classified +	$\Pr(\sim D +)$	26.58%
False - rate for classified -	$\Pr(D -)$	12.68%

Correctly classified	84.30%
----------------------	---------------

Logistic model for HP2sxlife, goodness-of-fit test

```

      number of observations =      363
number of covariate patterns =      359
      Pearson chi2(352) =      469.29
              Prob > chi2 =      0.0000

```

Measures of Fit for **logit** of **HP2sxlife**

Log-Lik Intercept Only:	-207.621	Log-Lik Full Model:	-142.004
D(356):	284.008	LR(6):	131.234
		Prob > LR:	0.000
McFadden's R2:	0.316	McFadden's Adj R2:	0.282
Maximum Likelihood R2:	0.303	Cragg & Uhler's R2:	0.445
McKelvey and Zavoina's R2:	0.483	Efron's R2:	0.385
Variance of y*:	6.366	Variance of error:	3.290
Count R2:	0.843	Adj Count R2:	0.394
AIC:	0.821	AIC*n:	298.008
BIC:	-1814.399	BIC':	-95.868

```

908 .
909 . scalar MainEffsxlifeFw3 = "age radhlw3 bf4 bf4m shrelaw3 shfamw3"

910 . scalar SigDoseSxlifeFw3="no"

911 . * xx female main effects model: no sign dose main effect
912 . * xx 6 signif main effects
913 . * xx no moderator effects significant
914 .
915 . *----- mediator models for Dose => sexlife impact
916 .
917 . di as input "testing possible sex life mediator effects for males"
    testing possible sex life mediator effects for males

918 .
919 . * age is a mediating effect for males for Dose=> sex life for men
920 . 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)

```

921 . glm age avgcumdosew3 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6336**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.7142
Deviance = 49927.38549	(1/df) Deviance	=	147.7142
Pearson = 49927.38549	(1/df) Pearson	=	147.7142

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

	<u>AIC</u>	=	7.839021
Log likelihood = -1330.633586	<u>BIC</u>	=	47957.2

age	OIM			z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.					
avgcumdosew3	.5433648	.2472657		2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376		66.95	0.000	47.09975	49.94067

```
922 . 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.)

```
923 .
924 . * illness is a mediating effect for males = > sex life for men
925 . des illw3
```

variable name	storage type	display format	value label	variable label
illw3	double	%8.0g		Total number of illnesses experienced in time period 1996-NOW

```
926 . glm illw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -461.99206
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.8919217
Deviance = 301.469521	(1/df) Deviance	=	.8919217
Pearson = 301.469521	(1/df) Pearson	=	.8919217

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

	<u>AIC</u>	=	2.729365
Log likelihood = -461.9920626	<u>BIC</u>	=	-1668.714

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.038211	.0192139	1.99	0.047	.0005524	.0758696
_cons	.4504952	.0563162	8.00	0.000	.3401176	.5608729

```
927 . glm HP2sxlife illw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 314.6325
Iteration 2: deviance = 314.577
Iteration 3: deviance = 314.5769
Iteration 4: deviance = 314.5769
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 314.5769306	(1/df) Deviance	=	.930701
Pearson = 334.8347324	(1/df) Pearson	=	.9906353

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

	BIC	=	-1655.607
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.406576	.0768494	5.29	0.000	.2559539	.5571981
_cons	-1.080731	.0906035	-11.93	0.000	-1.258311	-.9031518

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

928 .
929 . des radhlw3

variable name	storage type	display format	value label	variable label
radhlw3	double	%8.0g		Self-perceived Chernobyl health threat in wave 3

930 . glm radhlw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1695.1855**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1261.052
Deviance = 426235.7205	(1/df) Deviance	=	1261.052
Pearson = 426235.7205	(1/df) Pearson	=	1261.052

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

	<u>AIC</u>	=	9.983444
Log likelihood = -1695.185473	<u>BIC</u>	=	424265.5

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.9606492	.7224692	1.33	0.184	-.4553645	2.376663
_cons	46.19995	2.117563	21.82	0.000	42.0496	50.3503

```
931 . glm HP2sxlife radhlw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 292.0816
Iteration 2:  deviance = 288.766
Iteration 3:  deviance = 288.7109
Iteration 4:  deviance = 288.7109
Iteration 5:  deviance = 288.7109
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  MQL Fisher scoring                 Residual df     =       338
                  (IRLS EIM)                           Scale parameter =         1
Deviance          = 288.7109182                        (1/df) Deviance =  .8541743
Pearson           = 337.697009                          (1/df) Pearson  =  .9991036
```

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

```
BIC = -1681.473
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0170927	.0022806	7.49	0.000	.0126228	.0215625
_cons	-1.790621	.1598163	-11.20	0.000	-2.103856	-1.477387

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

```
932 .
933 .
934 . des bf4
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
935 . glm bf4 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1027.1072
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	24.77487
Deviance	= 8373.906252	(1/df) Deviance	=	24.77487
Pearson	= 8373.906252	(1/df) Pearson	=	24.77487

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

	<u>AIC</u>	=	6.053572
Log likelihood = -1027.107224	<u>BIC</u>	=	6403.723

bf4	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew3	-.0357675	.1012648	-0.35	0.724	-.2342429	.1627078	
_cons	12.54064	.2968079	42.25	0.000	11.95891	13.12238	

```
936 . 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.)

937 .
938 . des bf4m

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

939 . glm bf4m avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1060.7697**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	30.20008
Deviance = 10207.62832	(1/df) Deviance	=	30.20008
Pearson = 10207.62832	(1/df) Pearson	=	30.20008

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

	<u>AIC</u>	=	6.251587
Log likelihood = -1060.769747	<u>BIC</u>	=	8237.445

bf4m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.0292413	.1118039	-0.26	0.794	-.2483729	.1898903
_cons	20.35328	.327698	62.11	0.000	19.711	20.99556

```
940 . 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.)

```
941 .
942 .
943 . * age is a mediating effect for females for Dose=> sex life for women
944 . glm age avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1408.064
```

```
Generalized linear models                               No. of obs      =       363
Optimization      : ML                                 Residual df     =       361
Deviance          = 49734.51399                        Scale parameter = 137.7687
Pearson           = 49734.51399                        (1/df) Deviance = 137.7687
                                                         (1/df) Pearson  = 137.7687
```

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

```
Log likelihood    = -1408.06405                        AIC             = 7.768948
                                                         BIC             = 47606.63
```

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

```
945 . 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.)
```

```
946 .
```

```

947 . * illness is a mediating effect for females = > sex life for men
948 . des illw3

```

variable name	storage type	display format	value label	variable label
illw3	double	%8.0g		Total number of illnesses experienced in time period 1996-NOW

```

949 . glm illw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-562.81042**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.308042
Deviance = 472.2033151	(1/df) Deviance	=	1.308042
Pearson = 472.2033151	(1/df) Pearson	=	1.308042
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	3.111903
Log likelihood = -562.8104237	<u>BIC</u>	=	-1655.676

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.1284565	.0342268	3.75	0.000	.0613733	.1955398
_cons	.5563644	.0727696	7.65	0.000	.4137387	.6989902

```

950 . glm HP2sxlife illw3 if gender==2, fam(bin) irls scale(dev) link(probit)

```

```

Iteration 1: deviance = 400.2066
Iteration 2: deviance = 399.9405
Iteration 3: deviance = 399.9404
Iteration 4: deviance = 399.9404

```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 399.9403905	(1/df) Deviance	=	1.107868
Pearson = 359.3006709	(1/df) Pearson	=	.9952927

Variance function: $V(u) = u*(1-u)$ [Bernoulli]
 Link function : $g(u) = \text{invnorm}(u)$ [Probit]
 BIC = -1727.939

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.2312781	.0622433	3.72	0.000	.1092835	.3532726
_cons	-.8313252	.0911599	-9.12	0.000	-1.009995	-.6526552

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

951 .
 952 . des radhlw3

variable name	storage type	display format	value label	variable label
radhlw3	double	%8.0g		Self-perceived Chernobyl health threat in wave 3

953 . glm radhlw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1798.7074

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1185.454
Deviance = 427948.9522	(1/df) Deviance	=	1185.454
Pearson = 427948.9522	(1/df) Pearson	=	1185.454

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

Log likelihood = -1798.707367
 AIC = 9.921253
 BIC = 425821.1

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	2.751602	1.03038	2.67	0.008	.7320943	4.77111
_cons	57.70689	2.190692	26.34	0.000	53.41321	62.00057

```
954 . glm HP2sxlife radhlw3 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 385.4256
Iteration 2:  deviance = 385.0487
Iteration 3:  deviance = 385.0486
Iteration 4:  deviance = 385.0486
```

```
Generalized linear models          No. of obs      =       363
Optimization      :  MQL Fisher scoring  Residual df    =       361
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 385.0485907         (1/df) Deviance = 1.066617
Pearson           = 374.8310541         (1/df) Pearson  = 1.038313
```

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

```
BIC                                     = -1742.831
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0117559	.0023184	5.07	0.000	.0072119	.0162999
_cons	-1.417393	.1757229	-8.07	0.000	-1.761803	-1.072982

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

```
955 .
956 . des bf4    // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSIsoma)

```
957 . * bf4 is a mediting effect for females for Dose=> sex life for women
958 . glm bf4 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1109.6569
```

```
Generalized linear models          No. of obs      =       363
Optimization      :  ML          Residual df    =       361
Scale parameter = 26.6146
Deviance          = 9607.869105     (1/df) Deviance = 26.6146
Pearson           = 9607.869105     (1/df) Pearson  = 26.6146
```

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

Log likelihood	= -1109.656873	<u>AIC</u>	= 6.124831
		<u>BIC</u>	= 7479.99

	OIM					
bf4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.4386292	.1543885	-2.84	0.004	-.7412252	-.1360333
_cons	11.01475	.3282456	33.56	0.000	10.3714	11.6581

```
959 . 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 : ML 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.)

```

960 .
961 . des bf4m // soma recentered

```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```

962 . * bf4m is a possible mediating effect for female sex life
963 . glm bf4m avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1141.3116**

Generalized linear models		No. of obs	=	363
Optimization	: ML	Residual df	=	361
Deviance	= 11438.54371	Scale parameter	=	31.68572
Pearson	= 11438.54371	(1/df) Deviance	=	31.68572
		(1/df) Pearson	=	31.68572
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
		<u>AIC</u>	=	6.299237
Log likelihood	= -1141.311602	<u>BIC</u>	=	9310.664

bf4m	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew3	-.441173	.1684561	-2.62	0.009		-.771341	-.1110051
_cons	18.82772	.3581548	52.57	0.000		18.12575	19.52969

```

964 . 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.)

965 .
 966 . des shfamw3

variable name	storage type	display format	value label	variable label
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW

967 . glm shfamw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)

Iteration 0: log likelihood = -1798.0166

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1180.951
Deviance = 426323.4314	(1/df) Deviance	=	1180.951
Pearson = 426323.4314	(1/df) Pearson	=	1180.951

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

Log likelihood = -1798.016645
 AIC = 9.917447
 BIC = 424195.6

shfamw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	3.038333	1.028421	2.95	0.003	1.022665	5.054002
_cons	48.29894	2.186528	22.09	0.000	44.01342	52.58445

```
968 . glm HP2sxlife shfamw3 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 412.3031
Iteration 2:  deviance = 411.7515
Iteration 3:  deviance = 411.7513
Iteration 4:  deviance = 411.7513
```

```
Generalized linear models                                No. of obs      =       363
Optimization      :  MQL Fisher scoring                  Residual df     =       361
                   (IRLS EIM)                           Scale parameter =         1
Deviance          = 411.7512965                         (1/df) Deviance =  1.140585
Pearson           = 363.5689973                         (1/df) Pearson  =  1.007116
```

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

```
BIC = -1716.128
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw3	.003818	.0022067	1.73	0.084	-.000507	.0081429
_cons	-.850427	.1417252	-6.00	0.000	-1.128203	-.5726507

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

```
969 .
970 . des shrelaw3
```

variable name	storage type	display format	value label	variable label
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW

```
971 . glm shrelaw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1781.6583
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1079.169
Deviance = 389580.0745	(1/df) Deviance	=	1079.169
Pearson = 389580.0745	(1/df) Pearson	=	1079.169

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

	<u>AIC</u>	=	9.827318
Log likelihood = -1781.658257	<u>BIC</u>	=	387452.2

shrelaw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.719866	.9831048	0.73	0.464	-1.206984	2.646716
_cons	27.62247	2.09018	13.22	0.000	23.52579	31.71915

```
972 . glm HP2sxlife shrelaw3 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 415.8457
Iteration 2: deviance = 415.1882
Iteration 3: deviance = 415.1879
Iteration 4: deviance = 415.1879
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 415.1879244	(1/df) Deviance	=	1.150105
Pearson = 363.0035925	(1/df) Pearson	=	1.00555

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

	BIC	=	-1712.691
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw3	.0005023	.0023156	0.22	0.828	-.0040363	.0050408
_cons	-.6609704	.101163	-6.53	0.000	-.8592462	-.4626947

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

```

973 .
974 .
975 .
976 . *xx summary of mediating effects: age and illness mediate sex life for men
977 . * age illness radhlw3 bf4 bf4m (soma) medi
    > ate sex life for women
978 .
979 . scalar sxlifeMedMw3 = "age illw3"

980 . scalar sxlifeMedFw3 = "age illw3 radhlw3 bf4 bf4m"

981 . title4 "5. summary matrix contstruction for dose -> sexlife impact"
-----
5. summary matrix contstruction for dose -> sexlife impact
-----

982 .
983 . matrix define HP2sxlifeMw3 = J(1,8, 0)

984 . matrix define HP2sxlifeFw3 = J(1,8, 0)

985 . matrix colnames HP2sxlifeMw3 = hypnum ptnum wave gender medsig numMA sig num
    > Modsig numMed

986 . matrix colnames HP2sxlifeFw3 = hypnum ptnum wave gender medsig numM
    > Asig numModsig numMed

987 . matrix define HP2sxlifeMw3 = (1, 2, 3, 1, 0, 4, 0, 2 )

```

```
988 .      matrix define HP2sxlifefw3 = (1, 2, 3, 2, 1, 6, 0, 5)
```

```
989 .      matrix rowname HP2sxlifefw3 = HP2sxlifefw3
```

```
990 .      matrix rowname HP2sxlifefw3 = HP2sxlifefw3
```

```
991 .      matlist HP2sxlifefw3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2sxlifefw3	1	2	3	1	0	
> 4						
	c7	c8				
HP2sxlifefw3	0	2				

```
992 .      matlist HP2sxlifefw3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2sxlifefw3	1	2	3	2	1	
> 6						
	c7	c8				
HP2sxlifefw3	0	5				

```
993 . matrix define H1pt2w3 = ( HP2wkMw3 \ HP2wkFw3 \ HP2hmcrMw3 \ HP2hmcrFw3 \ HP
> 2spMw3 \ HP2spFw3 \ HP2prbfamMw3 \ HP2prbfamFw3 \ HP2sxlifefw3 \ HP2sxlifefw
> 3 )
```

```
994 .
```

```
995 .      matlist H1pt2w3
```

		c1	c2	c3	c4	c5	c
> 6							
> —							
	r1	1	2	3	1	0	
> 4							
	r1	1	2	3	2	0	
> 1							
	r1	1	2	3	1	0	
> 4							
	r1	1	2	3	2	0	
> 2							
	HP2spMw3	1	2	3	1	0	
> 2							
	HP2spFw3	1	2	3	2	1	
> 5							
	HP2prbfamM	1	2	3	1	0	
> 5							
	HP2prbfamF	1	2	3	2	0	
> 2							
	HP2sxlifeMw3	1	2	3	1	0	
> 4							
	HP2sxlifeFw3	1	2	3	2	1	
> 6							
		c7	c8				
	r1	0	4				
	r1	0	6				
	r1	0	2				
	r1	0	2				
	HP2spMw3	0	1				
	HP2spFw3	5	3				
	HP2prbfamM	0	1				
	HP2prbfamF	2	2				
	HP2sxlifeMw3	0	2				
	HP2sxlifeFw3	0	5				

```

996 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed

```

```

997 .      matrix rownames H1pt2w3 =  HP2wkMw3 HP2wkFw3 HP2hmcrMw3 HP2hmcrFw3 HP2p
> rbfhmMw3 HP2prbfhmFw3

```

```

998 .      matlist H1pt2w3

```

	hypnum	ptnum	wave	gender	medsig	numMASi
> g						
> —						
HP2wkMw3	1	2	3	1	0	
> 4						
HP2wkFw3	1	2	3	2	0	
> 1						
HP2hmcrMw3	1	2	3	1	0	
> 4						
HP2hmcrFw3	1	2	3	2	0	
> 2						
HP2prbfhmMw3	1	2	3	1	0	
> 2						
HP2prbfhmFw3	1	2	3	2	1	
> 5						
HP2prbfhmFw3	1	2	3	1	0	
> 5						
HP2prbfhmFw3	1	2	3	2	0	
> 2						
HP2prbfhmFw3	1	2	3	1	0	
> 4						
HP2prbfhmFw3	1	2	3	2	1	
> 6						
	numModsig	numMed				
HP2wkMw3	0	4				
HP2wkFw3	0	6				
HP2hmcrMw3	0	2				
HP2hmcrFw3	0	2				
HP2prbfhmMw3	0	1				
HP2prbfhmFw3	5	3				
HP2prbfhmFw3	0	1				
HP2prbfhmFw3	2	2				
HP2prbfhmFw3	0	2				
HP2prbfhmFw3	0	5				

```

999 .
1000 .
1001 .
1002 .
1003 . *===== Chunk 8      Dose => interests and Hobbies relationship
1004 . title  "6. Moderators and Mediators of the Dose = > interests and hobbies Im
> pact"

```

```

*****
> *
*****
> *
*****                                     ****
> *
*****                                     ****
> *
*****6. Moderators and Mediators of the Dose = > interests and hobbies Impact*
> ****
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****                                     ****
> *
*****
> *
*****
> *

```

```

1005 .
1006 . title4 " Hyp. 1. pt 2 Wave 3 Main effects Dose=> Interests and Hobbies impac
> t identification"

```

```

Hyp. 1. pt 2 Wave 3 Main effects Dose=> Interests and Hobbies impact identifi
> cation

```

```

1007 .
1008 . * Chunk 8 ---male models
1009 . forvalues j=3/3 {
      2. set more off
      3.
1010 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1011 .   foreach var in HP2inthob {
      5.       forvalues k=1/2 {
      6.   local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
      > bf40
      7.
1012 . 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 radhlw3 if gender==`k', coef nolog  difficult iter
      > ate(50)
     15.
     16.
     17.
     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 == 3

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: occ5w3 != 0 predicts failure perfectly
 occ5w3 dropped and 15 obs not used

note: occ6w3 != 0 predicts failure perfectly
 occ6w3 dropped and 4 obs not used

note: bf15m != 0 predicts failure perfectly
 bf15m dropped and 18 obs not used

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

note: _Ieduc_6 omitted because of collinearity
 note: occ8w3 omitted because of collinearity
 note: marrw36 omitted because of collinearity
 note: bf17 omitted because of collinearity
 note: radhlw3 omitted because of collinearity
 convergence not achieved

Logistic regression	Number of obs	=	276
	LR chi2(42)	=	117.91
	Prob > chi2	=	0.0000
Log likelihood = -51.649162	Pseudo R2	=	0.5330

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0817005	.0490304	1.67	0.096	-.0143972	.1777983
_Ieduc_2	-1.531634	1.790651	-0.86	0.392	-5.041245	1.977977
_Ieduc_3	-1.560462	.8580327	-1.82	0.069	-3.242176	.1212508
_Ieduc_4	0	(omitted)				
_Ieduc_5	-.5489736	.8124194	-0.68	0.499	-2.141286	1.043339
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-16.51737	2.253408	-7.33	0.000	-20.93397	-12.10077
occ2w3	-19.33038	2.062721	-9.37	0.000	-23.37324	-15.28752
occ3w3	-17.4588	2.676679	-6.52	0.000	-22.70499	-12.2126
occ4w3	-16.4147	2.207406	-7.44	0.000	-20.74113	-12.08826
occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-16.18451	2.199404	-7.36	0.000	-20.49527	-11.87376
occ8w3	0	(omitted)				
marrw31	.8557338	1.989444	0.43	0.667	-3.043506	4.754973
marrw32	1.067638	2.133137	0.50	0.617	-3.113233	5.248509
marrw33	-.0597494	1.809944	-0.03	0.974	-3.607174	3.487675
marrw35	4.178796	2.178555	1.92	0.055	-.091092	8.448685
marrw36	0	(omitted)				
inc1w3	14.99624	2.039372	7.35	0.000	10.99915	18.99334
inc2w3	15.54638	1.847372	8.42	0.000	11.92559	19.16716
inc3w3	16.08957	1.659414	9.70	0.000	12.83718	19.34196
inc4w3	20.06926	.	.	.	.	.
radhlw3	.0608448	.0162567	3.74	0.000	.0289822	.0927074
havmil	.004278	.0106932	0.40	0.689	-.0166802	.0252362
avgcumdosew3	-.3594081	.1656258	-2.17	0.030	-.6840288	-.0347874
bf1	-1.832947	.1402107	-13.07	0.000	-2.107755	-1.558139
bf4	-.1459909	.3386475	-0.43	0.666	-.8097278	.5177459
bf2	-.0007134	.0002919	-2.44	0.015	-.0012855	-.0001412
bf4m	-.0648788	.3169386	-0.20	0.838	-.6860671	.5563094
bf5m	-.0059221	.0033107	-1.79	0.074	-.0124109	.0005667
bf7m	-.00068	.0010134	-0.67	0.502	-.0026661	.0013062
bf8	.0000248	.0000707	0.35	0.726	-.0001137	.0001633
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	1.839453	.1331884	13.81	0.000	1.578408	2.100497
bf22	.000278	.0003035	0.92	0.360	-.0003168	.0008728
bf29	0	(omitted)				
bf30	.0006467	.000603	1.07	0.284	-.0005352	.0018286
bf40	.2996033	.3950361	0.76	0.448	-.4746533	1.07386
deaw3	-.6086988	.5212369	-1.17	0.243	-1.630304	.4129068
dvcew3	-.2319255	1.621511	-0.14	0.886	-3.410029	2.946178
sepaw3	-1.758194	2.087814	-0.84	0.400	-5.850234	2.333846
accdw3	.9189185	1.049895	0.88	0.381	-1.138839	2.976676

movew3	-1.391188	1.335043	-1.04	0.297	-4.007824	1.225448
illw3	-.3817302	.3999312	-0.95	0.340	-1.165581	.4021205
shfamw3	.0654585	.0176224	3.71	0.000	.0309192	.0999978
shhlw3	-.0105181	.0103515	-1.02	0.310	-.0308067	.0097705
shjobw3	-.0144707	.0115767	-1.25	0.211	-.0371606	.0082192
shrelaw3	-.0392022	.0137786	-2.85	0.004	-.0662077	-.0121967
suprtw3	.0070974	.0130297	0.54	0.586	-.0184403	.0326352
suchrw3	-.00232	.0110986	-0.21	0.834	-.0240728	.0194327
havmilsq	-7.67e-06	.0000192	-0.40	0.690	-.0000453	.00003
radhlw3	0	(omitted)				
_cons	-80.28913	.	.	.	.	.

Note: 32 failures and 0 successes completely determined.

Warning: convergence not achieved

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	23	7	30
-	15	231	246
Total	38	238	276

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	60.53%
Specificity	$\Pr(- \sim D)$	97.06%
Positive predictive value	$\Pr(D +)$	76.67%
Negative predictive value	$\Pr(\sim D -)$	93.90%
False + rate for true ~D	$\Pr(+ \sim D)$	2.94%
False - rate for true D	$\Pr(- D)$	39.47%
False + rate for classified +	$\Pr(\sim D +)$	23.33%
False - rate for classified -	$\Pr(D -)$	6.10%
Correctly classified		92.03%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      276
number of covariate patterns =    276
    Pearson chi2(231) =    123.26
        Prob > chi2 =    1.0000

```

Log-Lik Intercept Only:	-110.602	Log-Lik Full Model:	-51.649
D(219):	103.298	LR(42):	117.906
		Prob > LR:	0.000
McFadden's R2:	0.533	McFadden's Adj R2:	0.018
Maximum Likelihood R2:	0.348	Cragg & Uhler's R2:	0.631
McKelvey and Zavoina's R2:	0.982	Efron's R2:	0.500
Variance of y*:	180.636	Variance of error:	3.290
Count R2:	0.920	Adj Count R2:	0.421
AIC:	0.787	AIC*n:	217.298
BIC:	-1127.569	BIC':	118.151
Full main model for HP2inthob for wave= 3			

```

*****
> *
*****
> *
*****
> *
*****
> *
***** Full Nottingham Part 2 subscale models for male and then females *****
> *
*****
> *
*****
> *
*****
1 Jul 2012 20:40:07 *****
> *
*****
> *

```

```
i.educ          _Ieduc_1-8          (naturally coded; _Ieduc_1 omitted)
note: occ4w3 != 0 predicts failure perfectly
      occ4w3 dropped and 8 obs not used

note: occ5w3 != 0 predicts failure perfectly
      occ5w3 dropped and 5 obs not used
```

note: occ8w3 != 0 predicts failure perfectly
occ8w3 dropped and 1 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 11 obs not used

note: _Ieduc_8 omitted because of collinearity
note: bf17 omitted because of collinearity
note: radhlw3 omitted because of collinearity

Logistic regression	Number of obs	=	337
	LR chi2(49)	=	118.21
	Prob > chi2	=	0.0000
Log likelihood = -107.57156	Pseudo R2	=	0.3546

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0683881	.0247447	2.76	0.006	.0198893	.1168869
_Ieduc_2	-13.79024	962.4068	-0.01	0.989	-1900.073	1872.492
_Ieduc_3	-12.92792	962.4068	-0.01	0.989	-1899.211	1873.355
_Ieduc_4	-12.05387	962.4069	-0.01	0.990	-1898.337	1874.229
_Ieduc_5	-12.19345	962.407	-0.01	0.990	-1898.476	1874.09
_Ieduc_6	-13.09489	962.4068	-0.01	0.989	-1899.378	1873.188
_Ieduc_7	-13.1998	962.4102	-0.01	0.989	-1899.489	1873.089
_Ieduc_8	0	(omitted)				
occ1w3	-1.2723	3.511631	-0.36	0.717	-8.154969	5.61037
occ2w3	-2.590551	3.713618	-0.70	0.485	-9.869108	4.688006
occ3w3	-.8635752	3.536644	-0.24	0.807	-7.79527	6.06812
occ4w3	0	(omitted)				
occ5w3	0	(omitted)				
occ6w3	-.2036246	3.739879	-0.05	0.957	-7.533652	7.126403
occ7w3	-.4066434	3.50728	-0.12	0.908	-7.280786	6.467499
occ8w3	0	(omitted)				
marrw31	-2.820802	1.835568	-1.54	0.124	-6.418449	.776846
marrw32	-2.10882	2.397053	-0.88	0.379	-6.806958	2.589318
marrw33	-2.047151	1.625637	-1.26	0.208	-5.233341	1.13904
marrw35	-2.933509	1.682447	-1.74	0.081	-6.231043	.3640262
marrw36	-2.100943	1.718745	-1.22	0.222	-5.469621	1.267736
inc1w3	1.771469	3.538577	0.50	0.617	-5.164014	8.706952
inc2w3	1.229926	3.52319	0.35	0.727	-5.675399	8.13525
inc3w3	1.602207	3.508288	0.46	0.648	-5.273911	8.478326
inc4w3	2.650063	3.832399	0.69	0.489	-4.861301	10.16143
radhlw3	.0254128	.010363	2.45	0.014	.0051018	.0457239
havmil	.0052121	.0043654	1.19	0.232	-.003344	.0137682
avgcumdosew3	.0592875	.0898505	0.66	0.509	-.1168163	.2353913
bf1	-.0386178	.0465636	-0.83	0.407	-.1298807	.0526452
bf4	-.3299735	.2318908	-1.42	0.155	-.7844712	.1245242
bf2	5.14e-06	.0001261	0.04	0.967	-.000242	.0002523

bf4m	.24058	.2177227	1.10	0.269	-.1861487	.6673088
bf5m	-.0019924	.0019912	-1.00	0.317	-.0058951	.0019104
bf7m	-.000918	.0006896	-1.33	0.183	-.0022697	.0004336
bf8	6.91e-06	.0000428	0.16	0.872	-.0000771	.0000909
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.0290415	.0410365	0.71	0.479	-.0513885	.1094715
bf22	.000145	.000139	1.04	0.297	-.0001275	.0004175
bf29	.0000291	.0000389	0.75	0.455	-.0000472	.0001054
bf30	.0005863	.0003477	1.69	0.092	-.0000953	.0012679
bf40	-.1903404	.1540477	-1.24	0.217	-.4922683	.1115876
deaw3	-.0727208	.201017	-0.36	0.718	-.4667069	.3212652
dvcew3	-.3675995	.8921998	-0.41	0.680	-2.116279	1.38108
sepaw3	1.146748	.9391994	1.22	0.222	-.6940491	2.987545
accdw3	-.0400125	.5697822	-0.07	0.944	-1.156765	1.07674
movew3	.1242816	1.400684	0.09	0.929	-2.621008	2.869572
illw3	.0326786	.1772251	0.18	0.854	-.3146761	.3800333
shfamw3	-.0089451	.0081686	-1.10	0.273	-.0249552	.0070651
shhlw3	-.0019331	.0067351	-0.29	0.774	-.0151336	.0112673
shjobw3	.0022608	.0074164	0.30	0.760	-.012275	.0167966
shrelaw3	.0045217	.0078937	0.57	0.567	-.0109497	.0199931
suprtw3	-.0034378	.0085075	-0.40	0.686	-.0201123	.0132366
suchrw3	-.0106093	.0056039	-1.89	0.058	-.0215928	.0003741
havmilsq	-4.33e-06	6.65e-06	-0.65	0.515	-.0000174	8.70e-06
radhlw3	0	(omitted)				
_cons	7.330327	962.4125	0.01	0.994	-1878.964	1893.624

Note: 1 failure and 0 successes completely determined.

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	33	12	45
-	33	259	292
Total	66	271	337

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	50.00%
Specificity	$\Pr(- \sim D)$	95.57%
Positive predictive value	$\Pr(D +)$	73.33%
Negative predictive value	$\Pr(\sim D -)$	88.70%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	4.43%
False - rate for true D	$\Pr(- D)$	50.00%
False + rate for classified +	$\Pr(\sim D +)$	26.67%
False - rate for classified -	$\Pr(D -)$	11.30%
Correctly classified		86.65%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      337
number of covariate patterns =    337
    Pearson chi2(287) =    317.53
        Prob > chi2 =      0.1040
  
```

Measures of Fit for **logistic** of HP2inthob

Log-Lik Intercept Only:	-166.677	Log-Lik Full Model:	-107.572
D(280):	215.143	LR(49):	118.210
		Prob > LR:	0.000
McFadden's R2:	0.355	McFadden's Adj R2:	0.013
Maximum Likelihood R2:	0.296	Cragg & Uhler's R2:	0.471
McKelvey and Zavoina's R2:	0.678	Efron's R2:	0.373
Variance of y*:	10.209	Variance of error:	3.290
Count R2:	0.866	Adj Count R2:	0.318
AIC:	0.977	AIC*n:	329.143
BIC:	-1414.480	BIC':	166.974

```

1013 .
1014 . label var radhlw3 "Self-perceived Chernobyl health threat in wave 3"

1015 .
1016 . title4 "6. trimmed Moderators of male Dose => Interests and Hobbies Impact"

```

```

6. trimmed Moderators of male Dose => Interests and Hobbies Impact

```

```

1017 .
1018 . di as input "Wave 3 Main effects Dose=> Interests and Hobbies impact identif
> ication"
Wave 3 Main effects Dose=> Interests and Hobbies impact identification

1019 . forvalues j=3/3 {
2. set more off
3.
1020 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
> bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
4.
1021 . foreach var in HP2inthob {
5. local w3bf 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(depvar)'"
10. di _skip(4)
11. title "Full Nottingham Part 2 subscale models " "males on wave=`j'"
12. des bf5m shfamw3 radhlw3 bf4m
13. xi: logistic `var' age radhlw3 avgcumdosew3 shfamw3 ///
> 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 is
> 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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed
inc1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW
inc4w3	double	%15.0g	LABJ	Income allows to comfortably afford luxury items NOW
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= 3

chunk 8 H1 test:Gender= male model Wave = 3 for HP2inthob

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0503393	.0177324	2.84	0.005	.0155844	.0850941
radhlw3	.036284	.0076652	4.73	0.000	.0212606	.0513075
avgcumdosew3	-.1055965	.1287622	-0.82	0.412	-.3579659	.1467728
shfamw3	.015864	.0063173	2.51	0.012	.0034822	.0282458
bf5m	-.002198	.001127	-1.95	0.051	-.0044068	.0000109
_cons	-7.784484	1.20097	-6.48	0.000	-10.13834	-5.430625

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	11	6	17
-	27	296	323
Total	38	302	340

Classified + if predicted $\Pr(D) \geq .5$
True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	28.95%
Specificity	$\Pr(- \sim D)$	98.01%
Positive predictive value	$\Pr(D +)$	64.71%
Negative predictive value	$\Pr(\sim D -)$	91.64%
False + rate for true ~D	$\Pr(+ \sim D)$	1.99%
False - rate for true D	$\Pr(- D)$	71.05%
False + rate for classified +	$\Pr(\sim D +)$	35.29%
False - rate for classified -	$\Pr(D -)$	8.36%
Correctly classified		90.29%

Logistic model for HP2inthob, goodness-of-fit test

```

number of observations =      340
number of covariate patterns =    336
Pearson chi2(330) =    249.07
Prob > chi2 =    0.9997

```

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

Log-Lik Intercept Only:	-119.064	Log-Lik Full Model:	-84.583
D(334):	169.167	LR(5):	68.962
		Prob > LR:	0.000
McFadden's R2:	0.290	McFadden's Adj R2:	0.239
Maximum Likelihood R2:	0.184	Cragg & Uhler's R2:	0.365
McKelvey and Zavoina's R2:	0.495	Efron's R2:	0.236
Variance of y*:	6.512	Variance of error:	3.290
Count R2:	0.903	Adj Count R2:	0.132
AIC:	0.533	AIC*n:	181.167
BIC:	-1777.701	BIC':	-39.817

Note: bf4m is necessary for bf5 but if bf4m is in model bf5 is not signif.
Therefore, bf5 is not deemed significant.

```

1022 .
1023 . cap gen bf5mXd3 = bf5m*avgcumdosew3

1024 .
1025 .
1026 .
1027 . title3 "Wave 3 Main effects Dose=> Interests and Hobbies impact identificati
> on"

-----
title3 : Wave 3 Main effects Dose=> Interests and Hobbies impact identificatio
> n
    1 Jul 2012
20:40:10
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

1028 . forvalues j=3/3 {
      2. set more off
      3.
1029 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
>    bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.

```

```

1030 . foreach var in HP2inthob {
      5. local w3bf 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(dep
> ar)' "
      9. di _skip(4)
     10. title "Full Nottingham Part 2 subscale models for males in wave=`j'"
     11.
1031 .      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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed
inc1w3	double	%15.0g	LABJ	Income is not sufficient for basic neccessities NOW
inc2w3	double	%15.0g	LABJ	Income is just sufficient for basic neccessities NOW
inc3w3	double	%15.0g	LABJ	Income is sufficient for basics plus extra purchases/savings NOW

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0427782	.0194796	2.20	0.028	.004599	.0809575
radhlw3	.0323992	.0086278	3.76	0.000	.015489	.0493095
avgcumdosew3	-.0334024	.265555	-0.13	0.900	-.5538806	.4870758
shfamw3	.0129086	.006987	1.85	0.065	-.0007857	.0266028
bf4m	-.0374129	.040869	-0.92	0.360	-.1175146	.0426889
bf5m	-.0015707	.0014827	-1.06	0.289	-.0044767	.0013353
bf5mXd3	-.0002159	.0008473	-0.25	0.799	-.0018766	.0014448
_cons	-6.355059	1.990746	-3.19	0.001	-10.25685	-2.453267

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	11	8	19
-	27	294	321
Total	38	302	340

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	28.95%
Specificity	$\Pr(- \sim D)$	97.35%
Positive predictive value	$\Pr(D +)$	57.89%
Negative predictive value	$\Pr(\sim D -)$	91.59%

False + rate for true ~D	$\Pr(+ \sim D)$	2.65%
False - rate for true D	$\Pr(- D)$	71.05%
False + rate for classified +	$\Pr(\sim D +)$	42.11%
False - rate for classified -	$\Pr(D -)$	8.41%

Correctly classified	89.71%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

number of observations =	340
number of covariate patterns =	338
Pearson $\chi^2(330)$ =	244.95
Prob > χ^2 =	0.9999

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

```
1032 . scalar SigDoseInthbMw3 = "no"
1033 . scalar MainEffInthbMw3 = "age radhlw3 shfamw3"
1034 . scalar InthbMw3 = "none"
1035 .
1036 . *-----chunk 8   female moderator models
1037 . title "trimmed Moderators of female Dose => Interests and Hobbies Impact"
```

1 Jul 2012 20:40:11 ***

```

1038 .
1039 .
1040 . forvalues j=3/3 {
      2. set more off
      3.
1041 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1042 . foreach var in HP2inthob {
      5. local w3bf 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.
1043 . 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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed

Logistic regression

Number of obs = 363

LR chi2(4) = 85.17

Prob > chi2 = 0.0000

Log likelihood = -129.52718

Pseudo R2 = 0.2474

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0747817	.0159584	4.69	0.000	.0435038	.1060596
radhlw3	.0177314	.0055334	3.20	0.001	.0068862	.0285766
avgcumdosew3	.0423064	.0679809	0.62	0.534	-.0909337	.1755466
bf4	-.092667	.0312315	-2.97	0.003	-.1538797	-.0314543
_cons	-6.042759	1.092151	-5.53	0.000	-8.183336	-3.902181

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	27	10	37
-	39	287	326
Total	66	297	363

Classified + if predicted Pr(D) >= .5

True D defined as HP2inthob != 0

Sensitivity	Pr(+ D)	40.91%
Specificity	Pr(- ~D)	96.63%
Positive predictive value	Pr(D +)	72.97%
Negative predictive value	Pr(~D -)	88.04%

False + rate for true ~D	Pr(+ ~D)	3.37%
False - rate for true D	Pr(- D)	59.09%
False + rate for classified +	Pr(~D +)	27.03%
False - rate for classified -	Pr(D -)	11.96%

Correctly classified	86.50%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

number of observations = 363
number of covariate patterns = 361
Pearson chi2(356) = 495.06
Prob > chi2 = 0.0000

Log-Lik Intercept Only:	-172.113	Log-Lik Full Model:	-129.527
D(358):	259.054	LR(4):	85.171
		Prob > LR:	0.000
McFadden's R2:	0.247	McFadden's Adj R2:	0.218
Maximum Likelihood R2:	0.209	Cragg & Uhler's R2:	0.341
McKelvey and Zavoina's R2:	0.412	Efron's R2:	0.299
Variance of y*:	5.592	Variance of error:	3.290
Count R2:	0.865	Adj Count R2:	0.258
AIC:	0.741	AIC*n:	269.054
BIC:	-1851.142	BIC':	-61.593

```
1044 . scalar SigdoseInthbFw3 = "no"
1045 . scalar MainEffInthbFw3 = "age radhlw3 bf4"
1046 .
1047 . *-----chunk 8 testing female moderators
1048 . title "trimmed Moderators of female Dose => Interests and Hobbies Impact"
```

```
*****  
> *  
*****  
> *  
*****  
*****  
> *  
***** trimmed Moderators of female Dose => Interests and Hobbies Impact ***  
> *  
*****  
> *  
*****  
> *  
*****  
  
*****  
*****  
  
*****  
*****
```

```

1049 .
1050 .
1051 . forvalues j=3/3 {
      2. set more off
      3.
1052 . des age educ1-educ7 marrw`j'1-marrw`j'6 inclw`j'-inc4w`j' ///
      > bf1 bf4 bf9 bf11 bf4m bf15m bf30 bf40
      4.
1053 . foreach var in HP2inthob {
      5. local w3bf 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.
1054 . xi: logistic `var' age ///
      > radhlw`j' avgcumdosew`j' ///
      > bf4 bf4Xd3 ageXd3 radhlw3Xd3 ///
      > 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
marrw31	byte	%8.0g		marrw3==1. single
marrw32	byte	%8.0g		marrw3==2. cohabitating
marrw33	byte	%8.0g		marrw3==3. married
marrw34	byte	%8.0g		marrw3==4. separated
marrw35	byte	%8.0g		marrw3==5. divorced
marrw36	byte	%8.0g		marrw3==6. widowed

Logistic regression

Number of obs = 363

LR chi2(7) = 85.42

Prob > chi2 = 0.0000

Log likelihood = -129.40062

Pseudo R2 = 0.2482

HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.07069	.0194156	3.64	0.000	.032636	.1087439
radhlw3	.0190385	.0070172	2.71	0.007	.0052851	.0327919
avgcumdosew3	-.0765606	.6162688	-0.12	0.901	-1.284425	1.131304
bf4	-.0964948	.0400004	-2.41	0.016	-.1748942	-.0180954
bf4Xd3	.0029229	.020246	0.14	0.885	-.0367585	.0426043
ageXd3	.0035645	.0097808	0.36	0.716	-.0156055	.0227346
radhlw3Xd3	-.0011667	.003632	-0.32	0.748	-.0082854	.0059519
_cons	-5.898722	1.310131	-4.50	0.000	-8.466531	-3.330913

Logistic model for HP2inthob

Classified	True		Total
	D	~D	
+	28	10	38
-	38	287	325
Total	66	297	363

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

True D defined as HP2inthob != 0

Sensitivity	$\Pr(+ D)$	42.42%
Specificity	$\Pr(- \sim D)$	96.63%
Positive predictive value	$\Pr(D +)$	73.68%
Negative predictive value	$\Pr(\sim D -)$	88.31%

False + rate for true ~D	$\Pr(+ \sim D)$	3.37%
False - rate for true D	$\Pr(- D)$	57.58%
False + rate for classified +	$\Pr(\sim D +)$	26.32%
False - rate for classified -	$\Pr(D -)$	11.69%

Correctly classified	86.78%
----------------------	--------

Logistic model for HP2inthob, goodness-of-fit test

```

        number of observations =      363
    number of covariate patterns =      361
        Pearson chi2(353) =      496.78
            Prob > chi2 =      0.0000

```

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

Log-Lik Intercept Only:	-172.113	Log-Lik Full Model:	-129.401
D(355):	258.801	LR(7):	85.424
		Prob > LR:	0.000
McFadden's R2:	0.248	McFadden's Adj R2:	0.202
Maximum Likelihood R2:	0.210	Cragg & Uhler's R2:	0.342
McKelvey and Zavoina's R2:	0.413	Efron's R2:	0.301
Variance of y*:	5.602	Variance of error:	3.290
Count R2:	0.868	Adj Count R2:	0.273
AIC:	0.757	AIC*n:	274.801
BIC:	-1833.712	BIC':	-44.163

```
1055 . scalar InthbModFw3 = "none"
```

```
1056 .
```

```
1057 . title4 "Chunk 8  interests and hobbies testing mediator effects "
```

```
Chunk 8  interests and hobbies testing mediator effects
```

```
1058 .
```

```
1059 . * age is a mediating effect for males for Dose=> sex life for men
```

```
1060 .
```

```
1061 . glm age avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1330.6336
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	147.7142
Deviance	= 49927.38549	(1/df) Deviance	=	147.7142
Pearson	= 49927.38549	(1/df) Pearson	=	147.7142
Variance function:	V(u) = 1			[Gaussian]
Link function	: g(u) = u			[Identity]
		<u>AIC</u>	=	7.839021
Log likelihood	= -1330.633586	<u>BIC</u>	=	47957.2

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.5433648	.2472657	2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376	66.95	0.000	47.09975	49.94067

```
1062 . 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.)

```
1063 .
```

```

1064 . * illness is a mediating effect for males = > sex life for men
1065 . des illw3

```

variable name	storage type	display format	value label	variable label
illw3	double	%8.0g		Total number of illnesses experienced in time period 1996-NOW

```

1066 . glm illw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-461.99206**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.8919217
Deviance = 301.469521	(1/df) Deviance	=	.8919217
Pearson = 301.469521	(1/df) Pearson	=	.8919217

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

	<u>AIC</u>	=	2.729365
Log likelihood = -461.9920626	<u>BIC</u>	=	-1668.714

illw3	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew3	.038211	.0192139	1.99	0.047	.0005524	.0758696
_cons	.4504952	.0563162	8.00	0.000	.3401176	.5608729

```

1067 . glm HP2inthob illw3 if gender==1, fam(bin) irls scale(dev) link(probit)

```

Iteration 1: deviance = **234.8681**
 Iteration 2: deviance = **233.1574**
 Iteration 3: deviance = **233.1444**
 Iteration 4: deviance = **233.1444**
 Iteration 5: deviance = **233.1444**

Generalized linear models	No. of obs	=	340
Optimization : ML Fisher scoring	Residual df	=	338
(IRLS EIM)	Scale parameter	=	1
Deviance = 233.144425	(1/df) Deviance	=	.6897764
Pearson = 334.1788359	(1/df) Pearson	=	.9886948

[Bernoulli]
[Probit]

	EIM					
HP2inthob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.1917072	.0680987	2.82	0.005	.0582362	.3251781
_cons	-1.333765	.087554	-15.23	0.000	-1.505368	-1.162163

```
1068 .
1069 . des radhlw3
```

```
1070 . glm radhlw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1261.052
Deviance = 426235.7205	(1/df) Deviance	=	1261.052
Pearson = 426235.7205	(1/df) Pearson	=	1261.052

Log likelihood	= -1695.185473	<u>AIC</u>	= 9.983444
		<u>BIC</u>	= 424265.5

	OIM					
radhlw3	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.9606492	.7224692	1.33	0.184	-.4553645	2.376663
_cons	46.19995	2.117563	21.82	0.000	42.0496	50.3503

```
1071 . glm HP2inthob radhlw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 203.3027
Iteration 2:  deviance = 188.4084
Iteration 3:  deviance = 186.1904
Iteration 4:  deviance = 186.0891
Iteration 5:  deviance = 186.0888
Iteration 6:  deviance = 186.0888
```

```
Generalized linear models                                No. of obs      =       340
Optimization      :  MQL Fisher scoring                 Residual df     =       338
                  (IRLS EIM)                           Scale parameter =         1
Deviance          =  186.088809                        (1/df) Deviance =  .5505586
Pearson           =  318.4835319                       (1/df) Pearson  =  .942259
```

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

```
BIC = -1784.095
```

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0212428	.0025645	8.28	0.000	.0162164	.0262691
_cons	-2.562769	.2038548	-12.57	0.000	-2.962317	-2.163221

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

```
1072 .
1073 .
1074 . des shfamw3
```

variable name	storage type	display format	value label	variable label
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW

```
1075 . glm shfamw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1708.9012
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1367.012
Deviance = 462050.0805	(1/df) Deviance	=	1367.012
Pearson = 462050.0805	(1/df) Pearson	=	1367.012

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

	AIC	=	10.06412
Log likelihood = -1708.901202	BIC	=	460079.9

shfamw3	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew3	-.1212312	.7522098	-0.16	0.872	-1.595535	1.353073	
_cons	54.35361	2.204733	24.65	0.000	50.03242	58.67481	

```
1076 . glm HP2inthob shfamw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 226.2154
Iteration 2: deviance = 220.7262
Iteration 3: deviance = 220.4926
Iteration 4: deviance = 220.4922
Iteration 5: deviance = 220.4922
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 220.492229	(1/df) Deviance	=	.6523439
Pearson = 359.3118386	(1/df) Pearson	=	1.063053

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

BIC	=	-1749.691
-----	---	-----------

HP2inthob	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw3	.0109039	.0022452	4.86	0.000	.0065034	.0153045
_cons	-1.9049	.171268	-11.12	0.000	-2.240579	-1.56922

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

1077 .
1078 . des bf5m

variable name	storage type	display format	value label	variable label
bf5m	float	%9.0g		bf5m = max(0, ecprw3 - 75) * bf4m

1079 . glm bf5m avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-2273.014**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	37748.2
Deviance = 12758891.39	(1/df) Deviance	=	37748.2
Pearson = 12758891.39	(1/df) Pearson	=	37748.2

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

	<u>AIC</u>	=	13.38244
Log likelihood = -2273.013968	<u>BIC</u>	=	1.28e+07

bf5m	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	9.087842	3.952764	2.30	0.021	1.340566	16.83512
_cons	102.4403	11.58558	8.84	0.000	79.73302	125.1477

```
1080 . 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      :  MQL 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.)

```
1081 .
```

```
1082 . glm bf4 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0:  log likelihood = -1027.1072
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  ML            Residual df    =       338
Scale parameter = 24.77487
Deviance          = 8373.906252     (1/df) Deviance = 24.77487
Pearson           = 8373.906252     (1/df) Pearson  = 24.77487
```

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

```
Log likelihood      = -1027.107224    AIC              = 6.053572
                                         BIC              = 6403.723
```

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.0357675	.1012648	-0.35	0.724	-.2342429	.1627078
_cons	12.54064	.2968079	42.25	0.000	11.95891	13.12238

```
1083 . 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.)

```

1084 .
1085 .
1086 . * age is a mediating effect for females for Dose=> sex life for women
1087 . glm age avgcumdosew3 if gender==2, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1408.064**

Generalized linear models		No. of obs	=	363
Optimization : ML		Residual df	=	361
		Scale parameter	=	137.7687
Deviance	=	49734.51399	(1/df) Deviance	= 137.7687
Pearson	=	49734.51399	(1/df) Pearson	= 137.7687
Variance function: V(u) = 1				[Gaussian]
Link function : g(u) = u				[Identity]
		<u>AIC</u>	=	7.768948
Log likelihood = -1408.06405		<u>BIC</u>	=	47606.63

age	OIM		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

```

1088 . 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.)

```
1089 .
1090 . des bf4    // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4	float	%9.0g		bf4 = max(0, 24 - BSI_{soma})

```
1091 . * bf4 is a meditating effect for females for Dose=> sex life for women
1092 . glm bf4 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1109.6569**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	26.6146
Deviance = 9607.869105	(1/df) Deviance	=	26.6146
Pearson = 9607.869105	(1/df) Pearson	=	26.6146

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

	<u>AIC</u>	=	6.124831
Log likelihood = -1109.656873	<u>BIC</u>	=	7479.99

bf4	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.4386292	.1543885	-2.84	0.004	-.7412252	-.1360333
_cons	11.01475	.3282456	33.56	0.000	10.3714	11.6581

```
1093 . 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		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
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.)

```
1094 .
1095 . des bf4m // soma recentered
```

variable name	storage type	display format	value label	variable label
bf4m	float	%9.0g		bf4m = max(0, 32 - BSIsoma)

```
1096 . * bf4m is a possible mediating effect for female sex life
```

```
1097 . glm bf4m avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1141.3116
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	31.68572
Deviance = 11438.54371	(1/df) Deviance	=	31.68572
Pearson = 11438.54371	(1/df) Pearson	=	31.68572

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

	<u>AIC</u>	=	6.299237
Log likelihood = -1141.311602	<u>BIC</u>	=	9310.664

bf4m	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew3	-.441173	.1684561	-2.62	0.009		-.771341	-.1110051
_cons	18.82772	.3581548	52.57	0.000		18.12575	19.52969

```
1098 . 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.)

1099 .
1100 . des shfamw3

variable name	storage type	display format	value label	variable label
shfamw3	double	%8.0g		Percentage of strains and hassles related to family NOW

1101 . glm shfamw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)

Iteration 0: log likelihood = **-1708.9012**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1367.012
Deviance = 462050.0805	(1/df) Deviance	=	1367.012
Pearson = 462050.0805	(1/df) Pearson	=	1367.012

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

	<u>AIC</u>	=	10.06412
Log likelihood = -1708.901202	<u>BIC</u>	=	460079.9

shfamw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.1212312	.7522098	-0.16	0.872	-1.595535	1.353073
_cons	54.35361	2.204733	24.65	0.000	50.03242	58.67481

```
1102 . glm HP2sxlife shfamw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance = 329.7746
Iteration 2:  deviance = 329.2454
Iteration 3:  deviance = 329.2451
Iteration 4:  deviance = 329.2451
```

```
Generalized linear models          No. of obs      =       340
Optimization      :  MQL Fisher scoring  Residual df    =       338
                    (IRLS EIM)          Scale parameter =         1
Deviance          = 329.2450963         (1/df) Deviance =  .9740979
Pearson           = 344.0536463         (1/df) Pearson  =  1.01791
```

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

```
BIC                                     = -1640.939
```

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shfamw3	.0079286	.0021676	3.66	0.000	.0036802	.012177
_cons	-1.296137	.1536069	-8.44	0.000	-1.597201	-.9950731

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

```
1103 .
1104 . des shrelaw3
```

variable name	storage type	display format	value label	variable label
shrelaw3	double	%8.0g		Percentage of strains and hassles related to relationships NOW

```
1105 . glm shrelaw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1712.5647
```

Generalized linear models		No. of obs	=	340
Optimization	: ML	Residual df	=	338
		Scale parameter	=	1396.791
Deviance	= 472115.4213	(1/df) Deviance	=	1396.791
Pearson	= 472115.4213	(1/df) Pearson	=	1396.791

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

	<u>AIC</u>	=	10.08567
Log likelihood = -1712.564737	<u>BIC</u>	=	470145.2

shrelaw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	-.043239	.7603587	-0.06	0.955	-1.533515	1.447037
_cons	34.40857	2.228617	15.44	0.000	30.04056	38.77658

```
1106 . glm HP2sxlife shrelaw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 334.5762
Iteration 2: deviance = 334.3197
Iteration 3: deviance = 334.3197
Iteration 4: deviance = 334.3197
```

Generalized linear models		No. of obs	=	340
Optimization	: MQL Fisher scoring	Residual df	=	338
	(IRLS EIM)	Scale parameter	=	1
Deviance	= 334.3196545	(1/df) Deviance	=	.9891114
Pearson	= 339.7061699	(1/df) Pearson	=	1.005048

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

	BIC	=	-1635.864
--	-----	---	-----------

HP2sxlife	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
shrelaw3	.0060138	.002025	2.97	0.003	.0020449	.0099827
_cons	-1.058186	.1113913	-9.50	0.000	-1.276509	-.8398629

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

```

1107 .
1108 .
1109 . *xx summary of mediating effects: males only age and illw3 2
1110 . *xx          females: age
1111 .
1112 .
1113 .
1114 . * summary of sxlife moderator effects  none
1115 . scalar sxLifeMedMw3 = "age illw3"

1116 . scalar sxLifeMedFw3 = "age bf4 bf4m"

1117 .
1118 . * no sign main dose effect for males
1119 . * no male moderators
1120 . * 3 signif main effects in male main effect model
1121 .
1122 .
1123 . * no signif dose main effect for females
1124 . * 3 main female effects
1125 . * no significant female moderators
1126 . matrix define HP2inthbMw3 = J(1,8, 0)

1127 .          matrix define HP2inthbFw3 = J(1,8, 0)

1128 . matrix colnames HP2inthbMw3 =  hypnum ptnum wave gender medsig numMA sig numM
> odsig numMed

```

```
1129 . matrix colnames HP2inthbFw3 = hypnum ptnum wave gender medsig numMA sig numM
      > odsig numMed
```

```
1130 .      matrix define HP2inthbMw3 = (1, 2, 3, 1, 0, 3, 0, 2 )
```

```
1131 .      matrix define HP2inthbFw3 = (1, 2, 3, 2, 0, 3, 0, 3 )
```

```
1132 .      matrix rowname HP2inthbMw3 = HP2inthbM
```

```
1133 .      matrix rowname HP2inthbFw3 = HP2inthobF
```

```
1134 .      matlist HP2inthbMw3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2inthbM	1	2	3	1	0	
> 3						
	c7	c8				
HP2inthbM	0	2				

```
1135 .      matlist HP2inthbFw3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2inthobF	1	2	3	2	0	
> 3						
	c7	c8				
HP2inthobF	0	3				

```

1136 .      matrix define H1pt2w3 = ( HP2wkMw3 \ HP2wkFw3 \ HP2hmcrMw3 \ HP2hmcr
> Fw3 \ HP2spMw3 ///
>      \ HP2spFw3 \ HP2prbfamMw3 \ HP2prbfamFw3 \ HP2inthbMw3 \ HP2inth
> bFw3 )

```

```

1137 .      matlist H1pt2w3

```

	c1	c2	c3	c4	c5	c
> 6						
> —						
r1	1	2	3	1	0	
> 4						
r1	1	2	3	2	0	
> 1						
r1	1	2	3	1	0	
> 4						
r1	1	2	3	2	0	
> 2						
HP2spMw3	1	2	3	1	0	
> 2						
HP2spFw3	1	2	3	2	1	
> 5						
HP2prbfamM	1	2	3	1	0	
> 5						
HP2prbfamF	1	2	3	2	0	
> 2						
HP2inthbM	1	2	3	1	0	
> 3						
HP2inthobF	1	2	3	2	0	
> 3						
	c7	c8				
r1	0	4				
r1	0	6				
r1	0	2				
r1	0	2				
HP2spMw3	0	1				
HP2spFw3	5	3				
HP2prbfamM	0	1				
HP2prbfamF	2	2				
HP2inthbM	0	2				
HP2inthobF	0	3				

```
1138 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
1139 .      matrix rownames H1pt2w3 =  HP2wkMw3 HP2wkFw3 HP2hmcrMw3 HP2hmcrFw3 HP2s
> pMw3 HP2spFw3 HP2prbfamMw3 HP2prbfamFw3 HP2inthbMw3 HP2inthbFw3
```

```
1140 .      matlist H1pt2w3
```

	hypnum	ptnum	wave	gender	medsig	numMASi
> g						
> —						
HP2wkMw3	1	2	3	1	0	
> 4						
HP2wkFw3	1	2	3	2	0	
> 1						
HP2hmcrMw3	1	2	3	1	0	
> 4						
HP2hmcrFw3	1	2	3	2	0	
> 2						
HP2spMw3	1	2	3	1	0	
> 2						
HP2spFw3	1	2	3	2	1	
> 5						
HP2prbfamMw3	1	2	3	1	0	
> 5						
HP2prbfamFw3	1	2	3	2	0	
> 2						
HP2inthbMw3	1	2	3	1	0	
> 3						
HP2inthbFw3	1	2	3	2	0	
> 3						
	numModsig	numMed				
HP2wkMw3	0	4				
HP2wkFw3	0	6				
HP2hmcrMw3	0	2				
HP2hmcrFw3	0	2				
HP2spMw3	0	1				
HP2spFw3	5	3				
HP2prbfamMw3	0	1				
HP2prbfamFw3	2	2				
HP2inthbMw3	0	2				
HP2inthbFw3	0	3				

Male model wave 3 dose-hp2vactn moderator model

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

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: occ5w3 != 0 predicts failure perfectly
occ5w3 dropped and 18 obs not used

note: occ6w3 != 0 predicts failure perfectly
occ6w3 dropped and 4 obs not used

note: bf15m != 0 predicts failure perfectly
bf15m dropped and 19 obs not used

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

note: _Ieduc_6 omitted because of collinearity
note: occ8w3 omitted because of collinearity
note: marrw36 omitted because of collinearity
note: bf17 omitted because of collinearity
note: radhlw3 omitted because of collinearity
note: avgcumdosew3 omitted because of collinearity

Logistic regression	Number of obs	=	286
	LR chi2(45)	=	130.35
	Prob > chi2	=	0.0000
Log likelihood = -52.374274	Pseudo R2	=	0.5544

hp2vactn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1141267	.0450696	2.53	0.011	.025792	.2024615
_Ieduc_2	1.212945	1.630503	0.74	0.457	-1.982782	4.408672
_Ieduc_3	-1.181748	.8345653	-1.42	0.157	-2.817465	.4539703
_Ieduc_4	-.2703336	1.707405	-0.16	0.874	-3.616786	3.076119
_Ieduc_5	.0781642	.821705	0.10	0.924	-1.532348	1.688676
_Ieduc_6	0	(omitted)				
_Ieduc_7	0	(omitted)				
_Ieduc_8	0	(omitted)				
occ1w3	-13.38278	1622.421	-0.01	0.993	-3193.27	3166.504
occ2w3	-12.82938	1622.421	-0.01	0.994	-3192.717	3167.058
occ3w3	-12.16922	1622.422	-0.01	0.994	-3192.057	3167.719
occ4w3	-9.847245	1622.421	-0.01	0.995	-3189.735	3170.04

occ5w3	0	(omitted)				
occ6w3	0	(omitted)				
occ7w3	-10.21639	1622.421	-0.01	0.995	-3190.104	3169.671
occ8w3	0	(omitted)				
marrw31	2.471663	1.877772	1.32	0.188	-1.208702	6.152028
marrw32	3.882172	2.040109	1.90	0.057	-.116367	7.880711
marrw33	.7861586	1.848468	0.43	0.671	-2.836772	4.409089
marrw35	5.481699	2.097529	2.61	0.009	1.370617	9.592781
marrw36	0	(omitted)				
inclw3	12.51469	1622.421	0.01	0.994	-3167.373	3192.402
inc2w3	14.55722	1622.421	0.01	0.993	-3165.329	3194.444
inc3w3	14.35316	1622.421	0.01	0.993	-3165.533	3194.24
inc4w3	15.92527	1622.422	0.01	0.992	-3163.963	3195.813
radhlw3	.0197321	.0147075	1.34	0.180	-.0090941	.0485583
havmil	.0234742	.0160068	1.47	0.143	-.0078985	.054847
avgcumdosew3	.1032883	.1755565	0.59	0.556	-.240796	.4473726
bf1	-.4769574	.3289335	-1.45	0.147	-1.121655	.1677405
bf4	-.1442369	.2873042	-0.50	0.616	-.7073429	.4188691
bf2	.0000186	.0002978	0.06	0.950	-.0005651	.0006023
bf4m	-.1956152	.2497206	-0.78	0.433	-.6850586	.2938281
bf5m	-.0071533	.0043294	-1.65	0.098	-.0156388	.0013321
bf7m	.0000185	.0010386	0.02	0.986	-.0020172	.0020542
bf8	-.0000173	.0000922	-0.19	0.851	-.0001981	.0001635
bf15m	0	(omitted)				
bf17	0	(omitted)				
bf20	.4362509	.3222411	1.35	0.176	-.1953299	1.067832
bf22	.0001349	.0003106	0.43	0.664	-.0004739	.0007437
bf29	0	(omitted)				
bf30	-.0009931	.0006553	-1.52	0.130	-.0022775	.0002912
bf40	.5185801	.3611964	1.44	0.151	-.1893518	1.226512
deaw3	.2097501	.3135963	0.67	0.504	-.4048875	.8243876
dvcew3	2.012022	1.543197	1.30	0.192	-1.012588	5.036632
sepaw3	-2.054184	1.443349	-1.42	0.155	-4.883097	.7747288
accdw3	.2022258	1.25899	0.16	0.872	-2.265349	2.669801
movew3	-4.177869	1.807922	-2.31	0.021	-7.721331	-.6344073
illw3	-.4549089	.4293751	-1.06	0.289	-1.296469	.3866508
shfamw3	.0141549	.0145895	0.97	0.332	-.0144399	.0427498
shhlw3	.004885	.011315	0.43	0.666	-.0172919	.0270619
shjobw3	-.0003857	.0112584	-0.03	0.973	-.0224516	.0216803
shrelaw3	-.008433	.0120996	-0.70	0.486	-.0321477	.0152817
suprtw3	.0050194	.0152005	0.33	0.741	-.0247729	.0348118
suchrw3	-.0175411	.0097951	-1.79	0.073	-.0367391	.0016569
havmilsq	-.000046	.0000341	-1.35	0.178	-.0001129	.0000209
radhlw3	0	(omitted)				
avgcumdosew3	0	(omitted)				
_cons	-25.70032	13.82795	-1.86	0.063	-52.80261	1.40197

Note: 8 failures and 0 successes completely determined.

```

title3 : trimmed hp2hmcare main effects models for H1 no direct dose effect fo
> r male
1 Jul 2012
20:40:46
computer Macintosh (Intel 64-bit)
folder /Users/robertyaffee/Documents/data/research/chwk/phase3/Htests/H1tests
> /hlpt2
Data file chwide1jul2012.dta currently has 2402 variables and 703 obser
> vations

```

	hp2hmc~e	age	deaw3	shjobw3	bf7m	shjobw3	havmilsq
hp2hmcare	1.0000						
	340						
age	0.2761*	1.0000					
	0.0000						
	340	340					
deaw3	-0.0456	0.1402	1.0000				
	1.0000	0.2940					
	340	340	340				
shjobw3	-0.1006	-0.2840*	-0.1099	1.0000			
	0.9068	0.0000	0.7935				
	340	340	340	340			
bf7m	-0.1339	-0.0182	0.1015	-0.0869	1.0000		
	0.3860	1.0000	0.8986	0.9848			
	340	340	340	340	340		
shjobw3	-0.1006	-0.2840*	-0.1099	1.0000*	-0.0869	1.0000	
	0.9068	0.0000	0.7935	0.0000	0.9848		
	340	340	340	340	340	340	
havmilsq	-0.0347	0.0207	0.0454	-0.0558	-0.0420	-0.0558	1.0000
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
	340	340	340	340	340	340	340
radhlw3	0.2838*	0.3440*	-0.0287	0.0799	0.1399	0.0799	-0.0586
	0.0000	0.0000	1.0000	0.9959	0.2988	0.9959	1.0000
	340	340	340	340	340	340	340
avgcumdosew3	0.0272	0.1187	0.0324	-0.0140	0.0339	-0.0140	-0.0471
	1.0000	0.6490	1.0000	1.0000	1.0000	1.0000	1.0000
	340	340	340	340	340	340	340

	radhlw3 avgcum~w3	
radhlw3	1.0000	
	340	
avgcumdosew3	0.0721	1.0000
	0.9994	
	340	340

For males hp2hmcare on wave3 and d3 is not signif

Logistic regression

Number of obs = 340

LR chi2(7) = 52.51

Prob > chi2 = 0.0000

Log likelihood = -146.61786

Pseudo R2 = 0.1519

hp2hmcare	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0355627	.0137739	2.58	0.010	.0085664	.062559
deaw3	-.1753451	.1955831	-0.90	0.370	-.558681	.2079907
shjobw3	-.0061002	.0041748	-1.46	0.144	-.0142827	.0020822
bf7m	-.0006241	.0002098	-2.97	0.003	-.0010353	-.0002129
havmilsq	-1.46e-06	2.84e-06	-0.51	0.608	-7.03e-06	4.11e-06
radhlw3	.0182143	.0044455	4.10	0.000	.0095012	.0269274
avgcumdosew3	.0012605	.0491638	0.03	0.980	-.0950988	.0976199
_cons	-3.220671	.8063703	-3.99	0.000	-4.801128	-1.640214

1149 .

1150 . scalar SigDoseVactnMw3 = "no"

1151 . scalar MainEffVactnMw3 = "age bf7m radhlw3 "

> *

```
1165 . di as input "No sig main male dose main effects model"
      No sig main male dose main effects model
```

```
1166 . sw, pr(.1): logit hp2vacatn `myvarlist' if gender==1
              begin with full model
p = 0.8250 >= 0.1000 removing avgcumdosew3
p = 0.4319 >= 0.1000 removing deaw3
p = 0.4230 >= 0.1000 removing havmilsq
p = 0.2153 >= 0.1000 removing shjobw3
```

Logistic regression	Number of obs	=	340
	LR chi2(3)	=	38.31
	Prob > chi2	=	0.0000
Log likelihood = -105.99881	Pseudo R2	=	0.1530

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0582498	.0159119	3.66	0.000	.027063	.0894366
radhlw3	.0163308	.0053758	3.04	0.002	.0057944	.0268671
bf7m	-.0003954	.0002402	-1.65	0.100	-.0008662	.0000754
_cons	-5.639649	.9231625	-6.11	0.000	-7.449014	-3.830284

```
1167 .
1168 .
1169 . local cn8:colnames(e(b))

1170 . di "`cn8'"
      age radhlw3 bf7m _cons

1171 . local len8 = length("`cn8'")
```

```

1172 . di `len7'
      58

1173 . local len8b = `len8' - 6

1174 . di `len8b'
      16

1175 . local myvarlist = substr("`cn8'",1,`len8b')

1176 . di "`myvarlist'"
      age radhlw3 bf7m

1177 .
1178 .
1179 .
1180 . title4 "Trimmed male interaction dose=> vacation plans model"

Trimmed male interaction dose=> vacation plans model

1181 . logit hp2vacatn age radhlw3 ageXd3 bf7m avgcumdosew3 bf4m bf4mXd3 bf7mXd3 i
      > f gender==1

```

```

Iteration 0:  log likelihood = -125.15243
Iteration 1:  log likelihood =  -103.468
Iteration 2:  log likelihood = -95.130161
Iteration 3:  log likelihood = -94.528514
Iteration 4:  log likelihood =  -94.47901
Iteration 5:  log likelihood = -94.478195
Iteration 6:  log likelihood = -94.478195

```

Logistic regression	Number of obs	=	340
	LR chi2(8)	=	61.35
	Prob > chi2	=	0.0000
Log likelihood = -94.478195	Pseudo R2	=	0.2451

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0800514	.0379791	2.11	0.035	.0056137	.1544891
radhlw3	-.0025156	.0070187	-0.36	0.720	-.0162721	.0112409
ageXd3	-.0428824	.0401478	-1.07	0.285	-.1215705	.0358058
bf7m	.0002096	.000436	0.48	0.631	-.0006449	.001064
avgcumdosew3	3.600094	3.230198	1.11	0.265	-2.730977	9.931165
bf4m	-.1155875	.069371	-1.67	0.096	-.2515523	.0203772
bf4mXd3	-.0793872	.0595624	-1.33	0.183	-.1961273	.037353
bf7mXd3	.0002138	.0002797	0.76	0.445	-.0003343	.000762
_cons	-4.31894	3.045103	-1.42	0.156	-10.28723	1.649352

Note: 1 failure and 0 successes completely determined.

```
1182 .
1183 . scalar vactnModMw3 ="none"

1184 .
1185 . di as input "Trimmed Female model wave 3 main effects dose-hp2vacatn model
> "
Trimmed Female model wave 3 main effects dose-hp2vacatn model

1186 . forvalues j=3/3 {
      2. local w3bf bf1 bf4 bf2 bf4m bf5m bf7m bf8 bf15m bf17 bf20 bf22 bf29 bf30
> bf40
      3.
1187 . xi: logistic hp2vacatn age radhlw`j' avgcumdosew`j' ///
> deaw`j' suchrw`j' ///
> if gender==2, coef nolog difficult iterate(50)
      4.
1188 . }
```

```
Logistic regression                                Number of obs   =          363
                                                    LR chi2(5)      =          69.60
                                                    Prob > chi2     =          0.0000
Log likelihood = -132.71672                        Pseudo R2       =          0.2077
```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0916152	.0157813	5.81	0.000	.0606844	.1225459
radhlw3	.0117344	.0050394	2.33	0.020	.0018573	.0216115
avgcumdosew3	.0985606	.0692713	1.42	0.155	-.0372087	.2343299
deaw3	.3433813	.158229	2.17	0.030	.0332581	.6535045
suchrw3	-.0061918	.0037117	-1.67	0.095	-.0134666	.0010831
_cons	-7.50211	.9350027	-8.02	0.000	-9.334682	-5.669539

```

1189 .
1190 . scalar SigDoseVactnMw3 = "no"

1191 .
1192 . * summary of male moderating effects: no sign main dose effect in main effe
    > cts model
1193 . *          no signif male moderators
1194 . *          3 significant main effects in main effects model
1195 .
1196 . * summary of female moderation main effects: no signif main dose effect
1197 . *          3 signif main effects
1198 .
1199 . local cn9:colnames(e(b))

1200 . di "`cn9'"
      age radhlw3 avgcumdosew3 deaw3 suchrw3 _cons

1201 . local len9 = length("`cn9'")

1202 . di `len9'
      44

1203 . local len9b = `len9' - 6

1204 . di `len9b'
      38

1205 . local myvarlist = substr("`cn9'",1,`len9b')

1206 . di "`myvarlist'"
      age radhlw3 avgcumdosew3 deaw3 suchrw3

1207 .
1208 .
1209 . foreach var in `myvarlist' {
      2.   cap gen `var'Xd3 = `var'*avgcumdosew3
      3.   }

```

```

1210 .
1211 .
1212 . * female dose vacatn w3 models
1213 .
1214 . title4 "trimmed hp2vacatn wave3 main effects models for H1"

```

```
trimmed hp2vacatn wave3 main effects models for H1
```

```

1215 . di as input "For females hp2vacatn on wave3"
      For females hp2vacatn on wave3

```

```

1216 . sw, pr(.1):logit hp2vacatn `myvarlist' if gender==2
              begin with full model
p = 0.1548 >= 0.1000 removing avgcumdosew3
p = 0.1174 >= 0.1000 removing suchrw3

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(3)       =       65.18
                                                    Prob > chi2      =       0.0000
Log likelihood = -134.92371                      Pseudo R2        =       0.1946

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0872837	.0154104	5.66	0.000	.0570799	.1174875
radhlw3	.0131054	.0049947	2.62	0.009	.003316	.0228948
deaw3	.2791769	.1537034	1.82	0.069	-.0220763	.5804301
_cons	-7.430633	.9404734	-7.90	0.000	-9.273927	-5.587339

```
1217 . estat class
```

```
Logistic model for hp2vacatn
```

Classified	True		Total
	D	~D	
+	15	5	20
-	48	295	343
Total	63	300	363

Classified + if predicted $\Pr(D) \geq .5$
 True D defined as hp2vacatn != 0

Sensitivity	$\Pr(+ D)$	23.81%
Specificity	$\Pr(- \sim D)$	98.33%
Positive predictive value	$\Pr(D +)$	75.00%
Negative predictive value	$\Pr(\sim D -)$	86.01%
False + rate for true $\sim D$	$\Pr(+ \sim D)$	1.67%
False - rate for true D	$\Pr(- D)$	76.19%
False + rate for classified +	$\Pr(\sim D +)$	25.00%
False - rate for classified -	$\Pr(D -)$	13.99%
Correctly classified		85.40%

1218 . estat gof

Logistic model for hp2vacatn, goodness-of-fit test

number of observations =	363
number of covariate patterns =	291
Pearson chi2(287) =	335.34
Prob > chi2 =	0.0261

1219 . fitstat

Measures of Fit for **logit** of **hp2vacatn**

Log-Lik Intercept Only:	-167.516	Log-Lik Full Model:	-134.924
D(359):	269.847	LR(3):	65.185
		Prob > LR:	0.000
McFadden's R2:	0.195	McFadden's Adj R2:	0.171
Maximum Likelihood R2:	0.164	Cragg & Uhler's R2:	0.273
McKelvey and Zavoina's R2:	0.341	Efron's R2:	0.227
Variance of y*:	4.992	Variance of error:	3.290
Count R2:	0.854	Adj Count R2:	0.159
AIC:	0.765	AIC*n:	277.847
BIC:	-1846.243	BIC':	-47.501

```

1220 .
1221 . scalar SigDoseVactnFw3 = "no"

1222 . scalar MainEffVactnFw3 = "age radhlw3 deaw3"

1223 .
1224 . di as result " Full moderator model for females for dose=> Vacation plans"
      Full moderator model for females for dose=> Vacation plans

1225 . logit hp2vacatn age radhlw3 deaw3 suchrw3 avgcumdosew3 ageXd3 radhlw3Xd3 dea
      > w3Xd3  ///
      >      suchrw3Xd3 havmilsq if gender==2

```

```

Iteration 0:  log likelihood =  -167.516
Iteration 1:  log likelihood = -131.66933
Iteration 2:  log likelihood = -127.22328
Iteration 3:  log likelihood = -127.01792
Iteration 4:  log likelihood = -127.01661
Iteration 5:  log likelihood = -127.0166

```

Logistic regression	Number of obs	=	363
	LR chi2(10)	=	81.00
	Prob > chi2	=	0.0000
Log likelihood = -127.0166	Pseudo R2	=	0.2418

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.1051773	.0237507	4.43	0.000	.0586268	.1517279
radhlw3	.0086474	.0071994	1.20	0.230	-.0054632	.0227581
deaw3	-.018111	.2299772	-0.08	0.937	-.4688582	.4326361
suchrw3	-.0131465	.0051799	-2.54	0.011	-.0232988	-.0029941
avgcumdosew3	-.4455554	1.249774	-0.36	0.721	-2.895067	2.003957
ageXd3	-.0067688	.0178685	-0.38	0.705	-.0417904	.0282529
radhlw3Xd3	.0045845	.0048868	0.94	0.348	-.0049935	.0141625
deaw3Xd3	.3320908	.1608104	2.07	0.039	.0169081	.6472735
suchrw3Xd3	.0055826	.0032326	1.73	0.084	-.0007533	.0119184
havmilsq	-3.31e-07	8.64e-07	-0.38	0.701	-2.02e-06	1.36e-06
_cons	-7.357805	1.47262	-5.00	0.000	-10.24409	-4.471523

```

1226 .
1227 . di as result "trimmed female moderator model for dose=> vacation plans"
      trimmed female moderator model for dose=> vacation plans

1228 . logit hp2vacatn age avgcumdosew3 suchrw3 deaw3 deaw3Xd3 if gender==2

```

```

Iteration 0:  log likelihood =  -167.516
Iteration 1:  log likelihood = -136.37785
Iteration 2:  log likelihood = -133.24846
Iteration 3:  log likelihood = -133.21681
Iteration 4:  log likelihood = -133.21679
Iteration 5:  log likelihood = -133.21679

```

```

Logistic regression                                Number of obs   =       363
                                                    LR chi2(5)      =       68.60
                                                    Prob > chi2     =       0.0000
Log likelihood = -133.21679                      Pseudo R2      =       0.2048

```

hp2vacatn	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0997666	.0154683	6.45	0.000	.0694493	.1300839
avgcumdosew3	.0469958	.0857324	0.55	0.584	-.1210366	.2150283
suchrw3	-.0068988	.0037456	-1.84	0.065	-.01424	.0004423
deaw3	.1355918	.2007115	0.68	0.499	-.2577956	.5289792
deaw3Xd3	.2112882	.1167631	1.81	0.070	-.0175632	.4401397
_cons	-7.069816	.8971072	-7.88	0.000	-8.828114	-5.311518

```

1229 .
1230 . scalar VacatnModFw3 = "none"

1231 . *xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
    > xxxx
1232 . cap gen hp2vactn = HP2vacatn

1233 . title4 "Chunk 9 HP2vacatn plans mediator models for males"

```

Chunk 9 HP2vacatn plans mediator models for males

```

1234 .
1235 . * age is a mediator for males
1236 . glm age avgcumdosew3 if gender==1, fam(gaus) link(identity)

```

Iteration 0: log likelihood = **-1330.6336**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	147.7142
Deviance = 49927.38549	(1/df) Deviance	=	147.7142
Pearson = 49927.38549	(1/df) Pearson	=	147.7142
Variance function: V(u) = 1	[Gaussian]		
Link function : g(u) = u	[Identity]		
	<u>AIC</u>	=	7.839021
Log likelihood = -1330.633586	<u>BIC</u>	=	47957.2

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.5433648	.2472657	2.20	0.028	.058733	1.027997
_cons	48.52021	.7247376	66.95	0.000	47.09975	49.94067

```

1237 . 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.)

```
1238 .
1239 . * illness is a mediating effect for males = > vacatn for men
1240 . des illw3
```

variable name	storage type	display format	value label	variable label
illw3	double	%8.0g		Total number of illnesses experienced in time period 1996-NOW

```
1241 . glm illw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-461.99206**

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	.8919217
Deviance = 301.469521	(1/df) Deviance	=	.8919217
Pearson = 301.469521	(1/df) Pearson	=	.8919217

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

	<u>AIC</u>	=	2.729365
Log likelihood = -461.9920626	<u>BIC</u>	=	-1668.714

illw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.038211	.0192139	1.99	0.047	.0005524	.0758696
_cons	.4504952	.0563162	8.00	0.000	.3401176	.5608729

```
1242 . glm hp2vactn illw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =  247.0817
Iteration 2:  deviance =  245.9165
Iteration 3:  deviance =  245.9101
Iteration 4:  deviance =  245.9101
Iteration 5:  deviance =  245.9101
```

```
Generalized linear models                No. of obs      =       340
Optimization      :  MQL Fisher scoring  Residual df      =       338
                    (IRLS EIM)          Scale parameter =         1
Deviance          =  245.9100555         (1/df) Deviance =  .7275445
Pearson           =  334.9802312         (1/df) Pearson  =  .9910658
```

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

```
BIC                                     = -1724.274
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.1787158	.0693787	2.58	0.010	.0427362	.3146955
_cons	-1.278417	.0876012	-14.59	0.000	-1.450112	-1.106721

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

```
1243 .
```

```
1244 . des radhlw3
```

variable name	storage type	display format	value label	variable label
radhlw3	double	%8.0g		Self-perceived Chornobyl health threat in wave 3

```
1245 . glm radhlw3 avgcumdosew3 if gender==1, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -1695.1855
```

Generalized linear models	No. of obs	=	340
Optimization : ML	Residual df	=	338
	Scale parameter	=	1261.052
Deviance = 426235.7205	(1/df) Deviance	=	1261.052
Pearson = 426235.7205	(1/df) Pearson	=	1261.052

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

	AIC	=	9.983444
Log likelihood = -1695.185473	BIC	=	424265.5

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	.9606492	.7224692	1.33	0.184	-.4553645	2.376663
_cons	46.19995	2.117563	21.82	0.000	42.0496	50.3503

```
1246 . glm hp2vactn radhlw3 if gender==1, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 235.0568
Iteration 2: deviance = 230.1721
Iteration 3: deviance = 230.0122
Iteration 4: deviance = 230.0119
Iteration 5: deviance = 230.0119
```

Generalized linear models	No. of obs	=	340
Optimization : MQL Fisher scoring (IRLS EIM)	Residual df	=	338
	Scale parameter	=	1
Deviance = 230.0118626	(1/df) Deviance	=	.6805085
Pearson = 338.3882304	(1/df) Pearson	=	1.001149

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

BIC	=	-1740.172
-----	---	-----------

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0115045	.0021825	5.27	0.000	.0072269	.0157822
_cons	-1.814894	.1529622	-11.86	0.000	-2.114694	-1.515093

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

```
1247 .
1248 . title4 "HP2vacatn plans mediator models for females"
```

HP2vacatn plans mediator models for females

```
1249 .
1250 . * age is a mediator for females
1251 . glm age avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1408.064**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	137.7687
Deviance = 49734.51399	(1/df) Deviance	=	137.7687
Pearson = 49734.51399	(1/df) Pearson	=	137.7687

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

	<u>AIC</u>	=	7.768948
Log likelihood = -1408.06405	<u>BIC</u>	=	47606.63

age	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	1.058366	.3512614	3.01	0.003	.3699069	1.746826
_cons	48.94293	.7468173	65.54	0.000	47.47919	50.40666

```
1252 . 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.)

```
1253 .
1254 . * illness is a mediating effect for females = > vacatn
1255 . des illw3
```

variable name	storage type	display format	value label	variable label
illw3	double	%8.0g		Total number of illnesses experienced in time period 1996-NOW

```
1256 . glm illw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

```
Iteration 0: log likelihood = -562.81042
```

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1.308042
Deviance = 472.2033151	(1/df) Deviance	=	1.308042
Pearson = 472.2033151	(1/df) Pearson	=	1.308042

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

	<u>AIC</u>	=	3.111903
Log likelihood = -562.8104237	<u>BIC</u>	=	-1655.676

illw3	OIM					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
avgcumdosew3	.1284565	.0342268	3.75	0.000	.0613733	.1955398	
_cons	.5563644	.0727696	7.65	0.000	.4137387	.6989902	

```
1257 . glm hp2vactn illw3 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1: deviance = 334.6961
Iteration 2: deviance = 334.6441
Iteration 3: deviance = 334.6441
Iteration 4: deviance = 334.6441
```

Generalized linear models	No. of obs	=	363
Optimization : ML Fisher scoring	Residual df	=	361
(IRLS EIM)	Scale parameter	=	1
Deviance = 334.644123	(1/df) Deviance	=	.926992
Pearson = 362.8044598	(1/df) Pearson	=	1.004999

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

	BIC	=	-1793.235
--	-----	---	-----------

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
illw3	.041243	.0622857	0.66	0.508	-.0808348	.1633209
_cons	-.9706284	.0880746	-11.02	0.000	-1.143252	-.7980053

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

```
1258 .
1259 . * radhlw3 is a mediating effect for females => vactn
1260 . des radhlw3
```

variable name	storage type	display format	value label	variable label
radhlw3	double	%8.0g		Self-perceived Chernobyl health threat in wave 3

```
1261 . glm radhlw3 avgcumdosew3 if gender==2, fam(gaus) link(identity)
```

Iteration 0: log likelihood = **-1798.7074**

Generalized linear models	No. of obs	=	363
Optimization : ML	Residual df	=	361
	Scale parameter	=	1185.454
Deviance = 427948.9522	(1/df) Deviance	=	1185.454
Pearson = 427948.9522	(1/df) Pearson	=	1185.454

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

	<u>AIC</u>	=	9.921253
Log likelihood = -1798.707367	<u>BIC</u>	=	425821.1

radhlw3	OIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avgcumdosew3	2.751602	1.03038	2.67	0.008	.7320943	4.77111
_cons	57.70689	2.190692	26.34	0.000	53.41321	62.00057

```
1262 . glm hp2vactn radhlw3 if gender==2, fam(bin) irls scale(dev) link(probit)
```

```
Iteration 1:  deviance =   316.824
Iteration 2:  deviance =   314.9168
Iteration 3:  deviance =   314.905
Iteration 4:  deviance =   314.905
Iteration 5:  deviance =   314.905
```

```
Generalized linear models                               No. of obs      =       363
Optimization      :  ML Fisher scoring                Residual df     =       361
                   (IRLS EIM)                          Scale parameter =         1
Deviance          =   314.9050287                      (1/df) Deviance =   .8723131
Pearson           =   371.6251351                      (1/df) Pearson  =   1.029433
```

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

```
BIC = -1812.974
```

hp2vactn	EIM					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
radhlw3	.0106148	.0023181	4.58	0.000	.0060715	.0151582
_cons	-1.651184	.179583	-9.19	0.000	-2.003161	-1.299208

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

```
1263 .
1264 . * summary of male moderating effects: no sign main dose effect in main effe
> cts model
1265 . *          no signif male moderators
1266 . *          3 significant main effects in main effects model
1267 .
1268 . scalar VactnMedMw3 = "age illw3"

1269 . scalar VactnMedFw3 = "age illw3 radhlw3"
```

```

1270 .
1271 . *xx summary of moderator effects for females:
1272 .     * no signif main dose effect
1273 .     * 3 signif main effects in main effect model
1274 .     * 1 moderator: deaw3Xd3
1275 . title4 "7. SUMMARY MATRIX of dose - vacation plans impact"

```

```

7. SUMMARY MATRIX of dose - vacation plans impact

```

```

1276 . set more off

1277 .     matrix define HP2vactnMw3 = J(1,8, 0)

1278 .           matrix define HP2vactnFw3 = J(1,8, 0)

1279 . matrix colnames HP2vactnMw3=  hypnum ptnum wave gender medsig numMA sig numMo
    > dsig numMed

1280 . matrix colnames HP2vactnFw3=  hypnum ptnum wave gender medsig numMA sig numMo
    > dsig numMed

1281 .     matrix define HP2vactnMw3= (1, 2, 3, 1, 0, 3, 0, 2 )

1282 .           matrix define HP2vactnFw3= (1, 2, 3, 2, 0, 3, 1, 3 )

1283 .           matrix rowname HP2vactnMw3 = HP2vactnM

1284 .           matrix rowname HP2vactnFw3 = HP2vactnF

1285 .           matlist HP2vactnMw3

```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2vactnM	1	2	3	1	0	
> 3						

	c7	c8
HP2vactnM	0	2

```
1286 .      matlist HP2vactnFw3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
HP2vactnF	1	2	3	2	0	
> 3						
	c7	c8				
HP2vactnF	1	3				

```
1287 . matrix define H1pt2w3=(HP2wkMw3 \ HP2wkFw3 \ HP2hmcrMw3 \ HP2hmcrFw3 \ HP2sp
> Mw3 \ HP2spFw3 \ HP2prbfamMw3 \ HP2prbfamFw3 \ HP2inthbMw3 \ HP2inthbFw3 \ H
> P2vactnMw3 \ HP2vactnFw3 )
```

```
1288 .
```

```
1289 .      matlist H1pt2w3
```

	c1	c2	c3	c4	c5	c
> 6						
> —						
r1	1	2	3	1	0	
> 4						
r1	1	2	3	2	0	
> 1						
r1	1	2	3	1	0	
> 4						
r1	1	2	3	2	0	
> 2						
HP2spMw3	1	2	3	1	0	
> 2						
HP2spFw3	1	2	3	2	1	
> 5						
HP2prbfamM	1	2	3	1	0	
> 5						
HP2prbfamF	1	2	3	2	0	
> 2						
HP2inthbM	1	2	3	1	0	
> 3						
HP2inthobF	1	2	3	2	0	
> 3						
HP2vactnM	1	2	3	1	0	
> 3						
HP2vactnF	1	2	3	2	0	
> 3						

	c7	c8
r1	0	4
r1	0	6
r1	0	2
r1	0	2
HP2spMw3	0	1
HP2spFw3	5	3
HP2prbfamM	0	1
HP2prbfamF	2	2
HP2inthbM	0	2
HP2inthobF	0	3
HP2vactnM	0	2
HP2vactnF	1	3

```
1290 .      matrix colnames H1pt2w3 =  hypnum ptnum wave gender medsig numMASig numM
> odsig numMed
```

```
1291 . matrix rownames H1pt2w3 =HP2wkMw3 HP2wkFw3 HP2hmcrMw3 HP2hmcrFw3 HP2socprbMw
> 3 HP2socprbFw3 HP2prbfamMw3 HP2prbfamFw3 HP2inthbMw3 HP2inthbFw3 HP2vacatnMw
> 3 HP2vacatnFw3
```

```
1292 .      matlist H1pt2w3
```

	hypnum	ptnum	wave	gender	medsig	numMASi
> g						
> —						
HP2wkMw3	1	2	3	1	0	
> 4						
HP2wkFw3	1	2	3	2	0	
> 1						
HP2hmcrMw3	1	2	3	1	0	
> 4						
HP2hmcrFw3	1	2	3	2	0	
> 2						
HP2socprbMw3	1	2	3	1	0	
> 2						
HP2socprbFw3	1	2	3	2	1	
> 5						
HP2prbfamMw3	1	2	3	1	0	
> 5						
HP2prbfamFw3	1	2	3	2	0	
> 2						
HP2inthbMw3	1	2	3	1	0	
> 3						
HP2inthbFw3	1	2	3	2	0	
> 3						
HP2vacatnMw3	1	2	3	1	0	

```
> 3
HP2vacatnFw3 |          1          2          3          2          0
> 3
```

	numModsig	numMed
HP2wkMw3	0	4
HP2wkFw3	0	6
HP2hmcrMw3	0	2
HP2hmcrFw3	0	2
HP2socprbMw3	0	1
HP2socprbFw3	5	3
HP2prbfamMw3	0	1
HP2prbfamFw3	2	2
HP2inthbMw3	0	2
HP2inthbFw3	0	3
HP2vacatnMw3	0	2
HP2vacatnFw3	1	3

```
1293 .
1294 .
1295 .
1296 .
1297 .
1298 .
1299 . sjlog close, replace
```